Grant Agreement number: 265603
Project title: **Small Air Transport - Roadmap**

Instrument: Coordination and Support Action - Support Action (CSA-SA)

SEVENTH FRAMEWORK PROGRAMME

Deliverable reference number and title:

D1.2 Small air transport aircraft demand

Organization name of lead contractor for this deliverable: **Institute of Aviation**

Date of report preparation: January - June, 2011	Date of report issue: June 30, 2011
Deliverable: **D1.2 Small air transport aircraft demand** Task: T1.2.1 Small Air transport Aircraft Characteristics to be used for Demand Calculation	Version/Status: **V1** (draft: a,b,c; final: 0,1,2,3)

Approval Status (date, signature)		
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Project coordinator organization name: **INSTITUTE of AVIATION**	Duration: 18 month

Project funded by the European Commission within the Seventh Framework Programme (2007-2013)		
Dissemination		
PU	Public	X
PP	Restricted to other programme participants (including the Commission Services)	
RE	Restricted to a group specified by the consortium (including the Commission Services)	
CO	Confidential, only for members of the consortium (including the Commission Services)	

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Document Change Log:

Version	Author /Organisation	Date of Release	Description of the release	Modifications (sections affected and relevant information)
a	I. Laplace/M3S	2011/02/21	Document initialization	Draft document
1	I. Laplace/M3S	2011/06/30	Finalised document	All

Document Distribution List:

Number	Company	Company's short name	Company's Country	Name of the Company's Project Manager	Marking
1	Instytut Lotnictwa	ILOT	Poland	Krzysztof PIWEK	X
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1 EXECUTIVE SUMMARY

If different scenarios can be envisaged for the future European Transport System, one future element of such an advanced transport system will be transportation using small aircraft and small/regional airports.
SATS (Small Aircraft Transport System) aims at the segment of the transport market that is not served by scheduled air transport to fill a gap, which exists between Surface Transport and regular mass Air Transport. The challenge is to create a new mode of European transport by wider use of small aircraft using small and regional airports, enabling access to more communities in less time.
In the EPATS project, a gross estimation of the potential transfer of traffic to small air transport was made and showed that 7% (96 billon pas.km) of the future car travel (by means of affordable operating costs) in 2020 could be shifted to SATS. This would require a fleet of 89 000 small aircraft (4 to 19 seats), and generate up to 40 million flights per year
However, EPATS only provided preliminary results and it is necessary to refine the model to get more accurate estimations.
This report presents the refined demand model as well as the sensitivity of this model to changes in some parameters values.

2 PROJECT & REPORT OBJECTIVES

2.1 A vision of the European Transport System

Different scenarios can be envisaged for the future European Transport System depending on many factors (social needs, economy, fossil oil price and availability, environmental concerns, climate change, political choices and stability). A possible visionary European Transport System should be based on an environmentally sustainable, cost efficient, safe, seamless and co-modal passenger friendly system aiming to ensure mobility and cohesion for the European citizens while enabling economic growth.

"*More people and greater economic affluence mean more mobility and more transport. Some studies suggest that the number of cars in the world will increase from around 700 million today to more than 3 billion in 2050, creating serious sustainability problems unless there is a transition towards lower and zero-emission vehicles and a different concept of mobility is introduced in an environmentally friendly way.*"

Communication from the European Commission. A sustainable future for transport: towards an integrated, technology-led and user friendly system. Brussels, 17 June 2009 (European Commission 2009).

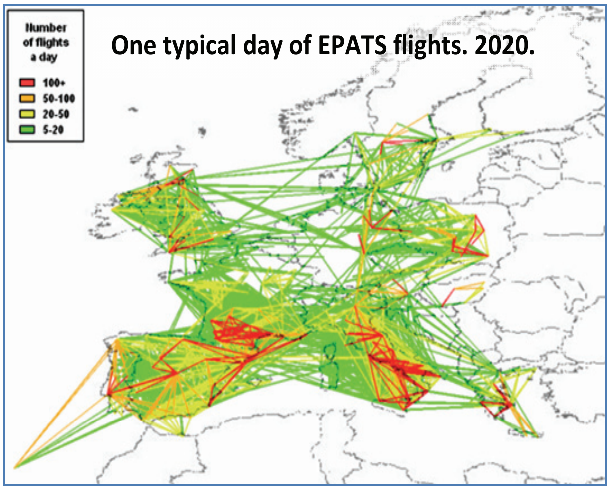
One future element of such an advanced transport system will be **transportation using small aircraft and small/regional airports**. This new transport mode will enable fast travel in areas of Europe where high speed trains or traditional airline connections are unavailable and will alleviate road congestion problems in a customer - and environmentally friendly way.

"general and business aviation complements regular air transport performed by commercial airlines and thus provides specific social and economic benefits such as increasing the mobility of citizens, the productivity of businesses and regional cohesion ".

European Parliament Resolution of 3 Feb 2009 on an Agenda for Sustainable Future in General and Business Aviation (European Parliament 2009).

2.2 What is the Small Aircraft Transport System (SATS)?

SATS aims at the segment of the transport market that is not served by scheduled air transport or high speed trains, resulting in a substantial need for road travel for short to medium distances, or to answer the specific needs of e.g. business, or to overcome a lack of an efficient mobility transport system.
The small aircraft transport mode provides to **fill a gap,** which exists between **Surface Transport** and regular mass **Air Transport.**



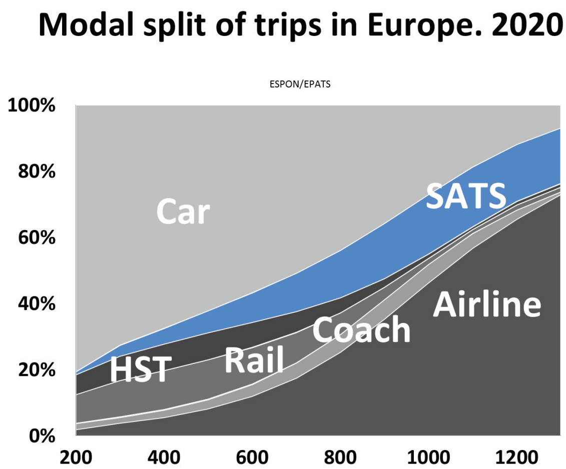
EUROCONTROL, D3.1 EPATS ATM, 2008 [3]

The challenge is to create a new mode of European transport by wider use of small aircraft using small and regional airports, enabling access to more communities in less time.
The main idea is to shift a substantial part of medium/long distance passenger car trips to small aircraft transportation to improve the efficiency of passenger transport, relief the congestion on roads and thus improving the environmental concern. Taking into account the travel cost and the value of time saved by air travel, SATS will offer an attractive alternative to travel by car for distances greater than 200 kilometers.

The Small Aircraft Transport System will use small 4 to 19 seater aircraft, single pilot crew and automated control & guidance, flying IFR operations, with propulsion systems that are tailored to the missions, using the network of regional airports, supported by appropriate ATM-ATC systems and an ICT infrastructure (Information and Communication Technology) to provide on-board network services, operational and administrative procedures. ((EUROCONTROL 2008), (EPATS Consortium 2008), (Institute of Aviation 2009), (Baron s.d.), (Baron, Mączka and Piwek, The Challenge of mobility in Europe n.d.))

2.3 The market potential of SATS

EPATS-STUDY showed that small aircraft transportation is beneficial for business travel in Europe, especially in southern France, Spain, Portugal and Italy, as well as in Eastern Europe (EPATS Consortium, EPATS T1.2 Airports and Facilities Data Base 2007), adding a new relevant market towards the current business aviation market which is currently more mature between London and Milano.



The EPATS project showed that **7% (96 billon pas.km) of the future car travel** (by means of affordable operating costs**) in 2020 could be shifted to SATS.** This would require **a fleet of**

89 000 small aircraft (4 to 19 seats), and generate up to **40 million flights per year** (Laplace I. 2008).

Such estimations were made with assumptions for 2020 available in 2008. Since this date, the world economic crisis raised and led to review the assumptions to be used for forecasts; especially in terms of fuel prices. Besides, the necessity of an update of the SATS demand estimation with new assumptions, a refinement of the model would also be interesting so as to provide more accurate estimations for 2020.

This report aims therefore at presenting this refined estimation of the potential traffic of SATS. To do this refinement, the first step consists of reviewing the different applicable demand model (including the estimation method developed in the context of the EPATS project), so as to identify the most relevant model in the context of SATS, taking in consideration data availability as well as complexity of the model. This state of the art is presented in chapter 3.

The following step consists of applying this relevant estimation method to the case of SATS, what is presented in chapter 4. This chapter deals first of all with the drivers of the SATS demand so as to be able to build the adapted model structure for the SATS demand model.

Results of the estimation are shown in chapter 5 for each considered scenario, while the chapter 6 presents a sensitivity analysis of the obtained estimation to changes in the values of several model parameters as for instance the fuel price value.

The last step of this estimation then remains in the validation of the obtained results. The validation is based on the feedbacks of operational people on these results and is presented in chapter 6.

The report ends by the conclusion in chapter 7.

3 STATE OF THE ART OF APPLICABLE DEMAND MODELS

This chapter presents the different existing demand forecasting models including the demand model developed in the EPATS project (Laplace I. 2008). The objective is to highlight the lacks advantages/disadvantages of each demand model to finally be able to identify the most suitable model to estimate the potential demand of small air transport (SAT).

3.1 Demand forecasting definition

Before anything can be said on the different types of demand forecasting models, first the concept of demand needs to be clarified. In his book "Straight and Level", Holloway (2008) (Holloway 2008) provides the following definition for demand. He states that: "Demand is the quantity of a product that customers are willing and able to purchase over a defined period of time."

In this definition three factors can be distinguished which determine the demand as a numerical quantity. First there is a group of people who are willing to purchase a product or service. This group is then reduced by the people who have the resources and intention to purchase the product. Finally to be able to quantize the concept of the demand, time is restricted to a finite period.

Both Holloway (Holloway 2008) and Doganis (Doganis 2002) mention three types of demand forecasting, which are used to forecast the demand for transportation with. These three types are Qualitative Methods, Time-series projections and Econometric/Causal methods.

In the early days of demand forecasting, often a qualitative method was used to predict the demand for the years to come. As more and more demand data was gathered on past years, time-series analyses came into use (Ortzar J.d.D. 2008). Finally as more elaborated transportation models were presented, causal and econometric came into play.

3.2 Qualitative method

An example of this method is the Delphi method. It depends on the judgment of industry experts who provide their opinions on the demand for the years to come. They use their knowledge of the current and past trends of passenger demand to estimate the future demand.

This is a very low-cost method which does not take long, but also is the least reliable as it is completely dependent on the views of one or more persons. Today this method is usually used by airlines to verify the outcome of the time-series projections or econometric analyses (Doganis 2002). For a practical example of the Delphi-method the reader is referred to the work of Mason and Alamdari (Mason K.J 2007).

3.3 Time-Series analysis

The main objective of this method is to simulate the demand trend for a given time period, based on known demand figures of the past (Andreoni-Postorino 2006). For example if the traffic flow between two regions over the last ten years is known, time series analysis can be used to determine the traffic flows for the years to come. Doganis (Doganis 2002) recommends in his book not to forecast a longer period ahead than about half the number of past years for which you have the data available. According to Brockwell and Davis (Brockwell P.J. 2002), the biggest disadvantage of time series analysis is that although the model is able to determine what will happen in the future, it cannot determine the reason for it. Therefore they call the time-series analysis method a black-box method. This is also the reason why they state that there is only value in using time-series analysis on the short-term. The main assumption on which the method

is based is that in the future things will continue as they were in the past. As the chance that unexpected events will happen increases when forecasting over more years, the value of the forecast decreases.

3.4 Causal or Econometric methods

This method forecasts the demand on the disaggregate level of the individual rather than on the aggregate level of overall traffic flow data on a certain connection as is the case for time-series analysis. The model consists out of a range of variables which all have an influence on the choice of a person for a certain alternative. By combining these variables with coefficients that are determined using maximum likelihood estimations and survey data, the modal choice is related to the decision maker. For a detailed overview of maximum likelihood estimation methods, the reader is referred to the book written by Train (Train 2009).
Examples of variables relating the modal choice to the decision maker, for the case of air transport demand forecasting model, are personal income and travel time. Not only objective variables, like travel time, but also subjective variables, like comfort level, can be added to the model. This of course only if enough stated preference data, for the sample to be representable for the entire population, can be gathered.
As the personal transportation market is a new market, no data is available on traffic flows of past years. This means that time-series analysis cannot be used as a forecasting tool as it relies completely on traffic flow data of past years. For the same reason, qualitative methods cannot be used as a forecasting tool. As the transport mode has yet to prove itself, it is difficult for industry experts to provide estimations based on trends of the past and an economic outlook of the future.
This has as a consequence that the model, which will be developed during this project, will have to be one of the causal/econometric family.

3.4.1 Discrete choice models

This model type produces forecasts based on traveler input data and transport mode characteristics, but not on traffic flow data. Because they do not depend on past traffic flows, the causal model is the main method used today to determine and forecast travel demand in emerging markets or estimate the impact of infrastructural changes (de Jong G. 2007). They can be used to estimate the potential future traffic flows of a transport mode and this way are a tool in the investigation of the possible consequences of future policies. de Jong et al. (de Jong G. 2007) provide the following definition for a causal model:
"it is a series of equations combining exogenous variables (the inputs) and coefficients that express how the endogenous variables (the outputs), such as travel demand or link flows, depend on the exogenous variables."
These exogenous variables are usually of a socio-economic nature. An example of such a socio-economic variable is GDP. There is a rule of thumb in the airline industry that demand for air travel in the world is related to the growth of the World Gross Domestic Product (WGDP) (Doganis 2002).
They have a wide range of applications and are not bound to forecasting transportation demand, although it is one of their main uses. You can use causal modeling to model any consumer choice ranging from the color of the car they buy to the mode of transport they will choose to get to work. As long as you can get enough observed variables that can relate the consumer to the choice for certain alternatives, the probability of the consumer choosing that alternative can be determined (Train 2009). The goal of this section is to investigate how causal models have been used in the past to forecast demand and how they are build up. This will be done by first looking at the theory behind them and then investigating two practical applications of two different causal models.

Train (Train 2009) defines discrete choice models in the following way:
"*Discrete choice modeling is part of the field of econometrics, which uses statistical techniques to evaluate and test economic theories*".

3.4.1.1 Discrete choice model theory

Over the years, different forms of discrete choice models have been developed and every time the limits of their use have been expanded further. The models can be divided into two major families: the logit models and the probit models (Train 2009). The basic logit model will be discussed in depth, as the literature review showed that this model is used in most of the cases.

The nested and mixed logit model can be considered as an expansion of the basic logit model and therefore only their improvements and restrictions will be stated. The probit model is hardly used in transport models as it requires extensive mathematical procedures and a very detailed input database to evaluate the choice probabilities. Therefore only the basic principles of this method will be stated in this literature review. For a detailed analysis of these models the reader is referred to the book by Train (2009). Before explaining the actual model, first the concept of utility, on which all the discrete choice models are based, must be explained.

Utility theory

In 1960, the concept of utility was derived for the first time by Marschak (Train 2009). According to Train (Train 2009), the models, based on utility maximization behavior, describe the relation of explanatory variables to the outcome of a choice, without reference to exactly how the choice is made. This explanation can be a bit vague; therefore the following mode choice example is presented to clarify.

When people make choices, they base them on certain attributes related to the alternatives.
For example, a person chooses to take the train instead of his car, because he doesn't like waiting in a traffic jam. In this case one of the attributes that is related to the alternatives is travel time. Another person may prefer the car, because it is cheaper. Therefore travel cost can also be considered as an attribute. These two attributes are both measurable by an observer. The travel time of both modes of transport can be determined and also the cost of each of them. There are also certain attributes that a third party observer cannot identify. An example of such an unobserved factor can be that a person chooses his car, because he does not like being around other people. This is the travelers personal and subjective opinion and is not a variable who's value can be easily looked up by the observer on for example the internet like it is the case for travel time and travel cost.

This is a limitation of the theory. Due to the complexity, and also irrationality, of the human mind, it is impossible to include every variable that plays a part in the decision of the modal choice. This means that utility theory will, even in the best case, always remain an approximation of the reality that it is trying to simulate. This does not mean that the theory is a useless tool. Results of utility theory based models haven proven already in the past that it can be a very accurate approximation of reality, but a lot depends on the situation that the model is trying to approximate (Train 2009). In theory, the observer knows that he has taken into account every attribute that influences the modal choice, when the model can give the correct modal choice decision based on the set of input parameter values of each individual that is inserted to the model.

To summarize, a person's choice for a certain alternative is based on both factors which can be observed by a researcher and factors that are invisible to him.

Train (2009) uses the following representation for the utility model in his book:

$U_{nj} = V_{nj} + \varepsilon_{nj}$

where

n = the decision maker

j = the amount of possible alternatives to choose from

V_{nj} = the representative utility

ε_{nj} = the random utility part

U_{nj} = the total utility of a certain alternative

V_{nj} is the function of observed variables or attributes like travel time and travel cost mentioned in the example above. This part of the utility is also called the representative utility and usually consists out of a linear equation of the different observable attributes. The factor ε_{nj} is the term of unobserved variables. These are factors that cannot be readily measured and therefore the researcher treats these factors as a random error vector. This vector has a probabilistic density dependent on the type of discrete choice model, but this will be explained later on.

Each of the alternatives has its own utility value and following the principle of utility maximization, the consumer will choose the alternative with the highest utility (Train 2009). This does not mean that always the alternative with the highest representative utility is chosen.
For example, alternative A has a representative utility of 4 and an unobserved utility of 1 for a certain traveler. When alternative B has a representative utility of 3 and an unobserved utility of 3, the consumer will choose alternative B. Or stated differently using a practical example. A person can choose between the car or the train to get to work. The car is cheaper than the train therefore, as fare is considered to be very important by most people, the representative utility for the car is 4 and that of train is 3. However, when the traveler takes the car to work, he is not able to talk to his friend who takes the train every day. Therefore, the unobserved utility of the car is equal to 1 while that of the train is 3. Weighing all the pro's and con's and because he values friendship more than the increase in cost, he will choose for the train. This is not a logical choice according to a third party observer as he only knows about the fare and not about the personal reasons. This example does illustrate that it cannot be assumed that the modal choice is only determined by the representative utility part.

Generalizing, the probability that a decision-maker n chooses alternative i can be written in the following way (Train, 2009):

$P_{ni} = Prob(U_{ni} \geq U_{nj}) \forall j \neq i$

What can also be written:

$P_{ni} = Prob(V_{ni} + \varepsilon_{ni} \geq V_{nj} + \varepsilon_{nj}) \forall j \neq i$

This equation can then be re-written to the following one:

$P_{ni} = Prob(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj}) \forall j \neq i$

Stated differently it doesn't matter whether U_{ni} and U_{nj} are 1000 and 998 or 5 and 3 respectively, the decision maker will choose U_{ni} .
For example, consider a model that has personal income as an input variable. The model can show that travelers that belong to a certain income class will always choose alternative A while people belonging to a higher income class will choose alternative B. If it is then also known how

many travelers belong to each of the income groups, the amount of travelers that choose a certain transport mode can be determined.
The main critique on utility theory is that it assumes that each decision maker is a "Homo Economicus". This means that the decision maker is perfectly discriminating and rational in his behavior and therefore will always choose the alternative with the highest utility ((Williams C.W.L 1982); (Jager W. 2000)). In practice however, this is not always the case as people are known for their irrational choices. The next section will elaborate on the different discrete choice models that are available to us today and which are all based on the principle of Utility maximization.

Logit Model

This model is the most popular and widely used of all the discrete choice models. Its wide application is mainly due to the fact that it has a closed-form formula which can evaluate the choice probability of each of the alternatives. This means that the model does not require simulation to be evaluated as is the case for probit models.

As mentioned before, the assumption of how the density of the random vector ε_{nj} is distributed is model specific. For the logit model it is assumed that ε_{nj} is independently, identically distributed (iid) ((Ashiabor S. 2007); (Train 2009)). Independent means that they are mutually independent, i.e. not correlated, and identically means that they all have the same probability distribution (Train 2009). This distribution is also called Gumbel and type I extreme value. The characteristics of a Gumbel distribution are almost the same as those of a normal distribution. The only visual difference is that a Gumbel distribution has fatter tails than a normal one (Train 2009). By assuming that the errors are not correlated to each other, the choice probabilities for each of the alternatives can be determined using a closed-form formula instead of extensive simulation methods. When using a probit model, it is assumed that a correlation does exist between the different error terms and the utility has to be calculated separately for each set of input parameters.

The density function of the ε_{nj} distribution is the following:

$$f(\varepsilon_{nj}) = e^{-\varepsilon_{nj}} \times e^{-e^{-\varepsilon_{nj}}}$$

And the cumulative distribution is:

$$F(\varepsilon_{nj}) = e^{-e^{-\varepsilon_{nj}}}$$

There are multiple ways to interprete this distribution. In his book, Train (Train 2009) answers the question: "What is meant by the distribution of ε_{nj}?". Train (Train 2009) states that the interpretation, that the researcher places on this density, affects the researchers interpretation of the choice probabilities. According to him, the most common interpretation of the unobserved utility part is the following:

First consider a population of travelers who all face the same observed utility V_{nj}. Stated differently, V_{nj} is assumed to be the same for each member of the population1. The unobserved part of utility is different for each member of the population2. The density $f(\varepsilon_{nj})$ is the distribution of the unobserved portion of utility within the population of people that face the same observed utility. Under this interpretation, the probability P_{ni} is the share of people who choose alternative i within the population of people that face the same V_{ni}.
As mentioned above, assuming that the errors or unobserved variables across different alternatives are independent from each other means that the ε_{nj}'s of different alternatives are not correlated to each other in any way (Ashiabor S. 2007). An example where unobserved factors

are related to each other can be illustrated by using the following example. A person needs to choose between driving his car or taking the train to work. An unobserved factor can be that the person does not like people around him and therefore chooses his car. If we add the possibility of taking the bus to work, we can establish that there is a relation between both taking the train and taking the bus to work as both are done while sitting with a lot of other people. Therefore the unobserved factors between those two alternatives are related to each other and the logit model cannot be used.

This example shows that assuming independent unobserved error-terms can be a very restrictive assumption. For a lot of cases, there is a correlation between the unobserved variables of different alternatives. In his book Train (2009) also argues that this does not have to be the case per se. When a researcher manages to obtain a representative utility function, which in fact is his desire, such that the remaining unobserved variables are reduced to only consisting of so-called white noise, the use of the logit model can be a perfect fit to reality. Because the assumption of independent error terms will often be the feature, that will prohibit the researcher to use the model, a lot of effort has been put into developing methods which still allow the use of a closed-form formula and on the other hand also allow some form of correlation over the ε_{nj}'s of alternatives (Ashiabor S. 2007). Models that allow for a relaxation of this restriction are the nested logit model and the mixed logit model. These will be treated later on in this chapter.

The derivation of the closed-form formula of the logit model will not be stated here as this is not part of the goal of this project. Instead, the end result will only be given here. If the reader is interested in knowing more about this derivation, he or she can find a deduction in the book by (Train 2009). The choice probability for the logit model is given by the following formula ((Ashiabor S. 2007); (Train 2009)):

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_j e^{V_{nj}}}$$

The main restrictions that have to be taken into account when using a logit model are the following:

- Systematic taste variation can be modeled but not random taste variation
- The logit model is based on proportional substitution across alternatives
- Logit models cannot handle situations where unobserved variables are correlated over time in repeated choice situations

First of all, only systematic taste variation, that can be included in the equation of the representative utility part, can be modeled because the error vector is assumed to be independent and thus uncorrelated. Stated differently, if everybody would value convenience in the same way, it can be included into the equation of the representative part of the utility equation.
Random taste variation, based on the personal opinion of a traveler, which is thus included in the unobservable part of utility cannot be taken into account because of the iid assumption explained earlier. For a practical example of systematic and random taste variation the reader is referred to the book by Train (Train 2009).
Secondly, the logit model uses proportional substitution across alternatives. This can be explained using the following example. A person needs to choose between taking the car or bus to work. It is assumed that the probability for both is 50%. When adding a third alternative, in this case a bus in a different color, proportional substitution dictates that the ratio between the probability of taking the car and the probability of taking the bus must stay the same. This leads to the only solution of each of the three alternatives having a probability of 33.33%.

In practice however, this cannot be the case because the attributes of both buses are so much alike. This characteristic of the logit model is also called independence of irrelevant alternatives (iia). The example used above of proportional substitution is the same as the red bus blue bus example which can be found in Ashiabor et al. (Ashiabor S. 2007); Baik et al. (Baik H. 2008); Train (Train 2009). The nested logit and mixed logit model do allow a certain degree of disproportionate substitution.

The final restriction is that basic logit models cannot handle a situation where unobserved variables are correlated over time in repeated choice situations. The model that will be developed for the EPATS project will only include one choice, the modal choice and not the route choice. This means that no repeated choices will have to be modeled. Therefore, no further elaboration will be made on this restriction in this report. For a complete explanation of this restriction, the reader is referred to the book written by Train (Train 2009).

Nested logit model

This model expands the second restriction of the basic logit model.

What the model does is partition alternatives which exhibit similar characteristics in subsets called nests. In these nests, proportional substitution as explained for the general logit model still holds. The big advantage of nested logit models is that this proportional substitution does not hold across different nests. To illustrate this characteristic of the nested logit model, the modal choice problem, used in the previous section, is used again. A choice has to be made between taking the car to work or using public transport.

The big difference with the basic logit model is that instead of four separate choices we know have two choices grouped in two nests as can be seen from Figure 1. In **Erreur ! Source du renvoi introuvable.**, the different probabilities when all alternatives are available can be found in the second column. When one of the alternatives is removed, it is possible to see that the increase in probability for the remaining modes of transport increase proportionally for modes that are in the same nest but disproportionally across nests. The disproportional increase is added to the model by adding a correlation factor λ_k into the closed form formula that evaluates the choice probabilities. It must be noted that the data presented in **Erreur ! Source du renvoi introuvable.** is fictional and is only used to indicate the feature of disproportional substitution.

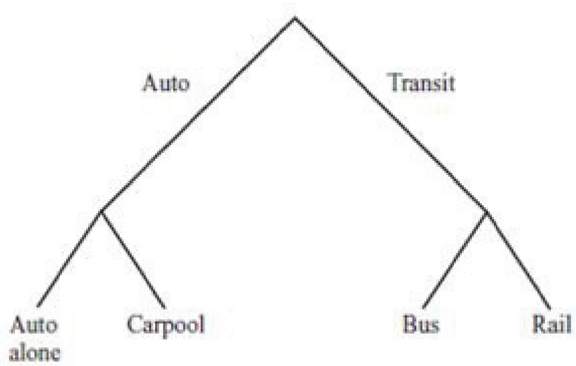


Figure 1: Tree diagram representing transport mode choice (Train 2009)

		Probability			
		With Alternative Removed			
Alternative	Original	Auto Alone	Carpool	Bus	Rail
Auto alone	.40	—	.45 (+12.5%)	.52 (+30%)	.48 (+20%)
Carpool	.10	.20 (+100%)	—	.13 (+30%)	.12 (+20%)
Bus	.30	.48 (+60%)	.33 (+10%)	—	.40 (+33%)
Rail	.20	.32 (+60%)	.22 (+10%)	.35 (+70%)	—

Table 1: Probability diagram representing the original probabilities and when one of the alternatives is removed (Train 2009)

The parameter λ_k is a nest specific measure of the degree of independence in unobserved utility among the alternatives in nest k. A high value for λ_k means more independent alternatives and less correlation and vice versa. If λ_k is set to 1, the formula reduces to the standard logit form. To be consistent with utility maximizing behavior, λ_k must fall in a specific range which is between zero and one (Train 2009).
The following formula is the closed-form formula which can be used to evaluate the probability that a consumer chooses alternative i. Again as the goal of this study is not to provide a detailed derivation of this formula, the interested reader can find a derivation of the formula in the book by Train (Train 2009). K is the amount of subsets, or nest, that are present in the model.

$$P_{ni} = \frac{e^{\frac{V_{ni}}{\lambda_k}} \left(\sum_{j \in B_k} e^{\frac{V_{nj}}{\lambda_k}} \right)^{\lambda_{k-1}}}{\sum_{l=1}^{K} \left(\sum_{j \in B_l} e^{\frac{V_{nj}}{\lambda_l}} \right)^{\lambda_l}}$$

Mixed logit model

According to Train (Train 2009), this model is the most versatile model. It can overcome all of the deficiencies of the standard logit model. This means that it allows for random taste variation. It doesn't have any restrictive substitution patterns and it allows for correlations between unobserved factors over time. Unlike the probit model the unobserved factors do not have to be normal distributed and the choice probabilities can be evaluated more easily than for a probit model. The notation of mixed logit is different from standard logit models and is an integral of standard logit probabilities over a density of parameters.
An extensive theoretical overview of the model can be found in the book by Train (Train 2009).
The main drawback of the model is the same as the one of the discrete choice models. To be able to estimate the coefficients that determine the representative utility, first, stated preference data is required that contains information on all the input parameters in combination with the mode choice made by the traveler. This way the correlation between the different input parameters can be estimated and the coefficients can be estimated that approximate reality most accurately.

Probit model

The main advantage of the probit model over the logit model is that it can handle all three limitations of the logit model. The main disadvantage of the model is that is does not have a closed-form formula to evaluate the choice probabilities. This means that for every traveler a simulation has to be run separately. From the results of this simulation the choice probability for a certain alternative can be determined by simply dividing the amount of people that opted for a certain alternative by the total amount of people that made a choice. This model can be very

appropriate when a large database, containing information on each of the input parameters and their relation to a certain choice, is available from which the correlation between alternatives can be readily determined. However as there are little statistics known about the personal air transport market, it is hard to determine the coefficients of the factors that influence the demand for personal air transport and their correlation that will allow for this method to be applied correctly. This is also a reason why this model is hardly used in practice to forecast transportation demand.

3.4.1.2 Case Study: The American TSAM Model

In this section, an introduction into discrete choice theory is given. Then a practical example of the use of discrete choice models will be discussed: the American Transportation Systems Analysis Model (TSAM) model.

In the United States, a transport model been developed, using the discrete choice method, that determines the demand for personal air transport. This model was developed after the National Aeronautics and Space Administration (NASA) suggested the development of a small aircraft transportation system to the American congress in 2000 (Ashiabor S. 2007).

The model was based on a 4-step approach consisting of trip generation, trip distribution, mode choice and trip assignment (Baik H. 2008). In the first step, are estimated the amount of trips that each region produces and attracts. In the second step, are distributed the generated trips over each of the regions involved based on socio-economic factors like for example amount of inhabitants and amount of commercial activity in that region. This is done using a gravity model. A detailed overview of the factors used in the gravity model can be found in the paper by Baik et al. (Baik H. 2008).

In the mode-choice step, a model is used that allows each traveler to choose his or her mode of transport to make the trip with. In the last step, they load each of the trips together with the mode of transport on each of the routes between the regions. Because NASA wants to investigate what the potential demand is for their proposed Small Aircraft Transportation System (SATS) system, it is especially important to accurately model the mode-choice of the traveler because this cannot be readily deduced from traffic data.

The first attempt made in the United States to use a discrete choice to estimate the demand for transport was done in 1976. Up till now, three other models have been constructed. An overview of them can be found in Table 2.

	Model Type	Data and Scope	Modes of Transportation	Variables in Utility Function	Market Segmentation
Stopher and Prashker (1976)	Multinomial logit	Database: 1972 NTS Scope: trips that start and end in MSAs 2,085 records from database	Automobile, commercial air, bus, rail	Relative time, relative distance, relative cost, relative access–egress distance, departure frequency	Trip purpose (business–nonbusiness)
Alan Grayson (1982)	Multinomial logit	Database: 1977 NTS Scope: trips that start and end in MSAs Selected observations from database	Automobile, commercial air, bus, rail	Travel time, travel cost, access time, and departure frequency	Trip purpose (business–nonbusiness)
Morrison and Winston (1985)	Nested logit	Database: 1977 NTS Scope: trips that start and end in MSAs 4,218 records from database	Automobile, commercial air, bus, rail	Travel time, cost, party size, average time between departures	Trip purpose (business–nonbusiness)
Koppelman (1990)	Nested logit	Database: 1977 NTS Scope: trips that start and end in MSAs Selected observations from database	Automobile, commercial air, bus, rail	Travel time, cost, departure frequency, distance between city pairs, household income	Trip purpose (business–nonbusiness)
Mode choice model in TSAM	Nested logit and mixed logit models	Database: 1995 American Travel Survey Scope: all trips regardless of origin or destination type 402,295 records from database	Automobile, commercial air, train, SATS	Travel time, travel cost, household income, region type	Trip purpose (business–nonbusiness) Household income

MSA = metropolitan statistical area.

Table 2: Overview of travel demand models constructed in the United States (Ashiabor S. 2007)

When looking at the second column of Table 2, which states the model type used, it can be seen that they only used models which are part of the logit family. The main reason for this is that probit models do not provide a closed form formula to evaluate the choice probabilities with and require extensive simulation techniques. In their conference paper Cooke et al. (2005) (Cooke S. 2005) state that a logit form was also chosen because this formulation can be extended to predict a mode choice when new additional alternatives are to be considered.

For the last model that the Americans developed, they investigated two types of models which are both member of the logit family. They choose the logit model mainly because of their ability to evaluate the choice probabilities with a closed-form formula instead of an extensive simulation. The nested logit model and the mixed logit model. A graphical representation of the proposed nested logit model can be found in Figure 2. In Figure 2, it can be seen that the Americans take two alternatives into account for the personal air transport option, here represented as SATS. These are the car and commercial aviation. The commercial aviation alternative is further subdivided based on the route chosen by commercial airline. This means that a traveler not only chooses whether to fly with a commercial airline but also which route he takes. Different routes are available because different airlines sometimes use different hub-airports. The rail mode of transport was investigated but not taken into account when calibrating the coefficients because they had insufficient data available to calibrate the coefficients with (Baik H. 2008).

For their analysis they did not take business aviation into account as a competitive transport mode. In the papers on the TSAM model, no reason for this is mentioned. The effect of the railway alternative on the demand for Personal Air Transport (PAT) would probably also be low, because the railway infrastructure is under developed in the United States.

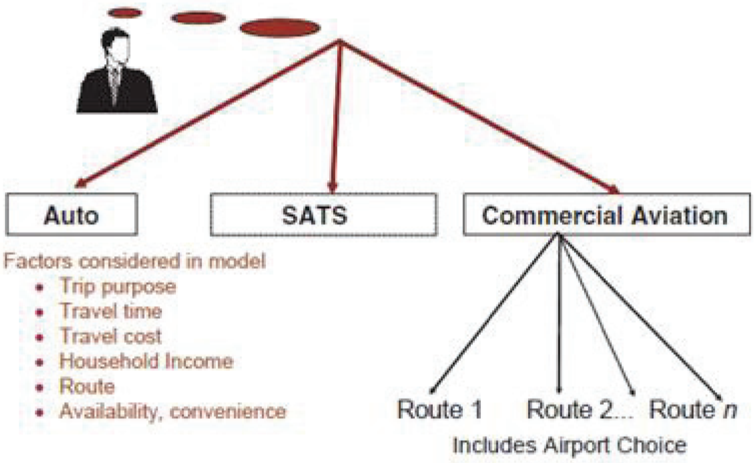


Figure 2: Tree diagram of the nested logit model

After they experimented with different forms of utility functions for the nested logit model they proposed the following form for the utility function (Ashiabor S. 2007):

$$U_{ij}^{klm} = \alpha_0 traveltime_{ij}^{k} + \alpha_1 travelcost_{ij}^{k1} + \alpha_2 travelcost_{ij}^{k2} + \alpha_3 travelcost_{ij}^{k3} + \alpha_4 travelcost_{ij}^{k4} + \alpha_5 travelcost_{ij}^{k5} + \alpha_6 shorttripdummy_{ij}^{m}$$

where:

U_{ij}^{klm} = Utility of a trip maker of income group l traveling from i to j by using transport mode k
α_0 =travel time coefficient
α_1 ; α_2 ; α_3 ; α_4 ; α_5 = travel cost coefficients for the different income groups
α_6 = dummy variable related to trip length

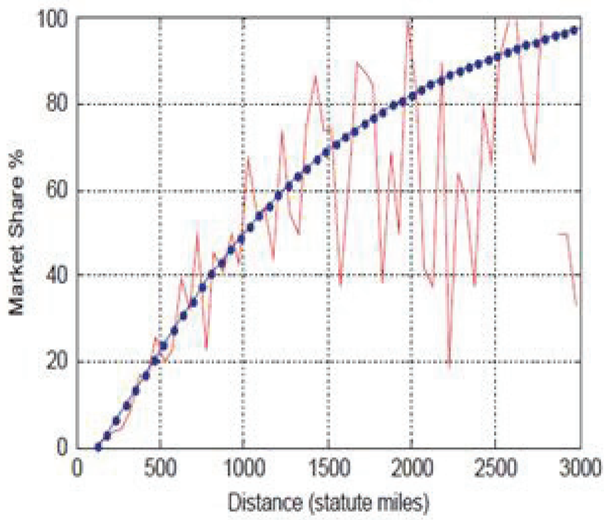


Figure 3: Market share of business air traveler that earns _ $30.000 per year (Ashiabor S. 2007)

For each traveler, only one of the five travel coefficients (α_1; α_2; α_3; α_4; α_5) will enter the utility function depending on the income class to which the traveler belongs. The other four coefficients are set to zero. The short trip dummy variable together with its coefficient, α_6, was added based on empirical analysis of travel choice patterns in American Travel Survey (ATS) data.

To summarize, the utility function is determined by a maximum of three terms. The Americans determined different coefficients for different income levels because their travel survey data showed that the market share of a certain mode of travel differs over the different income groups.

This means that different travelers of different income groups have a different sense of utility for travel. This can also be explained from a value of time point of view. Travelers who belong to the highest income level will also have a higher value of time then people from a lowest income group (McGrath R.N. 2002). As they value their time higher, they will use air travel for smaller distances than travelers from a lower income level.

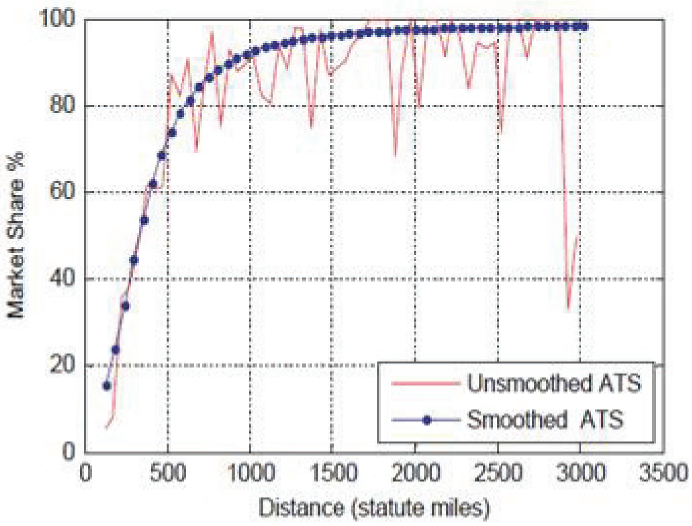


Figure 4: Market share of business air traveler that earns _ $150.000 per year (Ashiabor S. 2007)

Figure 3 and Figure 4 illustrate this difference in obtained market share for air travel. In Figure 3, it is possible to see that for the lowest income group, travelers that earn less than $30.000 per year, the market share of air travel is 20% when the travel distance is 500 miles. For the same distance, the market share is almost 70% for the group with the highest income level, which is more than $150.000 per year. In the figures, the red line represents the actual sampled data. The blue line is the smoothed approximation. The spiky behavior of the red line is due to the small sample size of interviewed travelers.

For the mixed logit model a similar utility function was developed. The only difference in the equation can be found in an adapted travel-time coefficient α_0 which now also contains a random normal distributed component and thus is not fixed anymore.

The main difference between the mixed logit and nested logit is not found in the equation. The main difference between the two models is that for the mixed logit model there are no nests anymore. This means that every different route which is available for the commercial airline alternative is now treated as a separate alternative on the same level as the SATS and car alternative.

3.4.2 The activity based model

This method was developed after researchers showed that travel is determined by a person's daily activities ((Axhausen K.W. 1992); (Ben-Akiva 1998)). In activity based modeling a researcher tries to uncover the relation between a daily travel pattern of a person and his social background. That there is a relation has already been proven by research ((Axhausen K.W. 1992); (McNally 1996); (Ben-Akiva 1998)). Relations have been established between activity demand and the type of the household and its size. For example, whether a person has children or not has an influence on the amount of trips that a person daily makes ((Strathman J.G. 1994); (McNally 1996); (Ben-Akiva 1998)).

A person's daily travel pattern is determined by the activities in which the person wants to engage in that day. For example, if a person needs to be at work in the morning at nine o'clock, he will commute to work before nine. In theory by knowing everybody's activity schedule, and their transport mode choice, the bottlenecks in the transport infrastructure can be identified. These bottlenecks can then be solved by investing in new transport infrastructure or upgrading the capacity of the existing infrastructure. Therefore activity based modeling can be a very good model to evaluate transport infrastructure changes with. By surveying the travel behavior after changes have been made, the impact of the change in infrastructure can also be evaluated. The major downside of this technique is that it requires knowing the daily travel habits of each person which means that a sample of the entire population must be established that can be considered representable. As every individual has its own daily schedule, this is not easy to do.

In their paper, Ben-Akiva and Bowman (Ben-Akiva 1998) investigate activity patterns of households in the Boston area based on a survey conducted in 1991. In the survey, the daily travel behavior of the subjects was investigated. They registered information on how many times the subject travels per day, which transport mode he chooses and whether he travels alone or not. Also socio-economic factors are registered about the person like his or her sex, marital status and whether he or she has children or not and how old they are. They concluded that travel scheduling decisions are made in the context of a broader framework. According to Ben-Akiva and Bowman (Ben-Akiva 1998), examples of factors that influence the decision are the performance of the transportation network at their disposal, the person's lifestyle and long range mobility.

To model the daily activity pattern and the choices involved, Ben-Akiva and Bowman (Ben-Akiva 1998) suggest a combination of two methods: an econometric discrete choice method and a hybrid simulation method. These methods are not alternatives for each other but each method has its own focus. The discrete choice method excels at the representation of a multi-dimensional choice and its output is a probability of the decision outcome. The hybrid simulation method is a method to generate the choice set and essentially it is a system of sequential decision rules that predicts the outcome of the decision process.

For the discrete choice method they opt for a nested logit discrete choice model. They chose the nested logit approach because its multi-level approach allows for different levels of successive decisions where the utility of a certain level is determined by its subsequent levels.

For example the utility of a certain workplace is determined by the utility of the transport modes to get to work. The activity based model can be considered to be the 2.0 version of the discrete choice approach. Where discrete choice models are interested in some characteristics that influence the modal choice of the traveler, activity based modeling takes into account the entire social background of the traveler.

In their report for the U.S. government's travel improvement program, RDC (RDC 1995) state that the main advantage of using an activity based approach instead of a regular discrete choice approach is that it is a better approximation of reality. How much more is yet to be determined as this model is not yet widely used. However as this kind of modeling provides more detail it also requires substantial more input data, down to the amount of children in the household, the time in the morning that the person starts commuting and when he returns home during the evening. They also state that an activity based approach is suitable for evaluating an existing transport infrastructure. As it is entirely based on and calibrated using survey results, it will be difficult to use it also to study new transport alternatives as no data is available yet to calibrate the coefficients of the model with. Therefore this model is more suitable to evaluate infrastructural changes where data is present on the transport modes than the demand for a new transport mode.

3.4.3 The generalized cost model

3.4.3.1 Generalised cost theory

The generalized cost model is based on the following principle. When a traveler is deciding on which transport mode he should take, he compares the (generalized) cost of each of the travel modes and selects the transport mode with the lowest one (Laplace I. 2008). This generalized cost is comprised of a travel cost, a time cost and parameters which are different for each specific traveler like punctuality, comfort and security (Laplace I. 2008).
This principle is comparable to that of utility maximization (Bruzelius 1981). The only difference is that for the generalized cost method every parameter is translated into a monetary cost. To transform time to a time cost, the principle of value of time is used. The value of time of a person is based on his hourly wage and whether the purpose of the trip is business or leisure. The value of time parameter is explained in depth in section 4.2.1.
To summarize, the generalized cost method can be represented in the following functional form (Laplace I. 2008):

$$C_g = C_{travel} + \sum C_i$$

With:
C_g = The generalized cost
C_{travel} = Direct travel cost borne by traveler dependent on travel distance
P
$\sum C_i$ = Sum of non-monetary costs: total travel time $\times$ value of time

The value of time input parameter is based on the personal income of the traveler or his personal disposable income. This depends on the trip reason which can be business or leisure (Laplace I. 2008).
A traveler chooses mode A over mode B when the generalized cost of mode A is lower than that of mode B. This can be written in the following way:

$$C_{travel_A} + Valueoftime \times Traveltime_A < C_{travel_B} + Valueoftime \times Traveltime_B$$

It has to be noted that the travel time parameter stands for the entire door-to-door travel process and not only the in-vehicle travel time ((Laplace I. 2008); (Grey 1978)). This means that also a frequency penalty has to be added for transport modes that are not on-demand like commercial airlines and trains. The travel cost is comprised out of the entire door-to-door travel cost, this means that also possible overnight stay costs are taken into account.

People also experience the different parts of the travel process in a different way. They will for example experience waiting at the gate on their aircraft in a different way when actually traveling on board. Therefore penalty factors are added to the different parts of the travel process (Grey 1978). These calibration factors are usually in the order of 0,5-2,0 ((Grey 1978); (Wardman 2001)). The calibration factor for in-vehicle travel-time usually is set to one (Wardman 2001).
The main critique on the model has been formulated by Grey (Grey 1978). In his paper he states that one cannot assign a constant value of time for an entire social class, because every individual has its own perception of value of time. He also states that discrete models have shown that the penalty factors that were assigned to the different parts of the door-to-door travel

process are not valid and that these also can differ considerably from person to person. It is therefore his opinion that discrete choice models should always be used and that generalized cost provides an incomplete and imperfect image of reality.

In his reply to the critique stated by Grey (Grey 1978), Searle (Searle 1978) states that: *"The meaning and validity of the whole process is manifested only in the usefulness of its results."* He states that both the generalized cost approach as well as the discrete choice model are imperfect models for an imperfect world, but both have their usefulness proven by their practical results. Because the human behavior is a complex science, it is difficult if not impossible to include all its aspects into a model, the discrete choice model makes an effort but this comes at the cost of needing a huge database of survey's containing data on the model variables. The generalized cost model is not able on its own to forecast the demand by transportation mode. To be able to determine how many people will choose for small air transport each year using the generalized cost model, a relation has to be found that relates travel distance and value of time to the amount of intra-European travelers and the distance of their trips per year. This relation can be determined by for example analyzing survey's that investigated how many trips a person takes per year on average, the distance of the trip and whether it is for business or leisure purpose.

If transport statistics of government agencies are available these can also be used to determine this relation. To guarantee the most accurate estimation of traffic between two regions or countries, data is required on the transportation infrastructure that connects both regions and the total traffic flow between the two regions.
The initial demand model for the EPATS project was based on generalized cost theory. An analysis of the model is given in the next subsection.

3.4.3.2 Case study: the EPATS project

One important goal of the EPATS project was to calculate the potential number of passenger-km that could be transferred from current transport modes to EPATS by 2020. These estimations aimed at providing a global indication of the future EPATS market. It must be pointed out that "inferred traffic" was not taken into account in this study.

Gross estimations were made at European level and at national level on identified regional flows in France and Poland. The calculations were made for the most modern current aircraft: six aircraft fulfilling the EPATS requirements were selected for the calculations. These aircraft represent the best compromise between cost and speed. They can be compared to car and traditional air transport (= "traditional aircraft").

The assumptions considered in the EPATS estimations are the following ones:

- A traveller chooses a transport mode by comparing the modes in terms of money and time. Comfort, security or punctuality were not taken into account due to the lack of data available on these aspects and the consequent difficulty to in integrating integrate such qualitative variables;
- Only connections between region with a low accessibility level were considered since EPATS aimed at opening up some European regions by providing a new way of travelling in areas badly served by air transport and not connected to the high-speed train network;

- The considered transport modes are car, commercial airlines and small air transport (also named personal air transport in EPATS (Laplace I. 2008))[1];
- The maximum distance range covered by a car per day is 800km.

EPATS estimation method

Figure 5 illustrates the method developed in the EPATS project to estimate the potential transfer of passengers to small air transport.
Made assumptions and collected data are used to get two important tools:

- Indifference curves between two modes of transport, allowing to identify the preference of a traveller between two transport modes according to its value of time level,
- The traffic distribution (in passenger-km) according to the trip distance and the traveller value of time.

Combining both tools helps to get a modal split giving for each couple (value of time/trip distance), the traffic level as well as the preferred transport mode.

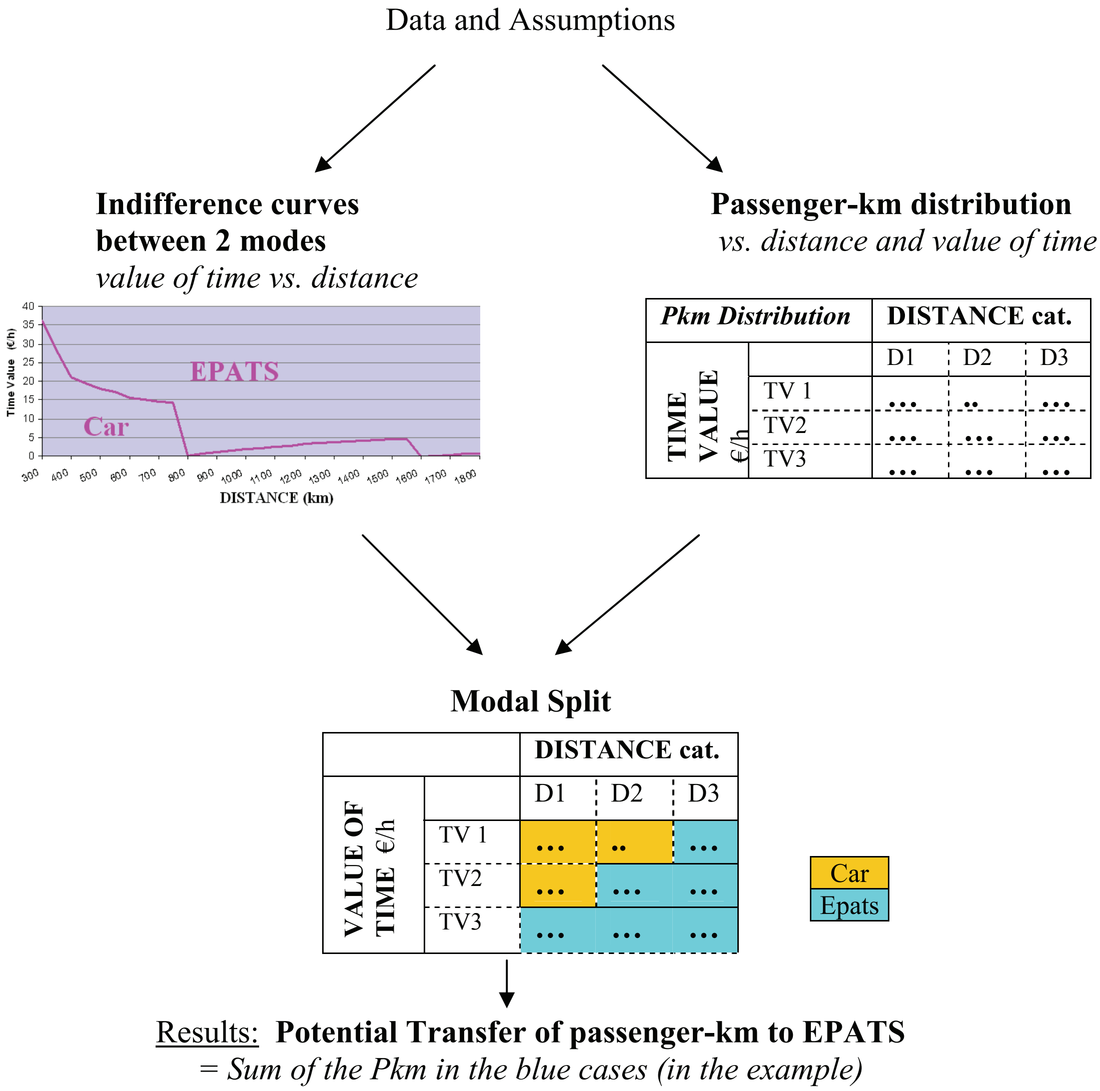


Figure 5: EPATS estimation method (Laplace I. 2008)

[1] The high-speed train transport mode was also considered but showed being always preferable to personal air transport, meaning that no transfer of passenger demand would be possible

Construction of indifference curves

The method used is the generalized costs minimization method taking in consideration the travel time, travel cost and value of time:

$$C_g = C_{travel}(d) + \underbrace{V_t \times T_{travel}(d)}_{\text{Time Cost}}$$

With: C_g = Generalized Cost

C_{Travel} = Travel Cost = Out-of-pocket Cost

d = Travelled Distance

V_t = Value of time

T_{travel} = Travel time = time spent in travelling or waiting

The travel time T_{Travel} can be separated into four distinct parts that can be more or less relevant according to the transport mode. Table 3 illustrates the relevancy of the different travel time parts according to the transport mode (where air transport mode refers to commercial airlines as well as to EPATS)

Time		Road transport mode	Air transport mode
Access time T_{access}	Time to go from origin point to the air transport mode		X
Egress time T_{Egress}	Time to go from transport mode to destination point		X
Transport time $T_{journey}$	Time spent in travelling with the transport mode	X	X
Additional time $T_{additional}$	Potential breaks the traveller can take	X	

Table 3: Relevancy of travel time parts according to the transport mode

The function is therefore:

$$T_{Travel} = T_{access} + \underbrace{\frac{d}{Vm}}_{T_{Transport}} + T_{egress} + T_{additional}$$

With: d = travelled distance
Vm = Average speed

It follows that the travel cost of each part of the travel time are presented in Table 4.

Cost		Road transport mode	Air transport mode
Access cost T_{access}	Cost to go from origin point to the air transport mode		X
Egress cost T_{Egress}	Cost to go from transport mode to destination point		X
Transport cost $T_{journey}$	Cost to travel with the transport mode	X	X
Additional cost $T_{additional}$	Costs of the potential breaks the traveller can take	X	

Table 4: Relevancy of travel cost parts according to the transport mode

The function is therefore:

$$C_{Travel} = C_{Access} + \underbrace{Distance \times C_{Unit}}_{C_{Transport}} + C_{Egress} + C_{Additional}$$

The way of getting the value of time is different according to the trip purpose:

- In case of business trips, the value of time depends on the salary of the traveller, therefore on his occupation.
- In case of leisure trips, passengers travel according to household budget. This means that the value of time depends on the disposable income per person, in other words the total household income divided by the number of persons in the household.

The estimation method then consists in constructing indifference curves, or in other words to plot "indifference time value" versus "travelled distance". These indifference curves enable to see clearly the preferred mode for a segment of the market, i.e. for a distance and a value of time given (see Annexe 1 for more explanations on the construction of indifference curves).

The indifference curve is the limit between the areas of preference for the modes. This is illustrated by the following graph:

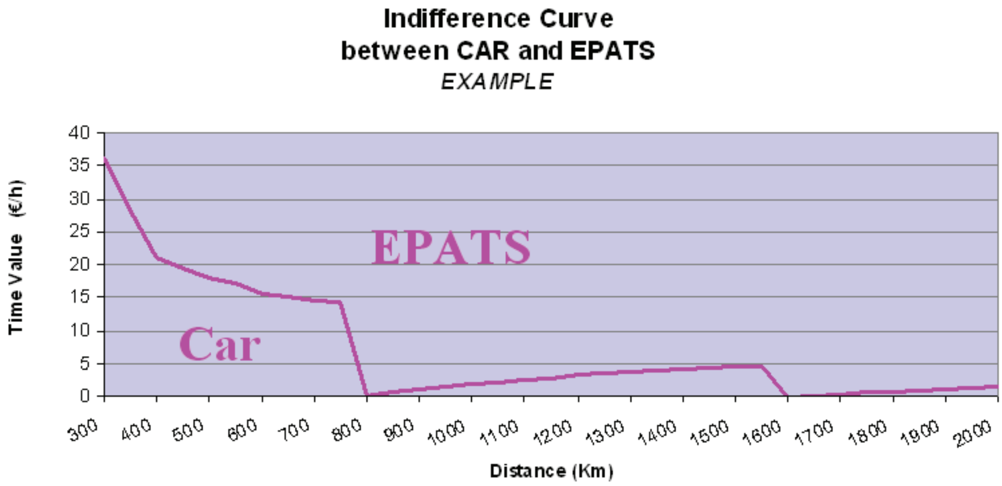


Figure 3-6: Example of indifference curve between car and EPATS
(Data source : ESPON)

In this example, EPATS is compared to car. Let's assume we are in the case where $T_{car} > T_{Epats}$ for any distance. Hence: EPATS is preferred above the curve, and car, below the curve. For instance, a person with a value of time of 15 € / hour will prefer using a car for trips of a distance 300 and 600 km. Above 600 km, this person will prefer EPATS.

Construction of the traffic distribution table

The passenger-km distribution table (by distance category and time value) required a long and meticulous work. Actually we had to proceed by steps to obtain it. The method is illustrated by the following schema:
As shown in **Erreur ! Source du renvoi introuvable.**, the methodology consists in obtaining first, the journeys distribution in % by population category; and second the journeys distribution in % by distance category.

"Population category" corresponds to a classification of the population by type of occupation for example, as well as by income class. The categories of population are linked to values of time. Afterwards, the multiplication of both distributions yields a double-entry table. The change from journeys to pkm distribution in % is very simple and only requires average distances and a formula. Lastly, the distribution of passenger-km in % is applied to the total number of passenger-km so as to build the table of passenger-km distribution in pkm.
The matrix must be built for the mode "car" and the mode "Aircraft", and for each one, there are two cases: Business and Leisure passenger.

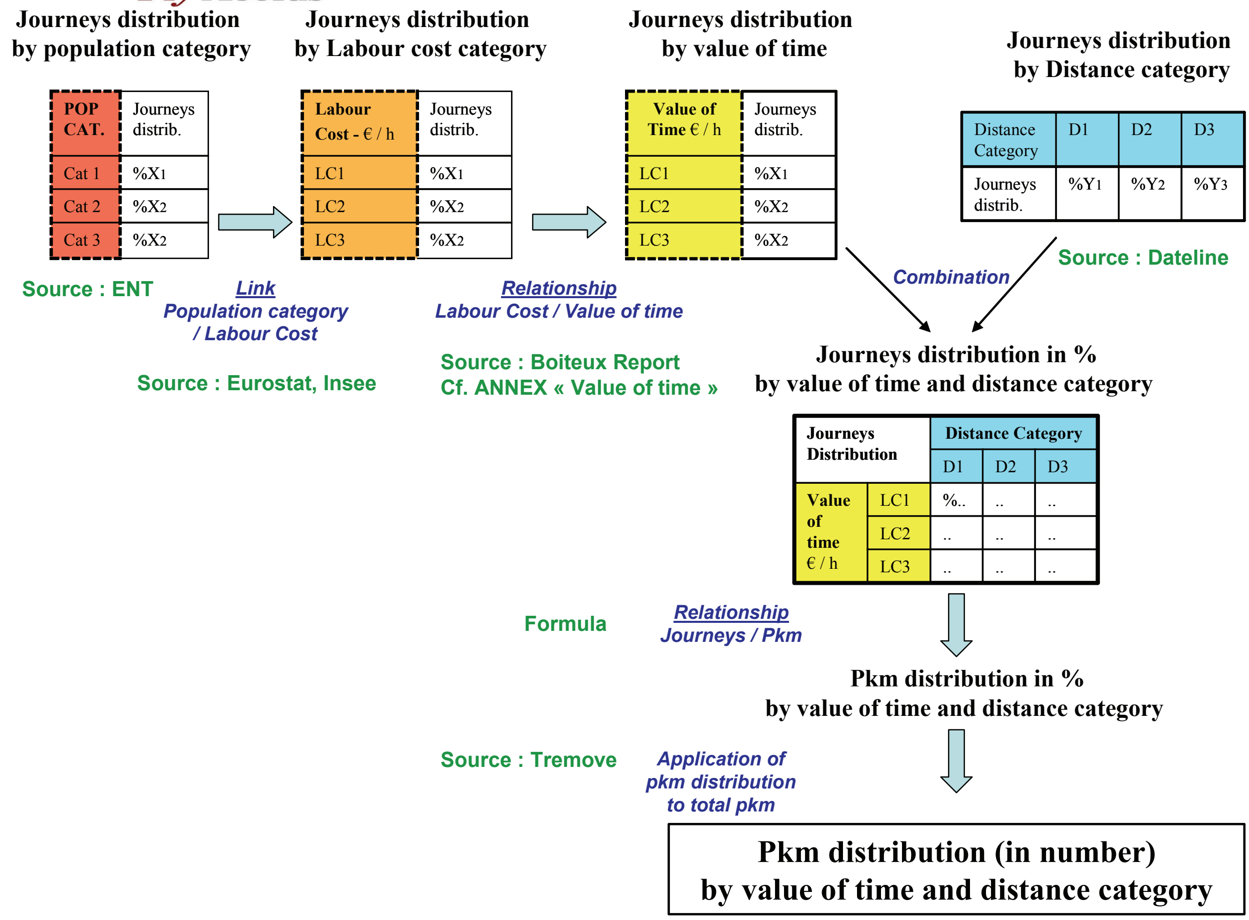


Figure 7: Methodology of the construction of passenger-km distribution table

Note: The schema gives in blue the links and in green the sources.

The model was run on 11682 potential connections between NUTS 21 countries: Austria (AT), Belgium (BE), Czech Republic (CZ), Denmark (DK), Finland (FI), France (FR), Germany (DE), Greece (GR), Hungary (HU), Ireland (IE), Italy (IT), Luxembourg (LU), Netherlands (NL), Norway (NO) Poland (PL), Portugal (PT), Slovenia (SI), Spain (ES), Sweden (SE), Switzerland (CH) , and United Kingdom (UK).
Results were that by 2020, the potential transfer of traffic to small air transport would reach 43 million of flights in Europe what would require 90 000 aircraft.

3.5 The monte-carlo simulation

In his paper, "An introduction to Monte Carlo simulation", Raychaudhuri (Raychaudhuri 2008) provides the following general definition for the Monte-Carlo (MC) simulation: "*a type of simulation that relies on repeated random sampling and statistical analysis to compute the results*". He also states that it can be seen as a methodical way of doing a what-if analysis. Raychaudhuri (Raychaudhuri 2008) states that there are four steps in developing a MC simulation. These are:

- Static model generation
- Input distribution identi_cation
- Random variable generation
- Analysis and decision making

In the first step, static model generation, the mathematical relations that transform the input variables to the output are established. In this step, no possible variation in input parameters is considered and every input value has a constant value.
In the second step, input distribution identification, every input parameter has to be investigated separately. The range of values that a certain input parameter can have, has to be determined together with the probabilities of each of the values. In the next step, random variable generation, a value has to be drawn from each of the distributions of each of the defined input parameters.
Then the model can be evaluated multiple times, each time drawing new random input values from the distributions (Int Panis, et al. 2004). This used to be the core step of the MC simulation, but today there are a lot of mathematical packages available that can perform this step. A math package that is often used to evaluate MC simulations in is Oracle Crystall Ball, which can be considered as a Microsoft Excel add-on ((Int Panis, et al. 2004); (Oracle 2010)).

In the last step, a statistical analysis has to be made of all the output values and the most likely outcome of the model can be determined. This statistical analysis usually consists out of sensitivity analysis. With the sensitivity analysis, an indication of the certainty of the model outcome can be determined (Sargent 2008). The outcome of a MC simulation is never certain, but by evaluating the MC multiple times a mean outcome and its standard deviation can be determined.

Huang et al. (Huang, Chang and Chou 2008) state that the biggest advantage of Monte Carlo simulation is that it can accurately approximate any type of stochastic process. Watanatada and Ben-Akiva (Watanatada et Ben-Akiva 1979) state that the biggest disadvantage is that the errors in forecasts are dependent on the sample size. This sample size is directly related to computational effort. As there are a lot of computer packages available today that can handle Monte Carlo, this isn't a problem anymore like it was in the seventies. The standard deviation of the outcome of a Monte Carlo simulation is inversely proportional to the square root of sample size, and therefore can be reduced by evaluating a larger sample.

3.6 Model selection for Small air transport

3.6.1 Trade-Off Criteria

To be able to choose a demand forecasting method in an objective manner, trade-off criteria are established. The methods are then all tested to these criteria and the method that scores the best is selected.

Ben-Akiva and Bowman (Ben-Akiva 1998) state in their paper the characteristics that any good demand forecasting model should have. These characteristics are used to determine the trade-off criteria for this project:

- Criterion 1: The method has the potential to evaluate multiple scenario's and policies
- Criterion 2: The resources required to develop the model are available
- Criterion 3: The method is able to investigate the influence of each of the input parameters separately
- Criterion 4: The data that is required for the model is available
- Criterion 5: The model is technically feasible within the specified time frame
- Criterion 6: The model can be easily operated and maintained
- Criterion 7: The model can be validated

Criterion 1: The first item on the list is a criterion that is a requirement for any forecasting model, the model used for this project will be no exception. This requirement has to do with the robustness that the model should have. It should not only be able to accurately forecast one possible future scenario but also easily adaptable to forecast various possible future scenarios.

Criterion 2: This criterion has to do with the availability of all of the tools that are required to construct the model. For example, if a certain software program is required for the development of a model, access to the software is required.

Criterion 3: This criterion has to do with the implementability of the model into Sat-Rdmp project. The model should be developed in such a way that it will be possible to investigate a single parameter in depth.

Criterion 4: The data should also be available. There is no point in selecting a method for which no data is available that can serve as input for the model, because this way it would not be possible to determine the demand for Small Air Transport (SAT).

Criterion 5: For this project, the time frame is also a factor that has to be taken into account. The selected forecasting method must also be realizable in the time available, which for the whole project is equal to 6 months. Technically feasible here means that the authors must be able to gain a thorough theoretical background on the model, program the model, apply it and validate it.

Criterion 6: The model should be developed in such a way that it can be adapted easily to evaluate different possible future scenarios. The difference with the first criterion is that this criterion is not about the ability of the model to evaluate different scenarios but the user-friendliness of the model.

Criterion 7: the validation of the model is one of the main challenges that must be overcome for this project. As no system data is available, the model should allow other validation techniques to be applied to its outcome.

3.6.2 Trade-Off

	Discrete Choice	Gen. Cost	ABM
Criterion 1	Green	Green	Green
Criterion 2	Green	Green	Green
Criterion 3	Orange	Green	Orange
Criterion 4	Red	Orange	Red
Criterion 5	Orange	Green	Orange
Criterion 6	Orange	Green	Orange
Criterion 7	Green	Green	Orange

Table 5: Trade-off table of the reviewed forecasting methods

A color coded scale shall be used to evaluate the different methods with. In Table 5, each model is assigned a column. Each criterion is assigned a row. If a model has no problem in satisfying a

criterion the cell corresponding to the row of that criterion and column of the model is assigned the green color. The color orange indicates that it is highly uncertain that the model will be able to satisfy the criterion. The color red indicates that the method is not able to satisfy the criterion. The color code is assigned, not only based on the characteristics of the method on its own, but also on how well the model is able to satisfy the criterion compared to the other models.

It can be seen in Table 5 that the first row is made up out of entirely green cells. This means that each of the model is able to satisfy the first criterion.

The second criterion is also no problem for any of the models as they all can be developed using MATLAB of which a license is available to the developer.

The third criterion is no problem for the generalized cost method. The effects of the variation of one variable while keeping the others on their average value can be evaluated. The other two methods have coefficients assigned to the input parameters that were calibrated using survey data. Therefore it is harder to determine what part of the input parameter variation is due to the parameter itself and how its variation is influenced by the coefficients. As the coefficients would be only calibrated using a sample of the entire European population, this could increase the uncertainty of the model.

When looking at criterion four in Table 5, it can be seen that the data required to set-up the discrete choice and activity based model is not available. This is because the models require European wide survey data on the travel habits of business passengers and their personal attitude towards PAT. As this kind of data is not available, this becomes an insuperable problem for those two methods. The input data required for the generalized cost method is available, because the input parameters are not considered to be correlated to each other and therefore the travel time and cost data can be gathered from different sources like for example the internet.

All the methods should be feasible in the specified time-frame, assuming the input data required can be found. The discrete choice method and activity based model were given the orange color, because of the extra time required to estimate and optimize the coefficients of the models. Calibration and optimization is not required when using the generalized cost method. The time it takes to estimate these coefficients, taking into account that the theory to perform these estimations has to be learned, is estimated to be at least three weeks more than the generalized cost method.

When looking at criterion six, it can be seen that the generalized cost method can be easily maintained and operated and therefore is assigned the green color. The other two methods were assigned the orange color because of the difficulty of obtaining updated data. The input data for these two models is based on the results of very large surveys and effort has to be put into recalibrating the coefficients in the model before any forecasts can be made. For the generalized cost model, no pre-processing has to be done on the data, making it a model that is easier maintained and operated.

The last criterion is no problem for the discrete choice model and generalized cost model. The ABM will be more difficult because it has never been used on such a large scale as the Sat-Rdmp project. Its results will therefore be more difficult to prove valid as no base of comparison exists.

3.7 Chapter summary

In this chapter, the different demand models that can be used for this project were analyzed. First it was determined that the model must be of the causal/econometric type, because no traffic flow data is available to perform a time-series analysis on.

First, the different types of discrete choice models were analyzed. These models use statistical techniques to evaluate and test economic theories. The main advantage of this type of model is that it can accurately predict the traveler's modal choice if the variables that determine the modal choice of the traveler are known. Discrete choice models are all based on the utility maximization principle. This principle states that the traveler will always choose the transport mode that gives him the highest utility. This utility is determined by summing up the utility of each of the variables that influence the demand. Each of these variables is scaled by a coefficient that gives an indication of how large the modal choice is determined by the variable. For example the variable `fare' usually has a large negative coefficient as the utility of the transport mode decreases with increasing fare level.

The major downside of this model type is also related to these coefficients. To determine these coefficients, detailed subject specific stated preference survey data is required. This data often is not available, which prohibits the model for being applied. To apply this model for this project, a survey containing data on travelers from each of the European member states would be required.

In terms of use, the major restriction of this model type is that it is only able to take into account observable variables. Observable variables are those on which information can be gathered from external sources, like for example the internet, or from stated preference surveys. Examples of such variables are travel time and travel cost. Personal taste variation that is different for each traveler and is not investigated in the survey cannot be taken into account by the model. To include these unknown factors in the model a random error term is added to the utility.

In a second step, the activity based model was reviewed. This model can be seen as the 2.0 version of the discrete choice model. It is based on the same utility maximization principle.

The main difference is that it goes a step beyond the level of detail that can be obtained in discrete choice models. It does so by incorporating the entire daily schedule and social-economic background of the traveler into the model. This has as a consequence that it becomes nearly impossible to apply the model to a large geographical scale, as is the case for the Sat-Rdmp project, as the daily schedules of a enormous amount of people need to be gathered.

Tean, the generalized cost model was reviewed. The generalized cost principle can be explained in the following way. The total cost of a trip consists out of a monetary cost, i.e. for example the fare of the transport mode used, and a non-monetary cost. This non- monetary cost consists is the summary of the total travel-time cost. The total travel time is the sum of all of the different parts of the entire door-to-door travel process. The total travel time is transformed to a cost by multiplying it with the traveler's value of time. This value of time is usually estimated based on the traveler's hourly wage and trip purpose. It needs no further explanation that a business traveler has a larger value of time than a leisure traveler.

The modal choice of the traveler is determined by calculating the generalized cost for each of the possible transport modes on a certain connection. The transport mode with the lowest generalized cost will be selected by the traveler. If the values of time of the travelers traveling on a certain connection are known, the market shares of each of the transport modes can be estimated.

The main drawback of this model is the assumption that the traveler will always choose for the option with the lowest generalized cost. This means that he would base his modal choice only on

the total travel time and travel cost. This is also known as the Homo Economicus assumption. Although past research has already shown that these factors play a major role during the modal choice decision process, there are also other factors that play a role. For example a company might have a contract with an airline to travel at a reduced price if they make a certain amount of trips using the airline. These things cannot be taken into account by the model.

A summary of the main advantage, disadvantage and limitation of each of the three model types can be found in Table 6.

Discrete choice models	Advantage	Able to accurately model the modal choice of the traveler
	Disadvantage	Requires detailed stated preference survey data which is often not available
	Limitation	can only include observable variables no personal taste variation
Activity based model	Advantage	Can attain the highest accuracy of all of the reviewed models
	Disadvantage	Requires entire daily schedules of the travelers
	Limitation	Difficult to apply to a large geographical area
Generalized cost model	Advantage	No survey data required
	Disadvantage	Model outcome has a lower accuracy compared to discrete choice models
	Limitation	Assumption that every person reasons as a Homo Economicus

Table 6: Summary of the characteristics of the reviewed demand models

This chapter ends by an overview of the model selection process. It was shown that **the best model to use for the Sat-Rdmp project is the generalized cost model**.
The main reason for this is the availability of data. Both the discrete choice model and activity based model require survey data and this for a sample that is large enough to be representative for the average European traveler. This data is not available in Europe at the moment and also cannot be gathered during the duration of the task of SAT demand estimation which is six months. This means that the generalized cost model is the best option to determine the demand for SAT.

4 DEMAND MODEL FOR SATS

This chapter aims at presenting a demand model aiming at estimating the demand for SATS. The chapter starts by dealing with the needs of refinement of the EPATS model.
The next step therefore consists to building a refined demand model by first of all studying the drivers of the demand of small air transport. Then, the demand model is presented.

4.1 Need of refinement of the EPATS demand model

In EPATS, a model was developed that determines the generalized cost for each transport mode based on travel time and cost functions. These functions consist out of average values for each of the input parameters, and are the same for every connection. By determining this for every transport mode and by assuming that the traveler bases his decision on travel time and cost, the modal choice is determined.

We can identify three main lacks in the EPATS model:

- The generalized cost formulas of the model do not take into account any coefficients or variables that simulate the behavioral aspect of the traveler. This means that it is assumed that each traveler experiences the different parts of the door-to-door travel process in the same way and that it does not matter for him, whether he is waiting or traveling inside the chosen transport mode.

- Travel times only depends on the distance range and on the transport mode speed but do not take in consideration the available transport infrastructure on the connection

- Due to lack of data, frequency penalties could also not be taken into account for the transport modes that do not offer on-demand service like commercial airlines.

- Due to lack of data, the considered value of time only differs according to the trip purpose (leisure/business) but not differs between persons travelling for the same purpose

4.2 Small air transport demand drivers

The travel demand drivers are the variables of which the equations of causal models consist out of. They are the factors on which the different transport modes are compared and thus determine the market shares for each of the transport mode. In chapter 3.4, the theory behind the causal models is explained.

Some of the drivers can be measured by an observer and are the same for every traveler, but some are also subjective because they are based on the traveler's personal opinion ((Ashiabor S., 2007); (Baik H., 2008); (Laplace I., 2008), (Train, 2009)). These parameters can only be quantified by doing surveys and asking the travelers on their opinion. An example of a demand driver that is the same for every traveler and can be measured by an observer is travel time. An example of a subjective performance indicator is convenience.

In Table 7, an overview is given of the travel demand drivers for air travel and urban travel (travel between different cities) as stated by (Doganis, 2002) and (Souche, S., 2010) respectively. (Lim, et al., 2004) state in their paper that the most common mobility measures of merit are door-to-door travel time and travel cost. In their model they also use a person's value of time ($/h) by dividing his annual income by 2080 (640 hours per week for 52 weeks per year), which is the amount of hours a person works annually on average. (Peeta, et al., 2008) state, based on a stated preference analysis, that travel distance, fare and level of accessibility are the key factors that will determine the demand for personal air travel. In their analysis on the American transportation system, (Cooke S., 2005) state that the factors that determine the choice for personal air travel are similar to those for airline travel. They state that for airline travel the major contributing factors are the time and/or cost advantages that it can offer its customers over other modes of transportation.

factors affecting air travel demand		factors affecting urban travel
objective	subjective	objective
level of personal disposable income	convenience	income level
fare level	attitude towards air travel	fare level
travel time		available supply
GDP		population size and growth
population size and growth		

Table 7: Factors affecting travel demand (Doganis, 2002) **and urban travel demand** (Souche, S., 2010)

(Lewe, et al., 2004) divide the input parameters up in an economic, social and psychological category. Economic factors are GDP, household income and fuel price. Examples of social factors are demographic characteristics like age and gender. A psychological factor can be the traveler's perception of safety of the transport mode. Comparing these factors to the ones mentioned in Table 7, it can be seen that all of the factors in the table can be placed in one of the three categories. The factors that are given in the first column in Table 7 are also the ones on which the American TSAM and European EPATS transport models are based.
In Table 7, it is stated that the level of personal disposable income is a factor that determines air travel demand. This level of personal disposable income is derived by dividing the total household income by the number of individuals in the household. According to (Doganis, 2002) this is one of the most important parameters determining leisure travel demand. This is different from annual personal income, which is not divided by the amount of people in the household. Personal annual is the income factor that is used to determine business travel demand.

4.2.1 Value Of Time

The value of time parameter is often used in transport infrastructure valuations to incorporate the traveler's personal income (VTPI, 2009). The Value of Time (VOT) parameter can be seen as a way to incorporate the traveler's personal income into the model, which has a large impact on the traveler's modal choice ((Doganis, 2002); (Peeta, et al., 2008); (Souche, S., 2010)). Therefore it is useful to investigate this parameter in depth and identify the available possibilities in integrating this factor into a demand model.

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(McGrath R.N., 2002) defined VOT in the following way on p.326 of the journal Technovation: "The amount of additional out of pocket costs a traveler is willing to pay for the benefit of a reduction in travel time".

In literature, the parameter is also often called the subjective value of travel time (SVTT) or just subjective value of time (SVT) ((Galvez, et al., 1998); (Armstrong, et al., 2001)). (Gonzalez , 1997) argues that the definition of VOT is determined by the assumptions made. She states that as long as an individual is free to choose the amount of time spent on work and that the wage rate per hour is fixed and independent from the amount of time worked, the value of time of the individual is equal to the wage rate. However when any of these assumptions are not valid or changed, the values of time can differ a lot from the individual's wage rate.
In discrete choice models, value of time is incorporated into the model implicitly. When discrete choice models are used to forecast transport demand, the utility function usually is determined by time and money parameters combined with coefficients that are estimated based on survey data. When keeping the value of utility constant and calculating the rate of substitution between the time and money parameters , the value of time of the individual can be determined ((Gonzalez , 1997); (Jara-Diaz, et al., 1999)).
The following studies where found in which explicit values are stated of VOT's that were determined using discrete choice models. The (VTPI, 2009) determined the VOT for an average business traveler using road or railway transport to be equal to 21 euro/h which is comparable to the EU average of 24 euro/h determined by Shires and de Jong (2009). A model developed by (Seshadri, et al., 2007) determined that the VOT of air travelers lies around 65 euro/h. (Ghobrial, et al., 1995) determined that on average the VOT should lie around 37 euro/h. From this we can conclude that there is no consensus on the value of time of a person when using discrete choice models. No study was found that investigated the reason for the large difference in calculated values of time

For the generalized cost method used in EPATS by (Laplace I., 2008), the value of time parameter is implemented explicitly. The general idea is to convert the travel time parameter to a cost parameter, by multiplying it with the person's value of time. For business trips, the value of time can be determined by the person's annual income or by social status by allocating a certain value of time to a certain working class.
It has already been investigated in the past what the value of a person's time needs to be, for him to consider personal air transport. (McGrath, April 2002) estimated this value to be equal to $49 per hour. This is equal to a person that earns about $100,000 USD per year ((McGrath, April 2002).

4.2.2 Travel Party Size

As mentioned at the end of the previous section, the travel party size can have a serious impact on the attractiveness of PAT (Personal Air Transport) as a transport alternative. Because all of the air taxi companies in Europe at the moment charge a price per flight hour for the entire aircraft and not per seat, the total cost per passenger halves when two passengers are using the air taxi instead of one. Therefore, it is also interesting to investigate how large travel parties for EU domestic trips on average are. (Laplace I., 2008) mention one survey in their paper that showed that the size of the travel party varies from one country to another. They give the example of the Danish that travel alone on 40% of their journeys while the Spanish and Austrian prefer traveling in groups of at least three persons.

In the American Travel Survey (DOT, 1997) the average travel party size has been investigated and the results can be found in figure 4-7. In the first column of the figure the travel party size distribution for business trips is given. Business trips account for the most single travelers. 65% of these trips are made by an individual (DOT, 1997). For leisure trips, of which the result can be found in the third column, this is only 16%. In the report they also state that the larger party-size

for leisure trips could be a reason why air-travel is selected less frequently as a transport mode, which already could be seen in Figure 8. The report concludes that the average travel party size is 1.9 persons for business trips. It should be noted that this is for domestic travel in the United States and not international flights. For international travel to the United States the average travel party size for business purpose was equal to 1.3 persons in 2008 and 1.2 in 2009 according to the International Trade Administration of the U.S. Department of Commerce.

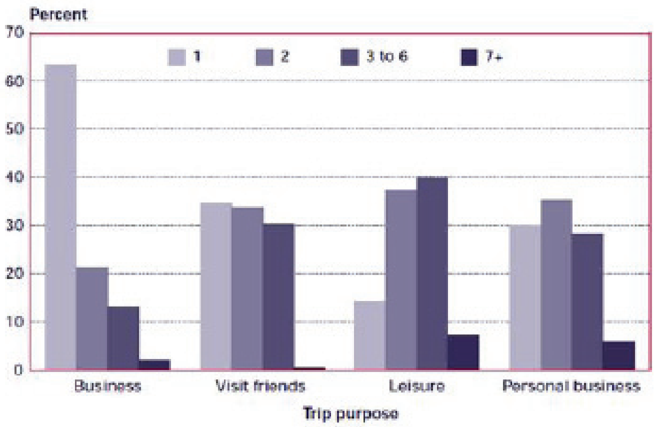

Figure 8: Trip purpose by travel party size (DOT, 1997)

4.3 Structure and logic of the new SAT demand model

In this chapter, the structure of the model and each of the sub models is explained. Also the logic behind the programming of the model is explained. In the first section, an overview of the main model structure is given. Next, the structure of each of the sub models will be explained in depth.

In Chapter 3.6, it was determined that the generalized cost model was the best alternative for this thesis project. In Section 3.4.3, it was explained that the generalized cost model determines the modal choice on a disaggregate, i.e. individual, level. When you know the person's value of time and the travel time and cost for each transport mode alternative for a certain connection, the model is able to determine the best choice for that person. This of course while assuming that each traveler is a Homo Economicus, i.e. a rational person that bases his modal choice on total travel time and cost.

To be able to use this model to determine the market share for each transport mode on that connection, the value of time of each individual traveling on the connection should be inserted into the model. By summing the amount of times that a certain transport mode is selected as the best alternative and then dividing this amount by the total amount of travelers, the market share of each of the transport modes can be determined. By doing this for each possible connection in Europe and then multiplying these market shares with the total traffic flow per connection, the absolute demand can be determined for each transport mode.

Unfortunately, the value of time data for each person traveling on a certain connection is not available. This means that this data needs to be estimated. This can be done by using a Monte-Carlo simulation. The Monte Carlo (MC) simulation draws a value in a random fashion from a specified probability distribution. This means that if the probability distribution is known of a person belonging to a certain value of time interval, the MC simulation can be used to simulate the individuals traveling on a certain connection. The probability distribution is determined by using the results of a survey that investigated the annual income of international business

travelers. For this project, the MC is also used to generate a value for the amount of people traveling together in a group on the connection, i.e. the Travel Party Size (TPS) parameter.
An important advantage of the MC is that it does not require the correlation between two input parameters to be known. For example, in this case the relation between the Value of Time (VOT) and TPS does not have to be known beforehand but is automatically established by letting the MC draw a sufficient amount of times. According to (Rohacs, 2010) this relation is established after 10,000 draws.

In each of the flow-charts of the sub-models, a data block called `intrinsic VOT coefficients' can be found. In each of the generalized cost formulas, these coefficients are multiplied with the different parts of the total door-to-door travel time. They represent how the traveler experiences each of the different parts of the travel process.

4.3.1 Main Model Structure

The developed program consists out of two parts. The simulation module is responsible for determining the generalized costs for every trip generated by the Monte Carlo for every connection. The data processing module is responsible for determining the market shares by looking at how many times each transport mode is selected as the best alternative for each connection. An overview of the model structure can be found in Figure 9.

4.3.2 The Simulation Model

In Figure 9, it can be seen that the simulation module consists out of two main building blocks. The Monte Carlo simulation and the Generalized Cost (GC) model. In the Monte Carlo building block a random draw is made out of the probability distributions of the VOT and TPS parameters. Stated differently, this means that a virtual trip is constructed that consists out of a number of people, which all have a certain value of time.
These parameters are then inserted into each of the transport mode sub-models of the generalized cost building block. These then calculate the generalized cost for every connection that is included into the model. After the models computed the generalized costs for each of the transport modes, these generalized costs are saved into a generalized cost matrix. Each transport mode has its own matrix.
Then the process is repeated and a new trip is generated in the Monte Carlo simulation. The generalized costs are added to the generalized costs matrices of the transport modes on a new row. This means that when the simulation is done, i.e. when for each of the 10,000 randomly generated trips the generalized costs are calculated, there are 5 matrices with 10,000 rows and 44,944 columns, one row per trip and one column for each connection (212 NUTS-2 regions).

4.3.3 The Data Processing Module

In the next step, the generalized cost of the cell that is located on the first row and the first column of each of the transport mode matrices is compared to the cell value on the same position of the other transport mode matrices and the lowest one is registered in a new matrix. This is then done for every cell in the matrix. By comparing this matrix again with each of the GC transportation mode matrices, the amount of times that a certain transport mode is selected as the best alternative for each of the columns, i.e. each of the connections can be determined. By dividing this number with the total amount of trips that were generated, i.e. 10,000, the market share for each of the transport modes and for every connection is determined.

To transform this market share figures into absolute demand figures, the market shares have to be multiplied with the total amount of business traffic flow on each connection.

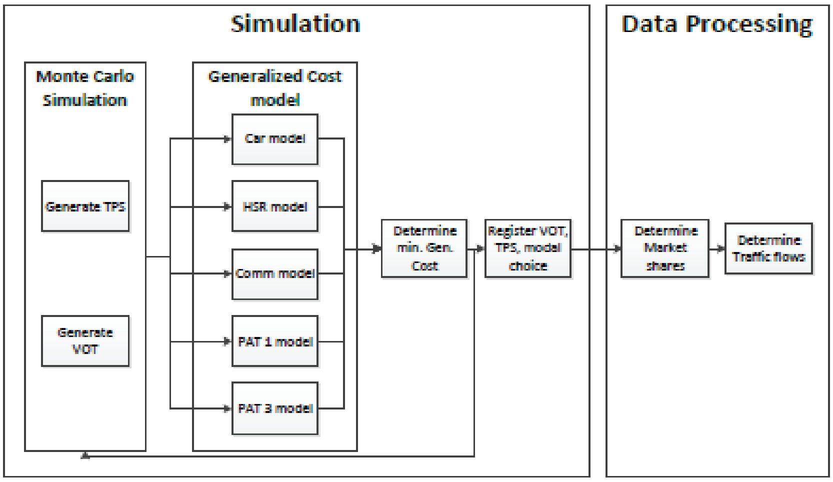

Figure 9: Schematic of the proposed model

4.4 SAT Demand model

As can be seen in Figure 9, the simulation building block consists out of five other models. In this section, the structure of the GC models of each of the five transportation modes are explained. Each of the generalized cost formulas consists out of two types of data. Data that is the same for each connection and originates from a literature review and data that is different for each connection and originates out of the ETIS database. For each of the flowcharts, the parameters that originate from the literature review are grouped in the "general input parameters" block. The data from the European Transport policy Information System (ETIS) database is grouped in the "ETIS database" block. The model only takes into account a single leg of the complete travel process. This means that the model "starts" when the traveler embarks on his trip and "ends" when he has reached his destination. The return trip and costs made while staying at his destination are not taken into account.

The main reason, to only model a single leg instead of the entire trip, is that only the service frequency is known for the High-Speed Railway (HSR) and commercial airline flights, no timetables are included in the model. Therefore, it is not known whether the passenger can take for example a return right back home the same day. It is also not known how many of the multi-day trips are due to the fact that there is no return flight or ride back home the same day and how many are due to the fact that work requires multiple days to complete. This means that for some cases, hotel costs would have to be taken into account due to the lack of service of the used transport modes, while for other cases hotel costs would be incurred even if there would be a possibility to get home the same day and thus must not be included into the GC model.

In the following subsections the model structures and the flow of each of the input parameters through the model is explained. The input parameters for each of the transport modes are determined by analyzing all the different steps that have to be taken to complete the entire door-to-door travel process for each of the transport modes.

4.3.1. Car Model

In Figure 10, the flowchart for the GC model of the car can be found. It can be seen that the VOT and TPS parameters that were generated by the Monte Carlo simulation are loaded into the car model.

If the trip distance is too long to be completed in one day, hotel costs have to be added to the total monetary cost. To determine the distance for which this is the case the following approach was used. It is assumed that a person is able to work and travel for a maximum of 13 hours a day. The reader has to keep in mind, that for each of the sub-models, hotel costs are only added in a sub-model if an overnight stay is required to get to the final destination 13 hours in one day. Next it is assumed that the person takes 6 hours to conduct his business on location. This means that he has 3.5 hours to travel to his destination and 3.5 hours to get back home again. Taking into account break time, it is assumed that he is able to cover 80 km/h. This means that the max range of trips that can be conducted in the same day is 280km.

The program has only a hotel cost for one night included, because it is assumed that every connection can be completed when driving for two days and that no business travel will be conducted by car for trips that take longer than two days to accomplish. For the rare case that more than two full days of driving time are required, it is assumed that more efficient ways of transportation are available in the model and that the car alternative will not be chosen. The analysis of the model will show whether this assumption is justified or needs to be changed.

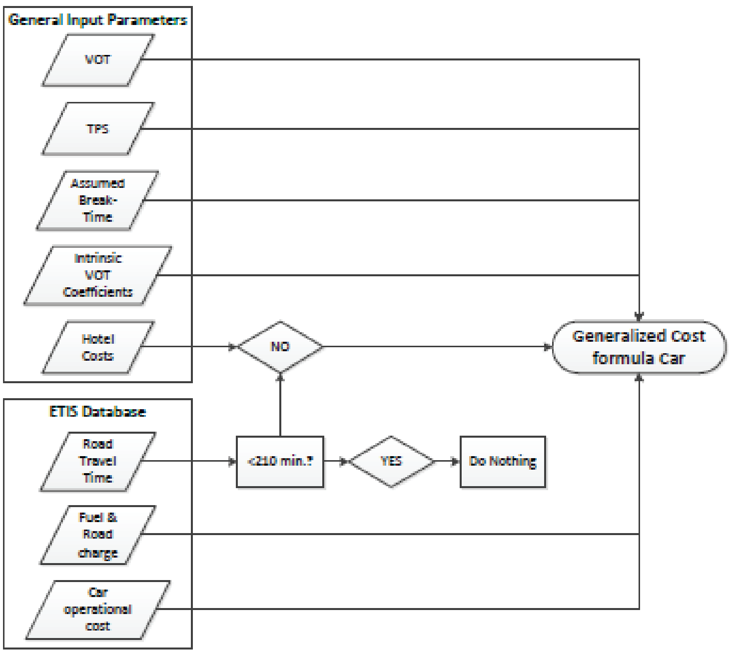

Figure 10: Flowchart car model

4.3.2. High-Speed Railway Model

The ETIS database contains information on both high-speed railway connections as regular railway connections. Therefore, the low-speed connections have to be filtered out as only the high-speed railway system is considered to be a transport alternative. The filter was constructed in the following way. It consists out of determining the average speed on each of the railway

connections. The average speed is determined by dividing the rail distance by the average in-vehicle rail travel time. If this is below a pre-set value, the generalized cost is set to a very high value and thus the program as the best option will never select this transport mode.

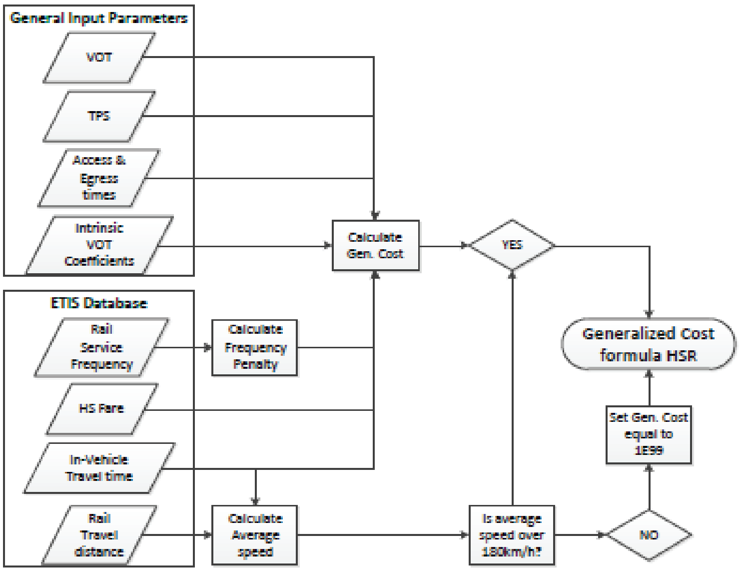

Figure 11: Flowchart HS rail model

The (International Union of Railways, 2010) states that high-speed railway obtains a speed of 200km/h on upgraded tracks and 250km/h on new tracks. When these boundaries were checked with ETIS database data for connections that are known to have a high-speed railway connection, it was found that for most of these connections the average speed was lower. This is the case because ETIS takes into account the waiting times incurred along the way due to stops. This means that the average speed for a high-speed connection can drop to 180km/h due to the amount of stops made in stations along the way. Therefore the filter is set to extract only the connections of which the average speed lies above 180km/h.

How the filter is implemented in the model can be seen in the high-speed railway flowchart that is given in Figure 11.

4.3.3 Commercial Airline Model

In Figure 12, it can be seen that in the ETIS database, only the total, i.e. door-to-door, travel time for commercial air transport is given. This means that in order to be able to compare commercial airlines with the other transport modes on the same level, i.e. with the different parts of the door-to-door travel process multiplied by their intrinsic values of time coffcients, these dfferent parts will have to be estimated.

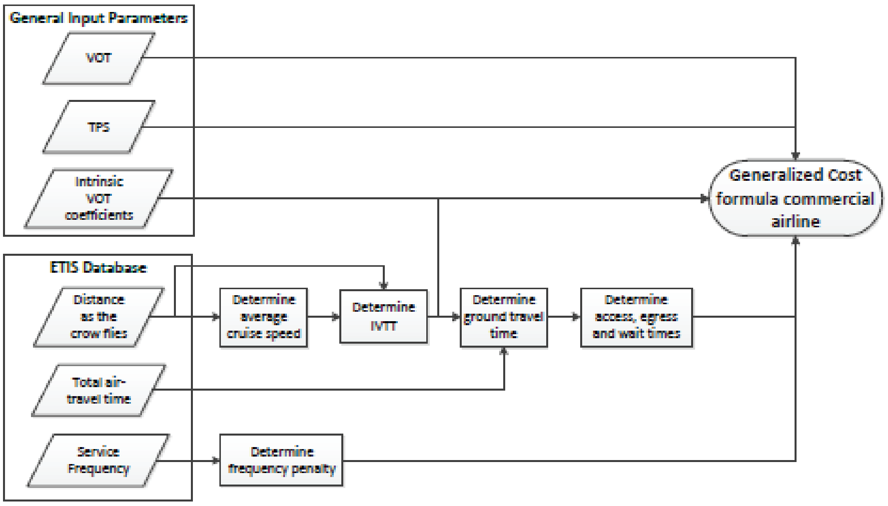

Figure 12: Flowchart commercial airline model

To calculate the ground time part of the average total travel time, which is given by the ETIS database, the following approach was used in the model. First a constant cruise speed was assumed for a certain trip length interval. For trips up to 250km, it is assumed that the aircraft flies with a constant speed of 300km/h. For trips of 250 to 500km, the average speed is assumed to be 400km/h. For trips between 500 and 800km, the average speed is assumed to be 600km and for trips over 1000km the average speed is assumed to be 800km/h. These average speed were estimated by dividing the distance as the crow ies by actual travel times given by online airline ticket websites (Kayak, 2010).

In the next step, the distance as the crow ies is divided by the above average travel speeds to calculate the air travel time. Then this value is subtracted of the total average travel time yielding the total ground time of the trip. This total ground time is then divided by four to get an estimation of the access time, wait time origin airport, wait time destination airport and egress time. Each of the parts is then multiplied with the appropriate intrinsic value of time factors. It must be noted that this is only an approximation of the air and ground time. By dividing the total ground time by four to calculated the different parts of the ground time, it is assumed that the passenger time spends equal amounts of time in access, wait and egress times, which will not always be the case.

4.3.4 Personal air transport Model

As can be seen in the flowchart of the PAT model, which is displayed in Figure 13, the main difficulty, of modeling the door-to-door travel process, is that before the generalized cost is taken into account as an alternative, first it must be checked whether the flight is feasible. Flight feasibility is determined by the payload weight of the aircraft and the travel distance.
The payload weight in turn is determined by the travel party size. In the model, the name PAT 1 is used for operations with piston aircraft, PAT 2 for turboprop aircraft and PAT 3 is used for VLJ traffic.
During a previous phase of the EPATS project, payload-range diagrams were found for piston Aircraft, turboprop and VLJs (Majka, et al., 2007). By assuming that a person has a certain weight and carries along a bag which also has a certain weight, the range restrictions can be deduced from the diagrams. It can be assumed that an average passenger weighs 80kg each and the pilot also weighs 80kg. Further it is assumed that the pilot has a bag that weighs 6kg and the

passengers each have a bag that weighs 12kg. The total payload weight for 1, 2 and 3 passengers can be found in Table 8.

Combining this information with the payload range diagrams the max range for both the piston, turboprop aircraft and VLJ can be determined. These max ranges can be found in Table 9.
The results in Table 9 have as a consequence that the model must be programmed in such a way that PAT cannot be selected as a possible transport mode if the combination of travel party size and travel distance cannot be handled by the aircraft type.

	1 passenger	2 passengers	3 passengers
pilot (kg)	80	80	80
pilot bag (kg)	6	6	6
passenger weight (lg)	80	160	240
passenger bags (kg)	12	24	36
total weight (kg)	**178**	**270**	**362**

Table 8: Passenger weight assumptions

Maximum range	1 passenger	2 passengers	3 passengers
Piston	870 km	800 km	/
Turboprop	2212 km	1978 km	1745 km
VLJ	2500 km	2300 km	2250 km

Table 9: Maximum range of piston, Turboprop and VLJ dependent on travel party size

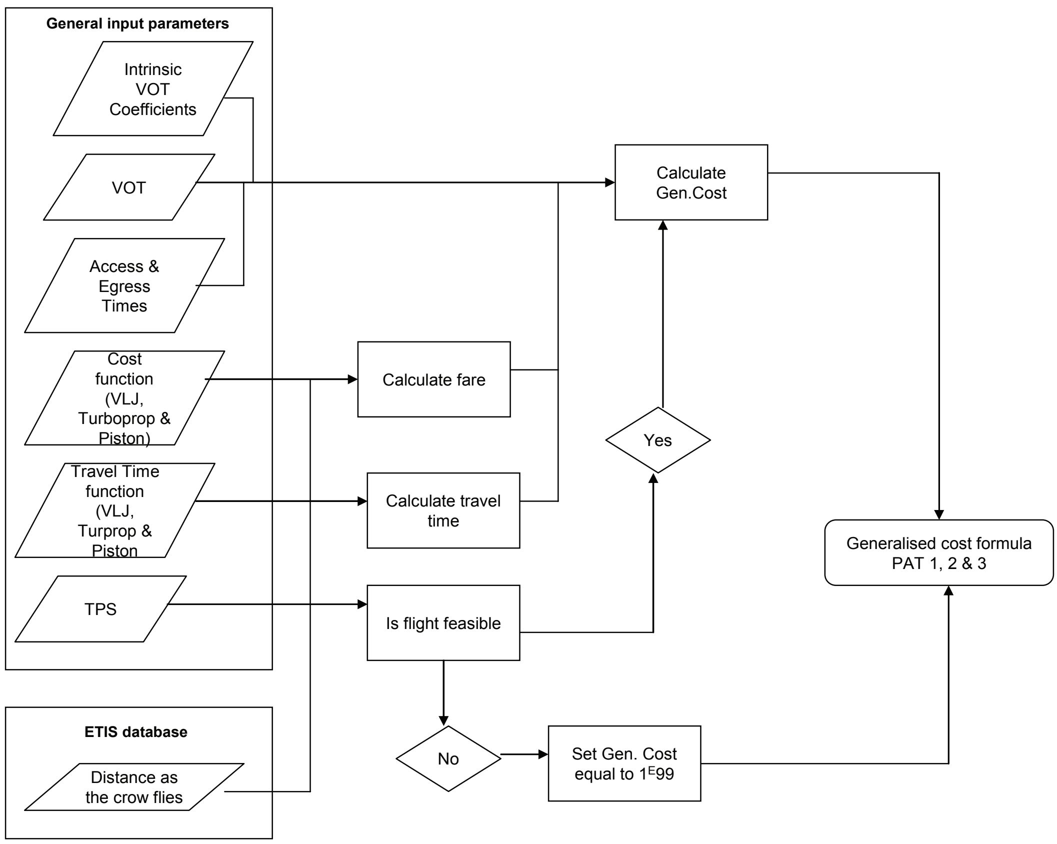

Figure 13: Flowchart PAT model

4.5 Chapter summary

In this chapter, the structure of the developed program using the generalized cost model was given. It was explained how the model exists out of two main building blocks, a simulation module and a data processing module. The simulation module determines the generalized cost for every connection that is present in the model. The generalized costs are determined by inserting the value of time and travel party size input parameter data into each of the transport mode sub models. The outcome of the simulation module are 5 matrices of 10,000 rows and 44,944 columns. One matrix for every transport mode. One row for every MonteCarlo generated trip and one column for every connection.

In the data processing module the market share of each transport mode for every connection is determined by determining for many of the trials each transport mode has the lowest generalized cost. Then this percentage is multiplied with the total amount of business travel traffic flow on the connection to obtain the absolute traffic for each of the transport modes. In Section 4-3, the flowcharts of each of the transport modes were given. The diffculties in obtaining the same level detail of the input parameters of the generalized costs for each of the transport modes were explained. The assumptions made to solve these challenges were also given together with the logic behind the choices.

5 ESTIMATION OF THE FUTURE DEMAND FOR SATS

This chapter presents the estimation results for considered scenarios for 2030. The goal of this chapter is to develop and evaluate a base case scenario. The results of this scenario will serve as a point of reference for the sensitivity analysis that is conducted in Chapter 6 and for Chapter **Erreur ! Source du renvoi introuvable.** in which the results of possible future scenario's are validated. When developing a demand forecasting model that must be able to forecast demand on a European scale, it is impossible to develop the model in such a way that it takes into account every travel situation for every region in terms of travel time and travel cost. Therefore it is important that, before the results of a demand forecast are stated, first, all the choices, that had to be made to be able to determine the forecast, are given. This is done in Section 5.1.

5.1 Base case scenario

For the base case scenario that is analyzed, several choices had to be made by the author regarding the values of different input parameters to quantify the demand for Personal Air Transport (PAT). These choices all have their own impact on the model outcome. They are stated below, together with the logic behind the choice.

Choices had to be made concerning the fare level for PAT, the amount of total traffic that is conducted for business purposes in Europe and the year from which the total traffic flow data is used. The following choices were made:

- The fares of piston aircraft and VLJs of the PAT mode were determined based on single leg fares, not return flights
- 15% of all the travel in Europe is conducted for business purposes.
- The traffic flows are estimations based on data from the year 2000

Single leg fares: Single leg fares were extracted from air taxi company websites to determine the fare function for piston, turboprop aircraft and VLJs. This, because the ETIS database also

provides traffic flow estimations based on single leg trips. Depending on the type of business model of the air taxi company, the price for a single leg or a return flight can vary considerably.

15% of all traffic is business: The ETIS database provides traffic flows between the different NUTS-2 regions. These traffic flows include both leisure travel and business. Because the model only takes into account travel for business purposes, a certain percentage of the total amount of trips has to be assumed that is conducted for business. For the base case scenario, this percentage is set to 15%. In the report by (Laplace I., 2008), it is stated that 15% of short term domestic travel is done for business purposes. According to the DATELINE survey that investigated the travel habits of over 80.000 Europeans, 20% of the long-distance journeys are conducted for business purposes.

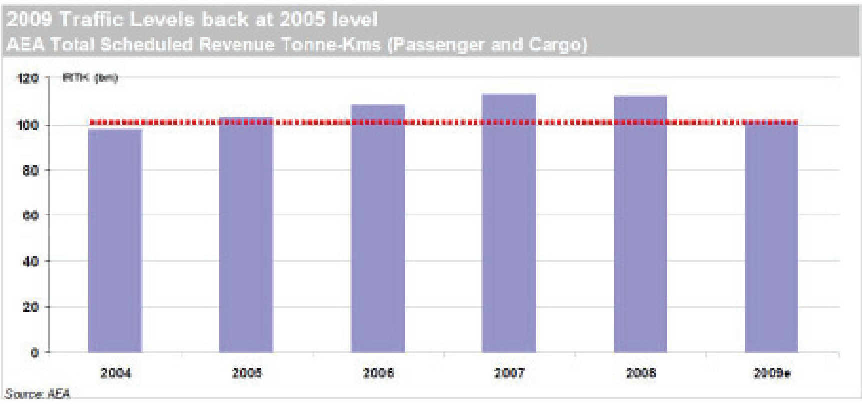

Figure 14: Evolution of total scheduled air traffic grow in Europe from 2004 up to 2009 (Association of European Airlines, 2009)

Year 2030 traffic flows: It is decided to model the 2030 traffic flows based on the current state of the market. This means using the dataset of estimated traffic flows for the year 2011.
Additionally a forecast for 2030 can be generated through:

- decreasing the costs for PATS with 20% over 20 years (McGrath, April 2002)
- increasing the cost for commercial airlines with 1% per 20 years (http://www.denverpost.com/business/ci_16495832)
- increasing the cost for HS rail with 1% per 20 years (Szimba, et al., 2007)
- and increasing the cost for cars with 3.7% per year (Bonotaux, et al., May 2000)

At first sight, traffic data from the year 2000 seems outdated, but one has to realize that traffic at the end of 2009 was back at the level of 2005 due to the crisis as can be seen in Figure 1 (Association of European Airlines, 2009). Adding to this, it also has to be taken into account that it took a few years to gather all the data and construct the database.
Also the reader is reminded of the following general restrictions that were explained earlier on in the report:

- Only high-speed railway connections are taken into account in the model, the regular railway transport mode is not included
- No business aviation passengers are present in the model

Only high-speed railway connections: In the model only the high-speed rail transport mode is included and not the regular railway transport mode. This, because it was determined that regular

railway services will not be a competitive transport mode for PAT as its operating distance interval is not in the range of that of PAT.

No business aviation passengers: There are four reasons why these are not included into the model. First of all, the traffic flows of business aviation passengers are only known on a\ member state level and not a Nomenclature of Territorial Units of Statistics (NUTS)-2 level, which makes it difficult to ensure the same level of detail as for regular business travelers.
Secondly, the values of time of these individuals are not known and neither is the travel party size distribution, which makes it difficult to include them into the Monte Carlo simulation.
Thirdly, the main goal of the EPATS project is to determine how many travelers using conventional transport modes would choose for PAT and not how many travelers, already using a form of personal air transport, would transfer. The fourth and final reason is that the model presented here does not include the parameters that are important for the business aviation traveler. The current model is based on the combination of travel time and cost, which are important parameters for business travelers using conventional transport modes. The business aviation traveler probably cares less about cost and more about comfort and level of service, which are not taken into account in this model. Also because personal air transport is a lot cheaper than charter services, while offering comparable travel times, the business aviation passengers do not have to be included into the model as it is already known that the model would determine that each and everyone of them will transfer to PAT. Therefore, if one wants to include them in the forecast following the approach used in the model, one can just add them to the outcome of the model after aggregating the traffic flows from a NUTS-2 to a national level.

5.2 SAT Demand estimation

To determine the total traffic flow of passenger between each of the NUTS-2 regions, the scheduled airline traffic flow is added to the road traffic flow. For the NUTS-2 connections, that also contain the high-speed railway transport mode as an alternative, the passenger traffic flow is also added to the total traffic flow1. For other connections, the railway traffic flow is not added because there is no low-speed railway travel alternative present in the model. This means that the low-speed railway traffic flow would be divided over the other transport modes leading to a bias in the absolute demand estimation. By multiplying the outcome of the generalized cost model with the estimated traffic flow between the different NUTS-2 regions, the demand for personal air transport is determined.

5.3 Chapter summary

In this chapter, the base case scenario was developed and evaluated. This scenario will be used as a point of reference for the sensitivity analysis that is part of the validation process.
A summary of the entire conducted validation and verification process is given in chapter **Erreur ! Source du renvoi introuvable.**.

In Section 5.1, the choices for the values of the input parameters were explained. The three main assumptions that were made to estimate the annual demand for PAT are:

- The fares of piston, turboprop aircraft and VLJs of the PAT mode were determined based on single leg fares, not return flights
- 15% of all the travel in Europe is conducted for business purposes.
- The traffic flows are estimations based on data from the year 2000

6 SENSITIVITY ANALYSIS ON THE ESTIMATION OF THE FUTURE DEMAND FOR SATS

6.1 Importance of sensitivity analysis

Mathematical models are in general defined by a series of equations, input elements, parameters, and variables aimed to characterize the process being investigated. Therefore, the result of the model is usually a source of uncertainties, due to the lack of initial data and the choice of the key elements. Seeing as this imposes a limit to the confidence related to the output – especially for decision making – the analyst should demonstrate the relevance of the model, which calls for a sensitivity analysis and a validation.

Sensitivity analysis is a process that varies the model input parameters over a reasonable range and observes the relative change in response (Saltelli , et al., February 2004). The main purpose is to estimate the sensitivity of one model parameter relative to an other. Sensitivity analysis is also beneficial in determining the direction of future data collection activities. For instance the parameter for which the model is sensitive (meaning that it drives significantly the result) might call for accurate determination or detailed characterization. On the other hand, a model insensitive data requires the analyst to assess its possible reasons or even revise the model with updated parameters. For that reason, as the Figure 15 indicates, the sensitivity analysis is a valuable tool for model building and evaluation. Beside the assessment of the sensitiveness related to the input parameters, the result of the sensitivity analysis also supports:

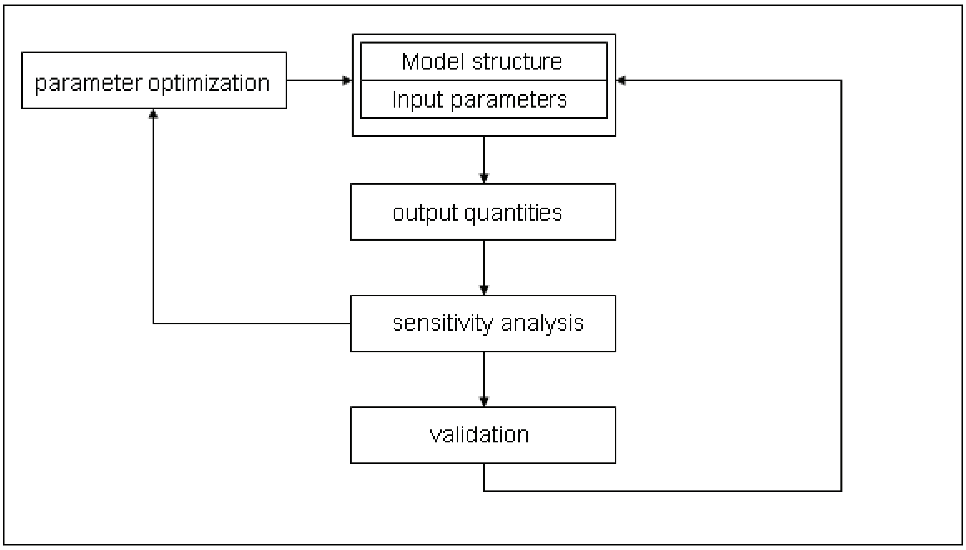

Figure 15: The role of sensitivity analysis and validation in the scientific method applied.

- model calibration and simplification,
- parameter optimization,
- decision making in investigating critical parameters, optimal solutions and assessing the risks related to certain business cases or strategies,
- communication of results being therefore more credible and understandable.

6.2 Standard methods to perform sensitivity analysis

There are several possible procedures to perform sensitivity analysis (Isukapalli, January 1999). Among others (e.g. analytical (Tatang, 1995), (Doughtery, et al., 1979), computer algebra based [(Horwedel, January 1992), (Hwang, et al., 1997)], simple sampling), the most commonly selected method is usually the Monte Carlo sampling-based technique due to its ability to incorporate the probability density functions of the independent variables (Isukapalli, January 1999). Similarly to Monte Carlo Simulation, this sensitivity analysis in this method consists of the following steps:

- specify the target function and select the input of interest,
- assign a distribution function to the selected variables,
- generate the matrix **M** of inputs with the appropriate distributions,
- evaluate the model and estimate the distribution of the dependent variable,
- assess the influence and relative importance of the input elements,

where **M** is the matrix of inputs [210] specifying the independent variables $Z_2^{(1)}$, $Z_2^{(2)}$, …, $Z_i^{(N)}$ with the size of the Monte Carlo experiment (N):

$$\mathbf{M} = \begin{bmatrix} Z_1^{(1)} & Z_2^{(1)} & \dots & Z_r^{(1)} \\ Z_1^{(2)} & Z_2^{(2)} & \dots & Z_r^{(2)} \\ \dots & \dots & \dots & \dots \\ Z_1^{(N-1)} & Z_2^{(N-1)} & \dots & Z_r^{(N-1)} \\ Z_1^{(n)} & Z_2^{(N)} & \dots & Z_r^{(N)} \end{bmatrix} \quad (6.1)$$

To visualize the N values of the inputs Z_i against the output Y, scatterplots are used, due to their advantage if the parameter relationships are supposed to be non-linear. Once plotted on a common scale for Y, these enable to visualize the sensitiveness of the parameters. For example, if the two variables are strongly related, than the data points should form a systematic shape (e. g. a straight line or a clear curve). On the other hand, figures representing rather a uniform could of points over the range of the input parameter is the evidence for the fact that the factor is less – or not – influential.

6.3 Sensitivity of the SAT demand

While the Monte Carlo sampling-based method is powerful to assess the results in function of numerous different input parameters ranging in a wide scale, unfortunately it is only applicable in relatively simple models. In more complex demanded models, as the one developed for the SAT-Rdmp project, it requires significant computational power, which even by considering the partners acknowledged facilities was unfortunately unavailable. Seeing this drawback, finally a simple sampling method was selected. In this technique, instead of taking numerous samples from the appropriate distributions of the input variables, only a limited amount of examples are used. To capture the uncertainty in the development of the input parameters, this work

considered a +/-5 and +/-10 percent of change relative to the base case number for the input parameters considered in the sensitivity analysis.

In complex models with numerous input parameters, the extensive treatment of the sensitivity analysis is considered to be too complex. For this reason, only a limited example of the input parameters are considered, those envisioned to have the highest impact on the system behaviour (result). Numerous sources in demand modelling and related works claim that the most critical parameter to take into account is the total operating cost (TOC) of the envisioned small aircraft operations. This basically has two major reasons: on one hand it is clear the with TOC decrease the demand usually gets higher, but on the other hand this is the input which accounts for the highest uncertainty. Seeing this last, it is therefore crucial to know what would be the demand if the TOC would be finally slightly lower or higher than expected. The sensitivity of the demand would be different for other model variables, but this is not assessed within the context of this project.

Using the input variable Z_i, representing the TOC of SAT, the model response to the sensitivity analysis is given in the Figure 16. This shows that on average the relationship between the Y and Z_i is a curve, and not a uniform cloud of points, which is clearly the evidence for the fact that the demand is driven by the TOC of small aircraft. The sign of the relationship is also reasonable, since as expected, the small aircraft demand rises with its TOC decrease, while it falls off with TOC increase. The key numbers indicate that the total small aircraft demand (including pistons, turboprops and jets) is to change by +9,03% and -7,8% once the TOC would be -10% and +10%, respectively relative to the base case of the simulation.

The slope of the curve indicates a reasonable sensitiveness, which is fully in line with the expectations and results of the related works. Unfortunately at the given scale of the Figure it is

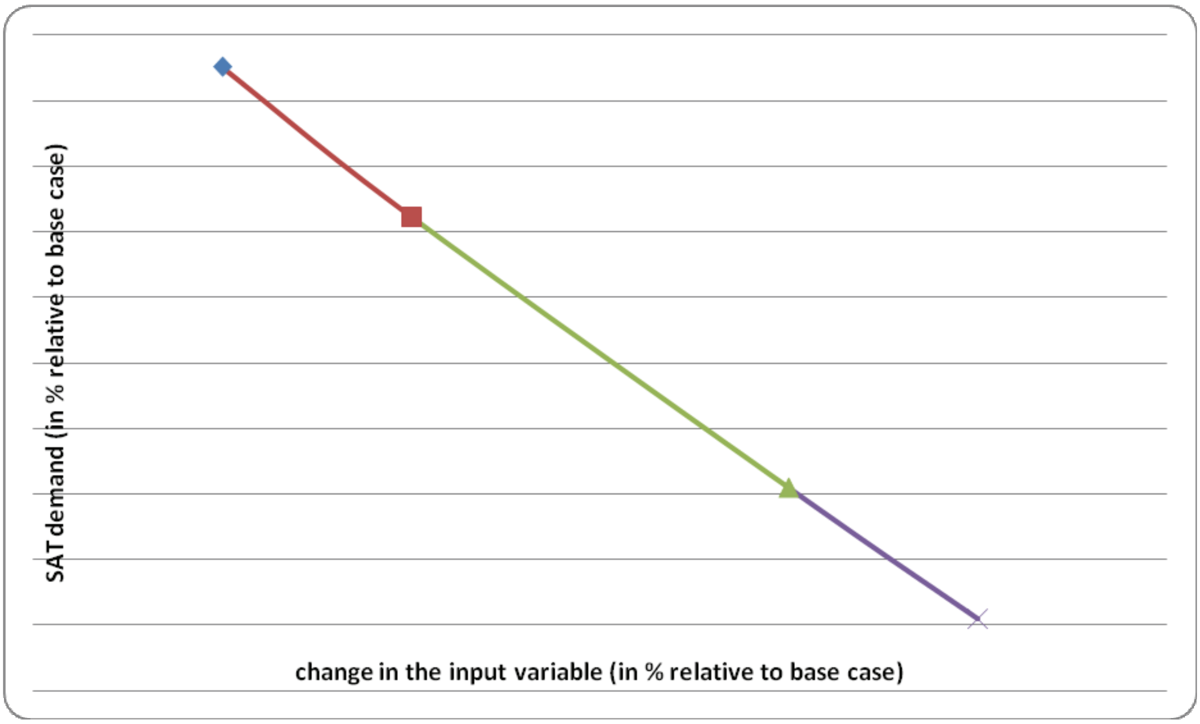

Figure 16: Sensitivity analysis of the total SAT demand (including pistons, turboprops and jets) towards the total operating cost of small aircraft.

difficult to notice, but there is a non-linear relationship between the independent and the dependent variable. Seeing the characteristics of the mathematical model, all these results justify a reasonable method.

6.4 Chapter summary

Due to the unclear development of the independent variables defining the future small aircraft demand, it is critical to assess the demand sensitivity once the input gets slightly different than expected. In addition, sensitivity analysis is also a powerful tool to assess the sensitivity of each variable and assess whether reasonable variables were retained in the model.
Due to the high complexity of the develop method, this sensitivity analysis considered only the most important variable, the total operating cost of small aircraft. The results showed the evidence for a clear relationship between the TOC and the demand. The sign is fully in line with the expectations, while the slope is also to comply with the outcome of the related works. The key numbers indicate that the total small aircraft demand (including pistons, turboprops and jets) is to change by +9,03% and -7,8% once the TOC would be -10% and +10%, respectively relative to the base case of the simulation.
The results of the sensitivity analysis justify a reasonable demand modeling method.

7 CONCLUSION

The refined demand model differs from the model developed in EPATS on 3 points:

- <u>Improvement of the generalized cost formula</u> to take in consideration:

   - The service frequency for commercial airlines and high-speed rail companies
   - Different values of time by segment of the entire door to door travel process (access time, waiting time, in vehicle travel time, Egress time) to take into account that people experience different parts of the travel process in a different way

- Improvement of the considered travel time values by NUTS2 connection:
   - Use of the ETIS database (European Transport Policy Information System) to get accurate travel time on each NUTS2 connection according to the available infrastructure

- Improvement of the relevancy of considered values of time:
   - One specific value of time is used for each person travelling on a certain connection. Values of time are generated by a Monte Carlo simulation based on a survey that investigated the annual income of international business travellers

Including all these improvements in the demand model, leads to a more accurate demand model for small air transport.
The three main assumptions that were made to estimate the annual demand for SAT are:

- The fares of piston, turboprop aircraft and VLJs of the SAT mode were determined based on single leg fares, not return flights
- 15% of all the travel in Europe is conducted for business purposes.
- The traffic flows are estimations based on data from the year 2000

The sensitivity analysis shows the evidence for a clear relationship between the TOC and the demand. The key numbers indicate that the total small aircraft demand (including pistons, turboprops and jets) is to change by +9,03% and -7,8% once the TOC would be -10% and +10%, respectively relative to the base case of the simulation.
The estimation results of SATS demand by 2030 will be provided in an updated document, in frames of preparation of deliverable D2.2 – Impact parameters & simulation model.

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Task: T1.2.1 Small Air transport Aircraft Characteristics to be used for Demand Calculation

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Annexe 1: Indifference curves between two modes of transport

The comparison of the generalized costs enables to compare modes and to choose the one that minimizes generalized cost for a given journey.

Thus, when a traveller with a value of time V_t compares two transport modes, mode i and mode j, he will choose the one having the smallest generalized cost, i.e.:

The traveller chooses the mode i if: $Cg_i < Cg_j$

Or if: $$C_{travel_i} + V_t \times T_{travel_i} < C_{travel_j} + V_t \times T_{travel_j}$$

Or else if: $$C_{travel_i} - C_{travel_j} < V_t \times (T_{travel_j} - T_{travel_i})$$

This gives 2 options:

The traveller chooses the mode i if:

$$\frac{C_{travel_i} - C_{travel_j}}{T_{travel_j} - T_{travel_i}} < V_t \quad when \quad T_{travel_j} - T_{travel_i} > 0$$

$$\frac{C_{travel_i} - C_{travel_j}}{T_{travel_j} - T_{travel_i}} > V_t \quad when \quad T_{travel_j} - T_{travel_i} < 0$$

We therefore introduce the notion of "**Indifference time value**", Vt_I :

$$Vt_I = \frac{C_{travel_i} - C_{travel_j}}{T_{travel_j} - T_{travel_i}}$$ (in € / h)

If a passenger's time value is equal to the Indifference Time Value, then s/he will have no preference for one mode of transport over another.

In addition, the value of time can be expressed as a function of the distance since cost and time depends on the distance. The idea is therefore to **construct indifference curves**, or in other words to plot "indifference time value" versus "travelled distance". **These indifference curves enable to see clearly the preferred mode for a segment of the market, i.e. for a distance and a value of time given.**

Hence:

The traveller (with a value of time Vt) will choose the mode i if:

$$V_t > Vt_I \quad when \quad T_{travel_j} - T_{travel_i} > 0 \quad \textit{(Above the curve)}$$

$$V_t < Vt_I \quad when \quad T_{travel_j} - T_{travel_i} < 0 \quad \textit{(Below the curve)}$$

To summarize, the indifference curve is the limit between the areas of preference for the modes. This is illustrated by the following graph:

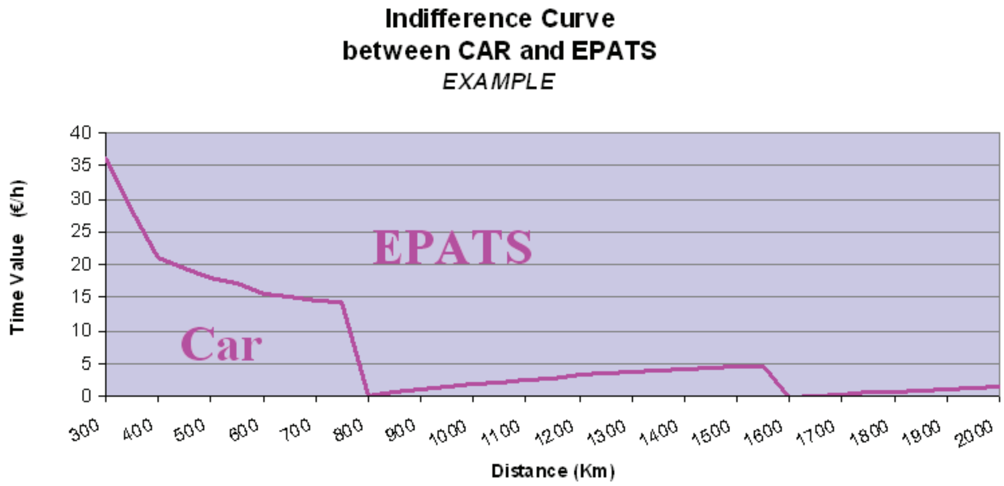

Figure 8-1: Example of indifference curve between car and EPATS (Data source : ESPON)

In this example, EPATS is compared to car. Let's assume we are in the case where $T_{car} > T_{Epats}$ for any distance. Hence: EPATS is preferred above the curve, and car, below the curve. For instance, a person with a value of time of 15 € / hour will prefer using to use a car for trips of a distance 300 and 600 km. Above 600 km, this person will prefer EPATS.