Improving the representation of modal choice into bottom-up optimization energy system models – The MoCho-TIMES model

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Highlights:

- Novel methodology for representing modal choice into energy system models is presented
- Heterogeneity of transport users is introduced to differentiate modal perceptions
- Preferences accounted through monetization of intangible costs
- Value of time and level of service variables are accounted by the model
- Approach paves the way to new policy analyses involving novel attributes

Abstract:
This study presents MoCho-TIMES, an original methodology for incorporating modal choice into energy-economy-environment-engineering (E4) system models. MoCho-TIMES addresses the scarce ability of E4 models to realistically depict behaviour in transport and allows for modal shift towards transit and non-motorised modes as a new dimension for decarbonising the transportation sector. The novel methodology determines endogenous modal shares by incorporating variables related to the level-of-service (LoS) of modes and consumers' modal perception within the E4 modeling framework. Heterogeneity of transport users is introduced to differentiate modal perception and preferences across different consumer groups, while modal preferences are quantified via monetization of intangible costs. A support transport simulation model consistent with the geographical scope of the E4 model provides the data and mathematical expressions required to develop the approach. This study develops MoCho-TIMES in the standalone transportation sector of TIMES-DK, the integrated energy system model for Denmark. The model is tested for the Business as Usual scenario and for four alternative scenarios that imply diverse assumptions for the new attributes introduced. The results show that different assumptions for the new attributes affect modal shares and CO_2 emissions. MoCho-TIMES inaugurates the possibility to perform innovative policy analyses involving new parameters to the E4 modeling framework. The results find that authority's commitment to sustainability is crucial for a paradigmatic change in the transportation sector.

1. Introduction

Transport is a key driver of economic development and it plays a fundamental role in supporting quality of life. However, it is also responsible for approximately 28% of total final energy use and for 23% of the world energy-related CO_2 emissions [1]. Transport is regarded as the most complicated sector to decarbonise, due to multiple reasons. Its rate of growth of energy use and CO_2 emissions is 2% a year, the highest among all the end-use energy sectors. Moreover, the global growth of transportation activity has been tracking that of GDP and is strongly linked to the increase of population and incomes [2]. Mobility demand per capita in non-OECD counties is still far below the levels in OECD countries, but is expected to grow at fast pace [3]. While the power and heat sectors have many efficient and renewable energy based technologies available to enable a technology switch, the transportation sector lags behind. Some low-carbon technologies have appeared in the market [4], but they are still characterised by high investments costs that slow a large-scale deployment. Moreover, new transportation technologies have to face the slow turnover rate of the existing vehicle stock and the lock-in effect originated by the existing infrastructure. So far, the efforts to reduce transportation emissions by technological improvements and fuel standards have been offset by the increase of activity. The International Energy Agency (IEA) estimates in its baseline scenario a doubling of current transport energy use by 2050 and slightly more than a doubling of associated CO_2 emissions worldwide [5]. Experts agree on the strategy to pursue a reduction in transport externalities. The IEA suggests a combination of four technological and behavioural measures to promote concurrently: avoiding travelling, shifting to different modes, improving vehicle performance and switching to lower-carbon fuels [5]. Another set of measures suggested includes development of efficient technologies, changes in pricing and budgeting, changing attitudes, infrastructure supply, innovative institutional arrangements and development of new methods [6]. Given these premises, it is clear that the behavioural dimension plays a key role and that a behavioural change is a precondition for the decarbonisation of the transportation sector.

Energy system models are powerful tools for supporting long-term decision making and planning in the energy sector. In this paper we focus on a specific family of them, the TIMES/MARKAL models, belonging to the category of energy-economy-environmental-engineering (E4) optimization models. TIMES and MARKAL models have been used for more than three decades to identify least-cost resources and technology deployment pathways towards greenhouse gas (GHG) emission-free energy systems and exploring alternative scenarios under several constraints [7], [8], [9], [10], [11], [12]. The major strength of E4 models lies in their ability to provide a detailed representation of the technological, economic and environmental dimensions of the integrated energy system and in their capability to explore decarbonisation pathways considering cross-sectoral dynamics and synergies. On the other hand, E4 models are still weak at depicting consumer behaviour [13], [14], [15]. This lack, to a certain extent, has reduced the credibility of E4 models' policy evaluations [16]. E4 models normally represent only a "system wide" decision maker, with perfect information and foresight and who takes rational decisions only based on pure economic criteria. However, individuals' preferences and behavioural attitudes are a fundamental aspect of decision making in the transportation sector. Therefore, the behavioural dimension shall be integrated in E4 models, to validate their application in transport policy analysis. This paper aims at filling this gap by proposing a new methodology, called MoCho-TIMES, that enables to incorporate modal choice (the choice that individuals make in selecting the means of traveling, e.g. car, public transport, bike or walk, for a specific trip) within E4 optimization models. Integrating modal choice within E4 models helps to identify the barriers limiting modal shift to zero- and low-carbon modes and to understand what kind of policies and regulation mechanisms can potentially trigger such modal shift. The theoretical basis of consumer choice is presented in Section 2, which reviews as well the representation of modal choice in transport and energy system models. Then, Section 3 presents all the aspects of this novel methodology. The results for the Business as Usual (BaU) scenario and for the alternative scenarios are analysed in Section 4, which also provides some insights on the capabilities of the approach. A discussion of the most innovative and critical aspects of MoCho-TIMES is provided in Section 5, together with recommendations for future research. Finally, Section 6 presents some concluding remarks of this study.

2. Theory and representation of modal choice

Modal choice consists of an individual facing two or more alternative transportation modes among which to choose. Given the finite and exhaustive set of mutually exclusive choice alternatives, modal choice can be represented by discrete choice models [17]. According to the classical formulation of discrete choice models [18] [19], individuals choose among the available alternatives based on an index of preference, called utility, which depends on the characteristics of the alternatives and on the characteristics of the individual. Traditionally, in discrete choice models the utility is a linear function of parameters and attributes, plus an error term, which accounts for the fact that the modeller is able to capture only a subset of all the attributes affecting modal choice [19]. These attributes are generally socioeconomic variables, which account for diversity in modal perception across the population, and level-of-service (LoS) variables, defining the characteristics of the alternatives as perceived by the consumers. Moreover, alternative-specific constants (ASC) are used to take attributes that are not under the modeller's control into account. Discrete choice models calculate the probability that a consumer chooses a certain alternative from the choice set by comparing the utilities of the different alternatives. A rational consumer will choose the alternative from which he gets the greatest utility. The most popular technique for modeling modal choice has been through logit and probit models, because they are able to account for variation of preferences across the population [17]. An important characteristic of modal choice is that it is a spatial problem: the choice of the mean of transport for a trip strongly depends on the trip length, on its origin and destination and on the local availability of public transport and transport infrastructure.

A review of the LoS, socio-economic and demographic attributes highly relevant for mobility behaviour has been performed. Table 1 recollects the attributes affecting modal choice in some transport models found in the literature [20], [21], [22], [23], [24], [25], [26].

Table 1: Attributes relevant for modal choice in transport models

	Attribute	LTM [20]	RMS [21]	CSTDM [22]	NTM [23]	Cherchi et al., 2002 [24]	Cherchi et al., 2003 [25]	De Jong et al., 2004 [26]
Demographic	Age	x	x	x	x		x	x
	Gender	x	x	x	x	x	x	x
	Presence of children	x	x	x	x			
	Level of education		x				x	
	Role in the family						x	
	Geography location	x	x	x	x			
	Licence ownership			x	x	x	x	x
	Car ownership	x	x	x	x	x	x	x
	Household size			x	x			x
Socioeconomic	Income	x	x	x	x		x	x
	Employment status/labour market association	x	x	x	x		x	x
	Student enrolled			x				

	Number of weekly working hours (part-time/full-time)			x			x	
	Freelence/employee			x		x	x	
LoS Car	Free time	x	x	x				
	In-vehicle time				x	x	x	x
	Monetary cost	x	x	x	x	x	x	x
	Congestion time	x	x	x				
	Distance	x	x	x	x			x
	Comfort					x	x	
	Ferry time/cost	x			x			
	Parking/Toll cost	x	x	x	x	x		x
LoS public transport	In-vehicle time	x	x	x	x	x	x	x
	Initial waiting time	x	x	x				
	Transfer waiting time	x	x	x	x	x	x	x
	Transfer time	x	x	x		x	x	x
	Access/Egress time		x	x	x			x
	Distance	x	x	x	x			x
	Transit fare	x	x	x	x	x	x	x
	Reliability						x	
	Comfort						x	
	Delay/Reliability					x	x	
LoS non-motorized	Travel time	x	x	x	x	x	x	x
	Distance	x	x	x	x	x		x

Transport models have a long tradition of representing modal choice. Their structure generally consists in four steps: trip generation, trip distribution, modal choice and route assignment. In the third stage, modal shares are traditionally determined though multinomial logit model (MNL) or nested logit model (NMNL) accounting for many attributes describing the observed characteristics of the modes and the observed characteristics of the consumers. These types of transport models are normally characterized by a high level of population segmentation, with the rationale that behaviour is an individual feature and therefore attempts to capture it should be pursued to provide as much heterogeneity as possible. The population is traditionally segmented based on demographics and socio-economic variables, which allow differentiating the LoS of the modes across consumer groups. More recently, the use of attitude-based consumer disaggregation is becoming popular [27]. Considering attitudes of the population as criteria for consumer segmentation, in particular travel behaviour and willingness to change behaviour, provides a better starting point for initiatives promoting sustainable transport. In fact, it allows for establishing priorities and targeting different groups of people with ad hoc policies [26], [28]. Moreover, empirical results show a link between lifestyle and sustainability in travel behaviour, claiming a paradigmatic shift in transport regulation from demand management towards lifestyle adjustments [29].

In the field of energy system modeling, the improvement of the behavioural dimension of transport and the representation of modal choice is an innovative topic. Traditionally, in optimization E4 models the end-use mobility demands are specified exogenously for each mode. Several technologies compete to fulfil the projected mode-specific mobility demands. However, technologies compete within a mode, but not between modes, thus preventing endogenous modal shift [30]. This was a limitation, because modal shift is an efficient lever to cut CO_2 emissions in the transportation sector. At first, the contribution of modal shift towards GHG-emissions reduction was determined by means of "what if" analyses, which assess the effect of exogenously assumed levels of modal shift on the whole energy system and on the environment [5], [31], [32], [33]. Recently, the interest of researchers is addressing the integration of modal choice [13], [16]. A review of the representation of behaviour in integrated energy and transport models recognised two main approaches to incorporate behaviourally realistic modal choice into bottom-up (BU) optimization E4 models [13]. The first and most traditional approach consists of linking an E4 model with an external simulation transport model that incorporates the behavioural variables in a non-linear framework (such as constant elasticities of substitution, or an MNL model) and that determines the modal shares [34], [35], [36]. The other approach consists of determining modal shares directly within the E4 model, by broadening its classical structure to integrate some transport-specific variables relevant for modal choice, such as those in Table 1 [37], [38], [39]. Despite the development of the second method requires substantial changes in the traditional model structure to incorporate transport-related attributes, integrating modal choice directly within the E4 model has several benefits. First, modal shift is evaluated with a whole-energy system perspective, which strengthens the reciprocal implications of transformations in the energy and transportation sectors. This is particularly important, as the energy and transportation sector are expected to become more strictly integrated in the future. Then, it inaugurates the possibility to assess novel policies involving transport-related and behavioural variables within an E4 model. MoCho-TIMES belongs to the second category of the taxonomy described above.

3. Methodology

The methodology proposed in this paper aims to incorporate behaviourally realistic modal choice in optimization E4 models. The E4 model used in this study is the TIMES (The Integrated MARKAL EFOM System) model, and the approach presented is called MoCho-TIMES (Modal Choice in TIMES). TIMES is a model generator developed and maintained by the Energy Technology Systems Analysis Program (ETSAP), a Technology Collaboration Programme of the IEA [40]. It is a partial equilibrium, linear optimization model for the energy system: it determines the solution as the minimization of the sum of the total system cost of the energy system discounted to a reference year, subject to certain restrictions. TIMES is based on the bottom-up approach and thus it is said to be "technology-rich", because it describes the technical, economic and environmental characteristics of the technologies of the energy system in detail. These characteristics make it a powerful tool for energy planners to identify the most cost-effective portfolio of resources and technologies to fulfil future energy-service demands under several constraints. TIMES is also a valuable tool for performing long-term energy system analyses, for assessing long-term dynamics across different sectors of the energy system, for testing policies affecting the energy system and for exploring alternative scenarios. A detailed description of TIMES is provided by [40] while [39] and [41] describe the traditional representation of the transportation sector within TIMES models. While this study integrates the methodology into a TIMES energy systems model, the intention is to produce a tool replicable by any E4 model.

The development of MoCho-TIMES relies on and requires a transport simulation model, consistent with the geographical scope of the analysis, which works as support model. This support model includes modal choice and is the main source of data for implementing the methodology hereby proposed. For this demonstrative study, the support model is the Landstrafikmodellen (LTM), also called "the Danish National

Transport Model" [42], [43]. A detailed description of LTM and of its representation of modal choice is provided in Section 3.1.
This demonstrative version of MoCho-TIMES has been developed as a standalone model, which includes only the transportation sector of TIMES-DK, the integrated energy system model for Denmark [30], [44], [45]. The passenger transport demands are defined exogenously from the base year (BY) of 2010 until the end of the time horizon (2050) and are expressed in million-passenger kilometres (Mpkm). The modes that compete to fulfil such travel demands are: private car, bus, train, S-train, metro, bike and walk. Modes are not represented by a unique technology, but include several technologies with different powertrains. The model optimizes the system, determining the least-cost modal shares and vehicle shares that satisfy the mobility demands simultaneously, and subject to the constraints described below in this section. The novel modeling features characterising MoCho-TIMES are described in detail in Section 3.2.
The authors acknowledge previous work by [41], [46] and [47] as source of inspiration for the approach of MoCho-TIMES. Nonetheless, a primary difference is that MoCho-TIMES enables incorporating modal choice in E4 models, while MESSAGE-Transport [41] and COCHIN-TIMES [46] improve the representation of vehicle choice.

3.1 The Danish National Transport Model LTM

The Danish National Transport Model (LTM), is a comprehensive transport demand model for Denmark [42]. Based on a simulation framework, it is able to forecast the passenger and freight transport demand in Denmark from 2010 until 2030. It is highly disaggregated geographically, in order to be able to represent mobility flows between zones: it includes 907 zones for Denmark and 371 zones for the surrounding countries. The main source of data is the Danish National Travel Survey, also denominated TU survey [48]. This survey has been investigating the travel habits of the Danish population by recollecting mobility diaries and socio-economic data since 2006.
Within LTM, the passenger transport model consists of several interacting sub-models. First, the population-synthesizer forecasts the characteristics and the distribution of the Danish population in a given year. Then, the population is grouped into households and input into the demand model, which determines the mobility demand. Finally, such demand is iteratively assigned to the transport infrastructure (to account for the fact that an increase in demand corresponds to more congestion) until reaching convergence. The final output of LTM describes how the demand related to the modes car, bus, train, S-train, metro, walk and bike is distributed across the zones in each year. A detailed description of LTM is provided by [43]. Within the scope of this study, it is worth focusing on the travel demand model and in particular on the modal choice step, useful to understand the modeling decisions adopted for developing MoCho-TIMES. The demand model consists of three steps:

- Trip generation: it determines the total number of trips generated and attracted in each zone. For this purpose, an MNL model considering the socio-economic characteristics of the households is used
- Trip distribution: the number of trips generated and attracted is used to predict the most likely trip flow pattern between origins and destinations through a gravity model. The output of this step is a cross-modal origin-destination (OD) matrix, which describes the trip distribution pattern across the zones
- Modal choice: an MNL model calculates modal shares comparing the utility functions of the modes available. The outputs of this step are the mode-specific OD matrices

Modal choice in LTM is performed every year (y) considering a wide range of attributes. As anticipated in Section 2, the attributes relevant for modal choice are socio-economic variables and LoS variables. The LoS covers a wide range of attributes related to travel-time components, as shown in Equations 1-3 (for each year y). The travel time for car ($Time_{car}$) is calculated as a combination of free-flow travel time (fft_{car}), congestion time (ct_{car}), ferry-sailing time (fst_{car}) and ferry-waiting time (fwt_{car}) multiplied by some penalty factors (congestion penalty (cp), ferry-sailing penalty (fsp), ferry-waiting penalty (fwp)). All the attributes for the LoS of car are calculated in the route assignment model. For public transport, the travel time ($Time_{PT}$) is determined in a schedule-based assignment model. It consists of four components, namely in-vehicle time (inv_{PT}), departure waiting time (dpw_{PT}), waiting time at the stop (wtt_{PT}) and walking time (wkt_{PT}), weighted by some penalty factors (waiting penalty ($wttp$), walking penalty ($wktp$). For non-motorized modes the travel time ($Time_{NM}$) is just the travel time itself (tt_{NM}).

$$Time_{car,y} = fft_{car,y} + ct_{car,y} * cp + fst_{car,y} * fsp + fwt_{car,y} * fwp \quad \text{Equation 1}$$

$$Time_{PT,y} = inv_{PT,y} + dpw_{PT,y} + wtt_{PT,y} * wttp + wkt_{PT,y} * wktp \quad \text{Equation 2}$$

$$Time_{NM,y} = tt_{NM,y} \quad \text{Equation 3}$$

In LTM, the LoS terms and the costs of each mode m are joined in a generalized time measure ($GTT_{m,y}$). As shown in Equation 4, the generalized time is obtained by taking the quotient of the cost component and the value of time (VoT).

$$GTT_{m,y} = Time_{m,y} + \frac{Cost_{m,y}}{VoT} \quad \text{Equation 4}$$

The VoT is the marginal substitution cost between travel time and travel cost and it states how much a consumer is willing to pay to reduce the travel time of one unit [49]. The VoT adopted in LTM and in this study differs between segments, depending on the purpose of the trip and on the income level of the consumer [50]. The relationship between the VoT and the income level is shown in Table 2, from which it results that richer people are willing to spend more to save travel time.

Table 2: Value of time by income group in DKK/hour (personal elaboration from [50])

Income class	**Personal income [100k DKK/year]**	**Weighted average VoT in 2010 [DKK/hour]**
Very Low	<200	50.8
Low	200-500	87.6
Medium	500-800	145.9
High	>800	240.5

For each mode, the generalized time and other dummy variables related to the socio-economic characteristics of the household and to the type of zone where the trip occurs are multiplied by the model parameters (obtained through log-likelihood maximisation) and finally aggregated in the utility functions [43]. The utility functions of the different modes are compared for every year within a MNL model, which determines the modal shares.

This overview of LTM is the fundamental background required to understand the main modeling choices done while developing MoCho-TIMES. In fact, MoCho-TIMES aims at being solely grounded on well-founded behaviour and consumer choice theory and relies on the data and mathematical expressions of the generalized time of LTM [48].

3.2 MoCho-TIMES: Overview and structure

Traditionally, E4 models assume a central, global decision maker who carries out decisions on behalf of the average consumer, with full information and perfect rationality while aiming to maximize the system's economic utility only accounting for costs. Under these modeling assumptions, the modal shares and the technology portfolio determined by the models represent a configuration optimum for the system, but not for the consumers' perspective. Moreover, new vehicles penetration is characterised by a sharp pattern: as soon as a technology becomes cost-effective, it obtains the entire market share. This phenomenon is denominated "winner-takes-all" behaviour or "knife-edge" behaviour [46]. However, modal choice depends on consumer preferences and, as highlighted in Table 1, the attributes affecting it are more than purely economic. Diverse groups of consumers have different perceptions of these attributes, which results in disparate preferences towards modal adoption. Therefore, incorporating consumer heterogeneity into the modeling framework is a precondition for representing realistic modal choice behaviour. In this way, each group of transport users chooses its own optimal set of modes and technologies, thus leading to a variety of modes each year. Beside heterogeneity, representing behaviourally realistic modal choice in E4 models requires incorporating the main variables affecting it, as described in Table 1. To account for these two major requirements, the innovative methodology of MoCho-TIMES consists in two main steps:

1. Divide transport users into heterogeneous groups with different modal preferences
2. Incorporate intangible costs (disutilities) that assume different values across the diverse groups of transport users

The rest of this section provides a description of these two modelling innovations in Section 3.2.1 and Section 3.2.2, then describes the other constraints required for developing MoCho-TIMES in Section 3.2.3 and finally provides an overview of the model structure in Section 3.2.4.

3.2.1 Incorporating demand-side heterogeneity

Population heterogeneity is required to account for the diversity of behaviour across different groups of consumers [51]. From a modeling perspective, incorporating heterogeneity consists of dividing transport users into groups characterized by different attitudes towards modal choice, which are reflected in different intangible costs. In MoCho-TIMES, heterogeneity is introduced by splitting the total travel demand into segments, each one associated to a specific group of transport users. Identifying the dimensions according to which transport users are split is crucial, because they need to capture the key differences between the groups and their modal preferences. The dimensions for the heterogeneity are a subset of the demographic and socioeconomic attributes in LTM:

- Region of residential location: Denmark East (DKE) and Denmark West (DKW)
- Type of residential location: urban (U), suburban (S) and rural (R)
- Income level of the household: high (H), medium (M), low (L), very low (VL)

Overall, this characterization of heterogeneity allows to differentiate 24 groups of transport users with different preferences in modal choice, as visible in Figure 1.

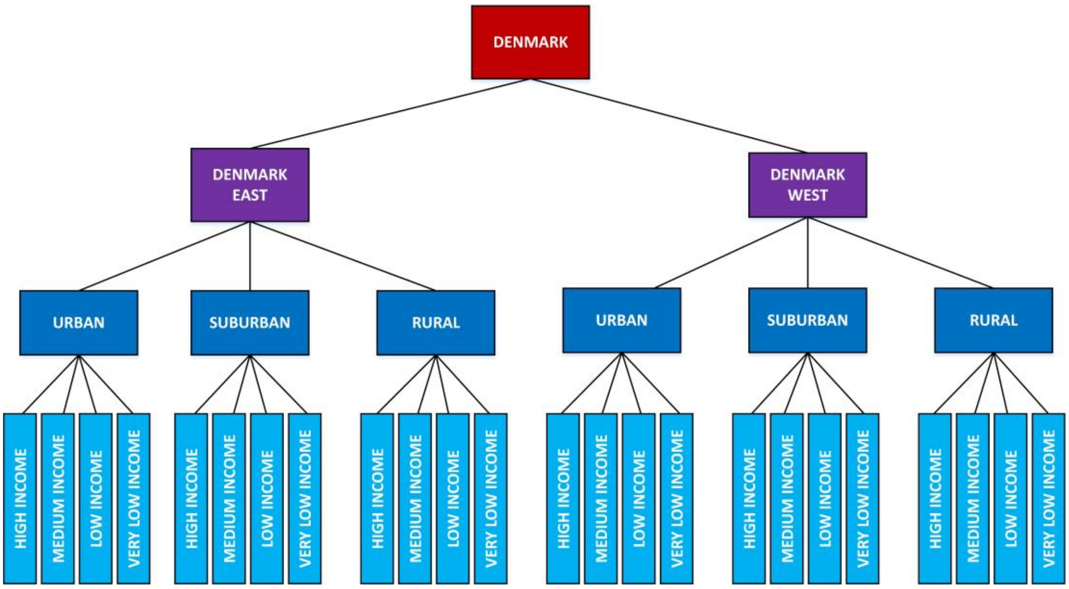

Figure 1: Schematic illustration of heterogeneous consumer groups

The first two levels of the segmentation introduce spatial characterisation in the model, which is fundamental when dealing with transportation analysis. The type of residential location, i.e. the type of area from which the trips depart, affects accessibility to public transport and attractiveness of car (e.g. metro and S-train are not available in DKW, waiting-time and walking-time for train are higher in rural areas and car is characterised by higher congestion-time in urban areas). Therefore, these splits enable differentiating the LoS of the modes across the population. The third split distinguishes the perception of the LoS of the modes for consumers living in the same residential location by considering their income levels. The rationale behind such a split is provided by Table 2, which shows that the income level affects the VoT, so that people weigh time and cost in a different way depending on their wedge. Consumer segmentation according to the income level is based on TU survey [52], while the split according to the type of residential location is based on the OD matrix of LTM. As shown in Figure 2, the zones of LTM are labelled as urban, suburban and rural, taking the density and the total population in every zone into account [53]. Matching the travel demand distribution provided by the OD matrix with the U/S/R label reveals how the total travel demand distributes across the types of urbanization.

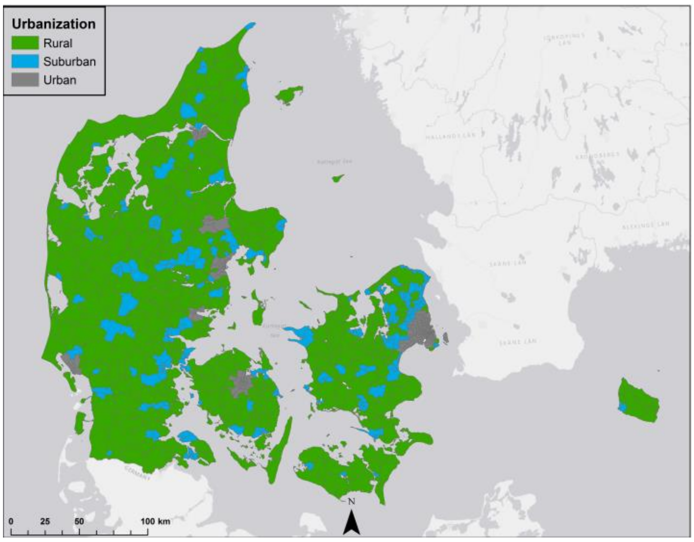

Figure 2: Classification of the zones of LTM by type of residential location

3.2.2 Quantifying modal preferences

After heterogeneity is integrated by splitting the mobility demand into segments corresponding to groups of transport users living in the same type of residential location and with similar income level, the intangible costs need to be incorporated in the model. These serve to capture the non-economic factors affecting modal choice into the expression of the generalized cost, as well as to differentiate modal perception across the heterogeneous demand segments through monetization. In order to incorporate intangible costs in the model, the expression of the modal cost is changed. The generalized cost (GC) characterising each mode (m), per each consumer group (cg) and in each year (y) is the sum of three terms, as shown in Equation 5: fuel cost (FC), non-fuel cost (NFC) (including operation and maintenance cost and investment cost) and intangible costs ($InCos$).

$$GC_{m,cg,y} = FC_{m,y} + NFC_{m,y} + InCos_{m,cg,y} \quad \text{Equation 5}$$

The latter term of Equation 5 is the one that introduces the non-monetary costs perceived by consumers and that differentiates the perception of the mode across consumer groups. In fact, the same mode has associated different intangible costs ($InCos$) for each consumer group. This is due to the expression of the intangible costs, shown in Equation 6: it is the product of the LoS, which is affected by the type of residential location, and the VoT, which is related to the income level of the cg. Other attributes that also contribute to the utility of a transport mode, e.g. car ownership, presence of children in the family, are not included in this formulation.

$$InCos_{m,cg,y} = LoS_{m,cg,y} * VoT_{m,cg,y} \quad \text{Equation 6}$$

The expressions of the LoS in MoCho-TIMES are the same as those in LTM described in Equations 1-3, in order to maintain consistency with the support model. In particular, the LoS in MoCho-TIMES are obtained aggregating the quantities of LTM at the level defined by the heterogeneity. Another important difference between MoCho-TIMES and the support model is that the latter characterizes modal perception through the generalized time (see Equation 4), while the novel model adopts the generalized cost. As optimization models take decisions based on least-cost criteria, the monetization of the LoS is required. It is worth noting that all the technologies belonging to the same mode are characterised by the same intangible cost. Nonetheless, the methodology is flexible enough to allow differentiating this cost across technologies, if required.

Figure 3 compares the intangible cost perceived by VL income consumers living in the three types of residential locations for Denmark East in 2030 with the non-fuel cost (the sum of the capitalized investment costs and operation and maintenance costs) and fuel cost. In all the residential locations and for all the modes, intangible costs account for the greatest share of the generalized costs. Moreover, Figure 3 shows that the intangible costs assume diverse values for the three types of residential location, which proves that the differences in modal perception of consumers living in urban, suburban and rural areas are reflected in the intangible costs.

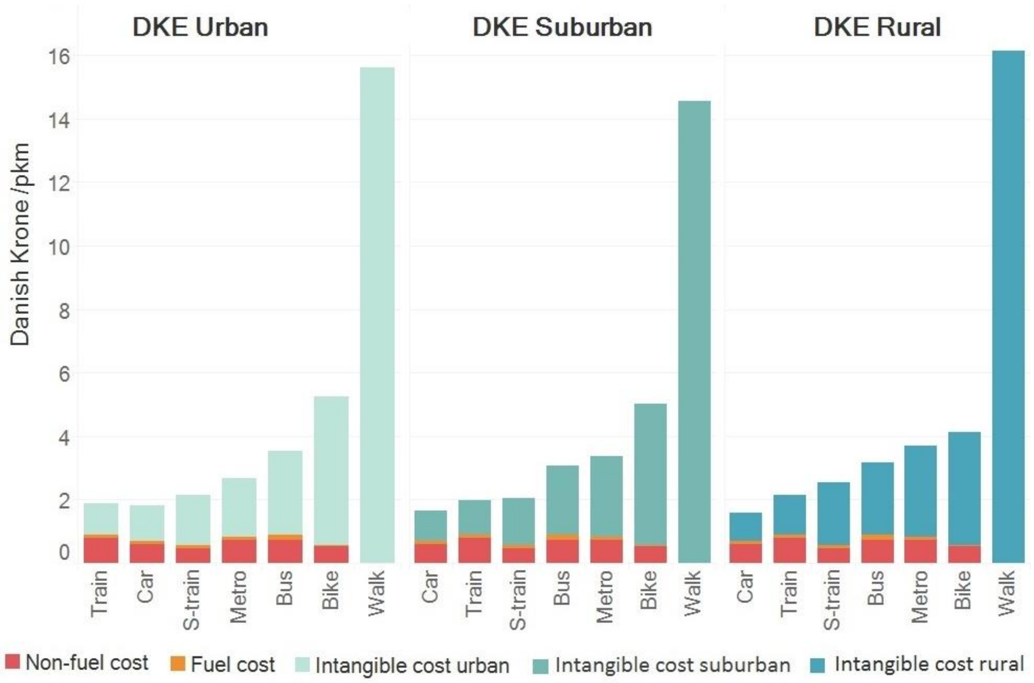

Figure 3: Comparison of non-fuel cost, fuel cost and intangible cost for VL income consumers in Denmark East in 2030 in the three types of residential locations

Consumers with different income levels are characterized by distinct magnitudes of intangible costs, as visible in Figure 4 (for suburban areas in Denmark East in 2030. Figures for the other urbanization types, in Denmark West and in other years are slightly different). This is evidence of the fact that the VoT is proportional to the income level (see Table 2). As a consequence, MoCho-TIMES adopts the modes characterised by better LoS to move high income groups, while for less attractive modes such as walk and bike it prioritizes consumers with lower income level. This is done while respecting the constraints described in Section 3.2.3.

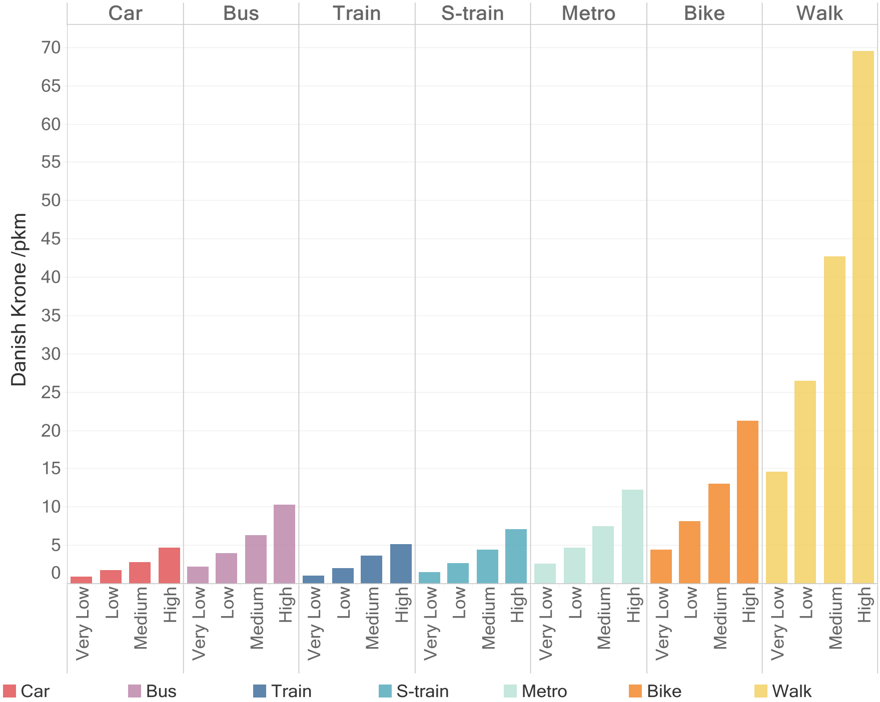

Figure 4: Intangible costs faced by consumers living in suburban areas in Denmark East in 2030 per mode and per income level

3.2.3 Incorporating the other variables influencing modal choice in MoCho-TIMES

In addition to consumers' heterogeneity and intangible costs, MoCho-TIMES also incorporates other parameters that influence modal choice. These are the monetary budget, availability of transport infrastructures, travel time budget, travel patterns, maximal modal shares and maximum rate of shift. A description of these features is provided in this section.

3.2.3.1 Monetary budget

Traditionally, E4 models determine the optimal configuration of the future energy system by comparing the lifetime costs of the technologies available and the fuel production chains as perceived by a central energy planner. The costs accounted are related to the supply of the energy resources and to the technology capacity expansion and operation: investment costs, fixed and variable operation and maintenance costs, fuel costs and delivery costs. Nonetheless, when incorporating modal choice in the modeling framework, the perspective of the central energy planner must be substituted with that of the consumers. These consumers also perceive other costs, such as availability of infrastructure, ticket fares for public transport and fuel taxes, parking cost, vehicle registration tax (VRT) and ownership tax for private car. In order to render comprehensively the mechanism of consumers' modal choice, these costs have been integrated into MoCho-TIMES. Fares for public transportation modes are calculated from the TU Survey [52], while for car the cost of parking is obtained from [54], the insurance cost from [55] and the registration and ownership taxes from [56]. Nonetheless, the central planner does not face these costs, which hence shall not be accounted in the total system cost. Therefore, these consumer-perceived costs of driving car and using public transport are included in the model as commodities, which are consumed by the modes in order to fulfil the travel demands. The model tracks how much consumer-perceived cost commodities are consumed by the four income groups (H, M, L and VL). In addition, income-group specific monetary budgets limit the consumption of the consumer-perceived cost commodities. The monetary budgets are obtained considering the monetary requirement in the BY of MoCho-TIMES calibrated to the baseline demand projection of the

LTM. The monetary budget ensures that the different classes of income groups do not spend for mobility more money than historically observed. At the same time, since the monetary budget includes both transit and private car, the constraint does not fix the relative modal shares of these two classes of mode and allows modal shift.

3.2.3.2 Transport infrastructure

Transport infrastructure is a key driver of travel demand and modal choice [6], [57], [58]. In transport simulation models such as [20] and [21], the level of utilization of the road network affects congestion time and travel time for car and thus influences the LoS. On the other hand, in energy system models transport infrastructures are more rarely represented. The rationale for incorporating infrastructure in MoCho-TIMES is that there must always be enough infrastructure capacity to accommodate the travel demand. There are five transport infrastructures represented in MoCho-TIMES: road for bus and car, three railways for train, S-train and metro and bicycle lane for bike. These transport infrastructures are not represented explicitly in the model, but as commodities that the modes consume in order to fulfil the mobility demand. The existing infrastructure commodities are free, but limited. The amount of extra travel demand with respect to the BY that the existing infrastructures can accommodate before saturating depends on their capacity utilization levels. These are calculated for each infrastructure as the ratio between the maximum traffic volume and the infrastructure capacity [59], [60]. After the existing infrastructures saturate, the model accommodates the extra travel demand by investing in new infrastructures, with a cost associated [61], [62]. More details regarding the representation of transport infrastructure are provided in [39].

3.2.3.3 Travel time budget

The rationale of the travel time budget (TTB) has been provided by [63], which claims that, in different geographical areas, historical periods and socio-economic contexts, people dedicate the same amount of time to mobility. The TTB has been incorporated in MoCho-TIMES to ensure that transport users dedicate to mobility an amount of time consistent with historical observations. From the modeling perspective, the TTB is a constraint that limits the availability of the travel time commodity, which is consumed by all the modes and technologies when fulfilling the travel demands. Travel time is constant across all the technologies belonging to the same mode (with the exception of electric and normal bikes). Moreover, travel times are specific to the region and type of residential area from which the trip originates. Travel times are obtained from TU Survey [52] as described in [39]. The TTB per capita for the BY of MoCho-TIMES is 58.4 minutes/day, very similar to that observed by TU survey, which is 54.8 minutes/day [52]. The difference between the two quantities is due to the fact that TU survey includes more modes in the analysis.

3.2.3.4 Modal travel patterns, maximal modal shares and maximum rate of shift

MoCho-TIMES characterizes the modal travel patterns, which define how modes contribute to meet the travel demands. The modal travel patterns for the BY, shown in Table 3, are obtained from TU Survey [52]. Some additional flexibility is provided to the model to fulfil the future travel demands. From year 2012 onwards, the travel patterns of private modes (car, bike and walk) are relaxed by 12% with respect to the BY, while those of public transport (bus, train, S-train and metro) are relaxed by 10%.

Table 3: Modal travel patterns in 2010

	Denmark East			**Denmark West**		
	Urban	Suburban	Rural	Urban	Suburban	Rural
Car	33%	35%	31%	18%	34%	48%

Bus	56%	25%	19%	32%	31%	37%
Train	52%	30%	18%	39%	37%	24%
Metro	92%	3%	5%			
S-train	75%	20%	5%			
Bike	50%	28%	22%	34%	24%	43%
Walk	72%	21%	7%	39%	40%	21%

Modal competition in MoCho-TIMES is regulated also through a set of constraints that limits the maximal modal shares in 2050. These upper bounds are calculated comparing the modal travel patterns in Table 3 with the distribution of the total travel demand across regions and urbanization types. The rate of modal shift is also limited, based on linear interpolation between the modal shares in the BY and the maximal modal shares in 2050. A more extensive discussion of these approaches is given in [39]

3.2.4 Structure of MoCho-TIMES

A simplified schematic overview of the structure of MoCho-TIMES is provided in Figure 5. Each mode can fulfil 24 demand segments, which correspond to the 24 heterogeneous consumer groups differentiated by region, type of residential location and income level (see Figure 1). The modes have an intangible cost associated to each demand segment. These costs monetize the modal perception of the consumer group associated to the demand segment and are calculated outside of the model as shown in Equation 6. Moreover, each mode contributes in its specific way to fulfil the demands, as defined by the travel patterns (see Table 3). To fulfil the travel demands, the modes do not just consume fuels, as in traditional TIMES models, but require in input also other commodities: infrastructure, travel time and consumer-perceived costs. These commodities are provided by some processes (on the left part of Figure 5), which availability is bounded. The existing infrastructures (represented by just one process in Figure 5) are limited, and when saturated the model can endogenously decide to invest in new infrastructures, which have associated costs. The TTB limits the overall consumption of travel time. The monetary budgets for the four income groups (represented by just one process in Figure 5) limit their expenditure in public transport and private cars.

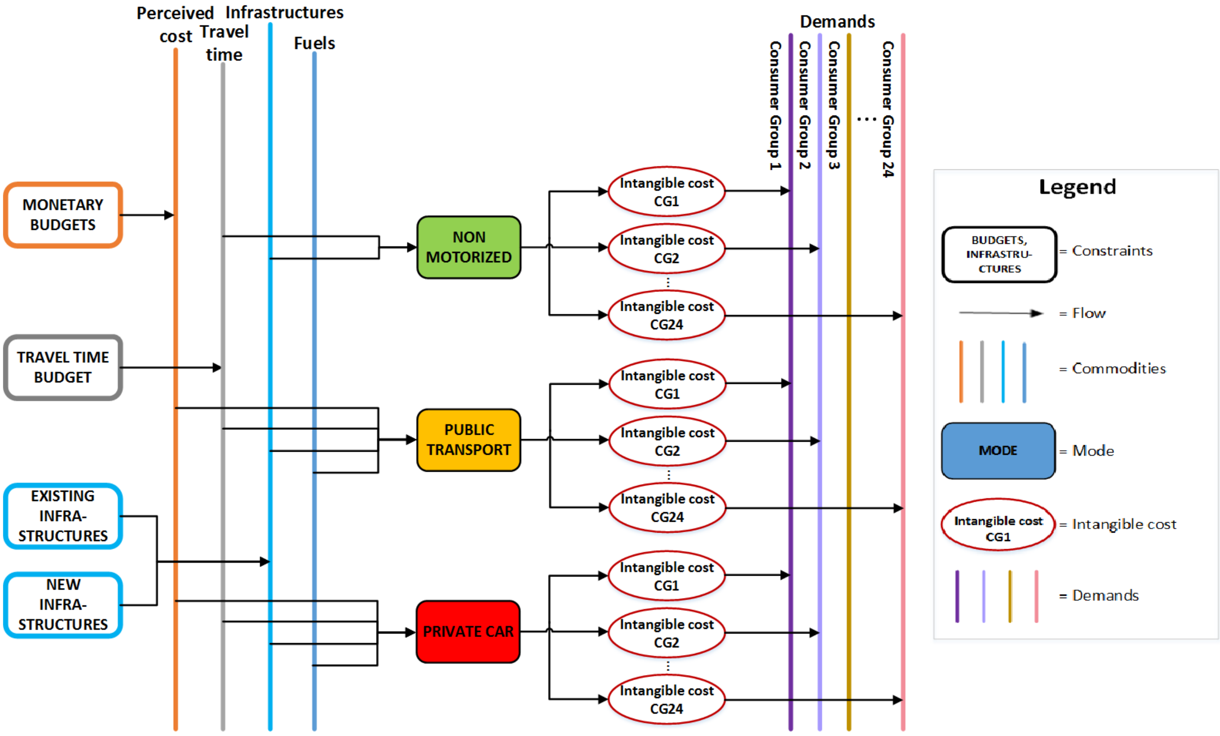

Figure 5: Scheme of the structure of MoCho-TIMES

3.3 Scenario definition

Five scenarios are analysed in this study: a BaU scenario and four alternative scenarios that involve different LoS of modes, consumer perceptions, taxation schemes, infrastructure deployments and incentives to public transport with respect to the BaU scenario. The two dimensions for the alternative scenario matrix are authority commitment (A) and individual commitment (I), both characterised by the dichotomy high/low (HI/LO). A schematic overview of the four alternative scenarios is provided in Figure 6.

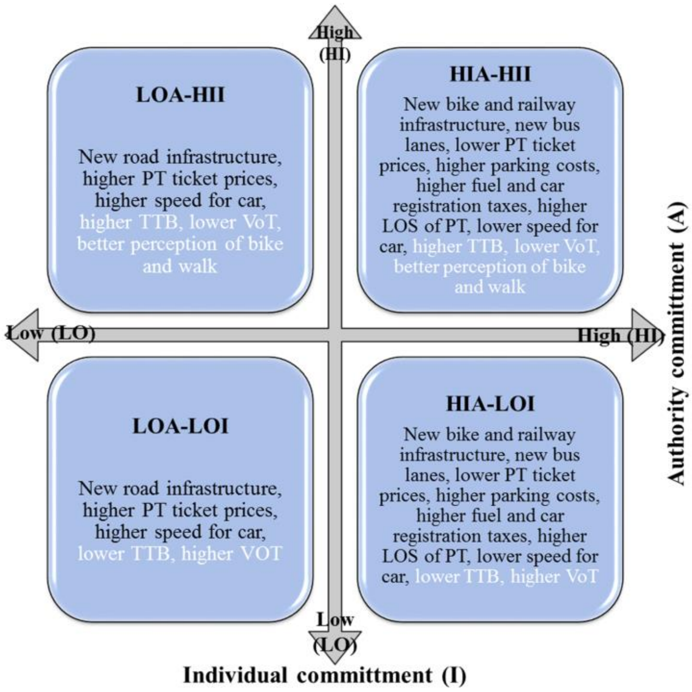

Figure 6: Scenario matrix, with authority commitment and individual commitment as dimensions

A general description of the four alternative scenarios follows. More details on the assumptions for the BaU and alternative scenarios are provided in Table 1 of Appendix I:

- *HIA-HII (High Authority commitment – High Individual commitment):* leaders and consumers are aligned in fighting climate change and local air pollution, aiming at a more sustainable transportation system. After 2020, the authority builds new bike lanes, bus lanes, one new metro line, one new S-train line and a new electrified railway. The Government also encourages the use of public transport by decreasing the fares and increasing parking prices, especially in urban areas. In order to promote the adoption of alternative fuelled vehicles (AFV) and efficient vehicles, the authority also increases the taxes on diesel and gasoline from 2020 and on natural gas from 2030. The VRT for cars in 2020 is set at the same levels as before the reform of 2016 [64] for fossil fuelled cars. On the other hand, plug-in hybrid (PHEV) only pay 20% of payable VRT and battery electric vehicles (BEV) and fuel cell electric vehicles (FCEV) are exempted from VRT. Following the investments in infrastructure, the careful urban planning and the integration of the public modes, the LoS of public transport after 2020 is assumed to improve by approximately 10% in this scenario. Instead, the lack of investments in new roads and the increase of public lanes lead to a decrease in car speed. High individuals' commitment towards sustainability consists of a greater willingness to spend time travelling (+10% TTB with respect to BaU), a better perception of the walking time and waiting time associated with the use of transit, a better perception of bike and walking, a lower availability to spend time in traffic with car and a reduction of the value of time (-10% VoT with respect to BaU).
- *HIA-LOI (High Authority commitment – Low Individual commitment):* the Government strives to promote a sustainable transportation sector and puts in practice the same measures as described in the previous scenario (HIA-HII). Nonetheless, regarding the individual commitment, transport users are reluctant to change behaviour. After 2020, consumers are more willing to spend time in traffic when using car transport with respect to BaU, but less willing to spend time accessing the public transport station and waiting for transit, and do not perceive any attractiveness in walking and

cycling. They dedicate less time to mobility (-5% TTB with respect to BaU) and give a high value to savings of travel time (+10% VoT with respect to BaU)

- *LOA-LOI (Low Authority commitment – Low Individual commitment):* this scenario corresponds to a future characterised by general disinterest towards climate change and environmental issues. The authority only builds new road infrastructure, thus improving only the LoS of car and bus. Moreover, it does not incentivize public transport fares, does not set new taxes on fuels, nor increase the VRT of fossil-fuelled cars. Consumers' low commitment towards sustainability is described in the same way as for the individual's commitment of HIA-LOI.
- *LOA-HII (Low Authority commitment – High Individual commitment):* individuals alone commit towards a more sustainable transportation sector, without any support from the Government. This scenario is characterised by the same variables as LOA-LOI concerning the authority commitment and by the same variables as HIA-HII concerning the individual commitment.

4. Results

MoCho-TIMES endogenously determines the modal shares from 2010 until 2050. It also determines the optimal technology fleet within each mode, the fuel consumption, fuel prices, investments in new transport infrastructures, emissions and other traditional outputs from E4 models. This section is structured as follows: firstly, Section 4.1 describes the results for the BaU of MoCho-TIMES, compares them with those of the support model LTM and focuses on the capability of the model to observe how modal shift occurs across diverse consumer groups. Secondly, Section 4.2 tests the behaviour of the model via a scenario analysis that evaluates how alternative assumptions for the newly incorporated variables affect modal share and CO_2 emissions.

4.1 Business as Usual scenario

Although MoCho-TIMES allows to analyse many aspects of the transportation sector, the focus of this study is primarily on modal shares, which are determined endogenously within the model. Figure 7 shows the modal shares for the BaU scenario, aggregated on all the demand segments. During the time horizon of the model, the total travel demand increases by about 31%. In the long-term, car transport is responsible for the majority of this increase, with a significant contribution from trains and bikes. In the medium-term, the activity of car is reduced due to the uptake of buses. These dynamics occur due to the unchanging vehicle prices of new cars in the medium-term, coupled with an improvement in the LoS of buses, which reduce the intangible costs for consumers. Nonetheless, after 2035 buses stop being used because the cost of car technologies significantly reduce, resulting in a shift towards cars. As road infrastructure saturates the model chooses to seize investing in more, but rather to adopt more train and bike transport. The increase in the use of metro and S-train is largely limited by the fact that it only exists in DKE and that it would require expensive investments in additional infrastructure. Walking strongly reduces with respect to the BY due to its high intangible cost.

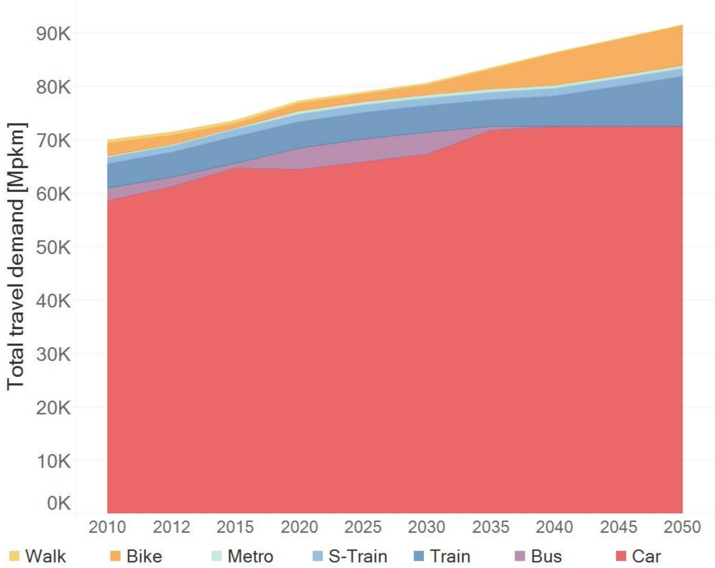

Figure 7: Aggregated modal shares in the BaU scenario

A comparison between the modal shares of MoCho-TIMES with those of its support model LTM is shown in Figure 8 for the years 2010, 2020 and 2030. The time horizon of LTM is limited to 2030, and so the comparison is drawn until this year. This comparison shows that MoCho-TIMES is able to reproduce the results of its support model satisfactorily. The modal shares of the two models in 2010 are identical and in 2020 and 2030 the main differences consists in the fact that the market share of bus transport for MoCho-TIMES is higher with respect to LTM, at the expense of train transport.

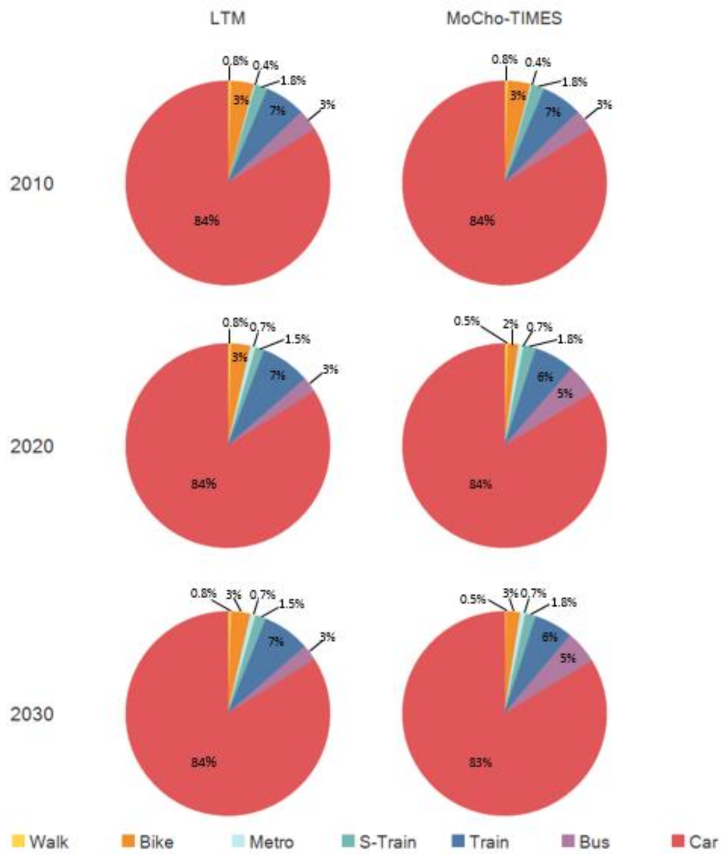

Figure 8: Comparison of modal shares between LTM and MoCho-TIMES for 2010, 2020 and 2030

MoCho-TIMES has the capability to analyse how modal shift occurs in the different types of residential locations (urban, suburban and rural) while providing insights on modal adoption for each consumer group. The modal shares of Figure 7 are the aggregated result of the underlying choices of the heterogeneous consumers, which are characterised by diverse modal perceptions and preferences. The differentiation of the intangible costs across consumer groups allows for modal shares to vary by type of urbanization and income level, as shown in Figure 9. The aggregated patterns of modal adoption shown in Figure 7 (e.g. mid-term buses uptake, car saturation and long-term uptake of bikes and trains) are also visible at a disaggregated level in Figure 9. The opportunity of observing modal shares at a consumer group level is extremely important, as it provides insight to which segmentation(s) modal shift actually occurs and allows to differentiate the willingness to adopt sustainable modes across different transport users. In this way, it is possible to identify groups which are most averse to modal shift, to understand their reasons and to tackle them with ad-hoc policies. Furthermore, Figure 9 shows that transport users who live in rural areas have fewer options available to shift away from travel via car, which leads to an increase of the use of car across all income groups in rural areas. Urban and suburban areas are served by a wider variety of modes, which allows lower income classes to decrease their use of car transport after 2040 with respect to the BY. The use of cars in urban areas begins to plateau in the medium to long-term. Across all types of urbanization, VL and L income classes are witnessed to be more willing to shift away from car as a mode of transport, while wealthier consumer groups are more reluctant to reduce their dependence on car. In particular, high-income groups have a tendency to use fast modes of transport to travel, while their adoption of slow modes, e.g. bike, is the lowest. In urban areas, there is a shift away from car transport mainly towards train and bike transport. The increase in train transport in this case is due to the better LoS offered by train in the long-term, such that its intangible costs become lower than that of car counterpart. The increase in the use of train, which is the fastest mode, leads time savings large enough to enable an increased use of bike, which is slow yet not expensive, while respecting the TTB constraint.

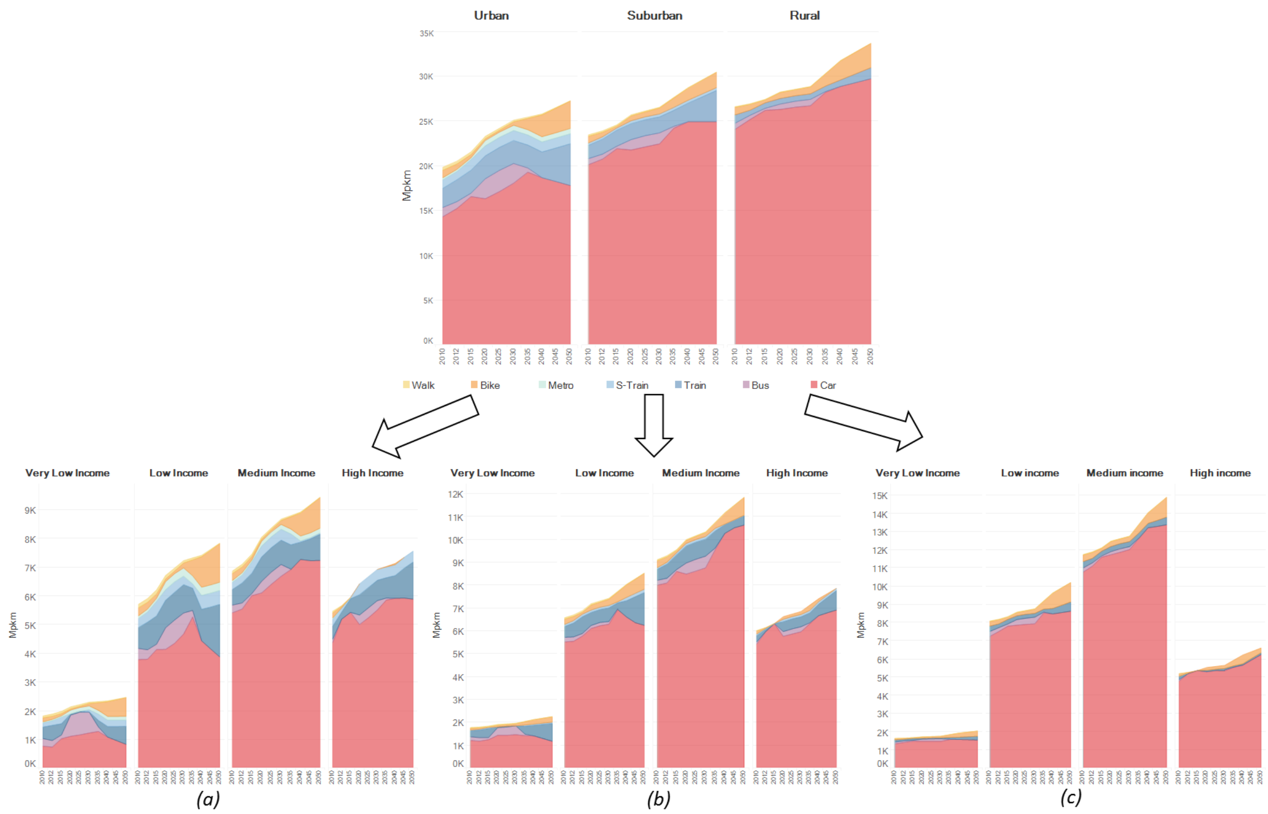

Figure 9: Modal shares for the three types of residence location, disaggregated at income group level (aggregated for DKE and DKW). (a) urban, (b) suburban, (c) rural

4.2 Alternative scenarios

The sensitivity of MoCho-TIMES to the assumptions of key variables is hereby tested via illustrative scenarios, which explore how alternative assumptions can result in larger share of public transport and low-carbon modes that can potentially reduce CO_2 emissions. The costs of these scenarios, such as total system cost, investment cost, O&M cost and fuel cost related to the modes, cost of new infrastructures and subsidies are excluded from the discussion.

For the four scenarios described in Section 3.3, MoCho-TIMES determines the modal shares shown in Figure 10. As expected, the diversity of assumptions for the variables results in different modal shares. The two scenarios that imply high commitment by the authority (HIA) are characterised by the lowest increase in the use of car transport. The HIA-HII and HIA-LOI scenarios mostly differ in the fact that in case of high commitment of transport users (HII) bike transport plays a major role in fulfilling future travel demand, while in case of low consumer engagement train transport is the mode characterised by the highest increase in the long-term. In the scenarios characterised by low commitment from the authority (LOA-HII, LOA-LOI), car is the main mode meeting the future extra mobility demand. These two scenarios mostly differ in that bike transport is used more frequently in the case of high commitment of consumers (but still less than in HIA-HII and BaU), while in case of low commitment of individuals, buses and trains are preferred alternatives. In particular, buses feature the most in the medium-term and trains in the long-term. Moreover, in these scenarios metro and S-train do not gain as much importance as in case of high authority commitment. While it is not reported in this paper, MoCho-TIMES has the ability to analyse how different consumer groups shift mode as a consequence of different assumptions, as shown for the BaU scenario in Figure 9.

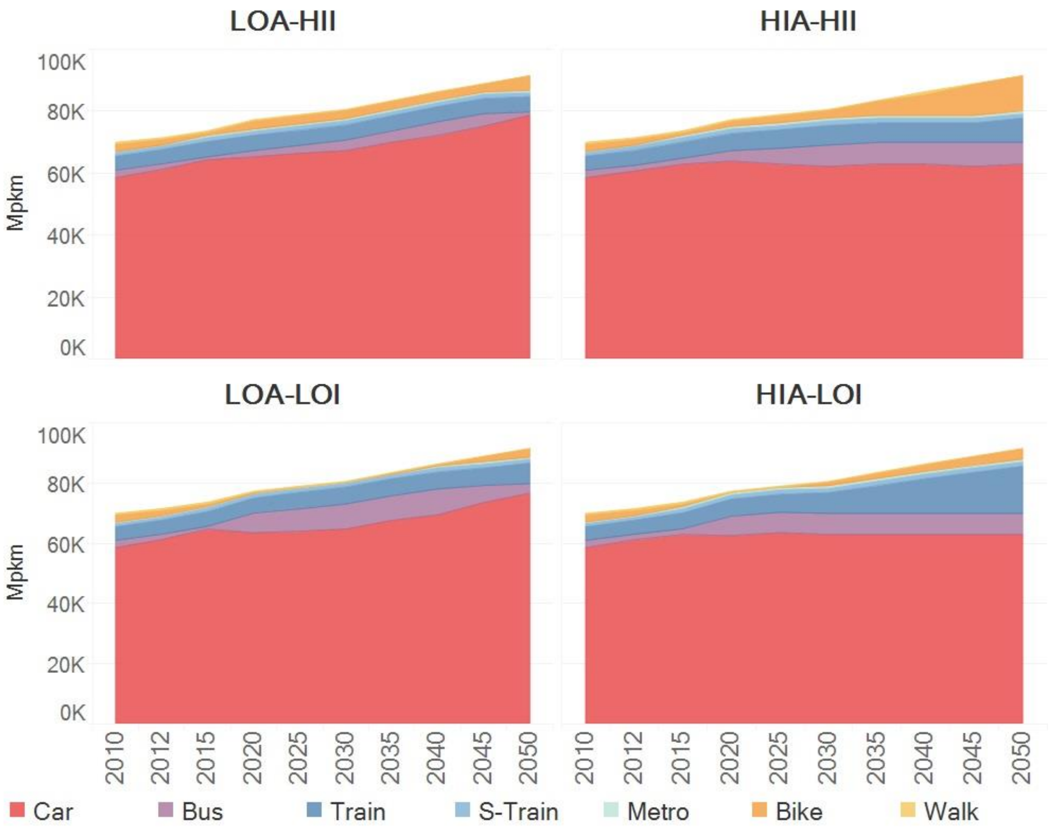

Figure 10: Modal shares in the four scenarios. HIA-HII: High authority commitment – High Individual commitment; HIA-LOI: High authority commitment – Low Individual commitment; LOA-LOI: Low authority commitment – Low individual commitment; LOA-HII: Low authority commitment, high individual commitment

The trend of CO_2 emissions from the Danish transportation sector is compared for the BaU scenario and for the four scenarios analysed in Figure 11. The HIA-HII and HIA-LOI scenarios, which are characterised by lower increase of car usage and high use of public transport and bike transport, in the long-term reach a deep cut of CO_2 emissions. On the other hand, the scenarios corresponding to a low commitment of authority imply even higher CO_2 emissions than in the BaU scenario. Even if these results are relative to the Danish context, they highlight that the authority commitment towards sustainability is of primary importance to significantly reduce the carbon intensity of the transportation sector. If the Government does not commit towards sustainability, all the efforts of individuals alone are mostly nullified.

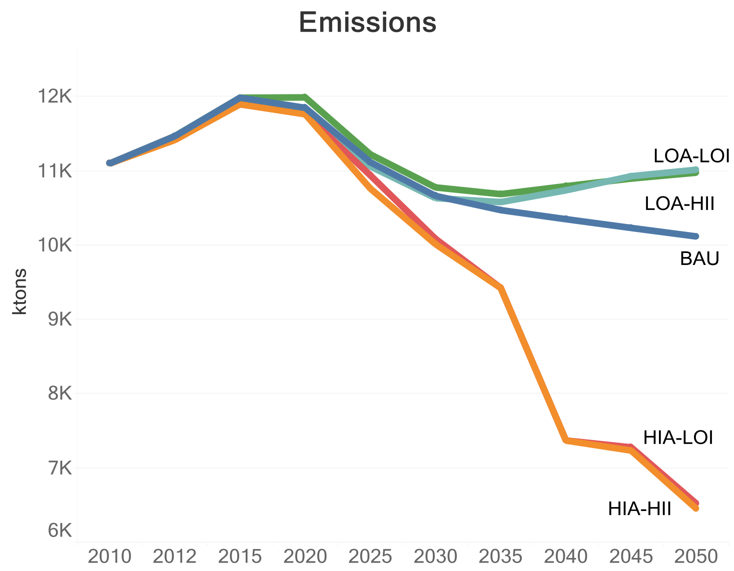

Figure 11: Trend of CO_2 emissions from BY until 2050 in BaU scenario and in the four scenarios analysed

5. Discussion and future research

MoCho-TIMES moves a step forward in the representation of human behaviour in BU optimization energy system models and improves the representation of consumers' choice in transport. The methodology proposed does not require any change in the TIMES code, although the model structure must be restructured, as shown in Figure 5. Moreover, a significant amount of data is required and the incorporation of the intangible costs implies several extra model calculations.

The main limitation of MoCho-TIMES is that its development requires a transport simulation model with the same geographical scope as the E4 model. The transport model works as a support model, providing a disaggregated description of the mobility demand (via an OD matrix) and of the LoS attributes. Fortunately, for many countries and regions dedicated transport models are available, e.g. LTM for Denmark [20], RMS for Ireland [21] and CSTDM for California [22]. Even when a transport simulation model for the geographical area analysed is not available, many of the data required for incorporating modal choice in E4 optimization models can be obtained from a geographically consistent travel survey. Concerning the use of transport models as support to the development of MoCho-TIMES, it is worth noting that the time horizon of the energy system model and of the transport simulation model may differ. In fact, E4 models are mainly used for exploring energy scenarios in the long-term, while transport simulation models are used to forecast the transport demand and the traffic distribution in the medium-term. Therefore, the latter category relies on data related to the socio-economic characteristics of the population and to the availability of infrastructure. This is the case for LTM, which forecasts the development of the Danish transportation sector until 2030, while MoCho-TIMES models the transportation sector with a time horizon of 2050. The difference in time horizon between the two models implies that the modeller has to make several assumptions for the transport-related variables between 2030 and 2050. A possible way to overcome this limit is performing some scenario and sensitivity analyses on the uncertain variables, as done in Section 4.2.

A further possible source of challenges lies in the fact that modal-choice within MoCho-TIMES is determined at a highly aggregated level, for macro clusters of consumers. As behaviour is an individual trait, any attempt to capture it should be pursued at individual level. The scientific literature shows that modal choice is deeply affected by behavioural features, hence transport models simulate modal choice at individual or household level [17]. Compared to these levels of detail, the heterogeneity integrated in MoCho-TIMES falls short. However, it manages to capture some variability of modal preferences across the population, enough to overcome the "mean-decision maker" perspective [41]. In fact, by splitting the mobility demand in several segments corresponding to different consumer groups, the model determines the optimal modal shares separately for each consumer group. The mix of modes within the demand segments is obtained from the combined action of the travel pattern constraints and the maximal modal shares, which respectively set some shares on how modes fulfil the demands and regulate the maximum penetration of each mode. The variation in modal shares across demand segments (see Figure 9) is obtained from the intangible costs, which differentiate consumer-specific modal preferences, and from the difference in the monetary budget across income-groups.

The authors find that the level of heterogeneity incorporated in this study is adequate for the scope of the analyses that are normally carried with E4 models. Nonetheless, the approach allows to define the number of heterogeneous consumers group in a flexible way. If an analysis needs a more refined level of heterogeneity for exploring consumers' choices more in depth, it is possible to split the overall mobility demand according to more dimensions. Possible additional dimensions are the socio-economic and demographic attributes listed in Table 1. Another valuable criterion for demand splitting is according to trip distance, which would enable a better regulation of competition between modes, as done in [39]. Theoretically, having as many demand segments as the number of households, or even individuals, would be ideal. Nonetheless, a high number of demand segments leads to model intractability. Therefore, finding a good trade-off between model size and representation of the population is crucial. An important effort for the modeller is that of determining the minimum number of dimensions that allows to create an exhaustive distinction between the main consumer groups. The comparison of the results of LTM and MoCho-TIMES until 2030 proves that the latter is able to reproduce the results of its support model suitably, even if with aggregated transport demands. An alternative approach to represent population heterogeneity and the differences of modal perception across the consumer groups consists in implementing the "clones", deviations from the "mean-consumer" perspective equivalent to the error term of the utility function of discrete choice models [46], [47]. For this approach, it is important to choose the right amount of clones that ensures variability of results, while avoiding model intractability, as observed by [13]. The use of the clones would ensure enough variation in the results as to avoid the "winner-takes-all" phenomenon.

Another shortcoming of MoCho-TIMES lies in its vague spatial framework. Transport models require a precise description of the spatial context, as they simulate modal choice after the origin and destination of the trips are identified (see Section 3.1). On the other hand, in MoCho-TIMES the only spatial reference is the region and the type of residential location (urban, suburban and rural). Therefore, the LoS attributes define the performances of the modes only at level of macro area. However, MoCho-TIMES is not meant to study what mode is adopted for a certain trip, but rather to analyse modal choice dynamics at aggregated level and to explore how modal shift and long-term changes in the whole energy system affect each other.

The final reflection concerns the ability of MoCho-TIMES of depicting modal-choice in a behaviourally realistic way. Consumers are characterized by perfect-information, perfect-foresight and perfect-rationality, due to the intrinsic nature of TIMES models. Even in transport simulation models, utility maximization, perfect-rationality and perfect-information are the assumptions underlying modal choice modeling. However, these situations are far from the reality, because choices are biased from optimality in many aspects. Recent studies on travel behaviour claim that choice mechanisms for modal choice are more complex than described by MNL models [58], [65]. Consumers deviate from rationality and utility maximization in three respects: nonstandard preferences, nonstandard beliefs, and nonstandard decision making [66]. These studies advocate a more extended use of evidences from behavioural economics in transport models in order to improve the representation of modal choice and other aspects of travel behaviour.

This paper has presented and tested the novel approach of MoCho-TIMES as a standalone mode, including only the transportation sector of TIMES-DK. The authors recommend as next step of research the integration of MoCho-TIMES within a whole energy system model, in order to introduce behaviourally realistic modal shift as an option to decarbonise the energy system. This enables assessing the effect of energy system dynamics on modal shares and vice versa, within a unique modeling framework. On one side, it allows to analyse how variations in the LoS of the modes and consumers' perception of the modes affect the rest of the energy system and, on the other side, how modal shares and fuel consumption in the transportation sector are influenced by decisions in the power and heat and other end-use sectors. It is especially important to integrate transport and energy system analysis in a unique framework, given that the transportation sector is expected to become increasingly integrated into the energy system, with more interconnection and cross-sectoral influences. Once MoCho-TIMES is integrated within the whole energy system, several new policy analyses can be performed with respect to traditional E4 models. To this extent is it worth noting that the intangible costs act for the transportation sector as an additional barrier to its decarbonisation. As observed by [41], when incorporating heterogeneity and intangible costs into the model, a higher carbon tax is required to achieve an equivalent GHG abatement with respect to a traditional E4 model. Although the methodology allows having a better insight on consumer choice, the inclusion of an extra cost-term makes CO_2 reduction measures for the transportation sector more expansive and thus more unlikely to happen than in other sectors. Consistency across sectors is fundamental to avoid this issue and therefore the improvement of the representation of behaviour in the transportation sector shall be matched with the inclusion of hurdle rates and intangible cost in the other energy sectors. Besides, it is important to consider that for MoCho-TIMES the total system cost is obtained subtracting the intangible costs out of the objective function. This is done to only account for the monetary costs incurred by the central planner.

6. Conclusions

MoCho-TIMES proposes a novel methodology to incorporate modal-choice within BU optimization energy system models. For this class of models, it fills the gap regarding the representation of behaviour in the transportation sector and inaugurates the possibility to perform scenario and policy analysis involving transport-related and soft variables, as advocated by [13]. For this study, the methodology has been developed and tested in the standalone transportation sector of Denmark. The approach is grounded on the consumer choice modeling theory, described in Section 2. The methodology of MoCho-TIMES is described in detail in Section 3. A transport simulation model consistent with the geographical scope of the E4 model in which modal choice is meant to be incorporated is required. The transport model works as a support model, which provides the data and the mathematical expressions for integrating modal choice in the E4 framework. MoCho-TIMES introduces heterogeneity of transport users and intangible costs to differentiate the LoS and the modal perception across different consumer groups. Overall, the innovative model structure and the constraints described in Section 3.2.4 contribute to the heterogeneity in outcomes: every year several modes contribute to fulfil the total travel demand, each mode being more or less suitable for a specific consumer group. Modal shares are not determined exclusively according to least-cost criteria, because MoCho-TIMES captures also other attributes affecting modal choice: the LoS of the modes and the socioeconomic and demographic characteristics of the consumer groups. This is the first study to the authors' knowledge that equips E4 models with modal choice without the use of an external model. This new feature on the one hand incorporates real household's modal preferences and perceptions, which increases the credibility of the policy analyses carried-out. On the other hand, it enables to understand in the same modelling framework how changes in modal perception, improvements in the LoS of the modes, technology improvements, infrastructure availability, market conditions and policy levers can lead to deploy low-carbon technologies that contribute to achieve a carbon-neutral transportation sector. These new capabilities of MoCho-TIMES are demonstrated in Section 4, which analyses in four illustrative scenarios how alternative assumptions of key variables influence modal shares and CO_2 emissions. Another praise of MoCho-TIMES consists in the fact that it provides insights on how modal shift occurs in the different types of residential location and for diverse consumer groups. This new insight enabled by the model is particularly valuable, as it allows to design more effective and efficient policies encouraging the transition to a fossil-free transportation sector. On the one hand, MoCho-TIMES identifies the consumers groups more willing to shift towards zero- and low-carbon modes, thus allowing to establish priorities. On the other hand, the novel approach supports the understanding of the most suitable policy levers to target the different consumers groups. The results in Section 4.1 show that a shift away from car transport is more likely to happen in urban and suburban areas rather than in rural ones, which are less served by public transport. Moreover, lower income classes seem more willing to shift away from car transport. Finally, the analysis of the trend of CO_2 emissions of the alternative scenarios points out that regulation and active participation of the Government in transport planning are fundamental to promote a paradigmatic shift in transport and to encourage the sustainable transition. The results of the model suggest that providing alternatives to car for traveling, building new infrastructures, improving the LoS and the accessibility to public transport, especially in rural areas, and setting up an effective taxation and incentive scheme are measures of primary importance to lead the transition of transport towards sustainability.

Acknowledgments

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Glossary

Alternative-specific constants (ASC)
Alternative fuelled vehicles (AFV)
Business as Usual scenario (BaU)
Base year (BY)
Battery electric vehicles (BEV)
Bottom-up (BU)
California Statewide Travel Demand Model (CSTDM)
Consumer group (CG)
Danish Kroner (DKK)
Denmark East (DKE)
Denmark West (DKW)
Energy-economy-environment-engineering (E4)
Energy Technology Systems Analysis Program (ETSAP)
Fuel cell electric vehicles (FCEV)
Gross domestic product (GDP)
Greenhouse gas (GHG)
High income level (H)
High Authority commitment – High Individual commitment (HIA-HII)

High Authority commitment – Low Individual commitment (HIA-LOI)
International Energy Agency (IEA)
Level-of-service (LoS)
Landstrafikmodellen, Danish National Transport Model (LTM)
Low income level (L)
Low Authority commitment – High Individual commitment (LOA-HII)
Low Authority commitment – Low Individual commitment (LOA-LOI)
Medium income level (M)
Million-passenger kilometres (Mpkm)
Multinomial logit model (MNL)
Modal Choice in TIMES (MoCho-TIMES)
Nested logit model (NMNL)
Origin-destination (OD)
Organisation for economic co-operation and development (OECD)
Plug-in hybrid (PHEV)
Regional Modeling System (RMS)
The Integrated Markal Efom System (TIMES)
Travel time budget (TTB)
The Danish National Travel Survey (TU)
Very low income level (VL)
Value of time (VoT)
Vehicle registration tax (VRT)

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