iSCAPE

Behavioral Recommendations for Urban Anthropogenic activities to population exposure and human health

D7.3

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Short Description	*The report integrates three deliverables that contain discussion on input/output links between the several components of integrated simulation platform, and then how this simulation platform outputs are helped in estimating exposure and health impacts of mobility-based structural interventions. The report also synthesizes key findings in relation to*

	informational and structural interventions and then put forward recommendations for exploitation of results and their further implementaitons.		
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This deliverable contains original unpublished work except where clearly indicated otherwise. Acknowledgement of previously published material and of the work of others has been made through appropriate citation, quotation or both.

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List of abbreviations

ABM	Agent based Model
ADMS	Atmospheric dispersion modelling system
AP	Attributable Proportion
CHAID	Chi-Square automatic interaction detection
CERC	Cambridge Environmental Research Consultants
CO_2	Carbon dioxide
CRF	Concentration response function
DOW	Description of work
DT	Decision trees
EEA	European Environmental Agency
EMIT	Emission Inventory tool
EU	European Union
FEATHERS	Forecasting Evolutionary Activity-Travel of Household and their Environmental RepurcussionS
FEBIAC	Fédération Belge et luxembourgeoise de l'Automobile et du Cycle
GIS	Geographic Information System
GPS	Global Positioning system
GTFS	General Transit Feed Specification
GUI	Graphical user interface
IPF	Iterative Proportional Fitting
MATSIM	Multi-agent transport simulator
NAEI	National atmospheric emission inventory, UK
NO_2:	Nitrogen Dioxide
NO_x:	Nitrogen Oxides
O_3:	Ozone
OD	Origin Destination
OVG	Onderzoek VerplaatsingsGedrag Vlaanderen
OSM	OpenStreetMap
$PM_{2.5}$	Particulate Matter with aerodynamic diameter less or equal to 2.5 μm
PM_{10}	Particulate Matter with aerodynamic diameter less or equal to 10 μm
PMD	Premature deaths

R2S	Route to school
RR	Relative Risk
SO_2	Sulfur dioxide
VITO	Flemish Institute of Technological Research
VMM	Flanders Environment Protection Agency
WHO	World Health Organization
YLL	Years of life lost
WP	Work package

1 Executive Summary

The purpose of this deliverable is to present details on three major aspects that are as follows: 1) A detailed description of input/outputs links between the behavioural simulator and environment simulator as part of the integrated simulation platform employed within WP 4 for testing a variety of structural interventions. 2) Estimating of exposure and discuss details about how activity-based approach helped in further improvement of exposure estimates in contrast to traditional methodology. 3) Quantification of health impacts in relation to structural interventions by employing the standard methodology recommended by EEA [2018] and also followed in Deliverable 5.3 of this project. These three aspects are covered well in Sections 4, 5 and 6 of this deliverable (which were originally planned as separate deliverables). Exposure are quantified using traditional methodology (we called it as static exposure) and using the results of our simulation framework where individual movements are also considered (we called it as Dynamic exposure). Results indicated that static approach underestimate exposure. Furthermore, in relation to structural policy scenarios, highest positive health impacts are achieved for Bologna as the reduction in Premature Deaths compared to the base case is about 20%. Although the exposure differences in Bologna are not that much as compared to Hasselt city, however, health benefits are higher due to the significantly large population than Hasselt.

In addition to the above, section 7 of the report summarizes the key findings in relation to the two different types of behavioural interventions, however, by giving more details of the informational interventions as these interventions are carried out as part of several other activities of the HASSELT living lab and scientific contributions are not well described in other iSCAPE deliverables. Structural interventions are discussed comprehensively in deliverables 4.2, 4.3, 4.4 and 4.5, therefore, key summary findings of these simulation experiments are discussed in section 7.2. Based on these key findings and lessons learned while carrying out these studies, the deliverable put forwards several key recommendations that can be considered as guidelines. These guidelines are not only helpful in design and implementations of similar kind of mobility-based behavioural interventions but can be used in other domains of behavioural change.

2 Introduction

This section describes the background and contextual details on which this deliverable for task 7.3 of work package (WP) 7 of the project is based. Furthermore, it describes the scope under which this deliverable is prepared keeping in view the description of work (DOW) for task 7.3, and other earlier related deliverables (such as deliverable 4.4 and 4.5) coming out from the WP 4. The text for task 7.3 primarily mentions the forward steps need to be taken in order to obtain more valuable findings from the work carried out in WP 4. This is done by translating the effects of a range of behavioural interventions tested using different frameworks into health impacts so that the effectiveness of such interventions can be measured on more profound grounds Task 7.3, originally planned to result in 3 deliverables (as per DOW). Based on the recent grant agreement amendment all these 3 deliverables are integrated into one (1) deliverable, with a viewpoint that these deliverables are closely linked to each other and provide inputs to the next in line. Based on the approved grant agreement amendment this report presents an integrated deliverable. Chapters titles explicitly represent the originally planned deliverables, to make a point that intended work is carried out as per DOW.

Within WP 4, an integrated behavioural simulation platform was developed for assessing a variety of mobility-based interventions (those belong to structural interventions). The development of the simulation platform was based on the concept of activity-based approach that provides the framework to model an entire activity-travel routine of an individual. For this purpose, a range of datasets was gathered and the platform was calibrated for three iSCAPE cities, namely Hasselt, Bologna and Vantaa. As mentioned in deliverables 4.2, 4.3 and 4.4, activity-based approach is more rigorous approach than traditional modelling approach as it considers activity-based tour chains as the individual unit of analysis. This approach tends to capture more detailed effects on a personal activity travel routine in reaction to some changes, e.g. restriction on car access to a particular area in an inner core area of city can effect in multiple ways; such as few individuals shift to other modes of travel to reach the destination where they would like to perform a particular activity, few of them may change their destination (if they are travelling to such destination for flexible activities i.e. other than work/education etc.), some may respond by changing their travel routes to by-pass such areas (i.e. by taking a detour route) etc.

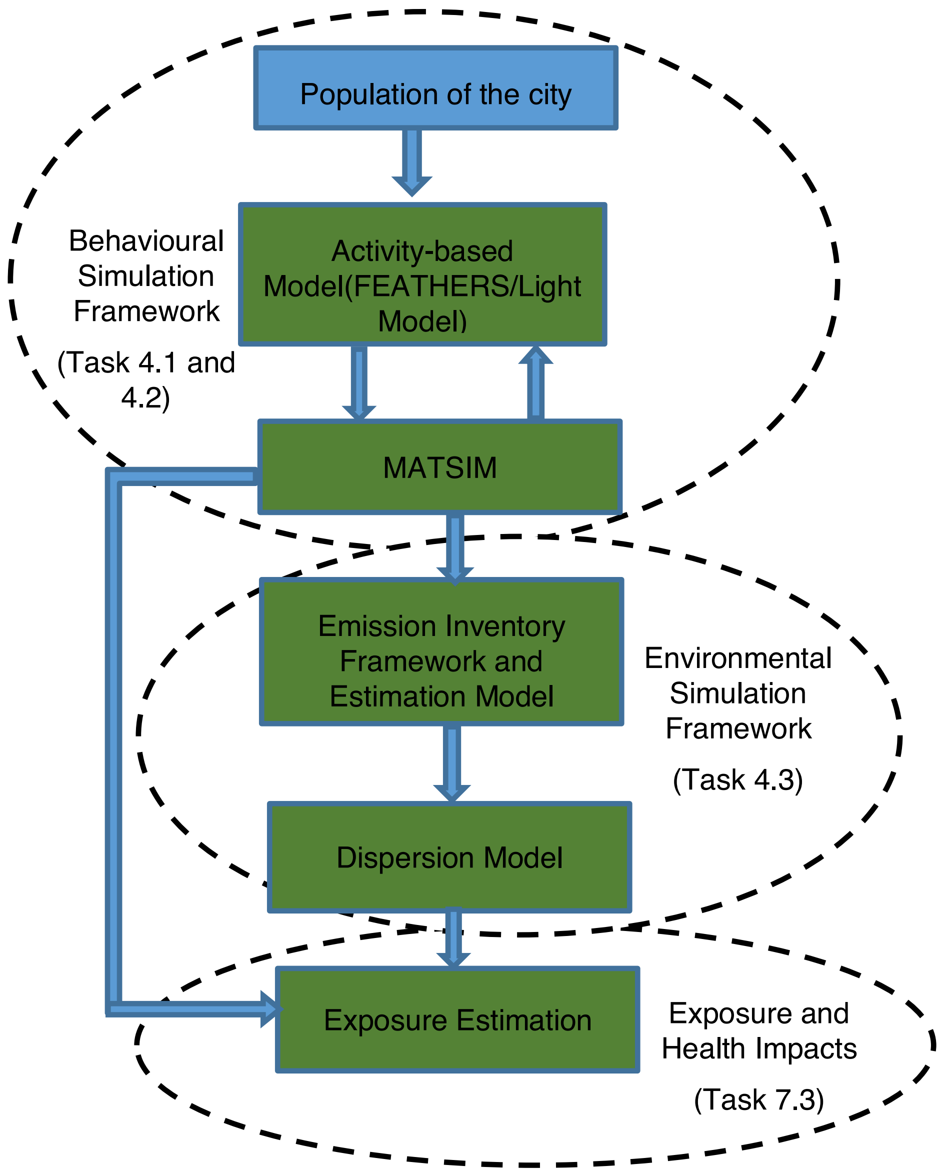

Figure 1: Overall Simulation Framework

Activity-based modelling framework (which is an agent-based microsimulation tool) is able to capture these different responses on the activity-travel routine of each individual in the population, and therefore, provide flexibility to track the movement of each individual in a simulated platform based on a defined time and space resolution. This is important for exposure assessment (i.e. how much and for how long an individual is exposed to a particular pollutant concentration level). Traditionally, even in recent EU [*EEA, 2018*] and WHO [*WHO, 2016a*] reports, this exposure is assessed based on residential location of an individual (i.e. the individual is considered as static). The movement of the individual in time and space is ignored. Use of an activity-based approach allows us to measure exposure considering an individual as dynamic, and therefore, provide a framework in which effects of different interventions can be assessed in a more appropriate manner (i.e. improved exposure assessment which in turn provide more realistic health impacts). To give readers an overall picture and to summarize this discussion, Figure 1 presents a framework taken from deliverable 4.4.

According to Figure 1, this deliverable is focusing more on presenting the details of information flow from behavioural to environmental simulation frameworks, their outputs and how these outputs are linked together to help estimate personal exposure (this is the content of originally planned deliverable 7.3). Furthermore, the details on the methodology used for estimation of personal exposure, and to what extent exposure estimates are improved following a dynamic approach in comparison to static approach especially for a population segment that is more vulnerable (e.g. older individuals etc.) (this is the content of originally planned deliverable 7.4). In addition to this, the report also provides health impacts by using the exposure assessment and using already existing health response functions and then developing the guidelines on the basis of findings of such analysis (this is the content of originally planned deliverable 7.5).

2.1 Scope of the Deliverable

Below we list the main scopes of this deliverable.

1) Literature synthesis in relation to dynamic exposure assessment and health risk assessment methodologies.
2) Illustration of the input-output link between the behavioural and environmental simulation framework. Most of the discussion is carried out in this respect in deliverables 4.4 and 4.5, as they report the implementation and results of such an interaction. However, to avoid duplication, we mainly focus on the data flow links and formats of input and output data. Furthermore, we will discuss more on the extent to which the interaction is exploitable in other regions/cities.
3) Exposure estimation methodology and results of differences with the traditional static approach for policy cases tested in three iSCAPE cities.
4) Health risk assessment framework to estimate health impacts for tested policies in different cities based on the methodology adopted in Deliverable 5.3. The discussion will also be made about involved uncertainties.
5) Recommendations from the results not just limited to health impacts, but also from the findings of the work presented in WP 4.

2.2 Layout of the Report

The report is structured along 8 key sections. Section 3 presents the literature synthesis on exposure estimates and health risk assessments methodologies. In section 4, we provide a detailed account of input and outputs links between integrated behavioural and environmental simulation platforms. Section 5 presents the exposure estimation results for three iSCAPE cities. Section 6 discusses the health risk assessment framework and provides estimation results by using exposure estimates. Section 7 summarizes the key findings on all mobility-based behavioural interventions employed in WP 4. Section 8 discusses the key recommendations on various aspects of work carried out in WP 4 in relation to mobility-based behavioural intervention and also work reported in earlier sections of this deliverable. Section 9 concludes this deliverable of the iSCAPE project.

3 Estimating population exposure and human health – Literature Synthesis

Models of travel behaviour have a long history starting from aggregated trip-based models to more recent individual-centric activity-based models. The emergence of activity-based models is based on the premise that the modelling framework should answer emerging policy questions which are primarily based on measuring air quality (i.e. appropriate emission analysis could become possible in response to behavioural changes) [*Kitamura*, 1996]. It has been noted that the interest is grown in development of integrated activity-based models with air quality models for appropriate prediction of emissions/air pollutant concentrations and to estimate individual exposure to these pollutants [*Beckx et al., 2009b, Beckx et al., 2009a*]. The prime argument for this integrated modelling framework is that the traditional exposure analysis techniques in the environmental literature are based on the assumption that considers population as static, however, pollutant concentration is different with respect to time-of-day and space.

The use of activity-based models within (microsimulation framework) can provide individual's geographic location (involvement in a particular activity) at a particular time-of-day, and therefore, the population as a whole is considered as dynamic. This approach provides a more appropriate measure of exposure to air pollutants. There are only limited studies available that have used such integrated modelling platforms. *Adnan and Passani* [*2017*] mentioned in the review report (as deliverable 1.3 of iSCAPE project) that out of 7 such studies only two studies have tested the few interventions in terms of predicting the changes in travel behaviour and translating these into changes in air pollutant concentration. Other studies are limited in terms of exposure analysis or validation of their study results with observations from monitoring stations. In addition to this, results from the exposure analysis are not translated in terms of health effects. *Dias and Tchepel* [*2018*] concluded in their review study that spatial and temporal variability of urban air pollution levels in combination with indoor exposures and individual's travel-activity patterns are key elements to a proper assessment of personal exposure. Urban areas offer several challenges, where large variations are observed in spatial and temporal dynamics and air pollution. Therefore, exposure estimation should incorporate these variations. Instantaneous exposure is defined as the exposure at an instant in time and is expressed in the same unit as the concentration (e.g., μg·m–3), however, when temporal dimension is incorporated, it can be measured as the integral of instantaneous exposure over the duration of exposure (units: ppm·h or μg·m–3·h) as shown in equation 1.

$$E_i = \int_{t_1}^{t_2} C_i(x,y,z,t)dt \qquad (1)$$

Where, E_i is the time-integrated exposure experienced by the individual *i*, $C_i(x,y,z,t)$ is the concentration occurring at a particular point occupied by the individual *i* at time *t* and spatial coordinate (x,y,z), corresponding t_1 and t_2 to the starting and ending times of the exposure event, respectively. There are only limited studies that actually compare the differences in dynamic and static exposure estimates. *Shekarrizfard et al.* [*2016*] found that there are significant differences in NO_2 daily exposure. The differences between dynamic and static exposures vary between −1 and +1 ppb for drivers and transit riders and −9 to +9 ppb for active commuters. These differences between the two measures demonstrate that the static method can either underestimate or overestimate the dynamic exposure. Furthermore, they also noted that during commuting, individuals are more exposed in comparison to the time they spend at home. Another study from [*Park and Kwan, 2017*] also showed a similar conclusion when analysing the exposure differences using several methods. These findings call for more attention because it is a less recognized but important methodological problem that can significantly affect the accuracy of exposure assessment in environmental health research.

According to [*WHO, 2016b*] health risk assessment involves three key steps: 1) estimation of exposure of the population to the pollutants 2) estimation of health risk using concentration-response functions and baseline health data and 3) estimation of uncertainties at various steps of the methodology. Concentration-response functions estimate the health impact per concentration unit of air pollutant. The [*EEA, 2018*] recommended using relative risk (RR) based concentration-response function, that capture the increase in mortality that can be attributed to a given increase in the air pollutant concentration. These RR functions are defined at the population level and cannot be assigned to a specific individual, however, if detailed baseline health statistics are available, these RR can be estimated for specific segments of the population (such as gender-based or Age-category based) as shown in [*Dhondt et al., 2012*]. It is further recommended that because of the linear nature of functional relationship instead of using a whole range of concentration values, counterfactual concentration should be used through which health impacts can be measured for values of concentration above some threshold value. In the case of $PM_{2.5}$ this threshold value is 0 μg/m^3, for NO_2 this value is 20 μg/m^3 and for Ozone, it is recommended as 70 μg/m^3 for Europe [*WHO, 2013*].

The effects of exposure to air pollution are of diverse nature. *WHO* [*2014*] mentioned that these are ranging from inflammation to premature deaths. Further, they have recommended that health assessment should be based on mortality, as this is the most serious outcome and the assessment can be more appropriate as good quality data is available from the regions. Mortality due to exposure to air pollution is estimated in terms of premature deaths and years of life lost. Both of these measures are defined as follows, definitions are taken directly from [*EEA, 2018*].

Premature deaths *(PD) are deaths that occur before a person reaches an expected age. This expected age is typically the life expectancy for a country, stratified by sex. These deaths are considered preventable if their cause can be eliminated.*

Years of life lost *(YLL) are defined as the years of potential life lost due to premature death. YLL is an estimate of the number of years that people in a population would have lived had there been no premature deaths. The YLL measure takes into account the age at which deaths occur and therefore the contribution to the total is greater for a death occurring at a younger age and lower for a death occurring at an older age.*

The literature synthesis reported above clearly reflecting the case that dynamic estimation of exposure is certainly not given its due attention despite studies are reported benefits of this approach. Furthermore, studies on the effects of policies are quite limited that considers the application of the complete model chain (as mentioned in Figure 1). The literature synthesis is helpful in determining the methodological steps, especially in relation to quantifying health impacts from exposure estimates. In general terms, the methodology adopted in this deliverable is consistent with estimation of health impacts for passive control system (PCS) interventions carried out in deliverable 5.3 of iSCAPE project.

4 Input-Output link with Atmospheric Dispersion Model

This section of the report provides details on the originally planned deliverable 7.3 according to DOW. An integrated simulation platform that has been discussed comprehensively in WP 4 deliverables is summarized here and then discussion is presented considering the following three points.

- Summarizing the discussion in relation to data inputs/outputs mentioned in D4.4 and D4.5 (from Behavioural and Environmental simulators)
- Input / Output data types and processing required to create dataset that are acceptable to consequent models in the framework
- Other existing model platforms and their integration

4.1 Simulation Model Framework

The overall diagram of the simulation platform that describes the complete model chain is presented in Figure 1. The two major modelling platforms (i.e. behavioural simulator and Environment simulator) are briefly discussed in this section to provide a context to this section of the deliverable. More details of these simulators can be seen from D4.2, D4.3, D4.4 and D4.5.

4.1.1Behavioural Simulation Framework

The behavioural simulator component of the model chain contain two simulation models. An activity-based model (to predict activity-travel schedules of individuals) and MATSIM (to execute the predicted activity-travel schedules on the transportation network to predict traffic volumes etc.). Within activity-based model, there exists a variety of models, almost all of which are formulated through a system of interconnected sub-models/components that predicts different decisions related to daily activity and mobility. Each sub-model is built using a Decision Trees (DT) approach. These DT can be considered as a cost/utility function. Available methods in statistics and machine learning can be used to induce a decision tree from data. A decision tree is developed by recursively splitting a sample of observations into increasingly homogeneous groups in terms of a given response variable. Activity-based model used in the case of Hasselt city utilizes the Chi-square automatic interaction detection (CHAID) algorithm which evaluates splits based on a Chi-squared measure of significance of differences in the response of the distribution between groups. In relation to Bologna and Vantaa, a lighter version of activity-based model was used because of limited availability of datasets (more details on this are described in D4.3). This lighter version of activity-based model is developed based on a few key rules and is able to provide activity-travel schedule for the population of two cities. This activity-travel schedule is an important input for the next simulator (i.e. MATSIM).

MATSIM is an activity-based, extendable, multi-agent and open-source simulation framework implemented in Java programming language. It is based on the co-evolutionary principle. Agents are optimizing their daily activity schedule by competing for space-time slots with other agents on road network. This is similar to route assignment in iterative fashion as done by other supply models (which are dynamic); however, MATSIM ensures agents identification within the network and also changes some dimensions of the activity schedules (such as time, mode and destination choices of activities) to bring the overall system to optimality. MATSIM requires as input the so-called *initial plans* (activity-schedule of an agent), which are output of FEATHERS or other ABMs. It also requires a complete transport infrastructure (such as road network with its essential details, Public transport fleet and operations data, signals data with green and red times in different time periods) to perform network assignment process. Apart from this input there is a range of parameters that can be considered as part of scoring module. Each agent plan is given a certain score, and MATSIM iteratively optimizes the score of a plan for each agent by slightly changing dimensions of activity-schedule in an iterative manner. Activity-based simulator provides the population and activity-travel schedule of each agent in the population which are considered as initial plans in the MATSIM (as depicted in Figure 2). In return, MATSIM executes these plans/schedules on the road network and estimates travel times. These travel times are converted into skim matrices and fed-back to activity-based model, that uses the new skim matrices and predicts new activity-schedules for each agent. These cycles run a few times so that outputs from each model are consistent. In case of Hasselt city, these two simulators are integrated to each other in the fashion described above. In case of Bologna and Vantaa, MATSIM simulator uses the outputs of the lighter version of activity-based model, and acts as standalone behavioral model where individuals plans are optimized based on the network conditions.

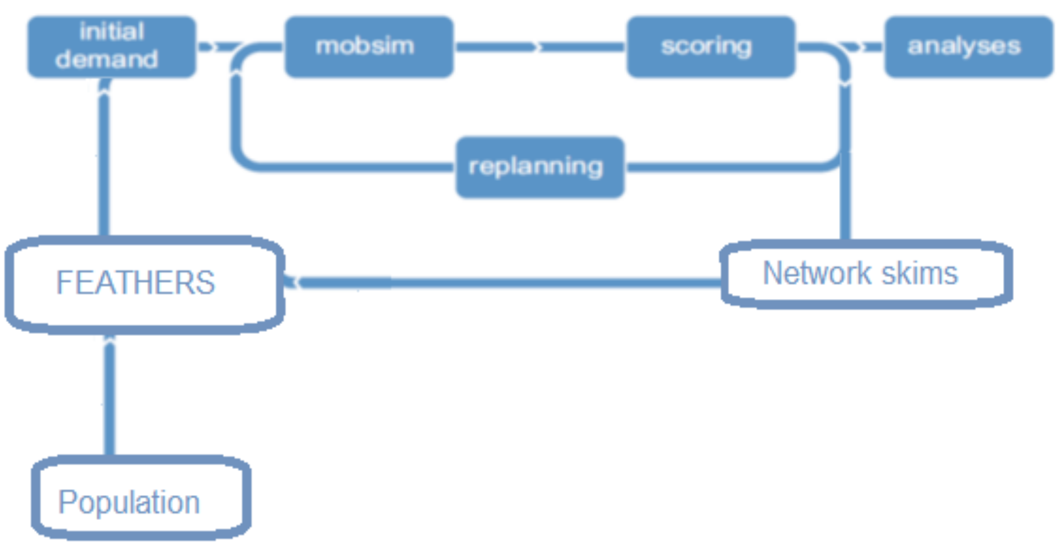

Figure 2: FEATHERS + MATSIM Integration

4.1.2Environmental Simulation Framework

Similar to behavioral simulation framework, environmental simulation framework also contain two major components. The first one is development of emission inventory from a large variety of sources (including traffic based on prediction of behavioral simulation framework). Another component of the environmental simulation framework is an Atmospheric Dispersion Modelling System (ADMS- URBAN), that uses inputs from the emission inventories and also require inputs in relation to meteorological conditions, to estimate ambient pollutant concentrations. The compilation and build-up of the emission inventory was built through the EMIT tool available from Cambridge Environmental Research Consultants (CERC) [*CERC, 2015*], which has the potential to calculate emissions across large urban areas for dispersion modeling with the ADMS-Urban model.

EMIT is a database tool for storing, manipulating and assessing emissions data from several sources (major roads, rail and industrial sources, minor road, commercial and domestic sources). EMIT allows to store emissions data that have been directly imported, or to calculate emissions from source activity data using emission factors. Alternately, EMIT can calculate emissions using a scaling of national or regional emissions by a local statistic such as population. In general, to develop an emission inventory for road sources, it is necessary to know traffic counts on a link-by-link basis or at least to have fuel consumption data. The emission factors are a set of data obtained from experimental results that relate emission rates for different pollutants to vehicle sub-categories. There are several different sets of emission factors available for road and rail traffic sources in the EMIT database, with the number of vehicle sub-categories ranging from 2 to 124, and for each of these there is a set of pollutant emission rates in g/vehicle/km. They vary with speed, and also with year. In this dataset the emission factor data are taken from the COPERT 4 model version 10.0 [*Katsis et al., 2012*] compiled as part of the UK National Atmospheric Emissions Inventory [*UK NAEI 2014*].

The source emission inventory was used as input to the dispersion modeling simulations. In this work, the ADMS-Urban model (version 4.1.1.0) developed by CERC was used (CERC, 2011) to calculate the concentration of pollutants emitted from the sources considered in the emission inventory. The ADMS-Urban model is a quasi-Gaussian plume air dispersion model able to simulate a wide range of passive and buoyant releases to the atmosphere. The dispersion of pollutants has been simulated with the Atmospheric Dispersion Modelling System (ADMS; CERC, 2017). This model has been already extensively verified within a large number of studies and its performance has been compared with other EU and US EPA models, such as CALPUFF, AERMOD for instance (e.g., Carruthers et al., 2000; Di Sabatino et al., 2008; Stocker et al., 2012). ADMS is able to resolve concentration gradients occurring close to various emission source types, including point, jet, line, area and volume sources. Typical applications of the model include the following: developing and testing policy on air quality; the development of air quality action plans; air quality and health impact assessments of proposed developments and use of the model for the provision of detailed street-level air quality forecasts (e.g., Hood et al., 2018; Zeng et al., 2017; Dėdelė and Miškinytė, 2015).

4.2 Input / Output Data and Processing

4.2.1Behvaioural Simulation Framework

4.2.1.1 Inputs

A variety of data is involved in the development of an activity-based model and executing simulation in MATSIM. More details regarding each input are provided below:

Household travel survey data: The household travel survey data contains information about individual and household level socio-economic attributes (such as Gender, Age, Vehicle ownership, Household location, driving license ownership, education and income level etc.) and also travel details of the individuals e.g. where they have travelled, which activities they have performed in a given day, how (travel mode) and when (time of the day) they have traveled. Usually planning agencies conduct this kind of survey every four/five years in a particular region for a population sample. In the case of Hasselt, this data was available as an OVG (Onderzoek VerplaatsingsGedrag Vlaanderen) survey to estimate parameters of sub-models within activity-based model. These models are estimated by making an association between individual/household characteristics and related travel decisions. Network skims and Land use data are also combined to develop such associations. **GPS based activity-travel routine data** for a few Bologna and Hasselt residents was collected for two weeks as part of task 4.1 of WP 4. Hasselt activity-based models were further adjusted in light of this data. Light activity-based model is then adjusted further with this data for the appropriate prediction of schedules for Bologna. In case of Vantaa, this dataset is not available, however, for Helsinki region (a major city near Vantaa), a variety of travel and activity related research has been published. Schedules are adjusted in light of such published data.

Network skims: The level of service information used in estimating the choice of the travel mode and time of day models is derived from network skims. Urban transportation planning agencies usually maintain travel time matrices (or skims) for a small number of pre-determined time windows, such as AM peak, PM peak, and off-peak, generated after the calibration of volume-delay functions (based on measurements from e.g., floating car data) and the assignment of OD matrices to the network for a number of time periods. Those skims contain zone-to-zone travel time, travel distance, travel cost (tolls if any) and public transit fares matrices. This zone-to-zone data is available for each of the three cities for which simulations are performed.

Land use data: Land use data is important for the modeling of destination choice of activities. This data provides information used to build attraction variables included in destination choice models. For example, the number of shops, number of schools, number of workers, number of recreational places with their areas etc.

Synthetic Population: This is the main input data required for the simulation purpose. Synthetic population is a processed data, obtained after employing iterative proportional fitting (IPF) or other similar algorithms on census data. **Census data** contains information about number of individual and household segregated on a variety of attributes such gender, age etc. for each geographical units (zone) within the city.

OpenStreetMap (OSM) data: this data is available open source for all cities. It contains information of road links along with their geometry and other features (such as speed limits, number of lanes), This data is then converted after necessary cleaning to provide a road network to MATSIM.

General Transit Feed Specification (GTFS) data: This data is available open source for all three cities for which simulations were carried out. This data contains information about public transport routes, stops and their schedule in a standard format. This data gives the necessary details to establish public transport network as an input to MATSIM after employing the necessary cleaning and integration process with OSM data.

Traffic volume data on important links of Bologna and Hasselt city is available from respective city agencies. In a similar manner instead of traffic volume, network travel time for important links is available for Vantaa. This dataset is used for calibration/validation of the final output from MATSIM.

4.2.1.2 Outputs

The behavioural simulation framework produces activity-travel schedules for each individual in the population. As an example, the schedule for a random individual can look like as the following model output (also depicted in figure 3):

Individual ID: 00001

0:00 hrs; home(zone 1)……7:30hrs trip to work using public transport (PT) (zone1 to zone 4),… 8:30am; arrival at work (zone 4)…..12:00hrs; trip to shoping and then comeback to workplace using taxi (zone 4 to zone 3 and vice versa)…..18:00hrs; trip for dinner at food center near home using PT (zone 4 to zone 1)…19:45 hrs; walk trip to home after completing dinner (zone 4 to zone 4)…20:00pm;arrival at home (zone 1)…next day….0:00am; home (zone 1).

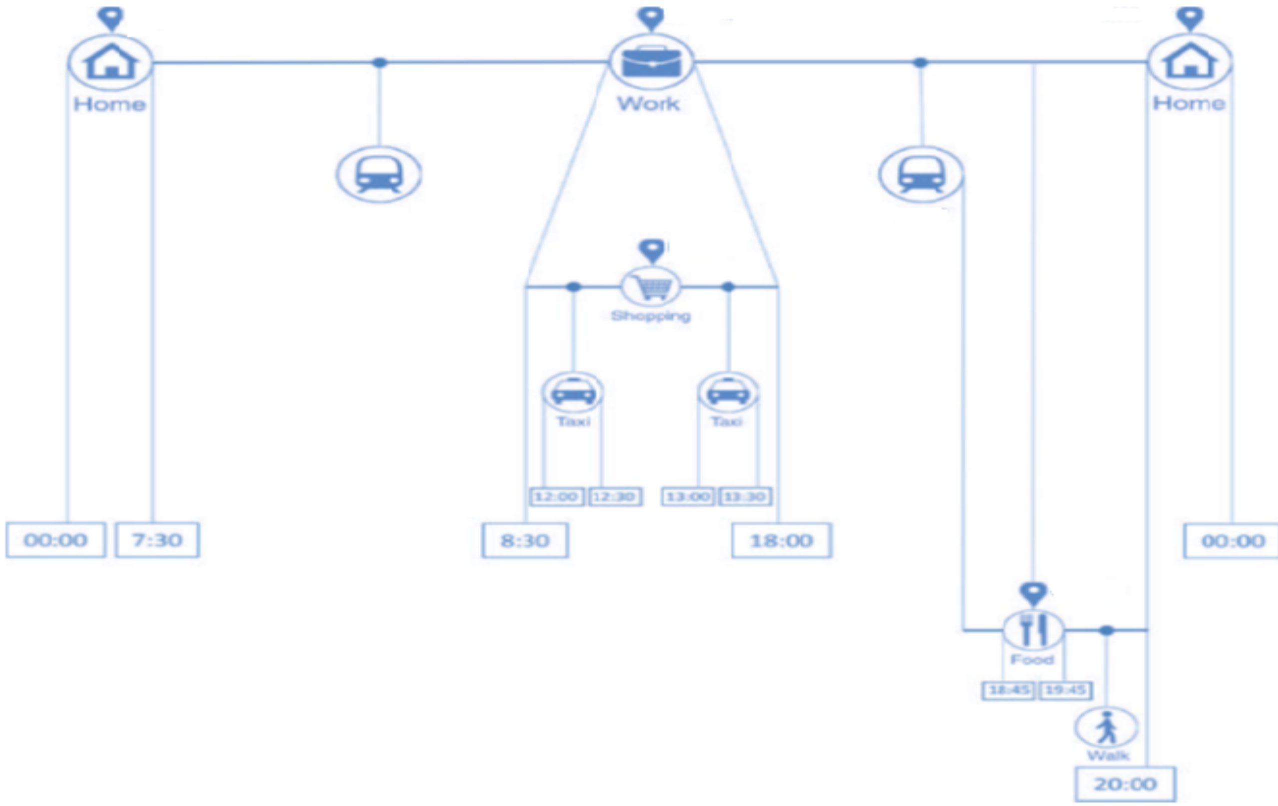

Figure 3: Activity schedule (typical), (Reworked figure, source:[Lovrić et al., 2016])

The predicted activity schedules are then provided to MATSIM by converting them into xml format. MATSIM executes these schedules and provides an output again in a xml format as follows:

Population executed plans (in the format as shown in Figure. 4) that includes information about individual id, activity start time/end times, travel mode, activity types in the plan, route followed (as link id numbers). In figure 4, an individual whose id is p000773, end an overnight home activity at 08:49:10. At this time, he/she took a car to travel to a destination associated with link number -4803553 (on a road network). This travel took a travel time of 04:01 minutes (distance 3072.61 meters). Leisure activity was performed at that destination, which ended at 10:00:14. The 5th line in the figure 4, represents a complete route (based on successive link numbers) that is followed. Individual then came home, and around 11:10:27 went for performing nondaily shopping activity. Finally he reached home at 13:31:09 and stayed there for the remainder of the day.

The only major difference in the MATSIM output with activity-based model output is the availability of route information. However, other aspects include the exact timing of performing a particular activity, travel distance, travel time information as well. These are times experienced by an individual within a simulation. In relation to visualization, MATISM platform does not provide any functionality to process such outputs, however, they do provide histograms and bar or line charts to provide some general statistics about aggregate simulation results. Additional algorithm is required to process such outputs (shown in Figure 5) to obtain data that could be provided to the next model in the chain. For example, we process MATSIM outputs in such a way that, we obtain a number of vehicles (car, bus etc.) that used a particular link on the road network in a particular hour. This output for the case of Hasselt can be seen from Figure 5 and is given as input to Environmental simulation framework.


```
<!-- ====================================================================== -->
- <person id="p000773">
  - <plan selected="yes" score="227.1000499039456">
      <activity end_time="08:49:10" link="-4894884" type="Home_1185"> </activity>
    - <leg trav_time="00:04:01" dep_time="08:49:10" mode="car">
        <route type="links" trav_time="00:04:01" distance="3072.6138619416574" end_link="-4803553" start_link="-4894884">-4894884 4433902 4938944 4938945 4938943 4800266
          4866240 4800267 4800268 4431155 4593582 4968172 4469414 4431160 4968171 4431087 -4803554 -4803553</route>
      </leg>
      <activity end_time="10:00:14" link="-4803553" type="Leisure_0060" start_time="08:53:11"> </activity>
    - <leg trav_time="00:04:38" dep_time="10:00:14" mode="car">
        <route type="links" trav_time="00:04:38" distance="3769.8069756576556" end_link="-4894884" start_link="-4803553">-4803553 4431085 4431086 4761326 4761328 -4431161
          -4431160 -4469414 -4968172 -4593582 -4431155 -4800268 -4800267 -4866240 -4800266 -4938943 -4938945 -4938944 -4433902 4894884 -4894884</route>
      </leg>
      <activity end_time="11:10:27" link="-4894884" type="Home_0030" start_time="10:04:52"> </activity>
    - <leg trav_time="00:06:43" dep_time="11:10:27" mode="car">
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          -4477241 -4477240 -4433316 4433319 4469282 4477239 4767880 -4980382 3237304 -4375908 4376000 4427999 -4427999</route>
      </leg>
      <activity end_time="13:24:26" link="-4427999" type="NonDailyShopping_0150" start_time="11:17:10"> </activity>
    - <leg trav_time="00:06:43" dep_time="13:24:26" mode="car">
        <route type="links" trav_time="00:06:43" distance="5695.842169033672" end_link="-4894884" start_link="-4427999">-4427999 -4376000 4375908 3237309 4980382 -4767880
          -4477239 -4469282 -4433319 4433316 4477240 4477241 -4800266 -4938943 -4938945 -4938944 -4433902 4894884 -4894884</route>
      </leg>
      <activity link="-4894884" type="Home_1185" start_time="13:31:09"> </activity>
    </plan>
</person>
```


Figure 4: MATSIM output- Activity-travel plan with route information

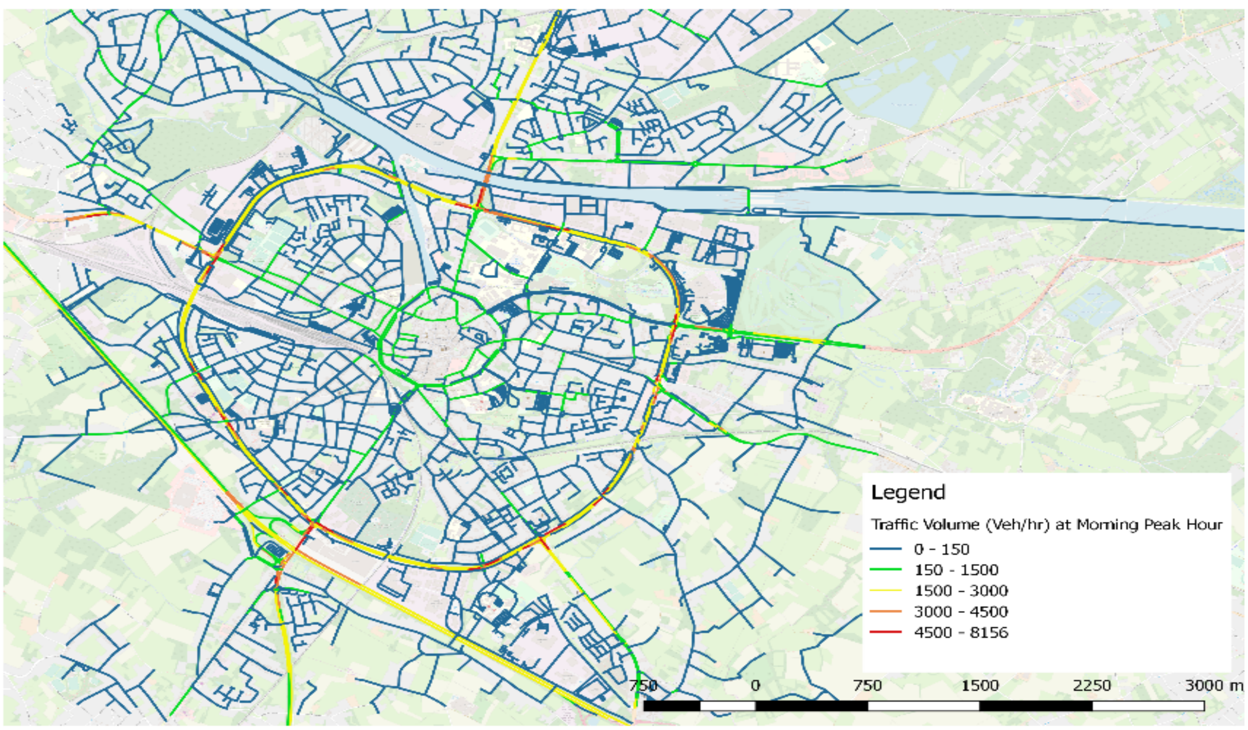

Figure 5: Morning peak hour traffic volume (vehicles/hr) on reduced Hasselt Network.

The usefulness of MATSIM output is that it could be processed in a variety of ways as required because of the richness of information it contains. The same MATISM outputs are then further processed to associate individual characteristics with an individual id, and then superimpose the space-activity time movement of the individual with the pollutant concentration maps (obtained from dispersion model) to estimate individual related exposure.

4.2.2 Environmental Simulation Framework

4.2.2.1 Inputs

Air emission inventory is a structured collection of both information about emissions and technological, economical and territorial data. In general, to develop such an inventory it is necessary to quantify all emissions of the different sources in the appointed area of the inventory during the selected time frame. Figure 6 provides a scheme to better comprehend the steps taken in iSCAPE to build up the emission inventory to be used for air dispersion modelling and type of data involved in it.

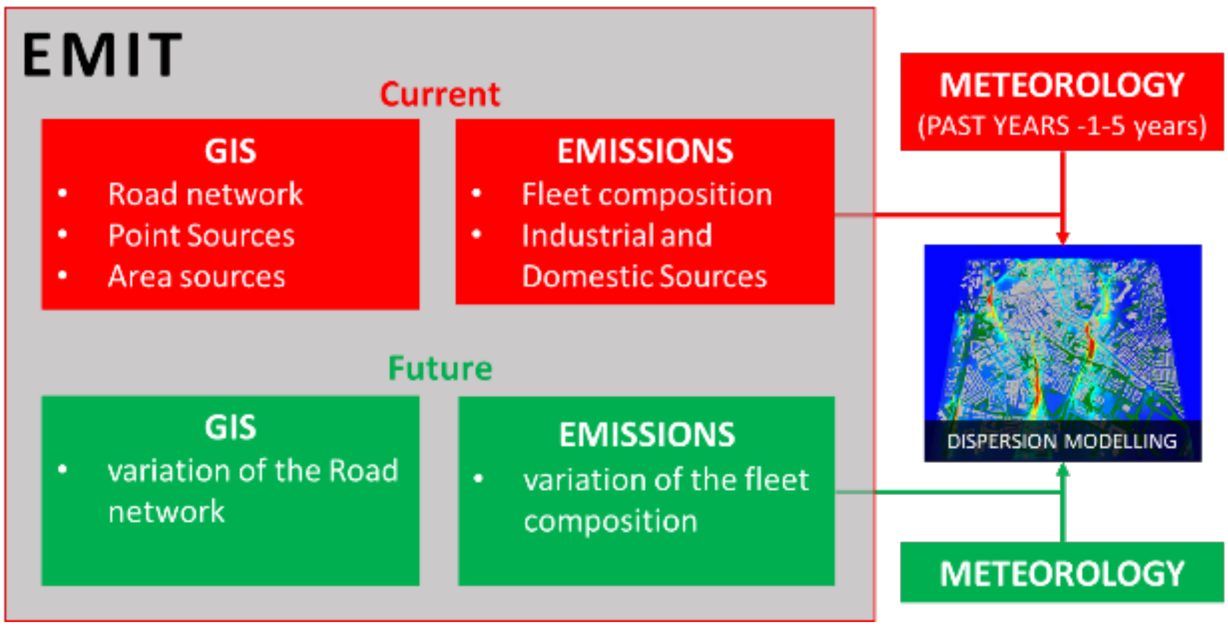

Figure 6. Schematic representation of the construction of the emission inventory with the EMIT software for its use in the ADMS-Urban dispersion model.

The most important dataset is the **traffic volume data** obtained as an output from behavioural simulator as shown in figure 5 (this dataset is provided in the shape file (.shp) format). Another important dataset is to obtain **emission factors**, which are derived from NAEI 2014. NAEI 2014 datasets include factors for:

- The regulated pollutants: NOx, VOC, CO and CO2; PM10; PM2.5; NO2; SO2.
- The unregulated pollutants: Benzene; 1,3 Butadiene; Methane; N2O; Benzo[a]Pyrene; Ammonia.

Emission factors of PM_{10}, $PM_{2.5}$, NOx, NO_2 and VOC (volatile organic compounds) released in June 2014 as part of the UK National Atmospheric Emissions Inventory (UK NAEI 2014) and including the effect of mileage and new fuels. In addition, CERC (CERC, 2015) suggests to use this dataset among the available ones to investigate the emission-reduction scenarios, as they include a number of vehicle subcategories that represent new vehicle technologies. The **fleet components** are a classification of traffic according to a relatively small number of broad categories used to describe the traffic composition. This classification is likely to be similar to that output from a traffic model or from traffic count observations. For road traffic, EMIT supports either standard fleet components with 3 categories (heavy traffic/light traffic/motorcycles) as well as the 11 components categorization. The route type describes the relative make-up of each fleet component, in terms of the percentage of that component in each vehicle sub-category. Route types can be year-dependent. EMIT calculates the emission rate (the mass flux of a particular pollutant from a specified source, g/s or kg/year) for all sources and allows to directly create the input files for ADMS-Urban.

The **emissions from residential heating sources** instead are modelled as area sources, because it is difficult to obtain specific emission data for each household. In general, there are two ways to assign an emission rate to each grid cell: 1) calculate emissions for sources using activity data and fuel consumption, together with emission factors; 2) scaling groups of sources using a known statistic (e.g., population, licensed vehicles, number of sites, …). In this case, the emission for each source can be calculated by applying the following simple relation:

$$E = \frac{STAT_{local}}{STAT_{country}} * E_{country}$$

For the specific case of residential heating, the statistic can be for example the number of local inhabitants and the total inhabitants of the country, for which emissions data are known.

Minimum input data for the modeling setup and for the representation of the modeled domain consists in the emission sources including **emission rates and time varying emission factors**, **meteorological data** (at least: air temperature, wind speed, wind direction, and either cloud cover either sensible heat flux either Monin-Obukhov length for estimating boundary layer height), and **background concentrations**. Within the model, the dispersion calculations are driven by hourly meteorological profiles of wind speed and direction, characterized through Monin-Obukhov lengh similarity theory. As such, input meteorological data are among the most important input parameters for modeling air pollution dispersion.

Additional options for the simulations include gaseous and particle dry and wet deposition; in case these options are selected, the user needs to include information on **dry deposition velocity** and **washout coefficients** for each pollutant for including dry and wet deposition in the dispersion simulations. Further, in case the wet deposition is also considered in the simulations, **precipitation** needs to be included in the meteorological dataset. The model includes the option to include the NOx photolytic chemistry module, which accounts for fast, near-road oxidation of NO by O_3 to form NO_2. In order to consider the NO_2-NO-O_3 chemical reactions in the simulations, **meteorological data need to include solar radiation and time and hour of the day**. The modelling also uses the ADMS-Urban NOx photolytic chemistry module, which incorporates both reactions for the photochemical reaction between nitric oxide (NO), nitrogen dioxide (NO_2), volatile organic compounds (VOC) and ozone (O_3), and reactions that govern the oxidation of sulfur dioxide (SO_2) leading to the formation of ammonium sulfate particles, i.e. particulate matter (PM). To use this scheme, **solar radiation information and background concentration data** for the critical pollutants NO_X, NO_2, O_3 and SO_2 are required. Background concentrations of air pollutants were obtained from the ARPAE monitoring network: Via Chiarini (in the western part of Bologna, measuring hourly data for NO_x, NO_2, O_3 and daily data for PM_{10}); Giardini Margherita (in the southern part of Bologna, measuring hourly data for NO_2). The meteorological dataset contained hourly sequential data measured by the Bologna airport weather station, considered the reference meteorological station for the city of Bologna not influenced by the presence of buildings in the city itself. In the case of Hasselt, background hourly concentrations, i.e. pollutant values deriving from sources outside the domain but that because of meteorological conditions and wind directions are transported to the domain, for NO_x, NO_2, O_3, PM_{10} and $PM_{2.5}$ were provided from

VMM as estimates for a virtual rural station in Flanders (average of all rural stations in the region). Time varying emission (i.e., weekday-Saturday-Sunday and monthly) factors were derived from the traffic simulations and knowing the operating hours of households for residential heating in Limburg in the winter season (from mid-October to March). In the case of Hasselt, the hourly meteorological dataset consisting of 2016 hourly observations of wind speed, wind direction, surface temperature, solar radiation, precipitation, and cloud cover, was used.

4.2.2.2 Outputs

The environmental simulation framework produces emission and concentrations map based outputs.

In relation to emission estimation, which require use of the NAEI emission factors for each class of vehicles on for each road link. the volume of heavy vehicles was estimated as the sum of buses and heavy vehicles obtained as output of traffic simulations, the share of motorcycles over the number of light vehicles output of traffic simulations was estimated from the average one in Belgium available from FEBIAC (Fédération Belge et luxembourgeoise de l'Automobile et du Cycle) (FEBIAC, 2018). Besides traffic counts for the different source categories during the rush hour, traffic simulations also provided factors through which the diurnal (weekday, Saturday and Sunday) and monthly variation of road sources can be estimated. As an example, Figure 7 presents NO_x emissions for the 850 road sources (major roads) considered in Hasselt.

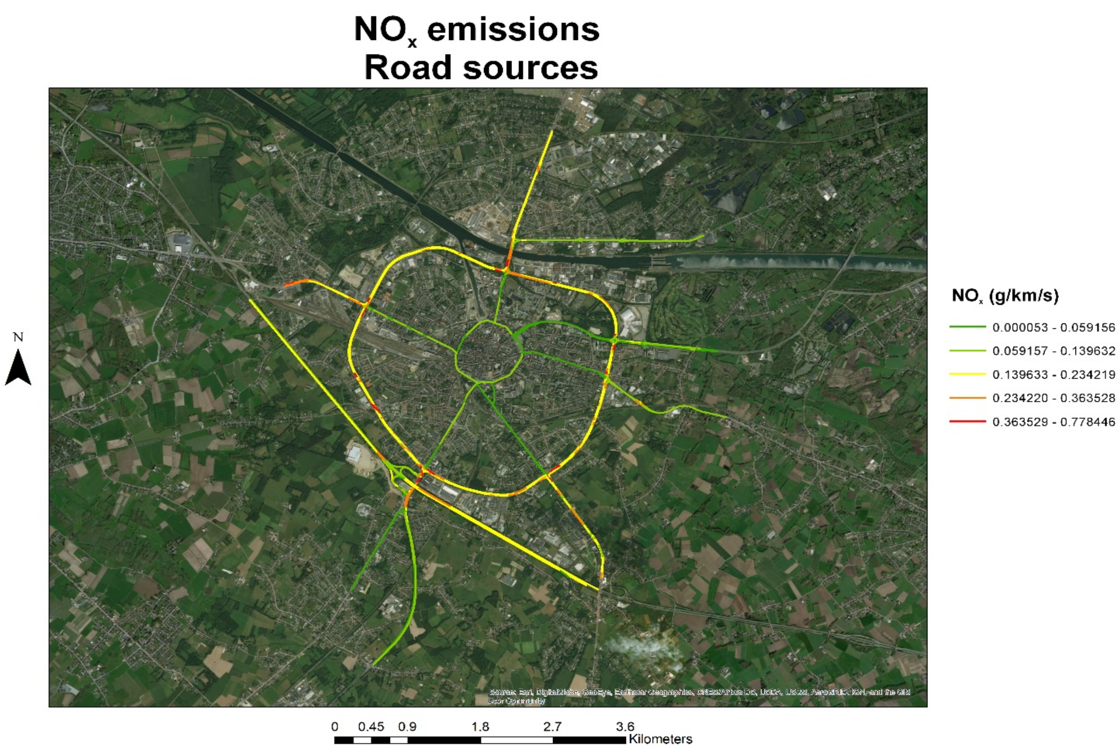

Figure 7. NO_x emissions (in g/km/s) for road sources considered as major roads in Hasselt in the present scenario.

Apart from road emission, other sources emissions are also inventoried in EMIT. For example, in the case of Hasselt, information on emissions for the whole city was derived from VMM (https://www.vmm.be/lucht/luchtverontreiniging/huishoudens/huishoudens), while population data in the city and in the surroundings was obtained from https://www.citypopulation.de/php/belgium-limburg.php. Monthly and diurnal variation of residential heating sources were estimated considering the normal operating hours and operating periods (Mid-October to March) of residential heating sources in households in Limburg from the 3E consulting company, 3E (http://www.3e.eu/). Figure 8 represents NO_x emissions from residential heating in Hasselt and its surroundings.

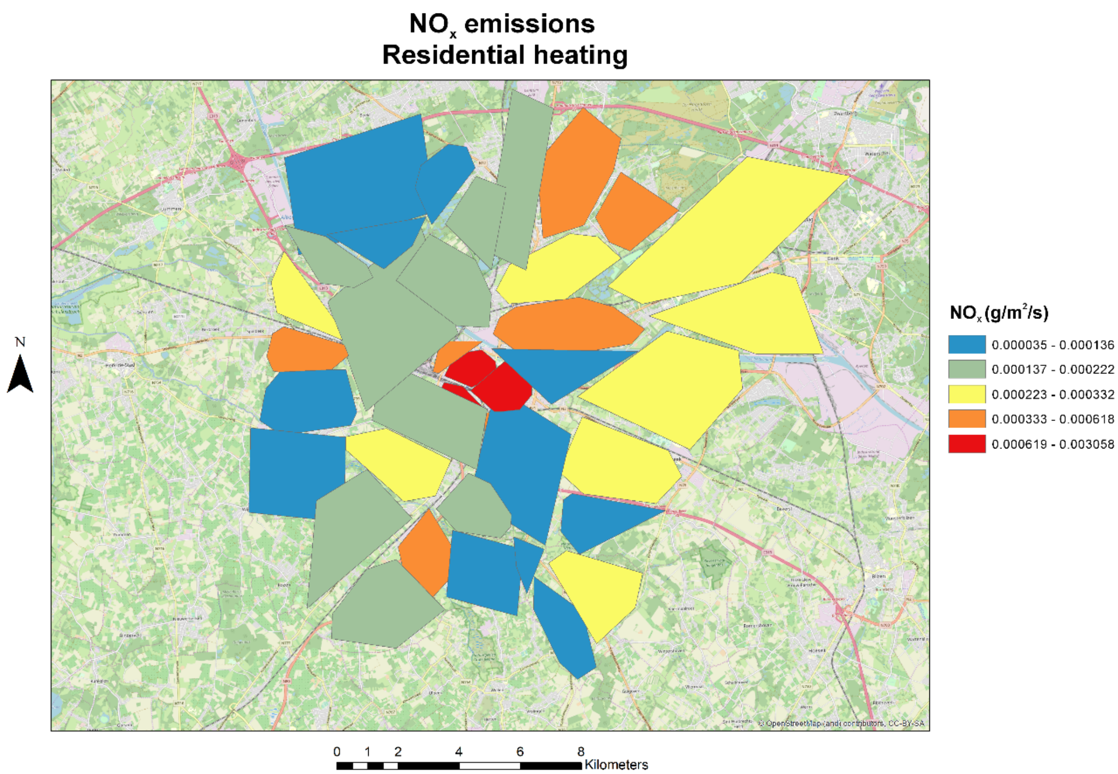

Figure 8. NO_x emissions (g/m²/s) from residential heating in Hasselt in the base case (present) scenario.

Figure 7 and 8 provides the notion in which EMIT framework produces outputs, the key point is that all emissions are linked with spatial units (i.e. roads, geographical areas etc.). The EMIT framework produces data in the shape file, which can be easily visualized in the GIS platform. Furthermore, it also provides the flexibility to convert data in any other required format for its further use in dispersion model. Similar outputs are produced for different pollutants and for other iSCAPE cities.

Using the ADMS-Urban tool, the simulations were conducted in two different ways:

- Short term - any gridded concentration output files will contain output for the first 24 lines of meteorological data only. If specified point output is selected will contain a set of concentrations for every line of meteorological data. This simulation type in particular was used for the verification and comparison of model outputs with measured values.
- Long term - the concentration output files will contain a single set of concentration data, averaged over all the lines of meteorological data. However, a file containing data at all output points for each meteorological line can be created for the long-term output. This simulation type in particular was used for evaluating the dispersion producing concentration maps in the current (baseline) scenario (base reference case) and in the simulations to be compared to it (policies, and climate change).

Output concentrations of short-term simulation are post-processed to calculate long-term averages as required for the validation. Output concentrations of long-term simulation are used to obtain the concentration maps for each pollutant in the various scenarios. The concentration outputs are then compared and validated with observed concentrations at different stations (this is reported in D4.5 in detail). D4.5 also presented concentration maps for a range of scenarios, however, the basic output is the distribution of concentration for some specific period in time and space. Figure 9 presents such output as an example, where NOx concentrations are shown for winter season for entire Bologna. This output is available in the form of shape file, which can be easily converted into other formats as required.

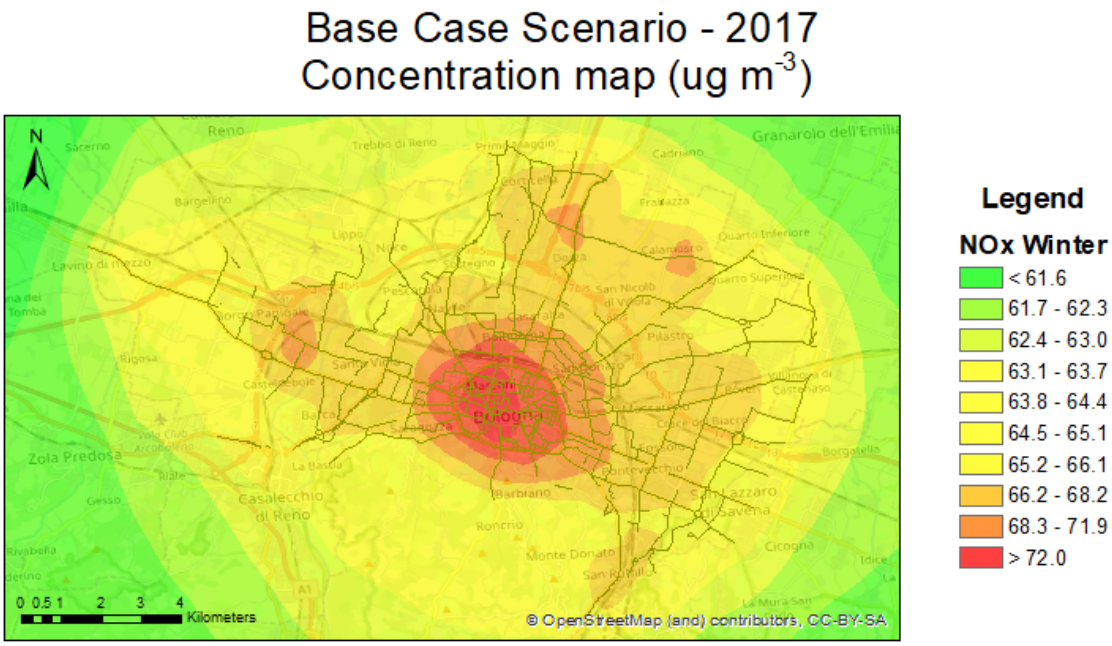

Figure 9. Concentration maps for NO_x in the 2017 Base Case scenario for Bologna. The maps represent concentration values averaged over the period considered.

4.3 Other Existing Models

Section 4.1 and 4.2 provide details from which input /output link can be established for the simulation platform shown in Figure 1. In this section, we briefly discuss the implications of using other alternatives components (especially within behavioral simulation framework because of extensive data requirements) with a simulation platform.

Activity-based approach as already mentioned requires activity-travel data to calibrate its models. Furthermore, MATSIM platform also requires detailed activity-travel patterns as input. This data is not easily available for many cities. Usually, transport planners/modelers collect other types of data that also represent people movements within the region. This data is known as Origin-Destination (OD) matrices (a data very similar to skim matrices) but representing the number of trips between the two points (often known as zones). Traditional transport modelling platforms such as TRANSCAD, OMNITRANS, TRIPS, EMME/2, VISSUM and many more uses such OD matrices to predict the number of vehicles on the roads (i.e. an output that is required by environmental simulator). On some occasions, more details within OD matrices are also available such as time-dependent OD matrices through which traffic volumes at a different time period of the day can also be determined. However, it is important to understand the consequence of using such a model. These are as follows:

- OD matrices are aggregate in nature and therefore, individuals (based on their socio-economic characteristics) cannot be distinguished at any stage of the model.
- There are mathematical models available that can also estimate such OD matrices. These models have aggregate variables that only reflect the attraction capability of geographic areas (landuse variables) and generalized cost functions (that contains travel time, travel distance etc.). These models do not incorporate socio-economic characteristics of individuals and hence, it is very difficult to test policies that are specific to a particular population segment, nor the effect of policies can be determined bases on a population segment.
- In addition to the above, these traditional platforms are not able to transfer the effects of policies from one trip to another. Trip are considered a separate entity, so it is not possible to determine the effect of policies on subsequent trips of the individuals in a day.
- Exposure estimate could also be affected because it is outputs of such traditional platform doesn't contain route information. Though, it is possible that the population in a region can be distinguished based on their home and activity locations at different times of day (if time-dependent OD matrices are available).

5 Personal exposure estimate improvements

This section of the report provides details on the originally planned deliverable 7.4 according to DOW. Discussion in this section are presented considering the following points.

- Definitions of dynamic and static exposure.
- Methodology is discussed to extract dynamic exposure.
- Results of application of methodology for three iSCAPE cities in base and policy scenarios along with their differences and comparison with static exposure.

5.1 Dynamic exposure vs Static exposure

Exposure of an individual to air pollution in urban setting results from a complex process and multifaceted iterations between the individual and ambient air, depending both on spatio-temporal dynamics of activity-travel routine of individual and air pollution concentration. Furthermore, it is not straight forward to measure exposure because air pollution is different in indoor and outdoor settings. Many recent studies have advocated this point and mentioned that health effects seem to be inappropriately assessed when these spatio-temporal dynamics are ignored in estimation.

5.1.1Definitions

According to *Kwan et al.* [*2015*], **static exposure** is evaluated considering an individual as a static entity, i.e. a non-moving object at a particular location (in the majority of the cases it is the residential location of the individual). As an aggregate assessment, the total number of people living in each square kilometer can be examined in relation to varying hourly concentrations for a well-defined area in the study area. While measuring static exposure individual activity-travel movements are ignored.

Dynamic exposure considers the effects of people's travel on their exposure. To obtain this value, people's location at different times of a day was first identified and their exposure at a particular time point was then determined based on where they were at that time. Finally, all exposure values thus identified for the time periods were summed up to obtain the person's dynamic exposure.

Few studies have measured the differences in the two approaches. They have concluded that there are significant differences between the estimation results. *Kwan et al.* [*2015*], further mentioned that it is also required to relate exposure estimate with population characteristics, as they found more differences in exposure estimate between individuals having low and high income compared to the differences between static and dynamic exposure. Based on this discussion, in the next section we discussed the methodology for estimation of exposure given the available datasets.

5.2 Estimation Methodology

The EEA [2018] methodology is only based on spatial distribution. They considered the number of people and concentration gridded value of the pollutant at an identical resolution such as 1 x 1 km^2 for exposure measurement. We have adopted the same methodology for estimating static exposure. For dynamic exposure, we considered the entire activity-travel journey of each individual (as obtained from MATSIM) and superimposed that to pollutant concentration maps (city-wide spatial distribution of pollutant concentration, based on output from environmental simulation framework) as illustrated in figure 10.

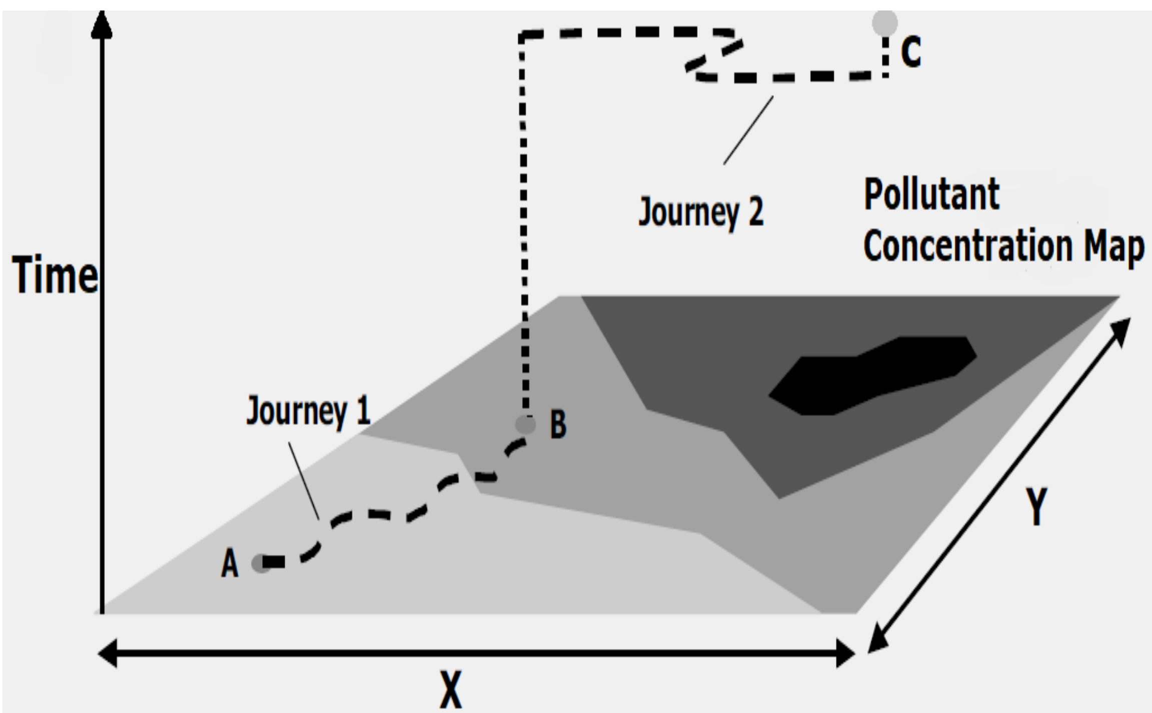

Figure 10. Dynamic exposure assessment based on the activity travel routine of an individual

Further methodological details for estimation of static and dynamic exposure are as follows:

- Pollutant concentration maps obtained as an output from the dispersion model is re-worked to have an average value corresponding to each 1x1 km^2 grid. This is done to have an exact match with the EEA methodology for measuring static exposure. The same pollutant concentration maps are used for estimating dynamic exposure.

- Individual activity-travel routine as obtained from MATSIM is re-worked to represents as a GPS-based trajectory points (Latitude, Longitude and timestamp). Two more columns in this data are introduced to identify whether a particular point is part of journey/trip or activity and if it is a part of the journey then which transport mode, and if that point belongs to activity then what is the activity type. In case of static exposure, the available synthetic population of three cities that also contain residential zone locations is used, however, that zonal structured is re-worked to have the same spatial resolution (i.e. 1 x1 km^2 grid structure)
- The individual trajectory points are mapped with concentration grid map, and a few more columns in the data set are introduced. Now each trajectory points have different pollutant concentration values associated with them. In the case of static exposure, this procedure is rather simpler as the whole population in each grid are mapped with a pollutant concentration value.
- For each individual in the population, a weighted average value of the concentration for the whole day is estimated. This is based on the summation of multiplying the time duration and associated concentration value an individual is exposed for the whole day divided by 1440 (total minutes in a day).
- Additionally, for both approaches and for several population characteristics (i.e. Gender, Age, Income, education level), exposure values are estimated.

Exposure estimates (especially dynamic exposure) can be more accurate if concentrations of pollutants are available for various microenvironments (e.g. individuals while driving a car is exposed to different concentration value, similarly indoor concentration of some pollutant could be different compared to outdoor because of different sources and several activities that are conducted indoor environment). Measuring pollutant concentrations is beyond the project scope and in an absence of such data, we are providing exposure estimate based on outdoor concentration levels as used in EEA [2018]. Additionally, this discussion further leads to appropriately translate the exposure to health effects. Majority of epidemiological studies and also EEA [2018] methodology is based on concentration response functions, which are based on outdoor/ambient pollutant concentration and not on the exact dosage of pollutant concentration. Therefore, the use of outdoor concentrations seems appropriate in the case when concentration response functions are used for estimating health impacts.

5.3 Estimates for three iSCAPE cities

Based on the methodology defined in section 5.3, exposure of the population is estimated for three iSCAPE cities, for which simulations have been carried out using an integrated simulation platform. We not only measured the exposure for the base cases but also for the two distinct policies simulated for each city. Sub-sections below provide results of application on methodology discussed in section 5.2.

5.3.1Hasselt Base case and Policy case

Based on the outputs produced by MATSIM and Dispersion Model, exposure estimation was done for two scenarios for HASSELT city. The first scenario represents the base case that has been validated further with varied type of measured data. The second scenario represents the policy 1 case, where car access is restricted at the inner ring of HASSELT and also roads within the inner ring. For HASSELT city, we also tested a scenario where bus frequency of a few routes have increased, however, the simulation results indicated that differences were not significant from the base case, therefore, it was not necessary to further evaluate the impact of this policy in relation to exposure and health impacts. The simulation results for these policies in relation to transport indicators (e.g. mode shares changes, traffic volume changes, which population segments are effected etc.) are mentioned in D4.4 and results in relation to emission changes and pollutant concentration changes are mentioned in D4.5. Therefore, we are focusing here on results that are obtained after the application of the methodology mentioned in section 5.2. Table 1 illustrates the summary of exposure estimate for various segments of the population for NO_2. Similar estimation was also done for PM_{10} and $PM_{2.5}$ as well.

Table 1: Exposure estimate for NO_2 (HASSELT City).

Population Segment	Base Case		Policy 1	
	Dynamic ($\mu g/m^3$)	Static* ($\mu g/m^3$)	Dynamic ($\mu g/m^3$)	Static* ($\mu g/m^3$)
Overall Population	44.3	39.2	41.5	37.2
Male	45.2	42.5	43.1	40.4
Women	43.5	36.4	40.3	35.1
Age (18-34 yrs)	44.8	38.6	41.3	37.4
Age (30-54 yrs)	46.7	40.2	43.6	39.1
Age (55-64 yrs)	45.9	42.4	43.2	40.3
Age (65-74 yrs)	43.3	38.3	40.0	37.1
Age (> 74 yrs)	39.9	38.5	37.2	36.9
Income (Low)	48.6	49.5	45.1	43.5
Income (moderate and high)	41.2	34.6	39.4	33.1

*static exposure numbers in the table are based on entire city averages (these numbers are average based on 1 x 1 km^2 grid values)

Table 1 presents a larger difference in static exposure of individuals having income from low to moderate/high categories, however, this difference is significantly lower for dynamic exposure values. This shows that when individuals movements are ignored, the difference between population segments are much higher. Policy 1 results in lower exposure values in both estimations approaches and differences seems significant for some population segments. It is interesting to note that even in static exposure case lower-income people are better off compared to their counterpart in the case of policy 1.

5.3.2Bologna Base case and Policy case

Based on the outputs produced by MATSIM and Dispersion Model, exposure estimation was done for two scenarios for Bologna city. The first scenario represents the base case that has been validated further with varied type of measured data. The second scenario represents the policy 1 case, where car access is restricted at in the inner ring and only electric cars are allowed inside the ring. Similar to the HASSELT case, other policies such as an increase in the bus frequency and changing the opening times of facilities, in general did not render any significant differences from the base case and, therefore, further analysis is not carried out. The simulation results for these policies in relation to transport indicators (e.g. mode shares changes, traffic volume changes, which population segments are affected etc.) are mentioned in D4.4 and results in relation to emission changes and pollutant concentration changes are mentioned in D4.5. Therefore, we focus here on results that are obtained after the application of the methodology mentioned in section 5.2. Table 2 illustrate the summary of exposure estimate for various segments of the population for NO_2. In the case of Bologna, we have summer season concentration as well as winter seasons, we, however, used here average of winter and summer concentrations as outputs are available for both seasons. Similar estimation was also done for PM_{10} and $PM_{2.5}$ as well for extreme values.

Table 2: Exposure estimate for NO_2 (Bologna City).

Population Segment	Base Case		Policy 1	
	Dynamic ($\mu g/m^3$)	Static* ($\mu g/m^3$)	Dynamic ($\mu g/m^3$)	Static* ($\mu g/m^3$)
Overall Population	47.8	42.9	41.5	37.5
Male	47.7	43.1	41.6	38.1
Women	47.8	42.8	41.5	36.7
Age (18-34 yrs)	51.6	48.3	46.2	40.3
Age (30-54 yrs)	51.1	47.2	45.1	40.4
Age (55-64 yrs)	51.3	47.5	45.3	40.1
Age (65-74 yrs)	44.8	38.5	39.2	35.8
Age (> 74 yrs)	42.6	35.1	38.1	34.4
Income (Low)	49.6	45.5	42.9	39.1
Income (moderate and high)	46.8	40.2	40.3	36.5

*static exposure numbers in the table are based on entire city averages (these numbers are average based on 1 x 1 km^2 grid values)

Table 2 shows that income categories have a lower difference in Bologna in relation to base case as well for the policy case. Exposure values are slightly higher compared to the Hasselt case. Higher exposure is noted for young and middle age groups for both static and dynamic approaches. Furthermore, dynamic exposure for older individuals is significantly higher compared to static exposure. Policy 1 shows promising results and is able to lower the average exposure of individuals significantly.

5.3.3Vantaa Base case and Policy case

Based on the outputs produced by MATSIM and Dispersion Model, exposure estimation was done for three scenarios for Vantaa city. The first scenario represents the base case that has been validated further with varied type of measured data. The second scenario represents the policy 1 case, where car access is restricted at a particular area of Vantaa (near a train station). Similar to the HASSELT case, an increase in the bus frequency of a few routes did not render any significant differences from the base case, and therefore, further analysis is not carried out. The simulation results for these policies in relation to transport indicators (e.g. mode shares changes, traffic volume changes, which population segments are affected etc.) are mentioned in D4.4 and results in relation to emission changes and pollutant concentration changes are mentioned in D4.5. Therefore, we focus here on results that are obtained after the application of the methodology mentioned in section 5.2. Table 3 illustrate the summary of exposure estimate for various segments of the population for NO_2. Similar estimation was also done for PM_{10} and $PM_{2.5}$ as well.

Table 3: Exposure estimate for NO_2 (VANTAA City).

Population Segment	Base Case		Policy 1	
	Dynamic ($\mu g/m^3$)	Static* ($\mu g/m^3$)	Dynamic ($\mu g/m^3$)	Static* ($\mu g/m^3$)
Overall Population	28.5	26.7	27.8	26.3
Male	28.5	26.9	27.8	26.5
Women	28.7	26.7	27.7	26.2
Age (18-34 yrs	29.2	27.3	28.6	27.5
Age (30-54 yrs)	28.9	27.1	28.4	27.3
Age (55-64 yrs)	27.3	26.5	27.2	26.2
Age (65-74 yrs)	26.7	25.3	26.4	25.1
Age (> 74 yrs)	25.2	24.5	25.0	24.8
Income (Low)	29.2	28.3	28.4	27.2
Income (moderate and high)	27.6	25.5	26.5	25.4

*static exposure numbers in the table are based on entire city averages (these numbers are average based on 1 x 1 km^2 grid values)

Table 3 shows that differences are lower in Vantaa for both exposure estimates. Furthermore, policy case has lower values than the base case but the differences are not significant. This is due to the consideration of small network for car access restriction compared to the city size. The effects of the policy are only at a local scale and city-wide statistics does not clearly depict them. Similar to the Bologna case, young and middle-age people are more exposed compared to older age people.

Table 1 to 3 demonstrate significant differences in the measurement of exposure estimation, and for all three cases, if city-wide statistics are measured, the static approach is underestimating the exposure. The next section discusses the translation of those exposure estimate into health impacts, which is defined based on mortality impacts.

6 Translating environmental effects into human health

This section of the report provides details on the originally planned deliverable 7.5 according to DOW. Discussion in this section are presented considering the following points.

- WHO [2016] and EEA [2018] methodology for health impact assessment, that is based on relative risk factors based concentration response functions (as adopted in Deliverable 5.3)
- Estimation of health impacts for the policy scenarios for three cities to complete the model chain in relation to both approaches of exposure estimate (as discussed in section 5).

6.1 Health risks assessment framework

We followed the methodology proposed by WHO [2016b] and EEA [2018] methodology to quantify health risk. Based on this methodology, mortality is the outcome which is a prime focus as it the most serious effect and usually data are available on this metric quite easily. This mortality is usually measured in terms of 'premature deaths' and 'years of life lost'. According to this methodology, the following information is required:

- Concentration-response functions (CRF);
- Baseline health statistics (mortality rates)

The concentration response functions are usually obtained from epidemiological studies, or meta-analysis studies, that bring together the findings of multiple epidemiological studies. In this analysis, we use findings from the World Health Organization [2013] that is also followed by EEA [2018]. Deliverable 5.3 of iSCAPE also followed the same approach while calculating the health impacts of passive control type interventions studied in the project. The EEA [2018] recommends the use of relative risk-based concentration response functions, which captures the increase in mortality that can be attributed to a given increase in air pollution concentration. These relative risk factors are population level statistics, therefore, cannot be assigned to a specific individual. It is very important to mention that exposure estimates are required to be assumed as average to the time period needed to match the development basis of the CRF. For NO2 and PM2.5, CRF requires the exposure that was assessed for a whole year, i.e. calculating the yearly average. Concentration maps produced from the dispersion model for all three cities are hereby assumed that it represents the yearly averages. Furthermore, for the dynamic exposure that considers the activity-travel pattern of the individuals, it is therefore required to assume that over the whole year individuals more or less follows the same activity-travel pattern. This assumption for a specific individual does not make sense, however, estimating the exposure of a group of individuals (i.e. for a particular population segment) may be appropriate in such cases. This is also required to employ the methodology as risk factors are also based on the population level. Based on the exposure values, the relative risk for each of the corresponding concentration or exposure values could be calculated as follows :

$$RR = e^{\beta \times E} \qquad (2)$$

where β is the CRF coefficient (Relative Risk factors) derived from WHO [2013] as given in table 4 for all-cause mortality. If linearity is assumed, an increase of 10 $\mu g/m^3$ of $PM_{2.5}$ is associated with a 6.2% increase in total mortality in the total population considered. The RR using expression 2, in this case, can be calculated as RR = exp ((0.062/10) x Exposure value). In the case of NO_2, the RR can only be calculated for exposure values of more than 20.

Table 4: Relative risk for a 10µg/m³ increase in concentration

Pollutant Metric	Health end-point	Relative Risk factors (β) (95% confidence interval per 10 µg/m³)	Age Group
$PM_{2.5}$	All-cause Mortality	1.062 (1.040-1.083	> 30
NO_2	All-cause Mortality	1.055 (1.031-1.080) on concentration > 20	> 30

Usually, an attributable proportion is calculated further following the standard formula (i.e. AP = (RR-1)/RR) that is further multiplied with baseline health statistics available for the region. For example, if gender and age-specific mortality rates are available (say M_g) then the number of attributable premature deaths (PMD) is given by: PMD = MR_g x Population x AP. For attributable Year of life (YLL) lost calculation, the attributable PMD needs to be further multiplied by age- or gender-specific remaining life expectancies (for example for age group of 30-54 years this remaining life expectancy for Flemish area is around 38 years on an average)[*Dhondt et al., 2012*]. The baseline health statistics for three cities in the form of mortality rates are provided in table 5. These are also reported in deliverable 5.3. They are based on crude death rates per person in EU member states from Eurostat [2019]. The 1.45 multiplier to account for the increase in mortality in age groups over 30 is calculated based on mortality rates for over 30-year-old population in Finland. Thus, the assumption is that the increase is similar in other iSCAPE cities – Eurostat does not classify crude death rates per age group.

Table 5: Base line health statistics from EUROSTAT for countries that include three iSCAPE cities.

City	All-cause Mortality rates (MR)*	All-cause Mortality rates (>30 years) (1.45 * MR)
Hasselt (Belgium)	0.0096	0.014
Bologna (Italy)	0.01	0.015
Vantaa (Finland)	0.0094	0.0013

*these death rates are provided as ratio of deaths per 1000 inhabitants

6.2 Estimation of health risk for three iSCAPE cities

Since the risk factors are available are part of the population that are over 30 years of age, therefore, we estimated health impacts for that population segment. Bologna has 72% of its population that is over 30 years and Hasselt and Vantaa have this percentage around 65%. Table 6,7 and 8 present the number of PMD over 30 years in relation to NO_2, for each city respectively and for both exposure estimates. The table represents the distribution of PMD over various segments of the population, this is only possible because of exposure estimates. If gender and age specific mortality rates would be available, numbers mentioned in the following table would be much more appropriate.

Table 6: Attributable PMD estimation due to NO_2 (HASSELT city)

Population Segment	Base Case		Policy 1		% Reductions	
	PMD Dynamic	PMD Static	PMD Dynamic	PMD Static	PMD Dynamic	PMD Static
Overall Population (above 30 years)	8.45	7.08	7.53	6.20	10.88	12.42
Male (above 30 year)	8.62	7.67	7.82	6.73	9.29	12.28
Women (above 30year)	8.13	6.06	7.04	5.37	13.42	11.16
Age (30-54 yrs)	8.90	7.51	7.99	6.23	9.75	12.09
Age (55-64 yrs)	8.45	7.62	7.25	6.45	10.1	14.45
Age (65-74 yrs)	7.89	6.45	6.87	5.73	12.3	10.75
Age (> 74 yrs)	7.78	7.15	7.01	6.32	10.63	13.35
Income (Low) (above 30year)	10.29	9.12	9.23	7.45	11.30	19.7
Income (moderate and high) (above 30year)	7.16	4.65	6.45	4.25	8.16	4.7

Table 7: Attributable PMD estimation due to NO_2 (Bologna city)

Population Segment	Base Case		Policy 1		% Reductions	
	PMD Dynamic	PMD Static	PMD Dynamic	PMD Static	PMD Dynamic	PMD Static
Overall Population (above 30 years)	51.84	43.26	40.77	33.03	21.35	23.64
Male (above 30 year)	51.75	43.46	40.67	31.81	20.1	22.78
Women (above 30year)	51.95	42.95	45.38	36.27	21.7	25.93
Age (30-54 yrs)	51.64	42.49	39.87	33.15	22.47	21.6

Age (55-64 yrs)	52.64	43.89	41.56	33.65	21.31	24.7
Age (65-74 yrs)	46.32	36.24	36.78	28.51	22.07	15.9
Age (> 74 yrs)	49.89	38.95	39.54	32.54	19.64	19.52
Income (Low) (above 30year)	61.23	56.23	46.87	37.58	23.94	33.0
Income (moderate and high) (above 30year)	49.7	39.22	38.54	29.64	21.70	19.32

Table 8: Attributable PMD estimation due to NO_2 (VANTAA city)

Population Segment	Base Case		Policy 1		%Difference	
	PMD Dynamic	PMD Static	PMD Dynamic	PMD Static	PMD Dynamic	PMD Static
Overall Population (above 30 years)	8.94	7.08	8.22	6.67	8.05	5.79
Male (above 30 year)	8.94	7.13	8.22	6.72	8.05	5.78
Women (above 30year)	9.09	7.23	8.19	6.59	9.02	6.15
Age (30-54 yrs)	8.65	7.56	8.16	6.32	7.78	5.74
Age (55-64 yrs)	8.32	6.87	7.45	6.45	6.77	7.56
Age (65-74 yrs)	8.41	6.57	7.32	6.78	8.75	5.46
Age (> 74 yrs)	8.59	6.32	7.55	6.50	7.78	3.87
Income (Low) (above 30year)	10.35	8.12	9.33	7.21	9.85	10.54
Income (moderate and high) (above 30year)	8.14	6.45	7.21	6.33	9.23	2.36

It could be noted that higher benefits are for Bologna in case of implementation of policy 1 as the reduction in PMD compared to the base case is around a magnitude of 20%. The exposure differences in Bologna for policy 1 case are not that much as compared to Hasselt city, however, health benefits are higher due to the significantly large population than Hasselt. Vantaa and Hasselt have lower a reduction in PMD. For all cities, it is noted that PMD reduction measured on static exposure are higher in HASSELT and BOLOGNA, however, for Vantaa these reductions are at a lower side in comparison to dynamic exposure estimates. This is because of the insignificant difference in exposure estimate for the VANTAA case because the overall effect of the policy is only at a local level. Similar, calculations are also carried out for $PM_{2.5}$.

In addition to estimation of PMD, for the case of HASSELT city, we also estimated YLL, because the data is available for remaining life expectancy for Flanders region in Belgium (we assumed similar distribution for HASSELT city). Table 9, provide details of such estimation only for the dynamic case. Overall, the results follow a similar pattern as seen in the case of PMD, however, the slight differences in the pattern are due to the difference in remaining life expectancies. The female population is better off along with population having age from 55 to 74 years.

Table 9: Attributable YLL estimation due to NO_2 (HASSELT city)

Population Segment	Remaining life expectancy	PMD (base)	YLL (base)	PMD (Policy 1)	YLL (policy 1)	%Reduction YLL
Overall Population (above 30 years)	22.36	8.45	188.94	7.53	168.37	10.88
Male (above 30 year)	20.85	8.62	179.72	7.82	163.047	9.28
Women (above 30year)	23.86	8.13	193.98	7.04	167.97	13.04
Age (30-54 yrs)	38.93	8.90	346.47	7.99	311.05	10.22
Age (55-74 yrs)	20.25	8.15	165.03	7.05	142.76	13.50
Age (> 74 yrs)	7.9	7.78	61.462	7.01	55.38	9.89

6.3 Uncertainties in estimation of health risk

There are a wide variety of uncertainties associated in the whole process. Within the health risk assessment process, the major source of uncertainty comes from the relative risk-based concentration-response function as they are taken from epidemiological studies. Usually, the relative risk reported at 95% confidence interval which is also recommended by *EEA* [*2018*]. Table 4 reported these confidence intervals, however, the results shown in section 6.2 are based on mean values. It could be easily extended further by using the lower and upper values of concentration response function. Additionally, it is also mentioned that health impacts estimated as PMD and YLL for different types of a pollutant cannot be simply added up to represent the combined effects. This is due to the fact that air pollution is a complex mixture of several air pollutants. EEA [2018] reported that there is almost 30% of double-counting present when premature deaths quantified for $PM_{2.5}$ and NO_2 are added together. Apart from the RR estimates, uncertainties in the results can be attributed to the following:

- Simulation platform and models within those platforms are developed based on the collected data that predict people movements. Methods, type of model, data, and the estimated parameters are all possible sources of uncertainties.
- Similar to the behavioural simulator, environmental simulator involved a range of process that uses different datasets, and models to produce pollutant concentration maps at some space time resolution. The results obtained from them are also subjected to some uncertainties.
- A variety of assumptions being made to simplify the process (e.g. Counterfactual concentration as absolute numbers, space time resolution for people movements and pollutant concentration maps that reflects only outdoor concentration (individuals are exposed to different values of concentration when involved in indoor activities), simulation

errors in the platform) can also introduce uncertainties in the reported results. Care must be taken when results are generalized.

7 Summary of Key findings on behavioral interventions

This section of the deliverable summarized the key findings of behavioral interventions tested as part of work package 4 that include informational and structural interventions. Informational interventions are carried out using a campaign approach by providing citizens customized information about their mobility-behavior to instigate a positive behavioral change (which is the key motive of the activities carried out in Hasselt living lab). D 4.1 discussed one such intervention in detail. The other type of interventions that are classified as structural interventions, are tested using an integrated simulation platform. Not only, the resulting transportation efficiency (i.e. D 4.4) is analyzed but also their impacts on air quality (D4.5), exposure and finally health impacts are also estimated (this deliverable). This section synthesizes the technical findings of the interventions. We first present the key findings of informational interventions.

7.1 Mobility-based informational interventions

Within the framework of iSCAPE project and WP 4, two different initiatives were taken that can be classified as mobility-based informational interventions. D4.1 presents the details of the first intervention study which is carried out in HASSELT city. The same intervention is then repeated in Bologna and Guildford. Some brief details and key findings are presented in the sub-section 7.1.1.

7.1.1 Intervention covering overall mobility behavior of citizens

The design of this intervention is developed following the four methods suggested in literature (i.e. Feedback, Justification, Cognitive dissonance, and Commitments). Customized information is provided to each individual in four different aspects.

1) Exposure to air pollutant,
2) Contribution in CO_2 emission (only if an individual used a car)
3) The extent to physical activity level.
4) Hot and cold start of car (only if an individual used a car)

Each participant received their informational pack that comprised of 4 sections based on the 4 aspects mentioned above; each section of this information contains three fundamental elements. These are as follows:

- A brief information to increase the awareness of participant regarding a particular aspect, which is easy to understand and digest.
- Feedback in terms of a quantitative measure of their behaviour on each aspect and description of its effect.

- Some recommended suggestions on how to change travel behaviour to decrease the effects along with its quantification. These suggestions are designed considering the ease in change for a particular participant (i.e. a consideration based on perceived behavioural control).

Some optional elements can also be included based on the results of the path model, e.g. more information to increase the awareness regarding each aspect and to inculcate positive attitudes and beliefs. Quantification information about peers (How other persons in the study are behaving compared to a single participant), which relate to the subjective norms. Along with the above, at the end of information pack, individuals are asked to give their commitments for some of the suggestions put forwarded in the 4 sections of the information pack. Also, a flexibility is provided to give the commitments on their own.

An informational pack is a web-based tool, along with the information and suggestion on each section as mentioned in the design section, various questions were asked from each section in order to gauge the understanding of the participant and also to ensure that individual has read all the information and remembered few key things. Additionally, the following key points were also taken into account for implementation of this intervention.

1) Recruitment of citizens for the long-term (for at most 5-6 weeks): As the intervention is based on the processing of GPS-based activity-travel routine data, therefore, the processing time is considered as minimum as possible. Most of the algorithms for analysis are rule-based and was easily programmed. Furthermore, citizens at the recruitment stage were provided a complete schedule of activities of this intervention, and periodically, during the study, they were reminded about those once the particular step was due.
2) The information pack contains a variety of information, help from designers are taken to make that information as readable as possible. The look and feel of the information pack is improved to make it attractive to read. Help from graphical illustrations and symbols are taken in this regard.
3) In order to facilitate the effectiveness of the informational intervention, participants are required to be divided into two groups, i.e. Control and Treatment group. Control group activity-travel routine is required to be measured twice, however they were not provided with any information. For the treatment group, they were also required to provide their behavioural information twice, i.e. pre and post-intervention along with the provision of the informational pack in between.

This intervention was first implemented for Hasselt city and then as a repeat exercise with a more sophisticated smartphone app, the intervention is carried out in Bologna and Guildford. In Dublin this intervention was also implemented, but due to low number of participants (N=5), the results are not that detailed. We therefore, focused only on the findings from three cities. Some key take-aways and finding of this intervention are as follows:

7.1.1.1 Algorithm Development and Pro-environmental Potential

An algorithm was developed to estimate the pro-environmental potential within an activity-travel behaviour of citizens of Hasselt, Bologna and Guildford. The details of the algorithm is explained in Ahmed et al [2018]. The algorithm uses activity-travel data (collected from a smartphone app) and integrates it with infrastructural data of the region/city. Then based on the application of some rules (that are taken from the literature) it identifies the pro-environmental potential exist in citizen's activity-travel behaviour. The focus of the algorithm to curtail car trips, and identify which one can be replaceable by walk, bicycle and Public Transport. In addition, it also identifies the number of hot and cold starts of car trips and excess out-of-home activities which could be further reduced, so that overall emissions and exposure of citizens can be decreased. Table 10 and 11 and 12 presents some of the key findings of the application of this algorithm.

Table 10: Participant Car Usage characteristics and its replaceable potential.

City	Statistics	Car Trips (Absolute and Mean values per person for 5-working days)					
		Within 1 km	**Walking potential**	**Within 3 km**	**Bicycle Potential**	**Total trips**	**Public Transportation Potential**
Hasselt	**Sum** (N=25)	0	0	82	23	192	42
	Mean	0	0	3.28	0.92 (28%)	7.68	1.68 (21%)
Bologna	**Sum** (N=18)	23	4	73	10	211	79
	Mean	1.28	0.22	4.06	0.56 (13%)	11.72	4.39 (29%)
Guildford	**Sum** (N=13)	21	1	62	16	202	57
	Mean	1.62	0.08	4.77	1.23(25%)	15.54	4.38 (15.35%)

Table 11: Cold start and non-mandatory outdoor activities and its replaceable potential.

City	Statistics	Cold Starts	Cold Starts Potential	Non-mandatory outdoor Activities	Non-mandatory outdoor Activity Potential
Hasselt	**Sum** (N=25)	115	39	52	18
	Mean	4.61	1.56	2.08	0.72
Bologna	**Sum** (N=18)	95	40	92	22
	Mean	5.28	2.22	5.11	1.22
Guildford	**Sum** (N=13)	102	35	78	14
	Mean	7.85	2.70	06	1.07

Table 12: Consequences of Replaceable car trips with in 3 km to cycling in a 5-days week per person

City	CO_2 Emissions Reduction (%)	Physical Activity Level Improvement (%)
Hasselt	8.01	10.65
Bologna	1.00	3.01
Guildford	2.77	9.85

The numbers in table 10 can be interpreted that in Hasselt, 21% car trips can easily be replaced by Public transport. For Bologna, this is 29% and for Guildford, it is around 15%. Similarly, there exist a significant potential for replacing car trips into bicycle trips. Additionally, reduction in CO_2 emission and increased level of physical activity is also significant, if only car-trips (for <3km) are replaced by bicycle. These numbers suggest that replaceable potential exists in the activity-travel behaviour of individuals and it should be exploited to instigate positive behavioural change. For this purpose, an overall mobility-behaviour based informational intervention was designed and implemented in three cities.

7.1.1.2 Intervention Effectiveness via Participant feedback

In the case of Hasselt, out of 40 participants in the behavioral intervention study, 25 of them provided feedback about the study. 10 participants declared that upon participating in the project pilot they changed their transport routine, while 14 participants responded they did not do so. This suggested that 40% participants change/adapted the behavior based on this intervention. In the case of Guildford, 22% participants change/adapted their behavior based on the given suggestion in the information pack. For Bologna case, 33% participants provided positive feedback in relation to modifying their behavior. **Overall, the intervention showed effectiveness for little more than 1/3rd of participants.**

7.1.2 Route to School Informational Intervention

This intervention was also designed and implemented on the similar notion as described for the intervention discussed in section 7.1.1. The main idea is to find out potential route to school that pose lesser threats in relation to exposure to NO_2, especially for the kids that are either use bicycle or walk to go to school from their home to vice versa. The target audience for this intervention is of course students who are travelling with their parents/guardians. The information package was designed for escorting parents and guardians. An online customized information package was designed that act as an intervention tool to influence the change in school travel behavior. The overall effectiveness of the customized information package also significantly depends on the structuring i.e. organization and presentation of the information. So each section of the Customized information package was organized as follows:

- Contextual information with infographics to increase the awareness related to air quality and pollutant exposure impacts, which was easy to understand and digest.
- Customized Feedback regarding a quantitative measure of current and alternative school travel choices with the description of their impacts in terms of pollutant exposure.
- Description of the personal benefits achieved in terms of reduction in pollutant exposure level by adopting an alternative route.
- General suggestions and tips on how to avoid pollutant exposure in an urban environment.

Further to avoid any confusion, the routes of the detected alternatives were marked on the GUI of google street maps and embedded in the Customized Information Package as shown in figure 11.

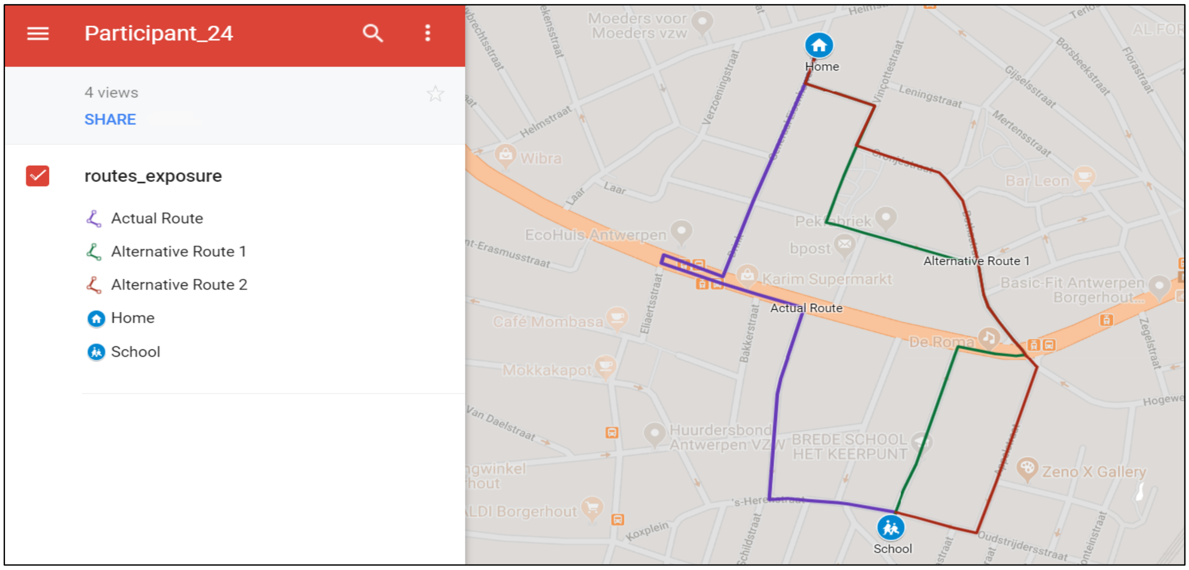

Figure 11. View of embedded routes in online Customized Information Package

This intervention was developed at Hasselt living lab, after a co-creation exercise conducted as part of the summer school organized by Hasselt living lab. However, part of an Antwerp city was selected to practically execute this intervention, as intervention demands to have availability of feasible routes within a school vicinity that offer significant exposure reduction. More details about design and implementation steps can be seen from Ahmed et al [2019].

7.1.2.1 Algorithm for determining availability of feasible alternative routes

The mechanism adopted to detect less polluted walking/cycling routes to school involves various processes and computations. It starts with retrieving recorded home to school routes from R2S platform developed at Transportation Research Institute, Hasselt University. This data is then used for identifying feasible walking/cycling alternative routes and ends by evaluating pollutant exposure involved per trip. The exposure is estimated based on the pollutant concentration maps of hourly annual NO_2 concentrations at 10 m^2 grid resolution obtained from Flemish Institute for Technological Research (VITO). This space resolution is important as it provides street level concentration, and therefore, feasibility of alternative routes can be determined. At the moment, this algorithm is based on several manual steps. Hasselt living lab is making an effort to completely automate these steps, so that similar studies can be carried out in other regions. The key findings in relation to availability of feasible alternatives routes is presented in Table 13.

Table 13: Participant's exposure category change from current to alternative routes

% Participant's exposure category shift from actual to alternative routes			
Alternative Routes	**Current Routes**		
	Low	**Moderate**	**High**
Low	30	17	7
Moderate	3	20	10
High	0	0	13
Grand Total	33	37	30

The number in each cell in table 13 is representing the percentage of the participants whose exposure category can possibly be changed, such as moderate to low, high to low etc. Three categories are defined i.e. Low, moderate and high to characterize the exposure of current and alternative routes. If the average concentration value is less than or equal to 40 ug/m^3, the route is categorized as having low exposure, moderate if values are between 41 – 50 ug/m^3 and high if values are greater than 50 ug/m^3. About 17 percent of the participant's exposure category changed from moderate (current route) to low (alternative route). Similarly, for 7 and 10 percent participant's exposure category can be shifted from high to low and high to moderate category. Therefore, it can be concluded that significant proportion i.e. 34 percent of the participants (highlighted in grey color) have alternative routes with better air quality as compared to their current choice of route. This potential route shift can significantly help to avoid health risks associated with high NO_2 concentrations.

7.1.2.2 Intervention Effectiveness via Participant feedback

In this section, some insights into the effectiveness of the implemented intervention are provided. The effectiveness is measured based on the responses of the questionnaire filled by the participants after the intervention. The feedback questionnaire asked the participants the following questions.

1. Did you learn something new by participating in this study? If you select YES, then please explain why?
2. Having learned about your exposure to air pollution, do you think you will change the way you escort your kid to school? Yes/No please explain
3. Do you think there is something you can do to reduce air pollution in your city? If you select YES, then please explain why?
4. Did you like the study? Rate from 1(hate) – 5 (love)

Around 88 percent of the participants mentioned YES as the response to the 1st Question. The responses are encouraging as most of them reported that participation in the study increases their knowledge related to pollutant exposure and further about the commuting to school in a healthier way. 77 percent of the participants responded positively to the 2nd Question by reporting that they started following the suggested alternative routes to school with the least exposure to air pollutants. We further analyzed the reasoning for those 23% participants who responded negatively to this question. 13% of them are those who also did not show agreement with the question asked about "environmental pollution in a locality is a concern" in their response to the introductory questionnaire. This means that there is a need for awareness campaigns to educate people about health impacts due to pollutant exposure. Another 10% participants were those who showed reluctance to follow the suggested alternative routes due to safety concerns. It is observed that the kids of these participants are mostly from the age category of 9 -12 years old. This concern is probably because kids started going to school independently at this age and parents are extra conscious about their safety. Some of the responses are provided as it is.

> "the alternative route is certainly greener but perhaps not safer for young cyclists due to lack of separate cycle path and footpath".
>
> "Because the alternative route is even more dangerous than the current one - first safety, then air pollution ....".

For question 3, 40 percent of the participants showed good civic sense by responding positively that they can take certain actions to reduce air pollution in the city. A couple of respondents showed a commitment to increase cycle use and reduce car use as much as possible. Some participants have an intention to plant trees in their locality. One of the participants has a plan to encourage municipality about the improvement in walking/cycling paths. The escorting parents from age group below 40 years seem more enthusiastic and pro-environmental as most of them fall in the age category of 30 – 40 years as mentioned in Table 1. Participants in overall like the study by giving a positive rating, the average score (from 104 participants) estimated is around 4.1 out of 5.

7.2 Mobility-based structural interventions

Within structural interventions, car access restriction in a particular area of the city and increase in bus frequency for a few routes are tested using an integrated simulation platform. The focus of the deliverable 4.4 was mainly to briefly describe the prototype behavioural simulation model and the results obtained by performing those simulations with tested policy scenarios for the three selected cities. Results are mainly focused on the effects on the transportation network efficiency and modal shares. Hasselt case behavioural simulation framework is more detailed and comprehensive. At the same time, the implementation of such a framework is time-consuming. Therefore, a light activity-based model was presented that uses simplified data for Bologna and Vantaa. Use of MATSIM in the simulation framework provides flexibility to employ a range of policy scenarios and at the same time, the results are as detailed as possible to obtain the impact of policies on a disaggregate level. The base case scenarios for Hasselt, Bologna and Vantaa are calibrated well enough with the error ranging from 0.15 to 0.3.

Deliverable 4.5 aims to describe and provide results about the effectiveness of behavioral changes related to mobility in contrasting air pollution both in the present as well as in the future scenarios in selected cities. In three cities, the outputs of numerical simulations carried out in the current (baseline) case were verified against air quality concentrations measured at air quality stations in the three cities, providing satisfactory results as indicated by a number of statistical parameters. In addition, the results of numerical simulations carried out in reference base case scenario served to provide insights on the pollution hotspots in the cities. In particular, simulations indicated that while in Bologna the whole city center represents a pollution hotspot, in Hasselt the outer ring road is significantly impacted by high concentrations of air quality pollutants. Furthermore, in this deliverable (D 7.3), earlier sections (sections 5 and 6) reported results obtained by employing methodologies to estimate exposure and health impacts in relation to mortality. It is not required to go into more details as these are already described in several deliverables related to WP 4. We present some key findings in table 14 to summarize these results.

Table 14: Summarized findings of policy scenarios tested using integrated simulation platform.

City	**Policies**	**Transport efficiency related Indicators**	**Air Quality Indicators**	**Health indicators**

		Increase use of PT	Population segments where significant modal share changes are noted	Traffic Volume Conditions	NO_2 Reductions	PM_{10} Reductions	(decrease in PMD)
Hasselt	Car Access Restrictions	👍	Students/Retired persons	👍	★★★	★★	★★
	Increase in Bus Frequency	👎	Students	👎	★	★	--
Bologna	Car Access Restriction with Electric Center	👍	Low income Population/ Students	👍	★★	★	★★★
	Opening Times of Facilities	👎	--	👎	--	--	--
	Increase in Buses (Electric)	--	--	--	★	★	--
Vantaa	Car Access Restrictions	👍	Females/ Students/ Non-Workers	--	★	★	★
	Increase in Bus Frequency	👎	--	--	--	--	--

Table 14 uses symbols to represents various indicators for representing policy efficacy. Number of stars (★) represent magnitude of positive effects. Thumbs up (👍) represents the significant effects in the positive direction and thumbs down (👎) indicate significant effects in the negative direction. Dash (--) represents non-significant effects. Based on this, table 14 indicates that car access restriction policy is more effective in all three cities compared to other tested policies, however, it also points out that this policy raises equity concerns (in relation to the type of people that change their mobility behavior in results of this policy).

8 Recommendations for Mobility-based behavioral interventions

8.1 Informational Interventions

There are a wide variety of lessons learned that could possibly be foreseen as recommendations for mobility-based behavioral interventions. In relation to informational interventions our recommendations (which are quite general and can be applied to the context other than mobility) are as follows:

1) *Significant potential exists that require periodic exploitation*

Results of our algorithms in relation to both interventions indicated the presence of a significant potential that should be exploited. Large scale implementation of similar intervention campaigns should be carried out also include an element of long-term engagement of citizens.

2) *Behavioural change targeted in the intervention is simple and easy to adopt (do not put too much burden)*

In both of our informational interventions, the identified replaceable potential is based on certain rules through which we make sure that we suggest alternatives that are feasible and do not put much burden. Though, overall mobility-behaviour based intervention was not as effective as the route-to-school. This further indicates that along with the easiness it also required that intervention target simple behaviour. Targeting too many behaviours at the same time may not render optimal results.

3) *Use of customized individual coaching approach*

Majority of the participants of the study wanted to know more about their behavior consequences rather than generalized information/awareness about related issues. This was also the significant point raised in co-creation and pilot workshops when interventions were in the development phase. This is also highlighted in interventions related to recycling and energy conservation. It also makes the information more personal which is then taken more seriously.

4) *Target behavioral change brings short and long term benefits*

This should be a vital aspect of any intervention that target behavioral change. As habits and behavior both have positive and negative consequences. It is utmost necessary that intervention should explicitly contain information about both short- and long-term benefits. Individuals, not always but most of the time, think rationally and trade-off benefits possible changes with other aspects (such as related cost/efforts) to make their choices. Detailed information on the associated benefits is helpful for decision making.

5) Intervention is based on the relevant issue (i.e. society in general is concerned with the issue)

This point could be a single most vital factor that causes a significant number of participants to follow the suggested alternative in relation to the route-to-school intervention. Antwerp is the most polluted city in Belgium, and every now and then air quality related news/stories are published in a wide variety of communication mediums (newspapers, TV, social media channels etc.). That situation has created increased awareness about the issue and the vast majority of the population within the city are concerned about it. The intervention is therefore, welcomed and appreciated.

6) Intervention can be more effective if the target audience is specific and more vulnerable

This is also a special characteristics of route-to-school intervention and could helped in its success. The audience we wanted to approach were very clear and also it is also focused more on school going children. Parents/guardian (Adults) are more sensitive to children health compared to themselves. We are not advocating to ignore carrying out campaigns focusing around adults, but the point we wanted to make is that the target audience of such a campaign should be decided with more clarity to make intervention campaign more effective.

8.2 Structural interventions

There is a wide array of structural strategies/interventions that could be tested before any concrete recommendations are made. We tested a limited set of structural interventions and there are many others (as discussed in deliverable 4.2) possible strategies that could also be tested using a methodological tool that integrate several simulation platforms to provide a wide variety of outputs to gauge policy effectiveness on various grounds. Our recommendations, therefore, are more general and they are as follows:

1) **Integrated agent-based simulators provide a profound framework for assessing structural interventions**

Use of Integrated (travel behaviour and air quality models) tools for intervention assessments is limited in this regard owing to associated complexities. With availability of open source platforms (especially MATSIM as used in this study) and rich datasets, it is now possible that such complex model can also be utilized as they offer a wide range of model and outputs, through which policies are assessed in more rigorous manner. Furthermore, it also provides the flexibility to estimate dynamic exposure, which is more appropriate compared to the static exposure.

2) **Structural interventions that are improving mobility may not always bring desirable improvement in air quality and health impacts and vice versa**

We tested limited number of policies in three cities. Simulation experiments made it quite clear that increase in bus frequency on its outlook seems appropriate and could bring benefits in relation to air quality and health impacts, however, transport indicators reflect a negative impact as increase in bus ridership is to an extent resulted from a shift of drivers/passengers from car but it is mostly due to shift of cyclist and walkers towards public transport. A complete model chain is therefore very necessary, that again further supports our first recommendation.

3) **Restricting car traffic intervention is more effective in relation to efficient mobility, air quality and health impacts, however, could raise equity issues.**

This is quite evident from the key findings (table 14), however, it shows the importance of having secured population characteristics to the very end of the model chain. Authorities now a days also focused more on the equity analysis, and in some countries/region it is now part of the policy evaluation framework. Additionally, in relation to this policy, results are of higher magnitude and substantial when such policy is implemented over a larger area. Otherwise, impacts are local, as seen in the case of Vantaa city.

4) **Informational & structural interventions should be coupled for optimal results.**

Given the effectiveness of both type of interventions assessed in this study, it is likely that if both type of interventions are coupled with each other in a real implementation settings for a particular cause, it may render more optimal results. There are no concrete examples of such implementations, however, such a program may be devised and impacts on behavioural change should be assessed.

9 References / Bibliography

Adnan, M. & Passani, A. 2017. Report on Behavioural Interventions. *iSCAPE H2020 EU Project.*

Ahmed, S., Adnan, M., Janssens, D. & Wets, G. 2019. A Route to school Informational Intervention for Air Pollution Exposure Reduction. Sustainable Cities and Society, https://doi.org/10.1016/j.scs.2019.101965

Ahmed, S., Adnan, M., Janssens, D., Brattich, E., Yasar A.-u.-H., Kumar, P., Di Sabatino, S., & Shakshuki, E. M., 2018. Estimating pro-environmental potential for the development of mobility-based informational intervention: a data-driven algorithm. Personal and Ubiquitous Computing, doi:10.1007/s00779-018-1187-5

Beckx, C., Panis, L. I., Arentze, T., Janssens, D., Torfs, R., Broekx, S. & Wets, G. 2009a. A dynamic activity-based population modelling approach to evaluate exposure to air pollution: methods and application to a Dutch urban area. *Environmental Impact Assessment Review,* 29**,** 179-185.

Beckx, C., Panis, L. I., Van De Vel, K., Arentze, T., Lefebvre, W., Janssens, D. & Wets, G. 2009b. The contribution of activity-based transport models to air quality modelling: a validation of the ALBATROSS–AURORA model chain. *Science of the Total Environment,* 407**,** 3814-3822.

Carruthers, D.J., Edmunds, H.A., Lester, A.E., McHugh, C.A., & Singles, R.J., 2000. Use and validation of ADMS-Urban in contrasting urban and industrial locations. International Journal of Environment and Pollution, 14, 363-374

CERC, 2011. ADMS-Urban User Guide. Version 3.1. Cambridge, UK, 324 pp., http://www.cerc.co.uk/environmental-software/assets/data/doc_userguides/CERC_ADMS-Urban4.1.1_User_Guide.pdf. *Accessed 16 Jan 2019*

CERC, 2015. EMIT Atmospheric Emissions Inventory Toolkit User Guide Version 3.4, Cambridge, UK, 390 pp, https://www.cerc.co.uk/environmental-software/assets/data/doc_userguides/CERC_EMIT3.4_User%20Guide.pdf Accessed 17 Jan 2019

Di Sabatino, S., Buccolieri, R., Pulvirenti, B., & Britter, R.E., 2008. Flow and pollutant dispersion in street canyons using FLUENT and ADMS-Urban. Environmental Modeling and Assessment, 13(3),369-381.

Dėdelė, A. & Miškinytė, A., 2015. The statistical evaluation and comparison of ADMS-Urban model for the prediction of nitrogen dioxide with air quality monitoring network. Environmental Monitoring and Assessment 187:578

Dhondt, S., Beckx, C., Degraeuwe, B., Lefebvre, W., Kochan, B., Bellemans, T., Int Panis, L., Macharis, C. & Putman, K. 2012. Health impact assessment of air pollution using a dynamic exposure profile: Implications for exposure and health impact estimates. *Environmental Impact Assessment Review,* 36**,** 42-51.

Dias, D. & Tchepel, O. 2018. Spatial and temporal dynamics in air pollution exposure assessment. *International journal of environmental research and public health,* 15**,** 558.

Eurostat 2019, Mortality and life expectancy statistics, https://ec.europa.eu/eurostat/statistics-explained/index.php/Mortality_and_life_expectancy_statistics

EEA 2018. Assessing the risks to health from air pollution. European Environmental Agency.

Hood, C., MacKenzie, I., Stocker, J., Johnson, K., Carruthers, D., Vieno, M., and Doherty, R., 2018. Air quality simulations using a coupled regional-to-local modelling system. Atmospheric Chemistry and Physics, 18, 11221-11245

Kitamura, R. Applications of models of activity behavior for activity based demand forecasting. Proceedings of Activity-Based Travel Forecasting Conference, 1996.

Katsis, P., Ntziachristios, L., & Mellios, G., 2012. Description of new elements in COPERT 4 v10.0, EMISIA SA Report No.12.RE.012.V1

Kwan, M.-P., Liu, D. & Vogliano, J. 2015. Assessing Dynamic Exposure to Air Pollution. *In:* KWAN, M.-P., RICHARDSON, D., WANG, D. & ZHOU, C. (eds.) *Space-Time Integration in Geography and GIScience: Research Frontiers in the US and China.* Dordrecht: Springer Netherlands.

Lovrić, M., Raveau, S., Adnan, M., Pereira, F. C., Basak, K., Loganathan, H. & Ben-Akiva, M. 2016. Evaluating Off-Peak Pricing Strategies in Public Transportation with an Activity-Based Approach. *Transportation Research Record,* 2544**,** 10-19.

Park, Y. M. & Kwan, M.-P. 2017. Individual exposure estimates may be erroneous when spatiotemporal variability of air pollution and human mobility are ignored. *Health & Place,* 43**,** 85-94.

Shekarrizfard, M., Faghih-Imani, A. & Hatzopoulou, M. 2016. An examination of population exposure to traffic related air pollution: Comparing spatially and temporally resolved estimates against long-term average exposures at the home location. *Environmental Research,* 147**,** 435-444.

Stocker, J., Hood, C., Carruthers, D., & McHugh, C., 2012. ADMS-Urban: developments in modelling dispersion from the city scale to the local scale. International Journal of Environment and Pollution, 50, 308-316.

WHO 2013. Health risks of air pollution in Europe – HRAPIE project. Recommendations for concentration–response functions for cost–benefit analysis of particulate matter, ozone and nitrogen dioxide. World Health Organization.

WHO 2014. Burden of disease from Ambient Air Pollution for 2012: Summary of results. March 2014 ed.: World health Oragnization.

WHO 2016a. Ambient air pollution: A global assessment of exposure and burden of disease. World Health Organization.

WHO 2016b. Health risk assessment of air pollution. General principles. World Health Organization.

Zeng, A., Mao, X., Hu, T., Xing, Y., Gao, Y., Zhou, J., and Qian, Y., 2017. Regional co-control plan for local air pollutants and CO2 reduction: Method and practice. Journal of Cleaner Production, vol 140, Part 3, pp. 1226-1235