# *GreenSTEP: Greenhouse Gas Statewide Transportation Emissions Planning Model*

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## *Abstract*

Global warming is likely one of the most serious and urgent issues facing the U.S. transportation sector. Major reductions in greenhouse gas emissions from the transportation sector will be needed in order to stabilize the climate and avoid the most serious effects of global warming. Travel models can play an important role in evaluating potential policies for reducing transportation sector greenhouse gas emissions. To do so, however, models will need to be expanded to address factors that are relevant to the management of greenhouse gas emissions. The GreenSTEP model was developed to fill this gap at a statewide level. The model combines household level modeling of vehicle types and usage with more aggregate level modeling of factors such as fuel types. The model is being used to assist in the development of a statewide strategy for reducing greenhouse gas emissions from the transportation sector in Oregon.

## *Context*

Global warming is likely one of the most serious and urgent issues facing the U.S. transportation sector. Left unchecked, global warming is likely to dramatically change climatic patterns around the world. People living in the U.S. will experience more frequent and severe heat waves, more prolonged droughts in some areas, and more frequent flooding in other areas (Karl 2009). The problem is urgent because emissions of greenhouse gases have been increasing rapidly in recent decades. To put this in perspective, it has been estimated that the oil consumed between 2000 and 2010 will equal one quarter of all oil that has been consumed (Sperling 2009).

Global warming is a particularly important problem for U.S. transportation professionals to address. The United States, with less than 5% of the world's population, accounts for about 28% of global greenhouse gas emissions (Karl 2009). Emissions from the transportation sector account for about 28 % of U.S. emissions (Cambridge Systematics 2009). Changes in climate due to global warming are forecasted to have a number of adverse consequences for U.S. transportation systems (TRB SR290 2008).

Many policy makers have begun to recognize and act on the urgency of this problem. Several states have adopted targets for reducing greenhouse gas emissions and are developing strategies and actions to achieve the targets. For example, laws passed recently in Oregon direct the Oregon Transportation Commission to develop a statewide strategy for reducing transportation sector greenhouse gas emissions and direct the state's Land Conservation and Development Commission to adopt metropolitan targets for reducing greenhouse gas emissions from light vehicles.

Travel modeling will play an important role in the formulation of policy at state and metropolitan levels. However, current travel models lack the capacity for addressing the range of policies that are likely to be considered for reducing greenhouse gas emissions. For example, models need to estimate the types and ages of vehicles owned in addition to the number of vehicles owned. It is also important that models be able to address factors for which there are incomplete data and a large amount of uncertainty (e.g. electric vehicles).

### ***Previous Work and General Approach***

Several modeling approaches have been used to estimate the effects of various policies and actions on transportation sector greenhouse gas emissions. The *Moving Cooler* study applied factors, derived from the literature, in policy bundles to estimate the effects of different policies on the amount of vehicle travel and greenhouse gas emissions (Cambridge Systematics 2009). Boies et. al. used a “wedges” analysis approach that modeled the effects of vehicle and fuel strategies using the LEAP model (Long-Range Energy Alternatives Planning) and a factoring approach to evaluate the impacts of land use and transportation policies (Boies 2008). Yang et.al. developed the LEVERS (Long-term Evaluation of Vehicle Reduction Strategies) spreadsheet model to evaluate emissions policies using the Kaya identity for evaluating the effects of different transportation and land use policies (Yang 2009).

The Oregon Department of Transportation (ODOT) developed the GreenSTEP (Greenhouse gas State Transportation Emission Planning) model to provide modeling support for the development of a statewide strategy for reducing transportation sector greenhouse gas emissions. The decision was made to develop GreenSTEP after it became apparent that existing models would not be able to address the wide variety of policy actions that would make up a statewide greenhouse gas strategy. GreenSTEP was first envisioned to be an aggregate sketch level planning model using a factoring approach to calculate the joint effects of a variety of policies, much like the models mentioned above. But not long into the development process, the decision was made to model household vehicle ownership and use at a household level. This would be combined with a more aggregate treatment of other factors that do not lend themselves to modeling at a household level. This decision was made in order to make best use of household travel survey data in the development of the model, improve policy sensitivity and interactions, and to reduce the double-counting problem that factoring models have.

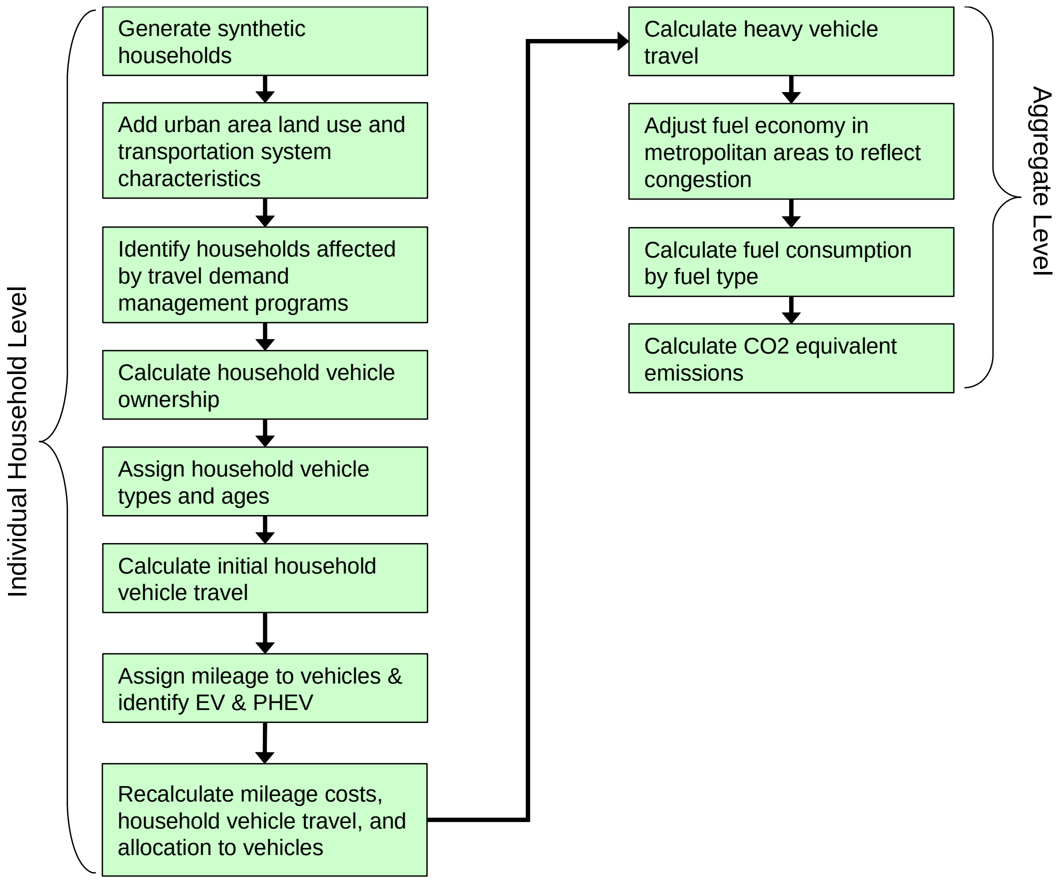
Although GreenSTEP “microsimulates” households and their vehicle and travel characteristics, it does this at a low level of spatial resolution and treats vehicle travel in an aggregate fashion (average daily vehicle miles traveled or DVMT). This is in keeping with the purpose of supporting the development of a statewide greenhouse gas reduction strategy. It is important that the model be kept simple enough so that a very many strategies can be modeled. Complex household level microsimulations like those used in travel activity and land use models would be excessive for the purpose and would limit the number and range of strategies that could be explored.

The 2001 National Household Travel Survey (NHTS) data were used to build most of the household travel and vehicle ownership models. There were several reasons for the decision to use the 2001 NHTS data rather than local data. First, a large share of the NHTS vehicle records are attributed with fuel economy and fuel price data. Second, it is important to use a data set that includes records of conditions that may be very different than what is presently the case in Oregon because some of the future scenarios to be evaluated may pose substantial changes in conditions. Third, the 2001 NHTS datasets are easy to use in model estimation because they are well organized and documented. Finally, local household survey data have become quite dated.

*Model Description*

The GreenSTEP model is composed of a number of modules that are applied in a linear fashion. Figure 1 illustrates the general structure of the GreenSTEP model.

**Figure 1. Design of GreenSTEP Model for Estimating GHG from Passenger and Truck Travel**




GreenSTEP creates a population of synthetic households from county-level population projections by age cohort. Households are composed of persons in each of 6 age categories. A simple income model assigns a household income based on number of people in each age category and the average per capita income for the region where the household is located. These attributes make the model emissions calculations sensitive to long-run demographic and economic changes.

Households are attributed with several relevant land use and transportation characteristics. The first of these is a development type – metropolitan, other urban, or rural – based on scenario input assumptions about the proportions of new development that will locate in each of these areas. Households are also assigned a density for their neighborhood/community of residence based on scenario inputs related to urban growth boundary expansion policies. Whether or not the household is located in a mixed-use "urban" neighborhood is modeled based on population density, but may be overridden based on scenario policy inputs. Finally, metropolitan area households are also assigned public transit, freeway and arterial service levels based on the metropolitan area where they are located and scenario inputs for the growth rates of each service relative to population growth rates.

Next, households are identified as to whether they are participants in a number of demand management programs including car-sharing, pay-as-you-drive (PAYD) insurance, parking pricing, employee commute options, and individualized marketing. Several models are used to identify household participation based on household characteristics and scenario policy inputs regarding participation rates. This model step also identifies households using eco-driving techniques and households equipping their vehicles with low rolling resistance tires.

Once households are provided with each of their socioeconomic, land use, transportation, and demand management attributes, a series of models are applied to calculate household vehicle ownership, vehicle types, and vehicle travel. These models are sensitive to the socioeconomic, land use, transportation systems, and demand management attributes of the households. They are also sensitive to the prices that households face.

The vehicle ownership model determines the number of vehicles owned by the household. It does this in two stages. First, it determines which of the following categories of vehicle ownership each household belongs to: 1) zero vehicles, 2) less than one vehicle per driving age person, 3) one vehicle per driving age person, 4) more than one vehicle per driving age person. These models are sensitive to the number of driving age persons in the household, whether only elderly persons live in the household, the income of the household, the population density and urban mixed-use character of the neighborhood where the household lives, and the freeway and transit system supplies in the metropolitan area where the household lives. The precise number of vehicles owned is established for the $2^{nd}$ and $4^{th}$ categories by random draw from distributions tabulated from the NHTS data. Vehicle ownership is adjusted for households that are identified as car-sharing program participants.

Once the number of vehicles owned by a household has been determined, a binary logit model is applied to determine how many household vehicles are automobiles and how many are light trucks. The latter category includes pickup trucks, sport-utility vehicles and vans. This model is sensitive to household income, the number of vehicles owned by the household, and the population density and urban mixed-use character of the neighborhood where the household resides. The model self-calibrates to a target light truck percentage if one is provided as an input.

Vehicle ages are modeled using joint distributions of vehicle ages by income group developed from the NHTS data and adjusted to reflect the vehicle age distribution in Oregon. An iterated proportional fitting process is used to adjust the joint distribution based on changes to the household income and vehicle age margins. The vehicle age margin may be varied to reflect increased or decreased fleet turnover rates.

The calculation of average household vehicle miles traveled (VMT) is done in two steps. This is necessary because:

- Household VMT is sensitive to the average household cost of travel per mile,
- The average household cost per mile depends on the mix of internal combustion engine vehicles (ICEV) and electric vehicles (EV) in the household and the cost of fuels, and
- The potential for EV use depends on household VMT.

The first step estimates household VMT based on an average household mileage cost calculated from the household vehicle characteristics to this point and average proportions of vehicles that are EVs and plug-in hybrid electric vehicles (PHEV). Later, after EVs and PHEVs have been assigned to households, average mileage costs are recalculated and household VMT is modeled using the recalculated costs.

Average household VMT is estimated using a linear regression model. This model is sensitive to the ratio of vehicles to driving age persons in the household, household income, the average household vehicle travel cost per mile, the density and urban mixed-use character of the neighborhood where the household resides, and the freeway and transit system supplies in the metropolitan area where the household resides. The average household vehicle travel cost per mile includes the fuel cost per mile (a function of fuel price, electricity price, fuel economy, and the proportions of VMT using fuel vs. electricity) and pricing programs that are expressed in terms of average cost per mile. These include PAYD insurance, parking pricing, VMT taxes, and carbon taxes. In addition, the cost per mile for car-sharing households is adjusted to reflect the full cost of travel for the portion of travel using car-share vehicles.

Several challenges had to be met in the development of the household VMT model. One of the most significant of these was that the NHTS, like most household surveys, does not collect average travel data. It collects household travel data for a particular survey day. Household travel on any particular day is likely to deviate substantially from the household average. Kuhnimhof and Gringmuth, using data from the multi-day German Mobility Panel, found that day-to-day variation in personal travel was much greater than the variation in travel between persons (Kuhnimhof 2009).

A simulation approach was taken to meeting this challenge. Models were developed for predicting the probability that a household would have some vehicle travel on any given day and for predicting the VMT if the household engages in travel. The latter model is a regression model which predicts a power transformed VMT value since the distribution of household VMT fits a power distribution. The latter model also includes stochastic procedure to incorporate the unexplained variation into the predictions. These models were then run hundreds of times for each household to generate a likely distribution of daily VMT for each household from which the average daily household VMT could be computed.

One of the advantages of this approach is that it produces a distribution from which other useful summary statistics may be calculated. In particular, the $95^{th}$ percentile and maximum VMT were calculated for use in the electric vehicle (EV) model.

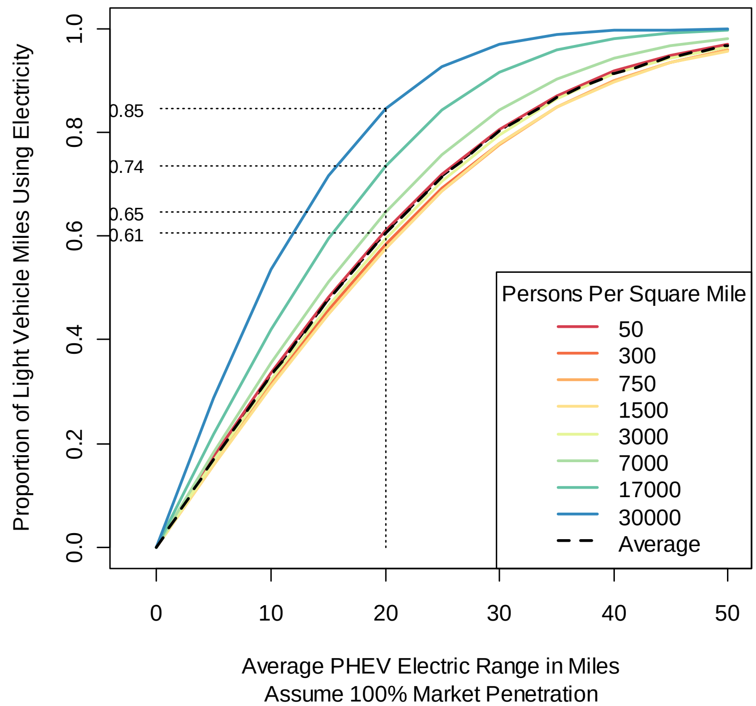
The average, $95^{th}$ percentile and maximum household VMT values are allocated among the household vehicles stochastically using distributions derived from the NHTS household vehicle records which included annual travel estimates based on odometer readings.

The $95^{th}$ percentile and maximum VMT values are used to determine which vehicles are candidates to be EVs. It is assumed that a household would consider an EV to be a viable substitute for an ICEV if the EV has a driving range sufficient to meet 95% of the household's anticipated daily uses of the vehicle, providing that the household has an alternative available for the other 5% of the days. Households without an alternative vehicle would need to meet all of their expected daily travel needs. The EV driving ranges to be modeled will be a function of assumptions made about the characteristics of EVs in the future and the availability of electric charging stations. Whether or not a candidate vehicle is designated an EV also depends on assumptions about the future market share of EVs.

The model also assigns plug-in hybrid electric vehicles (PHEVs). This is done stochastically based on what input assumptions are made about of the market share of PHEVs in future years.

Travel range is not an issue for PHEVs and does not enter into the assignment of these vehicles to households, but it does affect the proportion of household VMT that is powered by electricity. Figure 2 shows that the percentage of VMT powered from the electric grid increases with population density as well as battery range. This shows one of the benefits of a modeling approach over a factoring approach to analyzing transportation sector greenhouse gas emissions. The factoring approach treats the effects of advances in vehicle technology separately from land use and other transportation policies that affect VMT. The modeling approach shows that there important connections between technology and demand management.

**Figure 2. Travel Using Electricity by Average PHEV Range and Population Density**




A final adjustment is made to the distribution of household VMT among vehicles to reflect the potential for some vehicle travel to be diverted to light-weight vehicles. Light-weight vehicles are bicycles, electric bicycles, electric scooters, and similar vehicles that are small, light-weight and can travel at approximately bicycle speeds. This class of vehicles, though currently a minor mode of urban transportation, has the potential for having a significant impact on transportation emissions in the future. An indication of the potential can be seen in the production and use of electric bicycles in China where more than 1,000 manufacturers are estimated to be producing these vehicles and up to 120 million are estimated to be in use (Garrus, 2010). Modeling the potential future effect of light-weight vehicles is problematical because of limited information about this transportation mode. This problem is addressed in GreenSTEP with a model which predicts the proportion of household vehicle travel that is single-occupant vehicle travel occurring in relatively short distance tours. This enables analysis to be done on the potential for diversion of VMT to light vehicles.

Once household mileage has been assigned to different household vehicles, the average travel costs per mile are recalculated. Then the household VMT model is rerun to determine the final VMT result. This is then allocated to vehicles according to the same proportions as the original allocation. This is the final step of the disaggregate portion of the model. To carry out the rest of the GreenSTEP model, household quantities such as VMT are summed by county, development type (metropolitan, other urban, rural) and income group. This level of aggregation supports the data needs of the rest of the model but is still disaggregate enough to permit the calculation of a variety of performance measures including equity measures.

Truck, bus and urban passenger rail VMT are estimated with several simple calculations. Truck VMT is calculated from a growth rate that is based on the rate of statewide income growth. Truck VMT is split among metropolitan areas and non-metropolitan areas based on current year proportional splits of truck VMT on state highways. Bus and urban passenger rail VMT are calculated from scenario inputs for revenue growth. These are adjusted to account for non-revenue service miles.

Adjustments are made to the fuel economy of vehicles to account for the effects of metropolitan area congestion on travel speeds. VMT in each metropolitan area is split between freeways and arterials using a simple linear regression model that is a function of the lane mile ratio of freeways and arterials in the metropolitan area. Then estimates are made of the proportions of VMT experiencing each of five different levels of congestion based on the system-wide ratio of average daily traffic to lane miles. Each congestion level is associated with average trip speeds according to models developed by the Texas Transportation Institute for the Urban Mobility Study. Speeds are estimated with and without consideration of the effects of incidents. This makes it possible to test the effects of different levels of incident management on greenhouse gas emissions. Once metropolitan VMT has been allocated to speed bins, fuel economy is adjusted using response curves compiled by the Federal Highway Administration using the Environmental Protection Agency's MOVES model.

In the final steps of the model, the fuels consumed are allocated to fuel types. Each fuel has an associated carbon dioxide equivalent emissions level. Oregon-specific values are being developed for use in the GreenSTEP model by Oregon's Department of Energy and Department of Environmental Quality. Once the fuels are computed by type it is a straight-forward calculation to calculate greenhouse gas emissions.

***Conclusions***

It is critical for states and metropolitan areas to plan for a low-carbon transportation future. To do this they will need strategic planning models that are very different than the models that are currently being used to develop transportation plans and policies. These models need to be able to address a large number of factors that transportation models currently do not address. The models also need to address the interactions between these factors that are not addressed by spreadsheet and sketch planning models. For example, they will need to address interactions between fuel prices, vehicle fuel economy, and the amount of vehicle travel. Finally these models need to establish the right level of detail and complexity so that they are sensitive to policy issues, interactions and distributional effects, and yet can be set up and run quickly enough to enable the problem space to be effectively searched.

GreenSTEP was developed to meet these needs. It is sensitive to a large number of vehicle, fuels, land use, transportation system, and pricing factors that affect greenhouse gas emissions. It is highly disaggregate, operating at the individual household level, and yet simplifies the modeling of household travel. This enables the model to have a high degree of policy resolution and interactivity and yet be easy to set up and run quickly.

GreenSTEP should be transferable to other locations without too much effort because national datasets were used to estimate most of its components. The code for GreenSTEP and for estimating its components will be made available under an open source license to encourage further applications and development of the model.

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