CAV Energy and Demand Decomposition at the Aggregated National Level

July 05, 2018

A compact and aggregated model of road vehicle travel and energy use is constructed to consider the interactions of multiple relevant identified mechanisms (Wadud et al. 2016, Stephens et al. 2016) by which automation can alter efficiency and activity. Travel demand and vehicle use derives from a standard utility-theoretic specification of driver/traveler behavior. Vehicle efficiency, travel (vehicle-kilometers traveled), average travel speed, congestion, and travel time are endogenous. Following Small and Verhoef (2007) and others, utility derives from travel, aggregate goods consumption, and liesure, subject to individual budget and time constraints.

# 1. Introduction, Main Points, Key Factors

* Potential value of (goals for) compact/aggregate model:
  + determine minimum cost to achieve some level of energy use and level of mobility
    - large simulation models would have to do many simulations
  + simulate effect of changing costs from technological advances through vehicle automation, electrification, and sharing.

#### Important driving factors have an economic dimension

* Demand response to Automation and Shared Mobility
  + consumer behavior model drives demand response
  + particularly, following Small & Verhoef, others, consumer behavior model determines choice of travel VKT, vehicle efficiency, and travel time
  + Utility derives from travel, goods, leisure.
  + Utility maximization subject to joint budget and time constraints
* Endogenous interactions
  + Speed (highway free-flow) endogenous to trade-off energy cost, time and safety costs
  + Congestion – endogenous to vehicle mix, VKT, automation (determines average achieved speed)
  + Travel demand - endogenous to costs, including energy, congestion and safety, as well as travel time utility (VTT)
  + Distinguish between VKT and PKT, given car-sharing and ride-pooling
    - Compact representation of ride pooling choice
* CAV fuel efficiency follows one of three models
  + CAFE is binding
  + AVs achieve same MPG as CAFE average, counting some off-cycle benefits. AVs thus have similar intensity as MVs.
  + Cost effective case
  + AVs may be more efficient than standard, *if* further efficiency reductions are cost-effective from a private perspective
  + Technically feasible case

#### Key Questions (in order of attention paid here)

* How may vehicle fuel intensity/economy change?
  + [technical and behavioral factors]
  + [dependence on infrastructure, and degree of penetration]
* How will travel demand change?
  + See EEMS2017 study of travel demand for different VOTT reports 30-50% increase in energy, mostly from demand, depending on VOTT [ToDo: see what this implies for VKTDemandElas]
  + Travel patterns - details omitted
    - Impact: Trip chaining patterns
    - Impact: detailed drive cycle changes (power use over different segments of trip)
* to what extent can CAVs enable fuel switching or electrification?
* What are the implications of shared-mobility for energy use and VKT?
  + Important to differentiate shared vehicles (aTaxi or *ride-hailing*) and shared rides (*ride-pooling*)
  + Model through occupancy, incremental VKT from re-positioning, and implications to travelers' cost
* How/when will CAVs be adopted?(not addressed)
* What are the special challenges of the transitional period, when a mix of manual, partially automated, and automated vehicles will share the roadways? (not addressed)

#### Contributions of this paper

This paper describes a new aggregated framework, building on established travel demand literature, that account for key features of vehicle automation, and estimates demand and energy use implications. Unlike prior known aggregate work, which relied largely on fixed-coefficient scenario analysis or accounting, it integrates technological and economic factors, including fuel, vehicle and other travel costs, and incorporates energy and travel behavior responses to economic incentives. This work abstracts from much detail offered by microsimulation models, but complements that evolving work, which models detailed travel and energy implications of specific AV technologies using agent/micro/mesosimulation of travel and traffic in real-world spatial and road network models (MATSIM, BEAM, POLARIS, others). Our framework also is novel in the integration of a utility-based behavioral framework with technological detail and private and public costs, emphasizing the role of financial incentives in the form of costs, fees or taxation/subsidy of transport energy or road use. It extends the private utility maximization framework for travel behavior of Small and Parry 2005, Small and Verhauf 2007, and Leiby and Rubin 2017, combining it with the vehicle efficiency and automated vehicle technological details of Wadud et al 2016. It seeks to address the important issue of how to promote the mobility and energy benefits of CAV technologies while deterring potential adverse outcomes (congestion, emissions) which can have large unaccounted social costs.

#### Limitations

* An incomplete consideration of role of AV safety and its endogenous effect on travel costs and travel behavior.
* Includes only an approximate representation of the effects of AV technologies and systems on vehicle energy use for specific drivetrains, roadway network, traffic conditions, and drivecycles, such as can be modeled in more detailed vehicle and spatial models such as Autonomie, FASTSim, BEAM/POLARIS, etc.
* xxx

# 2. Decomposition of Energy and GHG Impacts of CAVs

The energy and GHG emissions of CAV transportation result from the interaction of a wide range of mechanisms, including the impact of vehicle technologies and vehicle design changes that alter vehicle operations and efficiency; system-level changes in infrastructure that alter traffic coordination, speeds, and patterns; and consumer behavioral responses that determine the number, length, and nature of trips demanded. The composition of the effects of many of these mechanisms can be conveniently accounted with a *Kaya Identity*, as used in transportation emissions by (McCollum & Yang, 2009, Greene and Plotkin, 2011) or equivalently the *Schipper ASIF framework* (Schipper et al. 2000, 2011). Mechanistic and scenario-base approaches of this type have been used to explore CAV impacts by Wadud, MacKenzie and Leiby (2016) and by Stephens et al. 2016. While this approch assumes a degree of separability in the impact of certain identified mechanisms on energy use, e.g. weight reduction and aerodynamic load reduction through platooning, this is supported in some cases by more detailed models and experimental data [cite XXX].

From this so-called *ASIF* approach the total GHG emissions are the product of

1. the level of **A**ctivity (e.g., passenger miles of travel),
2. the **S**hare of activity for each mode, vehicle, and fuel type,
3. the energy **I**ntensity of the mode and vehicle type (e.g., energy use per vehicle mile), and
4. the **F**uel carbon intensity (ghg emission mass per unit energy)

Transportation GHG emissions are then the sum over all transportation modes, vehicle types, and fuels of the product of {Transportation Services Activity[[1]](#footnote-27)} x {Shares of each mode-vehicle-fuel type} x {Energy Intensity} x {Fuel GHG Intensity}.

Energy use for particular vehicle type is given by total activity (travel demand) level , the share of travel on mode *m* and the average share-weighted energy intensity of travel by vehicle type and mode.

Vehicle energy intensity *I* is a function of a vector of CAV mechanism/technology levels.

Defining indices

* m = transportation mode
* v = vehicle type
* f = fuel type
* t = time period (year)

for sets[[2]](#footnote-28)

* M = set of transportation modes *m*
* V = set of vehicle types *v*
* F = set of fuel types *f*
* T = set of time periods *t*

The variables are

* = the transportation services Activity provided by type (passenger v.s freight, or LDV/HDV) [passenger-km or tonne-km traveled/yr]
* = occupancy of each vehicle type v in year t [pass/veh, or PKT/VKT, for passenger travel; tonne/veh for freight]
* = share of energy services in transportation mode m by vehicle type v in year t [unitless]
* = the share of energy-service share produced by fuel type f [unitless]
* = the energy intensity of vehicle v in mode m using fuel type f in year t [MJ/veh-km]
* = the GHG intensity of fuel f in year t [g CO2e/MJ (MegaT CO2e/EJ)]
* = energy use in form of fuel f by vehicle type v in year t [MJ/y]
* = GHGs emitted in year t by type v [MT CO2e/y]

Focusing on passenger travel, we can write Energy Use as

with units

Total Emissions are

Combining, overall total emissions per year are

Alternatively, in the form of a vector expression over vehicle types *v*,

for v x 1, v x f and f x 1. And

In the work here, road travel demand is divided into LDV and HDV (passenger and freight), at the minimum, and can be further decomposed into vehicle size classes, and drivetrain classes.

## Mechanisms by Which CAVs Can Alter Energy Use and Emissiona

We identified a set *K* of "Mechanisms" or "Technologies," each of which corresponds to a multiplier that can increase or decrease a component term in the ASIF decomposition. A mechanism can affect activities *A*, intensities *I*, or mode and fuel shares . In theory, a mechanism could also effect vehicle class shares or occupancy, but we do not yet consider such effects.

In the Scenario Approach, we can construct scenarios *s* that combine technology cases and demand cases . Multiplier values are indexed by year *t* (for selected years), vehicle class *v*, mechanism *k* and by the Technology/Demand scenario *s*, i.e. .

# [Aside: how to bold E in equation?](https://tex.stackexchange.com/questions/595/how-can-i-get-bold-math-symbols) \mathbf for bold non-italic \boldsymbol for bold\_italic  
  
SetK\_Mechs = c( # mechanisms by which automation alters energy and/or demand  
 "Platooning",  
 "De\_emphasized\_performance",  
 "Improved\_crash\_avoidance",  
 "Right-sizing",  
 "Eco\_driving",  
 "Congestion\_mitigation",  
 "Increased\_feature",  
 "Higher\_highway\_speeds"  
 # "Vehicle\_sharing", # Q: should Mechanism set include this?  
 # "Ride\_pooling", # Q: should Mechanism set include this?  
)  
  
SetV\_Class = c("LDV", "HDV") # Vehicle Classes  
SetT\_Years = c(2035, 2050)  
SetJ\_TechScen = 1:8  
SetD\_DmndScen = 1:7  
SetS\_Sense = c(  
 "Opt",  
 "Mid",  
 "Pess",  
 "Zero"  
)

The set of mechanisms *k* represented include Platooning, De\_emphasized\_performance, Improved\_crash\_avoidance, Right-sizing, Eco\_driving, Congestion\_mitigation, Increased\_feature, Higher\_highway\_speeds. We consider vehicle classes *v* in LDV, HDV. The model is explored over time for years *t* from 2035 to 2050.

# 3. Estimating Energy Impacts

Define the effects of automation on vehicle energy intensity through a set of identified technological and operational "mechanisms."

The estimation for the midcase energy intensity impacts of each mechanism is based on literature review[[3]](#footnote-31) and the external calculations of the authors. Ranges of values, for sensitivity cases and scenarios, are constructed for each mechanism *k*, for sensitivity cases *s* from "zero" through "pessimistic," "midcase," and "optimistic." Mechanism intensity effect values are differentiated by year *t* and Vehicle class *v*.

# Mechanism Effects on Intensity can be Optimistic, Midpoint, Pessimistic, or Zero (percent changes)  
# Effect is percentage reduction in Energy Intensity  
# VC.Year.Mechanism  
# v\_VClass t\_Year k\_Mech  
IEffects<-read.delim(textConnection("  
VC Year Mech Opt Mid Pess  
LDV 2035 Platooning -24.8 -14.25 -3.7  
LDV 2035 De\_emphasized\_performance -23.0 -14.0 -5.0  
LDV 2035 Improved\_crash\_avoidance -22.9 -14.2 -5.5  
LDV 2035 Eco\_driving -20.0 -12.5 -5.0  
LDV 2035 Congestion\_mitigation -3.4 -1.7 0.0  
LDV 2035 Right\_sizing -45.0 -33.0 -21.0  
LDV 2035 Higher\_highway\_speeds 7.0 14.5 22.0  
LDV 2035 Increased\_feature\_content 0.0 5.0 10.0  
LDV 2050 Platooning -24.8 -14.4 -4.0  
LDV 2050 De\_emphasized\_performance -23.0 -14.0 -5.0  
LDV 2050 Improved\_crash\_avoidance -22.9 -14.2 -5.5  
LDV 2050 Eco\_driving -20.0 -12.5 -5.0  
LDV 2050 Congestion\_mitigation -4.2 -2.1 0.0  
LDV 2050 Right\_sizing -45.0 -33.0 -21.0   
LDV 2050 Higher\_highway\_speeds 7.0 14.5 22.0  
LDV 2050 Increased\_feature\_content 0.0 5.0 10.0  
HDV 2035 Platooning -25.0 -17.5 -10.0  
HDV 2035 De\_emphasized\_performance 0.0 0.0 0.0  
HDV 2035 Improved\_crash\_avoidance 0.0 0.0 0.0  
HDV 2035 Eco\_driving 0.0 0.0 0.0  
HDV 2035 Congestion\_mitigation -3.4 -1.7 0.0  
HDV 2035 Right\_sizing 0.0 0.0 0.0  
HDV 2035 Higher\_highway\_speeds 0.0 0.0 0.0  
HDV 2035 Increased\_feature\_content 0.0 0.0 0.0  
HDV 2050 Platooning -25.0 -17.5 -10.0  
HDV 2050 De\_emphasized\_performance 0.0 0.0 0.0  
HDV 2050 Improved\_crash\_avoidance 0.0 0.0 0.0  
HDV 2050 Eco\_driving 0.0 0.0 0.0  
HDV 2050 Congestion\_mitigation -4.2 -2.1 0.0  
HDV 2050 Right\_sizing 0.0 0.0 0.0  
HDV 2050 Higher\_highway\_speeds 0.0 0.0 0.0  
HDV 2050 Increased\_feature\_content 0.0 0.0 0.0  
"),header=TRUE,sep="",strip.white=TRUE) #;  
# Default delimiter is white space. If there is a header and the first row contains one fewer field than the number of columns,  
# the first column in the input is used for the row names. Otherwise if row.names is missing, the rows are numbered  
# Source: "='[CAV Energy ASIF Framework WadudMacKenzieLeiby V20161024.xlsx]Energy Intensity Impacts'!$A$1:$M$26"  
# Note: Mid is average of Opt and Pess  
  
IEffects$Zero = 0.0 # include additional case of no-impact for each mechanism

#### Construct multiplicative factors to apply to energy intensities for each mechanism

Multipliers apply for each year *t*, vehicle class *v*, mechanism/technology *k*, sensitivity case *s*.

A multiplier value of 1.0 indicates no change and less than one implies a multiplicative reduction in energy intensity.

# Get (compound) case name and split into separate variables for each part  
  
#IEffects$EffectCase = row.names(IEffects)  
#IEffects = separate(data=IEffects, col=EffectCase, into=c("VC","Year", "Mech"), sep="\\.")  
  
# From percent-change to fractional-change, then to multiplier  
IEffectsm = IEffects %>% gather(key=EffectCase, value="IE", Opt:Zero) %>%  
 mutate(IE = IE/100.0) %>%  
 mutate(IM = 1+IE) # These Intensity Multipliers are the "mu" factors

## Warning: package 'bindrcpp' was built under R version 3.3.2

# IM = dataframe(TechScen, DmndScen, Mech, Year, VC) # intensity multiplying factors  
  
IM = IEffectsm %>% select(-IE) %>%  
 spread(key = EffectCase, value = IM)  
 # arrange(order(match(Mech, IEffects$Mech)))  
# sort columns same way as original data frame  
IM = IM[,c(colnames(IEffects))]  
  
kable(x = IM,   
 caption= "Intensity Multipliers by Vehicle-type, Year, and Case")

Intensity Multipliers by Vehicle-type, Year, and Case

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| VC | Year | Mech | Opt | Mid | Pess | Zero |
| HDV | 2035 | Congestion\_mitigation | 0.966 | 0.9830 | 1.000 | 1 |
| HDV | 2035 | De\_emphasized\_performance | 1.000 | 1.0000 | 1.000 | 1 |
| HDV | 2035 | Eco\_driving | 1.000 | 1.0000 | 1.000 | 1 |
| HDV | 2035 | Higher\_highway\_speeds | 1.000 | 1.0000 | 1.000 | 1 |
| HDV | 2035 | Improved\_crash\_avoidance | 1.000 | 1.0000 | 1.000 | 1 |
| HDV | 2035 | Increased\_feature\_content | 1.000 | 1.0000 | 1.000 | 1 |
| HDV | 2035 | Platooning | 0.750 | 0.8250 | 0.900 | 1 |
| HDV | 2035 | Right\_sizing | 1.000 | 1.0000 | 1.000 | 1 |
| HDV | 2050 | Congestion\_mitigation | 0.958 | 0.9790 | 1.000 | 1 |
| HDV | 2050 | De\_emphasized\_performance | 1.000 | 1.0000 | 1.000 | 1 |
| HDV | 2050 | Eco\_driving | 1.000 | 1.0000 | 1.000 | 1 |
| HDV | 2050 | Higher\_highway\_speeds | 1.000 | 1.0000 | 1.000 | 1 |
| HDV | 2050 | Improved\_crash\_avoidance | 1.000 | 1.0000 | 1.000 | 1 |
| HDV | 2050 | Increased\_feature\_content | 1.000 | 1.0000 | 1.000 | 1 |
| HDV | 2050 | Platooning | 0.750 | 0.8250 | 0.900 | 1 |
| HDV | 2050 | Right\_sizing | 1.000 | 1.0000 | 1.000 | 1 |
| LDV | 2035 | Congestion\_mitigation | 0.966 | 0.9830 | 1.000 | 1 |
| LDV | 2035 | De\_emphasized\_performance | 0.770 | 0.8600 | 0.950 | 1 |
| LDV | 2035 | Eco\_driving | 0.800 | 0.8750 | 0.950 | 1 |
| LDV | 2035 | Higher\_highway\_speeds | 1.070 | 1.1450 | 1.220 | 1 |
| LDV | 2035 | Improved\_crash\_avoidance | 0.771 | 0.8580 | 0.945 | 1 |
| LDV | 2035 | Increased\_feature\_content | 1.000 | 1.0500 | 1.100 | 1 |
| LDV | 2035 | Platooning | 0.752 | 0.8575 | 0.963 | 1 |
| LDV | 2035 | Right\_sizing | 0.550 | 0.6700 | 0.790 | 1 |
| LDV | 2050 | Congestion\_mitigation | 0.958 | 0.9790 | 1.000 | 1 |
| LDV | 2050 | De\_emphasized\_performance | 0.770 | 0.8600 | 0.950 | 1 |
| LDV | 2050 | Eco\_driving | 0.800 | 0.8750 | 0.950 | 1 |
| LDV | 2050 | Higher\_highway\_speeds | 1.070 | 1.1450 | 1.220 | 1 |
| LDV | 2050 | Improved\_crash\_avoidance | 0.771 | 0.8580 | 0.945 | 1 |
| LDV | 2050 | Increased\_feature\_content | 1.000 | 1.0500 | 1.100 | 1 |
| LDV | 2050 | Platooning | 0.752 | 0.8560 | 0.960 | 1 |
| LDV | 2050 | Right\_sizing | 0.550 | 0.6700 | 0.790 | 1 |

* Note "Right\_sizing" and "Increased\_features" apply only to LDV passenger travel.

## 3.2 Energy Intensity by Vehicle Type and Technology Scenario

We construct Scenario Multipliers for energy intensity, for Scenario *j*, Year *t*, Vehicle class *v* as a combination of the effect of all the mechanisms.

For each technology scenario *j*, year *t*, vehicle class *v* and mechanism *k*, the "EffectCase" or sensitivity *s* is specified, i.e.

for .

This determines the appropriate intensity multiplier for each mechanism, and the total energy intensity multiplier for each scenario is the product a all mechanism multipliers

# Load the descriptions of the scenarios  
mechScenAssumps = read\_csv(paste0("./Data/","CAV\_Scenario\_Master.csv"), comment = "#")  
# This table contains: scenario number and demand scenario number;  
# resulting multipliers for LDV and HDV in 2 years;  
# scenario name and description; and setting levels (Zero, Low, Mid, High) for each mechanism   
  
msa = mechScenAssumps %>%   
 select(-c(LDV\_Multipliers.2035:Scenario\_Description)) %>% # drop aggregatred result for scenario and Name, Description  
 gather(key=VehMechYear, value = EffectCase, LDV.Platooning.2035:HDV.Higher\_highway\_speeds.2050)  
msa = separate(msa, VehMechYear, c("VC", "Mech", "Year"), sep="\\.")  
msa$Year = as.integer(msa$Year)  
# As in ='[CAV Energy ASIF Framework WadudMacKenzieLeiby V20161024.xlsx]Policy+Scenario'!$A$11  
# As in '[CAV Energy ASIF Framework WadudMacKenzieLeiby V20161024.xlsx]Scenario Master'!$A$3:$F$11  
  
# Match Energy Intensity Impacts for each mechanism in the scenario to the   
# Scenario Assumptions for that mechanism:   
# IEffectsm$IM is the intensity multiplier for each VC, Year, Mech (mech) and EffectCase  
# msa$EffectCase is one of (Zero, Opt, Mid, Pess) for each VC, Year, Mech  
# IEffectsm has 128 = 2 x 2 x 8 x 4, while msa has 224 rows  
# merge, keeping matching rows from second, bringing in IE and IM for each Mech  
msa = left\_join(msa, IEffectsm, by = c("VC", "Year", "Mech", "EffectCase")) %>%   
 select(-c(Demand\_Scenario, IE)) # drop fractional reductions, keep multipliers  
  
# Overall energy intensity for the scenario is the product of mechanism multipliers  
EnergyIntensityChanges = msa %>%  
 group\_by(Year, VC, Scenario\_Number) %>%  
 summarize(NIE = prod(IM)-1) # product of multipliers across all Mech(anisms)  
# minus 1 for net change  
  
# Mechanism Impacts by Mechanism, EffectCase-level, Year (2035, 2050), and vehicle type (LDV, HDV) are in ='[CAV Energy ASIF Framework WadudMacKenzieLeiby V20161024Test20170709.xlsx]Energy Intensity Impacts'!$A$1:$Q$26  
EnergyIntensityChanges = arrange(EnergyIntensityChanges, Scenario\_Number, VC, Year)  
  
# Confirm: Following matches table "Net Energy Intensity Change by Scenario"  
# in workbook "='[CAV Energy ASIF Framework WadudMacKenzieLeiby V20161024Test20170809.xlsx]Scenario Master'!$A$1:$F$11"  
# Note: small diff in results for LDV 2035 Scenario 2 only in spreadsheet V20161024.  
# This is due to a transcription error in the older workbook for  
# LDV 2035 Congestion\_mitigation (intensity mult should be 1-3.4%)  
# in Cell "='[CAV Energy ASIF Framework WadudMacKenzieLeiby V20161024Test20170809.xlsx]Scenario Master'!$S$5"  
# Should refer to 2035 value at ='Energy Intensity Impacts'!$F$9, not 2050 value $N$9   
NetEnergyIntensityChangeTable = EnergyIntensityChanges %>%   
 unite(col=VC\_Year, VC, Year, sep="\_") %>%  
 spread(key=VC\_Year, value = NIE)  
  
# This table should match NetEnergyIntensityChangeTable  
NEIC\_test = mechScenAssumps %>%   
 select(c(Scenario\_Number:Scenario\_Name)) %>%  
 select(-c(Demand\_Scenario,Scenario\_Name))  
names(NEIC\_test) = sub("\_Multipliers.", replacement="\_", names(NEIC\_test))  
NEIC\_test = NEIC\_test[,names(NetEnergyIntensityChangeTable)] # make column orders match  
  
kable(x = NetEnergyIntensityChangeTable,   
 caption= "Net Energy Intensity Change by Scenario, Vehicle-type, and Year")

Net Energy Intensity Change by Scenario, Vehicle-type, and Year

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Scenario\_Number | HDV\_2035 | HDV\_2050 | LDV\_2035 | LDV\_2050 |
| 1 | -0.189025 | -0.192325 | -0.3228782 | -0.3268132 |
| 2 | -0.275500 | -0.281500 | -0.7674212 | -0.7693473 |
| 3 | 0.000000 | 0.000000 | 0.3420000 | 0.3420000 |
| 4 | -0.275500 | -0.281500 | -0.7162538 | -0.7186037 |
| 5 | -0.100000 | -0.100000 | 0.1026350 | 0.0992000 |
| 6 | 0.000000 | 0.000000 | 0.0000000 | 0.0000000 |
| 7 | -0.175000 | -0.175000 | -0.1853750 | -0.1868000 |

NEIC\_test\_err = sum(abs(NEIC\_test - NetEnergyIntensityChangeTable))  
  
# cat("Constructed Net Energy Intensity Changes match old workbook to within",  
# NEIC\_test\_err, "total absolute error.\n")

Note: Constructed Net Energy Intensity Changes match old workbook to within 1.287430810^{-9} total error.

# 4. Demand Response to CAVs

## 4.1 Key parameters for Demand scenarios

# listing of Demand-related Paramters and notes  
DemRespParamNotes <- read.delim(textConnection("  
DemParam : DemParamNote  
ElasVKT : Elas of travel w.r.t generalized cost,  
InsurCostRed : Reduction in insurance premiums (fraction) (superceded by DemScenCostReduction)  
ExclWearCost : Exclude Wear & Ownership Costs (Choose 0 or 1),  
C\_incrCAV : Incr vehicle capital cost fraction from automation (wear and ownership cost/mi),  
ShrECostInt : Share of energy effic cost gains internalized (visible) to driver (fraction, 0 to 1),  
I\_deltaCAV : Fuel energy cost reduction (from effic, fraction)  
"),header=TRUE,sep=":",strip.white=TRUE)  
  
DemRespParams<-read.delim(textConnection("  
 Low Med High  
LDV.ElasVKT -1 -1 -1  
LDV.InsurCostRed 0.6 0.7 0.8  
LDV.ExclWearCost 0 0 0  
LDV.C\_incrCAV 0 0 0  
LDV.ShrECostInt 1 1 1  
LDV.I\_deltaCAV -.7186 -.7186 -.7186  
HDV.ElasVKT -0.97 -0.97 -2  
HDV.InsurCostRed 0.4 0.6 0.8  
HDV.ExclWearCost 0 0 0  
HDV.C\_incrCAV 0 0 0   
HDV.ShrECostInt 1 1 1  
HDV.I\_deltaCAV -.2815 -.2815 -.2815  
"),header=TRUE,sep="",strip.white=TRUE) #;  
# Corresponds to data in "Demand Response Key parameters", but omits HDV low of 0.5 (unused)  
# ='[CAV Energy ASIF Framework WadudMacKenzieLeiby V20161024.xlsx]calcul Dem\_HDV'!$A$4:$L$10 and 'calcul Dem\_LDV'!$A$4:$L$10  
  
# Notes:  
# Source "Energy Intensity Impacts" sheet  
# Generalized cost includes: fuel+maintenance+accident+tolls+TRAVELtime  
# Fuel energy cost reduction: Import from 'Policy+Scenario' subsheet calculation for currently chosen technology scenario   
# LDV ElasVKT (HERS-ST technical report, August 2005 + Graham n Glaister 2002).  
# LDV InsurCostRed Reduction in insurance premiums . internet/celent report (superceded by Demand Scenario-dependent values)  
# LDV C\_incrCAV Wadud 2017  
# HDV ElasVKT Cambridge Sytematics, 2009  
  
DemRespParams$Zero = 0.0 # establish zero effect case (zero reductions, zero elas)  
DemRespParams["LDV.ShrECostInt", "Zero"] = 1.0 # kludge to fix this parameter to non-zero val  
DemRespParams["HDV.ShrECostInt", "Zero"] = 1.0  
  
DemRespParams$case = row.names(DemRespParams)  
DemRespParams = separate(data=DemRespParams, col=case, into=c("VC","Parameter"), sep="\\.")  
DemRespParamsm = DemRespParams %>% gather(key=EffectCase, value="value", Low:Zero)

(Note: Need to be clear which version of certain parameters dominate in subsequent application, e.g. from "DemScenCostReduction" vs "DemandResponseKeyParameters" tables. The "Low, Med High" cases in DemandResponseKeyParameters table are separate from the Demand Scenario cases in DemScenCostReduction table.

DemandResponseKeyParameters <- read.delim(textConnection("  
Name :Description :Low :Med :High :Note  
VMTElas :Elasticity of travel w.r.t. generalized cost :-1 :-1 :-1 :(fuel+maintenance+accident+tolls+ TRAVEL time) (HERS-ST technical report, August 2005 + Graham n Glaister 2002)  
InsReduc :Reduction in insurance premiums :0.6 :0.7 :0.8 :internet/celent report (Unused, scenario-dependent)  
ExclWearCost:Exclude Wear and Ownership Costs (1 True, 0 False) :0 :0 :0 :Choose 0 or 1 value  
C\_incrCAV :Incremental veh capital cost from automation :0 :0 :0 :Fractional (wear and ownership cost/mi)   
ShrECostInt :Share of energy efficiency costs 'visible' to driver :1 :1 :1 :0 to 1 (1 means full efficiency gain visible) (driver=person making trip choices) ???  
I\_deltaCAV :Fuel energy cost reduction (from energy efficiency) :0.3420 :0.3420 :0.3420 :Import from 'Policy+Scenario' subsheet calculation for currently chosen technology scenario  
"),header=TRUE,sep=":",strip.white=TRUE) #  
# Corresponds to "='[CAV Energy ASIF Framework WadudMacKenzieLeiby V20161024Test20180325r1.xlsx]calcul Dem\_LDV'!$A$4:$L$10" see also "calcul Dem\_HDV'!$A$4:$L$10"  
# Note: duplicative: DemandRepsonseKeyParameters duplicates DemRespParams for LDV, but adds "Fuel Energy cost reduction"  
rownames(DemandResponseKeyParameters) = DemandResponseKeyParameters$Name  
  
kable(x = select(DemandResponseKeyParameters, -Note), row.names = F,  
 caption= "Key Parameters for LDV Demand Response (for all Demand Scenarios")

Key Parameters for LDV Demand Response (for all Demand Scenarios

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Name | Description | Low | Med | High |
| VMTElas | Elasticity of travel w.r.t. generalized cost | -1.000 | -1.000 | -1.000 |
| InsReduc | Reduction in insurance premiums | 0.600 | 0.700 | 0.800 |
| ExclWearCost | Exclude Wear and Ownership Costs (1 True, 0 False) | 0.000 | 0.000 | 0.000 |
| C\_incrCAV | Incremental veh capital cost from automation | 0.000 | 0.000 | 0.000 |
| ShrECostInt | Share of energy efficiency costs 'visible' to driver | 1.000 | 1.000 | 1.000 |
| I\_deltaCAV | Fuel energy cost reduction (from energy efficiency) | 0.342 | 0.342 | 0.342 |

### Select a Single Scenario to Examine

CurrTechScen = 4  
CurrYear = 2050  
  
CurrDemScen = 1

For example consider Scenario 4, the "Strong responses" scenario, in year 2050.

Energy Intensity change is dependent on the Technology Scenario. Update demand response parameters with energy intensity reduction (by vehicle class and year) for this Technology Scenario,

nie = EnergyIntensityChanges %>% ungroup() %>%   
 filter(Scenario\_Number == CurrTechScen, Year == CurrYear) %>%   
 select(VC, NIE)  
  
# This assignment is awkward.  
#DemRespParams$NIE = EnergyIntensityChange$NIE # for matching VC, and Parameter=='I\_deltaCAV'  
DemRespParams %>% gather(key = Sens, value = value, Low:Zero) %>% # following assigns the same   
 mutate(value = ifelse((VC=="LDV" & Parameter=="I\_deltaCAV"), nie[nie$VC=="LDV",]$NIE, value),  
 value = ifelse((VC=="HDV" & Parameter=="I\_deltaCAV"), nie[nie$VC=="HDV",]$NIE, value)) %>%  
 spread(key=Sens, value=value) ->  
 DemRespParams  
DemRespParams = DemRespParams[,c( "VC","Parameter", "Zero", "Low", "Med", "High")] # reorder columns  
  
kable(x = DemRespParams, digits = 4,  
 caption= "DemRespParams: Important Parameters for the Calculation of Demand Reponse, by Vehicle-type, and Year")

DemRespParams: Important Parameters for the Calculation of Demand Reponse, by Vehicle-type, and Year

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| VC | Parameter | Zero | Low | Med | High |
| HDV | C\_incrCAV | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| HDV | ElasVKT | 0.0000 | -0.9700 | -0.9700 | -2.0000 |
| HDV | ExclWearCost | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| HDV | I\_deltaCAV | -0.2815 | -0.2815 | -0.2815 | -0.2815 |
| HDV | InsurCostRed | 0.0000 | 0.4000 | 0.6000 | 0.8000 |
| HDV | ShrECostInt | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| LDV | C\_incrCAV | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| LDV | ElasVKT | 0.0000 | -1.0000 | -1.0000 | -1.0000 |
| LDV | ExclWearCost | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| LDV | I\_deltaCAV | -0.7186 | -0.7186 | -0.7186 | -0.7186 |
| LDV | InsurCostRed | 0.0000 | 0.6000 | 0.7000 | 0.8000 |
| LDV | ShrECostInt | 1.0000 | 1.0000 | 1.0000 | 1.0000 |

## 4.2 Establish Base Travel Costs for Each Cost Component

### Simple Base Travel Time Cost Calculation

# Following calculation yields LDV Time cost per mile  
TravTimeCostBasePars <- read.delim(textConnection("  
var : V\_Class :local :intercity :average :Units :Source\_Notes  
VoTT : LDV :12.5 :18 :13.7986015 :$/hr :DoT; others=local; interstate urb+rur = intercity; average is VMT-weighted ave of local & intercity  
VMTtot : LDV :1560941 :482468 :2043409 :mi/yr :Highway Stat   
average\_speed : LDV : : :27.6 :mi/hr :EPA  
average\_TTC\_per\_mi : LDV : : :0.49994933 :$/mi :=VoT/AveSpeed  
VoTT : HDV : : :24.42778 :$/hr : vs Cambridge Systematics 2009 $30 ave  
VMTtot : HDV : : : :mi/yr :Highway Stat   
average\_speed : HDV : : :39.98 :mi/hr :ATRI 2012 'average industry operational speed'  
average\_TTC\_per\_mi : HDV :0.611 :0.611 :0.611 :$/mi :2011 Driver wages & Benefits, atri-online.org/2012/09/17/an-analysis-of-the-operational-costs-of-trucking-a-2012-update/"  
),  
header=TRUE,sep=":",strip.white=TRUE) #  
# as in "='[CAV Energy ASIF Framework WadudMacKenzieLeiby V20161024Test20180325r1.xlsx]calcul Dem\_LDV'!$A$35:$E$43"  
  
TravTimeCostBasePars %>% select(-Source\_Notes) %>%  
 kable(caption= "Travel Time Cost Base Parameters", digits=3)

Travel Time Cost Base Parameters

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| var | V\_Class | local | intercity | average | Units |
| VoTT | LDV | 12.500 | 18.000 | 13.799 | $/hr |
| VMTtot | LDV | 1560941.000 | 482468.000 | 2043409.000 | mi/yr |
| average\_speed | LDV | NA | NA | 27.600 | mi/hr |
| average\_TTC\_per\_mi | LDV | NA | NA | 0.500 | $/mi |
| VoTT | HDV | NA | NA | 24.428 | $/hr |
| VMTtot | HDV | NA | NA | NA | mi/yr |
| average\_speed | HDV | NA | NA | 39.980 | mi/hr |
| average\_TTC\_per\_mi | HDV | 0.611 | 0.611 | 0.611 | $/mi |

# str(TravTimeCostBasePars)  
row.names(TravTimeCostBasePars) = paste(TravTimeCostBasePars$var,TravTimeCostBasePars$V\_Class, sep=".")  
  
# Test computed vs. specified values in table  
cat("VoTT for LDV average value matches VMT-weighted average to within",  
 TravTimeCostBasePars["VoTT.LDV","average"] -   
 (TravTimeCostBasePars["VMTtot.LDV","local"]\* TravTimeCostBasePars["VoTT.LDV","local"] +  
 TravTimeCostBasePars["VMTtot.LDV","intercity"]\*TravTimeCostBasePars["VoTT.LDV","intercity"])/  
 (TravTimeCostBasePars["VMTtot.LDV","local"] + TravTimeCostBasePars["VMTtot.LDV","intercity"]),  
 "$/hr.\n")

## VoTT for LDV average value matches VMT-weighted average to within -3.663731e-09 $/hr.

cat("Average TTC per mile for LDV average value matches VoTT/speed to within",  
 TravTimeCostBasePars["average\_TTC\_per\_mi.LDV","average"] - # [$/hr]/[mi/hr]  
 TravTimeCostBasePars["VoTT.LDV","average"]/TravTimeCostBasePars["average\_speed.LDV","average"],  
 "$/mi.\n")

## Average TTC per mile for LDV average value matches VoTT/speed to within 2.898551e-10 $/mi.

cat("Average TTC per mile for HDV average value matches VoTT/speed to within",  
 TravTimeCostBasePars["average\_TTC\_per\_mi.HDV","average"] - # [$/hr]/[mi/hr]  
 TravTimeCostBasePars["VoTT.HDV","average"]/TravTimeCostBasePars["average\_speed.HDV","average"],  
 "$/mi.\n")

## Average TTC per mile for HDV average value matches VoTT/speed to within 0 $/mi.

### Base Vehicle Travel Cost Components

Specify the primary (private) cost components for base case (conventional, manual) road vehicle travel.

VehTravelCostCompons <- read.delim(textConnection("  
CostCat :LDVAlt :LDVAvgSedan :LDVAvgLtTruck :HDVOther :HDVClass8 :Units :Note  
MilesDriven :NA :11850 :11000 :NA :99000 :[mi/yr] :Base (MV) EDB-31 for LDVs, ATRI-2012 for HDVs  
Fuel :6.1 :14.59 :19.63 :NA :59.0 :[c/mi] :LDV changed for TEDB mpg  
Maintenance :5.3 :5.47 :6.15 :NA :19.4 :[c/mi] :Incl tires  
AccAndIns :7.0 :8.447257384 :8.490909091 :NA :6.7 :[c/mi] :Insurance will change for CAVs  
WearAndOwn :12 7 :29.907173 :43.49090909 :NA :18.9 :[c/mi] :Ownership, Wear & tear (depreciation)  
TollsFees :0.9 :0.0 :0.0 :NA :5.5 :[c/mi] :  
Parking :1.3 :2.109704641 :2.272727273 :NA :0.0 :[c/mi] :  
Time :34.4 :49.99493298 :49.99493298 :NA :61.1 :[c/mi] :VOTT will change for CAVs. For HDVs=Driver wages & benefits  
Registration : :5.147679325 :7.218181818 :NA :0.0 :[c/mi] :  
Total :67.7 :115.6667473 :137.2476603 :NA :170.6 :[c/mi] :  
Source :HERS-ST/2005 :AAA/2012 :AAA/2012 :ATRI/2012 :ATRI/2012 :NA :  
"),header=TRUE,sep=":",strip.white=TRUE) #  
# Operating cost components from   
# "='[CAV Energy ASIF Framework WadudMacKenzieLeiby V20161024Test20180325r1.xlsx]calcul Dem\_LDV'!$A$13:$D$27" and "calcul Dem\_HDV'!$A$13:$D$28"  
  
kable(x = select(VehTravelCostCompons, -c(LDVAlt, HDVOther, Note)),   
 caption= "Vehicle Travel Cost Components by Vehicle Type")

Vehicle Travel Cost Components by Vehicle Type

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| CostCat | LDVAvgSedan | LDVAvgLtTruck | HDVClass8 | Units |
| MilesDriven | 11850 | 11000 | 99000 | [mi/yr] |
| Fuel | 14.59 | 19.63 | 59.0 | [c/mi] |
| Maintenance | 5.47 | 6.15 | 19.4 | [c/mi] |
| AccAndIns | 8.447257384 | 8.490909091 | 6.7 | [c/mi] |
| WearAndOwn | 29.907173 | 43.49090909 | 18.9 | [c/mi] |
| TollsFees | 0.0 | 0.0 | 5.5 | [c/mi] |
| Parking | 2.109704641 | 2.272727273 | 0.0 | [c/mi] |
| Time | 49.99493298 | 49.99493298 | 61.1 | [c/mi] |
| Registration | 5.147679325 | 7.218181818 | 0.0 | [c/mi] |
| Total | 115.6667473 | 137.2476603 | 170.6 | [c/mi] |
| Source | AAA/2012 | AAA/2012 | ATRI/2012 | NA |

# transform dropping notes and assuring all values are numeric  
VTCostBase = select(VehTravelCostCompons, -c(LDVAlt, HDVOther, Units, Note)) %>%  
 filter(!CostCat %in% c("MilesDriven", "Total", "Source")) %>%  
 gather(key = VehType, value = VTCost\_cpm, -CostCat) %>%  
 mutate(VTCost\_cpm = as.numeric(VTCost\_cpm)) # all costs in cents/mi

## Warning: attributes are not identical across measure variables;  
## they will be dropped

# Check that input tables are consistent with regard to time cost per mile,  
# for 2 LDV categories and one HDV categopry  
ChkErrorDiff =  
 VTCostBase %>% filter(CostCat=="Time") %>% select(VTCost\_cpm)/100 -  
 c(TravTimeCostBasePars["average\_TTC\_per\_mi.LDV","average"],   
 TravTimeCostBasePars["average\_TTC\_per\_mi.LDV","average"],  
 TravTimeCostBasePars["average\_TTC\_per\_mi.HDV","average"])  
cat("Check: Input VTCostBase Time cost for LDVs and HDV matches Average TTC per mile to within", paste(ChkErrorDiff),  
 "cents/mi.\n")

## Check: Input VTCostBase Time cost for LDVs and HDV matches Average TTC per mile to within c(-2.00000016548074e-10, -2.00000016548074e-10, 0) cents/mi.

# Update Time cost in the Vehicle Travel Cost matrix for MVs (base), according to current Base Assumption set  
VTCostBase = VTCostBase %>%   
 mutate(VTCost\_cpm = ifelse((CostCat=="Time" & substr(VehType, 1, 3)=="LDV"),   
 100\* TravTimeCostBasePars["average\_TTC\_per\_mi.LDV","average"], VTCost\_cpm),  
 VTCost\_cpm = ifelse((CostCat=="Time" & substr(VehType, 1, 3)=="HDV"),   
 100\* TravTimeCostBasePars["average\_TTC\_per\_mi.HDV","average"], VTCost\_cpm)  
 )  
  
# sum across categories (excl miles and total) to check total cost by VehType  
x = VTCostBase %>%   
 filter(!CostCat %in% c("MilesDriven", "Total")) %>% # may be redunant  
 group\_by(VehType) %>%   
 summarize(Total = sum(VTCost\_cpm, na.rm = T)) # treat NA cost compnents as zero  
x

|  |  |
| --- | --- |
| VehType | Total |
| HDVClass8 | 170.6000 |
| LDVAvgLtTruck | 137.2477 |
| LDVAvgSedan | 115.6667 |

x = x %>% gather(key = CostCat, value = VTCost\_cpm, Total) # this allows appending to other costs  
  
VTCostBase = rbind(VTCostBase, x) # append total rows to travel cost array  
  
# established preferred row order  
costCompOrder = VehTravelCostCompons %>% filter(CostCat!="MilesDriven" & CostCat!="Source") %>% select(CostCat)  
costCompOrder$CostCat = as.character(costCompOrder$CostCat)  
  
x = spread(VTCostBase, key = VehType, value = VTCost\_cpm)  
rownames(x) = x$CostCat  
x = x[costCompOrder$CostCat,]  
  
kable(x = x, row.names = F,   
 caption= "Base Vehicle Travel Cost Components by Vehicle Type (cents/mi)")

Base Vehicle Travel Cost Components by Vehicle Type (cents/mi)

|  |  |  |  |
| --- | --- | --- | --- |
| CostCat | HDVClass8 | LDVAvgLtTruck | LDVAvgSedan |
| Fuel | 59.0 | 19.630000 | 14.590000 |
| Maintenance | 19.4 | 6.150000 | 5.470000 |
| AccAndIns | 6.7 | 8.490909 | 8.447257 |
| WearAndOwn | 18.9 | 43.490909 | 29.907173 |
| TollsFees | 5.5 | 0.000000 | 0.000000 |
| Parking | 0.0 | 2.272727 | 2.109705 |
| Time | 61.1 | 49.994933 | 49.994933 |
| Registration | 0.0 | 7.218182 | 5.147679 |
| Total | 170.6 | 137.247660 | 115.666747 |

## 4.3 Fractional Increase in VKT for Demand Scenarios

Calculate fractional change in demand, by Demand Scenario *d*, Year *t*, and VehicleClass *v*, based on changes in time cost, other vehicle fuel and operating costs, and VMT demand elasticity w.r.t generalized cost.

### Demand Scenario Cost Reduction Parameters and Demand Response Parameters Drive Demand Scenarios

Note: The definition of automation *demand* scenarios is by their impacts on selectec component costs (e.g. travel time costs, insurance costs). They are not CAV penetration scenarios. Penetration is assumed 100%.

DemScenCostReduction <- read.delim(textConnection("  
DemScen :VoTT :Insurance :Description  
1 :0 :-0.60 :Driver assistance, but no self-driving. Little benefits of comfort (0% reduction in VoT), lower end of insurance benefits (60%)  
2 :-0.05 :-0.60 :Driver assistance, but no self-driving. Some benefits of comfort (5% reduction in VoT), lower end of insurance benefits (60%)  
3 :-0.50 :-0.80 :Self driving. Large benefits of comfort + in vehicle use of time (50% reduction in VoT), large benefits of insurance (80%)  
4 :-0.80 :-0.80 :Extreme Self driving case. Large benefits of comfort + in vehicle use of time (80% reduction in VoT), large benefits of insurance (80%)  
"),header=TRUE,sep=":",strip.white=TRUE)  
# Source: Insurance cost reductions from Celent  
# Source: VoTT cost reductions hypothetical  
# Corresponds to "='[CAV Energy ASIF Framework WadudMacKenzieLeiby V20161024Test20180325r1.xlsx]DemandScenarios'!$A$1:$M$6"  
rownames(DemScenCostReduction) = DemScenCostReduction$DemScen  
  
# Assumed Reduction in Vehicle Travel Cost Components  
kable(x = DemScenCostReduction,   
 caption= "Vehicle Travel Cost Component Reduction by Demand Scenario")

Vehicle Travel Cost Component Reduction by Demand Scenario

|  |  |  |  |
| --- | --- | --- | --- |
| DemScen | VoTT | Insurance | Description |
| 1 | 0.00 | -0.6 | Driver assistance, but no self-driving. Little benefits of comfort (0% reduction in VoT), lower end of insurance benefits (60%) |
| 2 | -0.05 | -0.6 | Driver assistance, but no self-driving. Some benefits of comfort (5% reduction in VoT), lower end of insurance benefits (60%) |
| 3 | -0.50 | -0.8 | Self driving. Large benefits of comfort + in vehicle use of time (50% reduction in VoT), large benefits of insurance (80%) |
| 4 | -0.80 | -0.8 | Extreme Self driving case. Large benefits of comfort + in vehicle use of time (80% reduction in VoT), large benefits of insurance (80%) |

### Vehicle Travel Cost Shares by Component - Base

# divide every element by TotCost\_cpm to get shares  
VTCShrBase = VTCostBase %>% spread(key = CostCat, value = VTCost\_cpm) %>%  
 mutate\_at(vars(-c(VehType,Total)), funs( ./Total)) %>%  
 mutate(Total = 1.0) %>%  
 gather(key = CostCat, value=VTCost\_cpm, -VehType)  
VTCShrBase = VTCShrBase %>% spread(key = VehType, value=VTCost\_cpm)  
rownames(VTCShrBase) = as.character(VTCShrBase$CostCat)  
  
VTCShrBase = VTCShrBase[costCompOrder$CostCat,]  
  
kable(VTCShrBase, row.names = F,   
 caption= "Base Vehicle Travel Cost: Components Share by Vehicle Type")

Base Vehicle Travel Cost: Components Share by Vehicle Type

|  |  |  |  |
| --- | --- | --- | --- |
| CostCat | HDVClass8 | LDVAvgLtTruck | LDVAvgSedan |
| Fuel | 0.3458382 | 0.1430261 | 0.1261382 |
| Maintenance | 0.1137163 | 0.0448095 | 0.0472910 |
| AccAndIns | 0.0392732 | 0.0618656 | 0.0730310 |
| WearAndOwn | 0.1107855 | 0.3168791 | 0.2585633 |
| TollsFees | 0.0322392 | 0.0000000 | 0.0000000 |
| Parking | 0.0000000 | 0.0165593 | 0.0182395 |
| Time | 0.3581477 | 0.3642680 | 0.4322325 |
| Registration | 0.0000000 | 0.0525924 | 0.0445044 |
| Total | 1.0000000 | 1.0000000 | 1.0000000 |

### Cost Shares by Component - CAV Scenario

Costs (relative to Base) are adjusted for assumptions of each Demand Scenario and for the Energy Intensity change associated with the current Technology Scenario.

Base cost components are normalized and add to 1.0. Demand Scenario *relative* costs for each component *i* are relative to the Base (Manual Vehicle) level. Their total can be greater than or less than 1.0. Denoted , they depend on cost component *i*, Year *t* and Demand Scenario *d*, TechScenario *j*, Year *t*, Vehicle class *v*

* Fuel costs per mile are adjusted by the Scenario Multipliers for energy intensity, for TechScenario *j*, Year *t*, Vehicle class *v*. That is, for cost component

# Start with dataframe replicates the Base Cost Shares for each Demand Scenario  
VTCShrAlt = bind\_rows(VTCShrBase, VTCShrBase, VTCShrBase, VTCShrBase) # if 4 Demand Scenarios  
VTCShrAlt$DemScen = c(rep(1,nrow(VTCShrBase)),   
 rep(2,nrow(VTCShrBase)),   
 rep(3,nrow(VTCShrBase)),   
 rep(4,nrow(VTCShrBase)) )  
  
x = VTCShrAlt %>% gather(key = VehType, value = VCRel, -c(CostCat, DemScen))  
x$VC = substr(as.character(x$VehType), 1, 3) # extract V\_Class from VehType  
x = x %>% spread(key=CostCat, value = VCRel)  
  
# Get desired Demand Response Parameters, and append  
y = DemRespParams %>% select(-c(Zero, Med)) %>%   
 gather(key=Case, value=value, Low:High) %>%  
 spread(key = Parameter, value=value) %>%  
 select(-InsurCostRed) # Insurance cost reduction determined by Demand Scenario  
  
x = left\_join(x, y, by=c("VC")) # combines base cost shares and Demand Reponse Parameters for their adjustment  
x = left\_join(x, select(DemScenCostReduction, -Description), by=c("DemScen")) # appends Dem Scen multipliers  
VTCShrAlt = x

## 4.4 Calculate Adjusted Travel Cost Components for Scenario Conditions

# Changed costs under different automation scenarios (scenarios in DemandScenarios sheet)  
# Corresponds to "='[CAV Energy ASIF Framework WadudMacKenzieLeiby V20161024Test20180325r1.xlsx]calcul Dem\_LDV'!$G$14:$N$28" and "calcul Dem\_HDV'!$G$14:$N$28"  
# adjustments to each cost category in VehTravCostCompon  
  
# VehTravCostMult[C\_Categ, VSubClass] =   
# C\_Categ = c("Fuel", "Maintenance", "AccAndIns", "WearAndOwn", "TollsFees", "Parking", "Time", "Registration")  
# VSubClass = c("LDVAvgSedan", "LDVAveLtTruck", "HDVClass8", "HDVOther")  
  
# Apply adjustments to Cost (per mi) Components, across Demand Scenario (DemScen), Veh Type, and Case (Low - High)  
VTCShrAlt = VTCShrAlt %>% mutate(  
 Fuel = Fuel\*(1 + I\_deltaCAV\*ShrECostInt), # Fuel energy intensity reduction (from energy efficiency) \* Share of energy efficiency costs internalized by traveler  
 # "Fuel energy cost reduction" = 'Policy+Scenario'!D$11  
 Maintenance = Maintenance \* 1.0,  
 AccAndIns = AccAndIns \* (1 + Insurance), # (1+InsChange[DemScen]) # = "DemandScenarios!$O3"  
 WearAndOwn = WearAndOwn \* (1.0 + C\_incrCAV), # (1+CapitalCostChange)  
 TollsFees = TollsFees \* 1.0,  
 Parking = Parking \* 1.0,  
 Time = Time \* (1 + VoTT), #(1-VoTTChang[DemScen]) # = "DemandScenarios!N3"   
 Registration = Registration \* 1.0  
# Total = CostMult weighted by base CostFraction  
)  
VTCShrAlt$Total = 0  
VTCShrAlt %>% select(AccAndIns:WearAndOwn) %>% rowSums(na.rm=TRUE) -> VTCShrAlt$Total  
  
# Get main result (total relative cost) for all Demand scenarios, VehType, Cases, and elasticity of VKT  
RelCost = VTCShrAlt %>% select(DemScen, VehType, VC, Case, Total, ElasVKT)  
  
# Keep array of relative cost components for Demand Scenarios  
VTCShrAlt= VTCShrAlt %>%   
 filter(Case=="Low") %>% # to this point the Low and High are the same (they only differ in the applied ElasVKT)  
 select(DemScen:WearAndOwn) %>%   
 gather(key = CostCat, value = value, AccAndIns:WearAndOwn) %>% # reshape  
 spread(key = DemScen, value = value)  
  
VTCShrAlt = VTCShrAlt %>% gather(key=DemScen, value =value, c("1","2","3","4")) %>%  
 select(-VC) %>% spread(key=VehType, value=value) %>%  
 arrange(DemScen)  
  
kable(VTCShrAlt, row.names = F,   
 caption= "Alt Travel Cost Components Relative to Base, by Vehicle Type & Dem Scenario")

Alt Travel Cost Components Relative to Base, by Vehicle Type & Dem Scenario

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| CostCat | DemScen | HDVClass8 | LDVAvgLtTruck | LDVAvgSedan |
| AccAndIns | 1 | 0.0157093 | 0.0247462 | 0.0292124 |
| Fuel | 1 | 0.2484848 | 0.0402470 | 0.0354948 |
| Maintenance | 1 | 0.1137163 | 0.0448095 | 0.0472910 |
| Parking | 1 | 0.0000000 | 0.0165593 | 0.0182395 |
| Registration | 1 | 0.0000000 | 0.0525924 | 0.0445044 |
| Time | 1 | 0.3581477 | 0.3642680 | 0.4322325 |
| TollsFees | 1 | 0.0322392 | 0.0000000 | 0.0000000 |
| Total | 1 | 0.8790826 | 0.8601015 | 0.8655380 |
| WearAndOwn | 1 | 0.1107855 | 0.3168791 | 0.2585633 |
| AccAndIns | 2 | 0.0157093 | 0.0247462 | 0.0292124 |
| Fuel | 2 | 0.2484848 | 0.0402470 | 0.0354948 |
| Maintenance | 2 | 0.1137163 | 0.0448095 | 0.0472910 |
| Parking | 2 | 0.0000000 | 0.0165593 | 0.0182395 |
| Registration | 2 | 0.0000000 | 0.0525924 | 0.0445044 |
| Time | 2 | 0.3402403 | 0.3460546 | 0.4106209 |
| TollsFees | 2 | 0.0322392 | 0.0000000 | 0.0000000 |
| Total | 2 | 0.8611753 | 0.8418881 | 0.8439264 |
| WearAndOwn | 2 | 0.1107855 | 0.3168791 | 0.2585633 |
| AccAndIns | 3 | 0.0078546 | 0.0123731 | 0.0146062 |
| Fuel | 3 | 0.2484848 | 0.0402470 | 0.0354948 |
| Maintenance | 3 | 0.1137163 | 0.0448095 | 0.0472910 |
| Parking | 3 | 0.0000000 | 0.0165593 | 0.0182395 |
| Registration | 3 | 0.0000000 | 0.0525924 | 0.0445044 |
| Time | 3 | 0.1790739 | 0.1821340 | 0.2161163 |
| TollsFees | 3 | 0.0322392 | 0.0000000 | 0.0000000 |
| Total | 3 | 0.6921542 | 0.6655944 | 0.6348155 |
| WearAndOwn | 3 | 0.1107855 | 0.3168791 | 0.2585633 |
| AccAndIns | 4 | 0.0078546 | 0.0123731 | 0.0146062 |
| Fuel | 4 | 0.2484848 | 0.0402470 | 0.0354948 |
| Maintenance | 4 | 0.1137163 | 0.0448095 | 0.0472910 |
| Parking | 4 | 0.0000000 | 0.0165593 | 0.0182395 |
| Registration | 4 | 0.0000000 | 0.0525924 | 0.0445044 |
| Time | 4 | 0.0716295 | 0.0728536 | 0.0864465 |
| TollsFees | 4 | 0.0322392 | 0.0000000 | 0.0000000 |
| Total | 4 | 0.5847098 | 0.5563140 | 0.5051458 |
| WearAndOwn | 4 | 0.1107855 | 0.3168791 | 0.2585633 |

## 4.5 Fractional VMT Changes in CAV Scenario

Compute fractional increases in VMT from the changes in total generalized travel costs that result from automation.

For Demand Scenario *d*, Vehicle Type *v*, and Elasticity Case *c* (Low and High elasticity)

Note: The Elasticity of VKT with respect to (generalized) travel cost is key assumption. Does this include mode switching, vehicle efficiency, locational choices, etc? Sources for ElasVKT: (HERS-ST technical report, August 2005 + Graham and Glaister 2002)

# Change in VMT due to vehicle automation: for LDVCar, LDVLtTrk, HDVClass8  
# Pct increase in vehicle travel: low elasticity  
# Pct increase in vehicle travel: high elasticity  
  
# RelCost = VTCShrAlt %>% filter(CostCat=="Total")  
RelCost = RelCost %>% mutate(  
 fracVMTIncr = Total^ElasVKT-1.0  
)  
  
# Aggregate to single Elasticity Case value for VMT change fraction, for each of LDV and HDV  
# Pct increase LDV personal vehicles VMTdemand: arith ave of low & high elasticity; LDVCar and LDVLtTrk  
# Pct increase HDV vehicles VMTdemand: low elasticity  
VMTIncrease = RelCost %>% filter(!(VC=="HDV" & Case=="High")) %>%  
 select(-VehType) %>%  
 group\_by(VC, DemScen) %>%  
 summarise(fracVMTIncr = mean(fracVMTIncr))  
  
# % increase LD personal vehicles VMTdemand (averating Sedans and LtTrucks)  
VMTIncreaseTemp <- read.delim(textConnection("  
Var :ElasCase :LDV\_1 :LDV\_2 :LDV\_3 :LDV\_4  
LDpersonal\_vehicles\_VMTdemand: lowElas :-0.005489139 :0.014629222 :0.262314068 :0.488766916  
LDpersonal\_vehicles\_VMTdemand: highElas :-0.005489139 :0.014629222 :0.262314068 :0.488766916  
"),header=TRUE,sep=":",strip.white=TRUE) #  
  
#% increase LD personal vehicles VMTdemand :highElasticity :-0.55% :1.46% :26.23% :48.88%  
  
# VMTIncrease = VMTIncrease %>% select(-varName) %>%  
# gather(key = case, value = fracVMTIncr, -ElasCase) %>%  
# mutate(fracVMTIncr = as.numeric(fracVMTIncr)) %>%  
# separate(col = case, into = c("VehType","case")) %>%  
# spread(key = VehType, value = fracVMTIncr)  
# VMTIncrease$LDVave = (VMTIncrease$AvgSedan + VMTIncrease$LtTruck)/2.0

### Effects on VMT Demand from Elderly Drivers, and Car Sharing (Ride Pooling)

# multiplier factors on VMT to include larger travel by the elderly  
# NOTE: multiplier is for total VMT, age distribution included already  
  
# UnderServed Optional (USOption) multipliers  
ElderlyVMTmult <- read.delim(textConnection("  
USOption :multiplier :description  
0 :1.0 :no explicit effect of CAVs on elderly driving  
1 :1.023375114 :driving has a natural decay after 60  
2 :1.051206047 :driving remains same as 60, after 60  
3 :1.07209503 :1+increased number of licenses for young and old, most likely  
4 :1.106094734 :2+increased number of licenses for young and old  
"),header=TRUE,sep=":",strip.white=TRUE) #  
  
# multiplier factors on VMT to account for VMT decline in response to carsharing  
carSharingMult = 0.8 # multiplier is for total VMT. This is the high-end estimate  
  
# extends logic in "calcul Dem\_LDV" and "calcul Dem\_HDV"  
VMTIncrease$USOption = c(0, 0, 0, 0, 0, 1, 3, 4) # UnderservedOption for augmented DemScens  
VMTIncrease = VMTIncrease %>%  
 left\_join(select(ElderlyVMTmult, -description), by=c("USOption")) # combines base cost shares and Demand Reponse Parameters for their adjustment  
VMTIncrease = VMTIncrease %>% mutate(fracVMTIncr = (1+fracVMTIncr)\*multiplier - 1)  
  
# bind\_rows(select(ElderlyVMTmult, description), )  
  
  
# OUTPUT TO KAYA CALCULATION:  
# Fractional Increase in VMT for HDVs, for Demand Scenarios  
FracVMTIncreaseExample <- read.delim(textConnection("  
DemScen :VC :y2023 :y2050 :Notes  
1 :HDV :0.13315986 :0.13315986 :Cost-base response (with ElasVKT) only  
2 :HDV :0.15600896 :0.15600896 :Cost-base response (with ElasVKT) with Elderly multiplier effect option 1  
3 :HDV :0.42890465 :0.42890465 :Cost-base response (with ElasVKT) with Elderly multiplier effect option 3  
4 :HDV :0.68293679 :0.68293679 :Cost-base response (with ElasVKT) with Elderly multiplier effect option 4  
5 :HDV :0.68293679 :0.68293679 :HDV Same as DemScen 4  
6 :HDV :0.68293679 :0.68293679 :HDV Same as DemScen 4  
7 :HDV :0.68293679 :0.68293679 :HDV Same as DemScen 4  
1 :LDV :0.15900210 :0.15900210 :Cost-base response (with ElasVKT) only  
2 :LDV :0.21410345 :0.21410345 :Cost-base response (with ElasVKT) only  
3 :LDV :0.64978123 :0.64978123 :Cost-base response (with ElasVKT) only  
4 :LDV :1.08895536 :1.08895536 :Cost-base response (with ElasVKT) only  
5 :LDV :1.08895536 :1.08895536 :scenario 4 with higher elasticity  
6 :LDV :0.67116428 :0.67116428 :scenario 5 with shift to carsharing  
7 :LDV :0.31982499 :0.31982499 :scenario 3 with shift to carsharing1  
"),header=TRUE,sep=":",strip.white=TRUE) #  
# From 'calcul Dem\_LDV' and 'calcul Dem\_HDV' sheets  
  
# Check some calcs  
FracVMTIncreaseExample = FracVMTIncreaseExample %>% select(DemScen, VC, y2050) %>%   
 filter(DemScen<=4) %>%  
 left\_join(VMTIncrease, by=c("VC", "DemScen"))

## Warning: Column `VC` joining factor and character vector, coercing into  
## character vector

cat("Test output to Kaya (VMTIncrease table) matches example to within",   
 sum(abs(FracVMTIncreaseExample$y2050 - FracVMTIncreaseExample$fracVMTIncr)) )

## Test output to Kaya (VMTIncrease table) matches example to within 1.967125e-08

# 5. Policy and Scenario Calculations

VMT Demand Response: pick up chosen Demand Scenario, and value for chosen scenario, for years 2035 & 2050

LDV Demand impact (depends on scenario choice in B3) HDV Demand impact (depends on scenario choice in B3) Year 2035 2050 LDV penetration: automated/total stock 0.40 1.00 HDV penetration: automated/total stock 0.40 1.00

LDV Demand impact (depends on scenario choice in B3) (not year t dependent) HDV Demand impact (depends on scenario choice in B3) (not year t dependent) LDV penetration: total automated/total stock in 2050 HDV penetration: total automated/total stock in 2050

LDV Penetration rate=fullyauto/totalstock LDV Increase in VMT for each automated vehicle LDV VMT increase ratio/this is linked to calculation sheets

HDV Penetration rate=fullyauto/totalstock HDV Increase in VMT for each automated vehicle HDV VMT increase ratio/this is linked to calculation sheets

LDV Energy Intensity Multiplier, scaled by penetration HDV Energy Intensity Fractional Increase at full adoption - from above LDV Energy Intensity Multiplier, scaled by penetration HDV Energy Intensity Multiplier, scaled by penetration

# See '[CAV Energy ASIF Framework WadudMacKenzieLeiby V20161024Test20170809.xlsx]Policy+Scenario'"  
CAVmod = data.frame(Year = 2007:2050)  
CAVmod$CAVpenetration = 0.0  
CAVmod$CAVpenetration = # Fractional Increase in VMT for Demand Scenarios  
 c(rep(0,sum(CAVmod$Year<2020)),   
 seq(from=0.040, to=1.00, length.out = sum(CAVmod$Year>=2020)))

## Final Scenario Results Table for 2050

TranspEnergyUse\_AVScenario = TranspEnergyUseRef*((1+ModalEfficiencyFactors)^ReboundElas)*(1+FuelCarbonIntensities)\*(1+Modal Shares/Activity Factors)

# Scenario Summary 2050 Energy Intensity, VMP and Energy Use Changes at Full Adoption  
summaryScenarioResultsTableExample <- read.delim(textConnection("  
TechScen :LDV.EIntens :HDV.EIntens :LDV.VMTpveh :HDV.VMTpveh :LDV.EUse :HDV.EUse :Tot.EUse :ScenarioName  
2 :-76.93% :-28.15% :66.73% :42.89% :-61.54% : 2.67% :-44.71% :Have our cake & eat it too  
7 :-18.68% :-17.50% :11.91% :11.00% : -9.00% :-8.43% : -8.85% :Stuck in the middle at Level 2  
4 :-71.86% :-28.15% :67.12% :68.29% :-52.97% :20.92% :-33.60% :Strong responses  
3 : 34.20% : 0.00% :64.67% :44.94% :120.99% :44.94% :101.05% :Dystopian nightmare  
1 :-32.68% :-19.23% :14.26% :11.72% :-23.08% :-9.76% :-19.59% :Cautiously optimistic  
5 : 9.92% :-10.00% : 7.39% : 7.98% : 18.05% :-2.82% : 12.57 :Driver assist, limited other benefits  
"),header=TRUE,sep=":",strip.white=TRUE)  
# As in '[CAV Energy ASIF Framework WadudMacKenzieLeiby V20161024Test20170914r1.xlsx]Policy+Scenario'!$A$97:$I$105

## 5.2 Bar Chart Representation of Results

## Travel Time Budget

BGR2014:144 (referencing Shaefer et al. 2009) apply a Travel Time Budget constraint in the following straight-forward way:

Travel time (distance *D* over speed *S*) must equal reference travel time. (Appears that they apply this to all travel based on average speed, and assume a 50% increase in average speed.)

More generally, the travel time can be expected to vary in response to travel costs and income.

## Physical Constants

JoulePerBTU = 1054.8 # approx 1055. https://www.aps.org/policy/reports/popa-reports/energy/units.cfm  
BTUPerJoule = 1/JoulePerBTU  
BTUPerBOE = 5.45E6 # (barrel of oil equivalent) = BTU.  
BTUPerGalGaso = BTUPerBOE/42  
BTUPerCFNatgas = 983 # 1 cubic feet of natural gas = 983 BTU.  
# 1 exajoule = 174 million barrels of oil equivalent.  
kmPerMile = 1.60934  
literPerGal = 3.78541178  
kplPerMpg = kmPerMile/literPerGal  
MJPerGalGaso = 131.76 # http://www.convertunits.com/from/gallon/to/megajoule  
MJPerLiterGaso = MJPerGalGaso/literPerGal  
MJPerkWh = 3.6 # exact, definitional  
  
# Exajoule (EJ): EJ = 10^18 J. A quad and an ExaJoule are about the same, as are 1 BTU and a kJ  
EJPerquad = 1.055 # Quadrillion Btu(quad): 1 quad = 10^15 Btu = 1.055 EJ  
quadPerTWyr = 29.89 # Terawatt-year (TWyr): 1 TWyr = 8.76 x 1012 kWh = 31.54 EJ = 29.89 quad

## Vehicle Scenario Parameters

# Activity/Demand  
# TEDB U.S. Cars and Trucks in Use, 1970–2014(http://cta.ornl.gov/data/tedb35/Spreadsheets/Table3\_04.xls)  
LDVStock = 2.5E8 # US LD vehicle stock, Cars and (Lt) Trucks  
# TEDB: [Annual Mileage for Cars and Light Trucks by Vehicle Age](http://cta.ornl.gov/data/tedb35/Spreadsheets/Table3\_13.xls)  
VKTPerLDVyear = kmPerMile\*(12.337E3 + 14.081E3)/2 # ref travel demand/LDV, km/yr (ave of cars & trks @ age 5)  
  
# Energy Intensity  
AveLDVFuelEconomy\_MPG = 25 # base year ave LDV MPG  
AveLDVFuelIntensity\_Lp100k = 100/(AveLDVFuelEconomy\_MPG\*kplPerMpg) # MPG kpl to L/100k)  
# [Carbon Intensity for Gasoline & Substitutes, g CO2 e/MJ](http://www.energy.ca.gov/ab118/documents/2009-04-09\_meeting/2009-04-09\_Carbon\_Emission\_Graphs.pdf)  
  
# Carbon Intensity  
gCO2ePerMJGaso = 96 # for CA RFG,   
gCO2ePerMJCAElec = 41 # for CA electricity, ave gen mix "(gCO2/unit energy adjusted for energy economy ratio [EER])"  
  
# Computed paramters, reference conditions  
FuelUsePerLDVYear\_L = VKTPerLDVyear \* AveLDVFuelIntensity\_Lp100k/100 # Liters/LDV/yr  
LDVFuelUsePerYear\_L = LDVStock \* FuelUsePerLDVYear\_L # total LDV fuel use  
  
# Summarize Calc Parameters  
FuelUsePerLDVYear\_L

## [1] 2000.06

LDVFuelUsePerYear\_L

## [1] 5.00015e+11

# 6. Simple functions for MPG as a function of highway speed

## 6.1 Fuel Consumption vs. Speed - Thomas et al. Approach

* Source: Thomas, J., Hwang, H.-L., West, B., & Huff, S. (2013). Predicting Light-Duty Vehicle Fuel Economy as a Function of Highway Speed. SAE International Journal of Passenger Cars - Mechanical Systems, 6(2), 2013-01-1113. <doi:10.4271/2013-01-1113>

Thomas et al. performed "analysis of dynamometer testing results for 74 vehicles at steady-state speeds from 50 to 80 mph [80 to 129 km/h]. Data has been collected for 23 light-duty vehicles at ORNL's vehicle research laboratory and a valuable data set for 51 vehicles was loaned to ORNL by Chrysler, LLC under a non-disclosure agreement. Vehicles were tested in dynamometer laboratories at steady speeds from 40 to 80 mph [64 to 129 km/h], with the proper road-load applied. ... The study includes various sizes of sedans, wagons, and SUVs, as well as pickup trucks, minivans and a few "muscle" and sports cars. Vehicles from model years 2003 to 2012 with a wide variety of powertrains were represented" [ORNL researchers quantify the effect of increasing highway speed on fuel economy](http://www.greencarcongress.com/2013/01/thomas-20130117.html) Jan 18, 2013

**Summary of MPG vs. Speed data: Percent mpg decrease for a given 10 mph increase based on 74 vehicles.**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Speed increase | Average | Data range | Std. deviation | Middle 2/3s of vehicle data |
| 50 to 60 mph | 12.4 | 6.9-18.3 | 2.2 | 10.0-14.3 |
| 60 to 70 mph | 14.0 | 8.8-19.5 | 2.6 | 11.2-16.1 |
| 70 to 80 mph | 15.4 | 10.8-26.0 | 3.0 | 12.5-17.5 |
| All three speed increments | 13.9 | 6.9-26.0 | 2.9 | N/A |

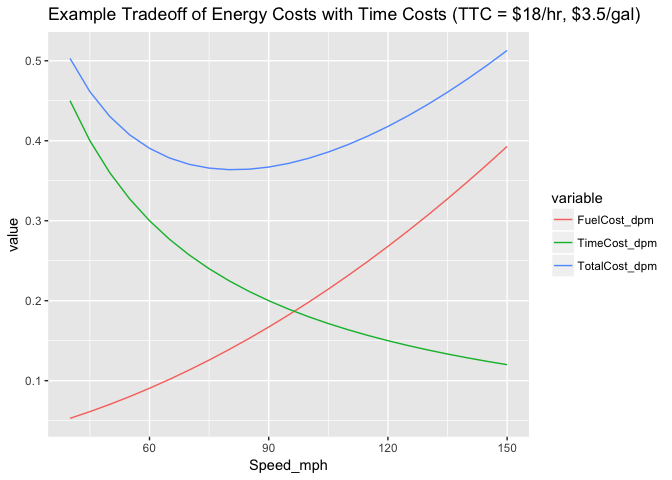
percentMPGdecreaseTHWH2014 <- function(S, refMPG = 25.0) {  
 # Based on Thomas, J., Hwang, H., West, B. and Huff, S., "Predicting Light-Duty Vehicle Fuel Economy as a  
 # Function of Highway Speed," SAE Int. J. Passeng. Cars - Mech. Syst. 6(2):2013.  
 # Model 1 (depends reference MPG for vehicle)  
 f\_a = ( 0.0533 \* refMPG^2 - 0.3580 \*refMPG )  
 f\_b = (-0.0062 \* refMPG^2 + 0.01345\*refMPG - 0.34192 )  
 MPG = f\_a + f\_b\*S  
 if (S<50)  
 return(NA) # function not defined for speeds below this min  
 else  
 return((refMPG-MPG)/refMPG)  
}  
  
mSet = seq(15,45,5) # alternative reference MPGs  
sSet = seq(40,100,10) # alternative speeds  
pmd = matrix(NA,nrow=length(mSet),ncol=length(sSet), dimnames = list(mSet, sSet))  
#pmd = data.frame(matrix(NA,nrow=length(mSet),ncol=length(sSet), dimnames = list(mSet, sSet)))  
for (i in 1:nrow(pmd)) {  
 for (j in 1:ncol(pmd)) {  
 pmd[i,j] = percentMPGdecreaseTHWH2014(sSet[j],mSet[i])  
 }  
}  
  
# pmd # percent MPG decreases  
kable(x = pmd,   
 caption= "Percent MPG Decreases With Speed (Rows are Ref Speed)")

Percent MPG Decreases With Speed (Rows are Ref Speed)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
| 15 | NA | 5.675733 | 6.699180 | 7.722627 | 8.746073 | 9.76952 | 10.79297 |
| 20 | NA | 6.674300 | 7.950760 | 9.227220 | 10.503680 | 11.78014 | 13.05660 |
| 25 | NA | 7.786840 | 9.339108 | 10.891376 | 12.443644 | 13.99591 | 15.54818 |
| 30 | NA | 8.956367 | 10.795840 | 12.635313 | 14.474787 | 16.31426 | 18.15373 |
| 35 | NA | 10.158457 | 12.291649 | 14.424840 | 16.558031 | 18.69122 | 20.82441 |
| 40 | NA | 11.380900 | 13.811880 | 16.242860 | 18.673840 | 21.10482 | 23.53580 |
| 45 | NA | 12.616911 | 15.348393 | 18.079876 | 20.811358 | 23.54284 | 26.27432 |

## 6.2 Fuel Consumption vs Speed - Berry Approach

S\_r = 71 # "Reference speed" km/h  
f\_r = 0.5 # "Aero losses fraction of total @ reference speed" unitless  
I\_r = 4.7 # "FC\_r, Fuel consumption @ reference speed" l/100km  
P\_gasdpg = 3.50 # "Gasoline Price $/gallon"  
P\_gasdpl = 0.92 # "Gasoline Price $/litre"  
P\_gasdpl = P\_gasdpg/3.785  
C\_timedph = 18 # "Cost of Travel Time $/hr"  
a\_0 = 0.143171 # "Intercept term in FC ratio curve"  
a\_1 = 0.00474448 # "Coeff on linear term in FC ratio curve"  
a\_2 = 0.0000742969 # "Coeff on squared term in FC ratio curve"  
  
s\_optkph = 127.2 # "Optimal speed" km/h  
# s\_optmph = 79.1 # "Optimal speed" mi/hr  
s\_optmph = s\_optkph/kmPerMile # "Optimal speed" mi/hr  
  
#I\_sopt = 9.16 # "FC @ optimal speed" l/100km  
I\_sopt = I\_r\*(a\_0 + a\_1\*s\_optkph + a\_2\*s\_optkph^2) # "FC @ optimal speed" l/100km  
  
C\_tot = 0.2331 # "Total Cost" $/km  
C\_tot = I\_sopt/100 + C\_timedph/s\_optkph # Total Cost $/km (fuel and time)  
MPG\_sopt = 25.66 # "MPG @ optimal speed" mpg  
MPG\_sopt = 235.2/I\_sopt  
  
# FC rel. to 65 mph 1.34  
# FC rel. to 70 mph 1.20  
  
TCdf = data.frame(Speed\_mph = seq(40,150,5))  
  
TCdf = TCdf %>%   
 mutate(  
 Speed\_kph = Speed\_mph \* kmPerMile,  
 FC\_lper100km = I\_r\*(a\_0 + a\_1\*Speed\_kph + a\_2\*Speed\_kph^2), # l/100-km  
 FC\_galpermi = (FC\_lper100km/100)\*kplPerMpg, # gal/mi  
 FE\_mpg = 1/FC\_galpermi,  
 Pace\_hrpermi = 1/Speed\_mph, # (hr/mi)  
 FuelCost\_dpm = FC\_galpermi\* P\_gasdpg, # ($/mi)  
 TimeCost\_dpm = C\_timedph/Speed\_mph, # ($/mi)  
 TotalCost\_dpm = FuelCost\_dpm + TimeCost\_dpm # ($/mi)  
)  
  
# TCdf  
  
# Plot the cost components, per mile  
TCdf %>% select(Speed\_mph, FuelCost\_dpm, TimeCost\_dpm, TotalCost\_dpm) %>%  
 gather(variable, value, FuelCost\_dpm:TotalCost\_dpm) %>%  
 ggplot(aes(Speed\_mph,value)) + geom\_line(aes(color=variable)) +   
 ggtitle("Example Tradeoff of Energy Costs with Time Costs (TTC = $18/hr, $3.5/gal)")



## Compute the Optimum Highway Speed for a Range of Time Costs and Fuel Costs

TotalTimeAndFuelCost <- function(speed\_mph, FC\_dpg=3.5, TC\_dph) {  
 # computes total travel costs (time and fuel) as a function of speed in mph  
 #   
 S = speed\_mph \* kmPerMile  
 FC\_lper100km = I\_r\*(a\_0 + a\_1\*S + a\_2\*S^2) # l/100-km  
 FC\_galpermi = (FC\_lper100km/100)\*kplPerMpg # gal/mi  
 FE\_mpg = 1/FC\_galpermi  
 FuelCost\_dpm = FC\_galpermi\* P\_gasdpg # ($/mi)  
 TimeCost\_dpm = C\_timedph/speed\_mph # ($/mi)  
 TotalCost\_dpm = FuelCost\_dpm + TimeCost\_dpm # ($/mi)  
}  
  
# nlm(f=, p, ..., hessian = FALSE, typsize = rep(1, length(p)),  
# fscale = 1, print.level = 0, ndigit = 12, gradtol = 1e-6,  
# stepmax = max(1000 \* sqrt(sum((p/typsize)^2)), 1000),  
# steptol = 1e-6, iterlim = 100, check.analyticals = TRUE)  
  
timeCostRange\_dph = 10.0 \* seq(from=0.1, to=2.0, by = 0.1) # $/hr  
fuelCostRange\_dpg = 2.0 \* seq(from=0.1, to=2.0, by = 0.1) # $/gal

# 7. Safety Costs Associated with Speed

* [Road safety - Speed](http://www.who.int/violence_injury_prevention/publications/road_traffic/world_report/speed_en.pdf) World Health Organization, 2004
* An increase in average speed of 1 km/h typically results in a 3% higher risk of a crash involving injury, with a 4-5% increase for crashes that result in fatalities.
* Speed also contributes to the severity of the impact when a collision does occur. For car occupants in a crash with an impact speed of 80 km/h, the likelihood of death is 20 times what it would have been at an impact speed of 30 km/h.
* WHO 2004 World report on road traffic injury prevention \*\* Crash Risk\*\*
  + WHO 2004 [World report on road traffic injury prevention](http://apps.who.int/iris/bitstream/10665/42871/1/9241562609.pdf)
  + <http://www.who.int/violence_injury_prevention/publications/road_traffic/world_report/en/>
  + The probability of a crash involving an injury is proportional to the square of the speed. The probability of a serious crash is proportional to the cube of the speed. The probability of a fatal crash is related to the fourth power of the speed (38, 39). [Chap 3, Crash Risk, p.78]
  + Empirical evidence from speed studies in various countries has shown that an increase of 1 km/h in mean traffic speed typically results in a 3% increase in the incidence of injury crashes (or an increase of 4-5% for fatal crashes), and a decrease of 1 km/h in mean traffic speed will result in a 3% decrease in the incidence of injury crashes (or a decrease of 4-5% for fatal crashes) (40).
  + Taylor et al. (41, 42), in their study on different types of roads in the United Kingdom, concluded that for every 1 mile/h (1.6 km/h) reduction in average traffic speed, the highest reduction achievable in the volume of crashes was 6% (in the case of urban roads with low average speeds). These are typically busy main roads in towns with high levels of pedestrian activity, wide variations in speeds and high frequencies of crashes.
  + A meta-analysis of 36 studies on speed limit changes showed, at levels above 50 km/h, a decrease of 2% in the number of crashes for every 1 km/h reduction in the average speed (43).
  + For car occupants in a crash with an impact speed of 50 miles/h (80 km/h), the likelihood of death is 20 times what it would have been at an impact speed of 20 miles/h (32 km/h) (48).

TABLE 3.4: Relative risks of involvement in a casualty crash for speed and alcohol

|  |  |
| --- | --- |
| Speed (km/h) | Speed (relative risk) |
| 60 | 1.0 |
| 65 | 2.0 |
| 70 | 4.2 |
| 75 | 10.6 |
| 80 | 31.8 |

Relative to a sober driver travelling at the speed limit of 60 km/h. (Source: Kloeden et al., 1997. See alos Kloeden et al. 2001)

### **Severity of crash injuries**

* Speed has an exponentially detrimental effect on safety. As speeds increase, so do the number and severity of injuries. Studies show that the higher the impact speed, the greater the likelihood of serious and fatal injury:
  + For car occupants, the severity of crash injury depends on the change of speed during the impact, usually denoted as v. As v increases from about 20 km/h to 100 km/h, the probability of fatal injuries increases from close to zero to almost 100% (46).
  + The probability of serious injury for belted front-seat occupants is three times as great at 30 miles/h (48 km/h) and four times as great at 40 miles/h (64 km/h), compared with the risk at 20 miles/h (32 km/h) (47).
  + For car occupants in a crash with an impact speed of 50 miles/h (80 km/h), the likelihood of death is 20 times what it would have been at an impact speed of 20 miles/h (32 km/h) (48).
  + Pedestrians have a 90% chance of surviving car crashes at 30 km/h or below, but less than a 50% chance of surviving impacts at 45 km/h or above (49, 50) (see Figure 3.3).
  + The probability of a pedestrian being killed rises by a factor of eight as the impact speed of the car increases from 30 km/h to 50 km/h (51).
  + Older pedestrians are even more physically vulnerable as speeds increase (52) (see Figure 3.4).
  + Excess and inappropriate speed contributes to around 30% of fatal crashes in high-income countries (53).
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## 7.2 Speed and Accident Risk

* Notes from [Speed and Accident Risk](http://ec.europa.eu/transport/wcm/road_safety/erso/knowledge/Content/20_speed/speed_and_accident_risk.htm), European Road Safety Observatory

Assessing potential effectiveness of speed reduction measures Based on work by Nilsson in Sweden, a change in average speed of 1 km/h will result in a change in accident numbers ranging between 2% for a 120 km/h road and 4% for a 50 km/h road. This result has been confirmed by many before and after studies of different speed reduction measures. This relationship is used by other Scandinavian countries and by Australian and Dutch safety engineers.

A similar relationship is assumed in Britain, based on empirical studies by Taylor, where changes in accident numbers associated with a 1 km/h change in speed have been shown to vary between 1% and 4% for urban roads and 2.5% and 5.5% for rural roads, with the lower value reflecting good quality roads and the higher value poorer quality roads.

Higher speeds: more accidents : High speed reduces the possibility to respond in time when necessary. People need time to process information, to decide whether or not to react and, finally to execute a reaction. At high speed the distance covered in this period is longer. At high speeds the distance between starting to brake and a complete stand still is longer as well. The braking distance is proportional to the square of speed (v2). Therefore, the possibility to avoid a collision becomes smaller as speed increases. This is well illustrated at a broad average level by Finch [24].

1 km/h increase in speed implies a 3% increase in accidents

In practice the relationship is more complex. ...The higher the speed, the steeper the increase in accident risk. The relationship between speed and accident risk is a power function:

Based on the principles of kinetic energy and validated by empirical data, Nilsson [[44](Nilsson,%20G.%20(1982)%20The%20effects%20of%20speed%20limits%20on%20traffic%20crashes%20in%20Sweden.%20In:%20Proceedings%20of%20the%20international%20symposium%20on%20the%20effects%20of%20speed%20limits%20on%20traffic%20crashes%20and%20fuel%20consumption,%20Dublin.%20Organisation%20for%20Economy,%20Co-operation,%20and%20Development%20(OECD),%20Paris)][[45](Nilsson,%20G.%20(2004)%20Traffic%20safety%20dimensions%20and%20the%20power%20model%20to%20describe%20the%20effect%20of%20speed%20on%20safety.%20Bulletin%20221,%20Lund%20Institute%20of%20Technology,%20Lund)] developed the following formula:

In words: the number of injury accidents after the change in speed (A2) equals the number of accidents before the change (A1) multiplied by the new average speed (v2) divided by the former average speed (v1), raised to the square power.

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1. We differentiate between transportation services (PKT) and vehicle travel (VKT). [↑](#footnote-ref-27)
2. Additional potential disaggregations include by region, vehicle size class, drivetrain type, and time of day (e.g. operating costs vary by time of day, as described in Bösch et al. 2017). [↑](#footnote-ref-28)
3. Wadud, MacKenzie and Leiby 2016. [↑](#footnote-ref-31)