Chapter Seven

Extension to LCA for Uncertainties, Environmental Impact and Weighting

7.1 Uncertainty Analysis

The models developed for LCA are just part of a wide range of models used in the design and decision making process of business, science and technology. Commonly, the models, which represent in some sense reality, contain areas of uncertainty. One approach is to select single appropriate values for each variable and parameter to be specified as input to the model and to assume that the output is treated as completely known or specified. This is the deterministic model and represents the type of model described in previous chapters. An alternative approach is to treat some or all of the variables and parameters of the model as being subject to uncertainty and as such, to be described by some appropriate probability law. It follows that the model output will display random characteristics which can be described only by some probability measures. This situation is an example of a random or stochastic model and while some simple models can be solved analytically to derive the probability measures, it has become more common to resort to numerical simulation. In this case a finite but usually large set of input data is generated, each member of the set representing a possible collection of input variables and parameters with the frequency of occurrence of each member following the assumed probability law. Stochastic analysis of the corresponding set of output data then provides an estimate of the effect of the inherent uncertainties. One such stochastic analysis package has been used with this LCA, ie the simulation software @RISK, developed by the Palisade Corporation. The software is used as an

Add-In to Microsoft Excel and has been added to the fuel, vehicle and life cycle spreadsheets.

It should be noted that the information used in the beginning of this Chapter is taken from the @RISK manual, Palisade (1994). Some examples and descriptive terms are taken directly from the @RISK manual. The elements of the underlying probability theory will be taken as read. A useful introduction may be found in Kottegoda and Rosso (1997).

7.2 Simulation Software

@RISK uses pseudo-random numerical simulation to combine all the uncertainties which the user identifies in a model. A range of values can be specified for each input variable with some measure of likelihood of occurrence for each possible value. The software can be used to analyse every possible outcome from each input and run hundreds or thousands of "what-if" scenarios. The results from the simulation can be collected, stored or transferred whilst another set of simulations is run. The software allows the user to define uncertainty cell values in Excel in term of probability distributions. Over thirty additional functions (compared to the standard Excel functions) exist, each of which allows the user to specify a different distribution type for cell values. The distribution functions can be added to any number of cells within any one singular or linked worksheet and can include arguments. For example a cell containing the distribution function normal (5,10) returns samples during a simulation from a normal distribution of mean value (5) and standard deviation (10), see later examples. Available distributions range from Beta to Weibull, see Palisade (1994) for an explanation. Two types of sampling are available, Monte Carlo and Latin Hypercube, see Appendix P. Both types, along with the selection of outputs, are entered with Windows style menus and dialog boxes.

7.3 Characteristics of General Risk

Risk can be either objective or subjective. The objective risk is based solely on theory, whereas describing a situation such as the future chance of sunshine is a subjective risk. Describing this type of risk is open-ended in that the user could alter HIS decision should new information become available. In reality risks are mainly subjective, which has obvious important considerations when performing a risk analysis in some technical or managerial situation

7.3.1 Assessing and Quantifying Risk

Once a risk has been identified the difficulties lie in attempting to quantify risk for uncertain situations. Quantifying risk means determining all possible outcomes a variable could take plus determining the relative likelihood of each. It should also be noted that each user would run the risk of disagreement with other users when a subjective quantification is made.

Once the risk has been quantified, it can be summarised using the probability distributions. All distributions use a set of arguments to specify their range, shape and size. As previously highlighted the normal distribution uses a mean and standard deviation as its arguments. The mean is an indicator of the value around which the curve will be centred and the standard deviation indicates the range or dispersion of values around the mean.

7.4 Developing the @Risk Model

Each Excel worksheet used in the LCA model contains a number of variables. These are the basic numbers of any model and are defined by the user. Variables are either certain (deterministic) or uncertain (stochastic). The nature of the stochastic variables can and must be described using probability distributions. In addition to the deterministic and stochastic nature of the variable, they are also either dependent or independent. An independent variable is totally unaffected by any other variable within a model. In contrast a dependent variable is determined by one or more variables in a model and for stochastic variables, this implies the introduction of an appropriate conditional probability distribution or other conditional statistic.

It should be noted that some stochastic variables may have such small ratios of standard deviation to mean (i.e. coefficient of variation) that they can be approximated by a single, deterministic value.

When running a risk simulation it is imperative to recognise dependency relationships between variables. Failure to do so can lead to unrealistic results.

7.4.1 Simulation

Simulation refers to a method of recalculation, whereby each time a "run or iteration" is complete, a set of different randomly selected values for the probability distribution set is generated, altering the results. Depending upon the number of simulations run the computer is calculating all valid combinations of the values of input variables to simulate all possible outcomes. The selection of values from the probability density functions (pdf) is referred to as 'sampling' and each recalculation of the Excel worksheet is referred to as an 'iteration'.

There are two basic types of Risk Analysis; both have the same goal, which is to derive a probability distribution that describes the possible outcomes of an uncertainty analysis. The first type is the one described in the Chapter, namely, simulation. Relying on the computer to deal with solving the worksheet repeatedly using a large number of possible combinations of input variable values. The second type is an analytical approach. Analytical methods require that the distributions for all uncertain variables can be described mathematically. The equations for these distributions are combined mathematically to derive another equation, which describes the distribution of possible outcomes. It is not a simple task to describe distributions as equations, and it is even more difficult to combine distributions analytically given more moderate complexity in a model.

7.4.2 Worksheets

Three Excel worksheets were developed and interfaced with the @RISK software, see Appendix G. Each spreadsheet, Life Cycle (Van) Simulation, Life Cycle (HGV) Simulation and Life Cycle (Bus) Simulation, combine the fuel and vehicle cycles and calculates the total life cycle results for each compound under investigation. Each worksheet will be dealt with in turn.

The first stage of the simulation involves the identification of the variables that have the greatest influence on the total life cycle emissions. In the calculation of GWP the contributions from CO_2, CO and CH_4 are considered. Human Toxicity (HT) to air, in the present study, consists of the contributions of SO_2, NOx, CO and PM. However the largest contribution to any one stage may or may not have an impact on the total GWP or HT impact due to the equivalency factors, see Equation 6.3 i.e. an emission of CH_4 may be smaller than that of CO_2, however a GWP equivalency factor of 25 is assigned to CH_4 and 1 to CO_2, making the total potential much higher than the absolute value. Therefore only the variables that have the largest impact on the total GWP and HT levels are simulated. As an example the variables identified in Table 7.1 below are used in the simulation of the Euro 4 van. The most significant contributors are highlighted in yellow and the second most significant values are highlighted in blue. The full detailed list of significant variables for each vehicle exists in Appendix N.

Identification of the most significant stages is the first step. It becomes clear to see that for a petrol van, the most significant stage in the formation of GWP and HT is F6. For GWP the F6 stage is by far the largest contributor and in the subsequent simulations, it only becomes necessary to model the variables that change the F6 value. In the formation of HT the largest contribution is from CO, which has the second largest contribution from NOx. The absolute values are similar; see Table 7.1b, 766t from CO and 647t from NOx. In the simulation both values are modelled, as both contribute to the total HT produced.

Table 7.1a: Euro 4 Van Stages chosen for Simulation

Van					
	GWP	HT			
	CO_2	NOx	PM	CO	SO_2
Petrol	F6	F6		F6	
Diesel	F6	F6	F6 and V3		
LPG	F6	F6	F6 and V3		
NG-CNG	F6	F6	F6 and V3		
NG-LNG	F6	F6	F6 and V3		
Electric	F4	F4	F6 and V3		F4
Green Electric	V1 and V4	V1 and V4	V3		
LFG-CNG	F6	F2 and F6	F6 and V3		
LFG-LNG	F6	F2 and F6	F6 and V3		

Table 7.1b: Contributors to Human Toxicity (all value in grammes equivalent)

	SO2	NOx	CO	PM
Petrol	54,455,712	646,961,802	766,115,548	213,961,648
Diesel	55,448,099	1,265,995,469	193,834,901	276,477,364
LPG	53,425,501	561,652,360	74,717,486	251,736,861
NG-CNG	82,267,134	693,596,970	138,785,386	249,987,537
NG-LNG	17,743,234	1,399,532,483	171,558,669	265,004,739
Electric	417,314,173	1,174,308,730	59,022,103	209,865,702
Green Electric	8,110,726	49,670,014	39,927,980	165,070,714
LFG_CNG	79,327,392	990,755,137	156,375,182	249,987,537
LFG_LNG	14,677,717	1,709,404,374	189,901,033	265,004,739

Key:

(yellow)	Largest contributor
(blue)	2nd largest contributor

For GWP the release of CO_2 via fuel combustion in the F6 stage dominates the complete life cycle results. The contributions from CO and CH_4 in the majority of cases are deemed second order and have little impact on the total GWP for each fuel in the life cycle of the large van, with the exception of the green electric vehicles which have effectively zero fuel cycle emissions. The CO_2 emissions in the F4 stage of the electric cycle are the most significant contributors to the total life cycle emissions. These emissions are derived from the production of electricity using the current UK generation mix of coal, oil and gas. The green electric vehicle emissions that contribute to GWP are so small that they are effectively zero.

In HT terms, the absolute values, see Table 7.1a, show that the largest contributor to HT for a petrol van is CO (766t). This value represents the actual life cycle emission of CO (923kg) multiplied by its HT equivalency factor (830). The 2nd largest contributors to HT are also significant contributors and are simulated along with the other variables.

7.4.3 Life Cycle (Van) Simulation – example of procedure

7.4.3.1 GWP

The life cycle of a van is simulated with the knowledge that F6, in all cases except the electric van, is the most significant contributor to the GWP impact. The variables used to derive the F6 values are listed in Table 7.2 and are assumed to be the mean values.

With the minimum and maximum limits estimated together with the relevant assumed distribution, a simulation can take place.

Table 7.2: Life Cycle Van Simulation in the F6 stage

Life Cycle (Van) Simulation				
	Mean Values	Minimum	Maximum	Distribution Type
Average Speed (kph)	20	10	30	Beta (5,5)
Distance travelled per day (km)	129	100	158	Beta (5,5)
Average mpg (petrol)	27.3			correlated to speed
Average mpg (diesel)	30.6			correlated to speed
Operational days (per year)	300	280	320	Beta (5,5)
Operational lifetime use (yrs)	10	8	12	Triang(8,10,12)

The F6 stage variables listed in Table 7.2 are simulated to find the amount of variation within each cycle. In the calculation of life cycle emissions, GWP and HT in the previous chapters, an assumed speed and mpg for petrol and diesel vans was taken to represent the average UK van. The values for average speed (20kph) and mpg 27.3 (petrol) and 30.6 (diesel) were used. Within this simulation the variables mpg and mph are correlated by assuming that all petrol and diesel is converted to CO_2 after combustion. Using the formula C_nH_{2n+2} and assuming that n=8 for petrol and 10 for diesel a correlation curve of g/km and kmpg was produced, see Appendix G. With the correlation complete, an equivalent mpg could be produced for the minimum and maximum speeds estimated.

Table 7.3: Life cycle Van Simulation in the F6 stage with correlation of mpg to mph

Life Cycle (Van) Simulation				
	Mean Values	Minimum	Maximum	Distribution Type
Average Speed (kph)	20	10	30	Beta (3,3)
Distance travelled per day (km)	129	100	158	Beta (3,3)
Average mpg (petrol)	27.3	18.1	33.1	correlated to speed
Average mpg (diesel)	30.6	23.6	32.7	correlated to speed
Operational days (per year)	300	280	320	Beta (3,3)
Operational lifetime use (yrs)	10	8	12	Triang(8,10,12)

Through the simulation a beta and triangular distribution was chosen to represent the variation in the datasets. In general, it was envisaged that the variation in data would be small and the majority of values in all simulations would be distributed around the mean value, therefore a normal distribution was initially chosen for the simulation. However, further investigation revealed that a normal distribution does not have definite maximum and minimum limits and the tails of the distribution continue exponentially. This would be unrealistic, given that there would be a very small possibility of a value being so large or small that it would not be physically possible i.e. a vehicle speed for a HGV that exceeds 100mph. Therefore a Beta distribution was chosen, which can have the same symmetrical shape as the normal distribution but with definite minimum and maximum cut-off limits. Where values in the simulation tend to group around the mean a beta (5,5) distribution is used. The values (5,5) refer to the alpha 1 and alpha 2 parameters of the shape of the curve and best represent the general shape of the conventional normal distribution curve.

A triangular distribution was chosen for the simulation of operational lifetime use. In general a triangular distribution represents a situation where there is a high possibility of values being grouped around the mean value but with a larger degree of scatter in comparison to the beta distribution i.e. there is a higher probability that some values will occur outside say, the 20^{th} and 80^{th} percentiles. Knowledge of the Ford Transit vans in operation across the UK has shown that the majority of vehicles will be in operation for 15 years before they are scrapped, however some vehicle may operate for a number of years less or more than this mean value in no particular order. A van has as much chance of operating for 13 years as it does for 17 years, due to various operational characteristics. In general city councils will operate vans, of this type, for less than 15 years, with Liverpool City Council changing their vehicles every 5-7 years, Carrington (2003). However since the vans are not scrapped after this short time period of 5-7 years, the total life cycle use of 15 years has been used. If, as with all variables, in the sensitivity analysis this variable has been identified as a significant contributor to the complete life cycle results, a review of the distribution used can be made.

Of the variables that have been identified as significant contributors to GWP and HT a Beta (5,5) distribution with a variation of 10% of the calculated mean value has been used. This 10% variation can, if necessary, be modified to the users specification. If for example one considers the contribution made to HT from a petrol van. In total the levels of CO and NOx in the F6 stage have the most significant contributions. These values have been calculated by multiplying the actual life cycle releases 923kg for CO and 75kg for NOx by their HT equivalency factors of 830 and 8600 respectively to produce values of 766t and 647t. As can be seen, less NOx is released in the life cycle of a large van, however the HT equivalent factor is higher and as a result the HT contribution is almost as high as that from CO. In the simulation, one takes 90% and 110% of these values, to represent a variation of 10%. If one considers CO, the F6 stage in the life cycle contributes the most to HT. In total, 19620g of CO are released per tonne of petrol delivered and used in the F6 stage; therefore one calculates the 10% variation of this mean value 90% (17658) and 110% (21582). These values then represent the upper and lower limits of the Beta (5,5) distribution.

In accordance with Table 7.1, the F4 stage of the electric cycle and the V1 and V4 stages of the green electric cycle were chosen for simulation. A Beta (5,5) distribution was chosen in both cases.

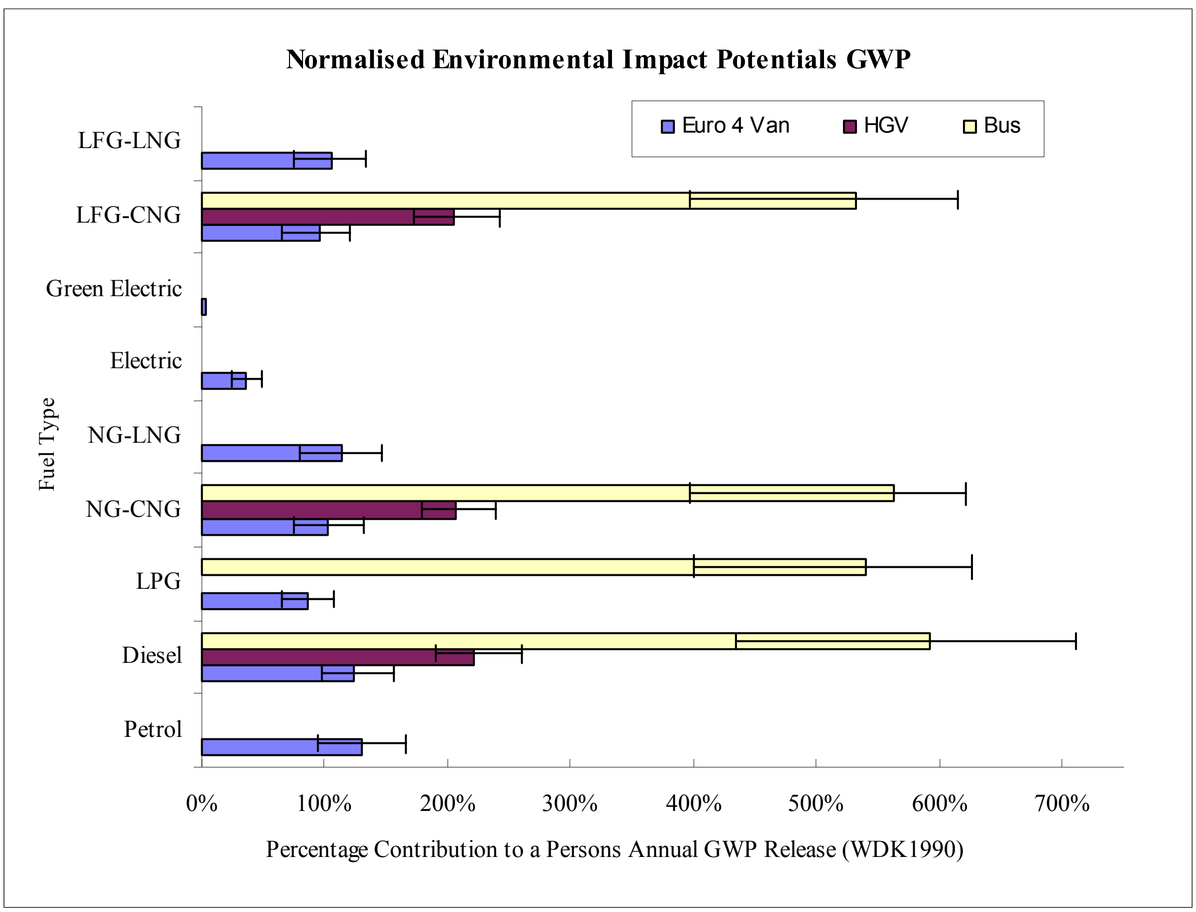
On completion of the life cycle van simulation, the 5th and 95th percentiles are calculated for each compound in each life cycle. These values between these percentiles then represent 90% of the data and are combined with the calculations of GWP for each fuel cycle in order to produce error bars with theoretical positive and negative percentile limits. Figures 6.1–6.4 are reproduced in this chapter, Figures 7.1- 7.4 with the error bars included in order to provide a visualisation of the extremities for each fuel and vehicle cycle. The subsequent impacts on the Normalised and Weighted potentials for GWP and HT can then be investigated. It must be noted that these extremities are based upon the simulations made in the present study. A separate simulation with different assumed distributions and values may yield different results. However, this simulation presents the most realistic analysis given the information available in the public domain. The vehicles investigated in the present study will be unlikely to exceed the minimum and maximum levels assumed in the simulation. It is unlikely that the vehicle speeds, mpg, distances travelled and operational lifetime uses would significantly alter for the vehicle and cycles chosen. If significant changes were to occur, the vehicles would be representative of different delivery cycles and not those specified in this study. The value of simulation is an indication of the degree of variation given as much as the absolute values obtained.

A sensitivity analysis is then calculated for the life cycles of the Ford Transit van, with over 1000 iterations, for comparisons to be made between the other cycles, see Table 7.2. This number of iterations is necessary in order for convergence to occur. Appendix G contains full details of each simulation. The sensitivity analysis provides a means of investigating which variables, of the ones selected for simulation, have the largest and smallest impact on the total life cycle emissions. The sensitivity is represented in graphs of correlation coefficient, for each life cycle under investigation, see Figures 7.1-7.4. Absolute values can be seen in Appendix O.

From Figure 6.1 one can see that the use of a petrol van contributes to 130% of the contribution to GWP from an average person in the World and Denmark in 1990. With the percentiles in place this percentage may be reduced to 104% or increase to 164%, see Appendix O. There is little change in the impact of a petrol van to GWP when using the assumed maximum and minimum limits during the 1000 simulations. The contributions that large vans make to GWP are small in comparison to the HGVs and buses. As can be seen in Figure 7.1 and Appendix O, the use of a diesel bus contributes some 588% to GWP, 4.5 times greater than a petrol van. The use of a HGV contributes 238% to GWP, 1.8 times greater than a petrol van. These relative impacts highlight the consequences of the choice of probability distributions. Whether a user chooses to use a Beta or Triangular distribution will have little effect on the relative impact of a van to a HGV or a bus. Moreover, the range chosen for each variable has little influence on the relative impacts i.e. should the user choose to specify a larger variation for a particular variable, the result calculations for GWP would not significantly alter, unless the variable itself is significantly altered. These results also highlight the relative impacts within each life cycle and the unimportance of the F1-F5 stage and the vehicle cycle, which in the calculation of GWP, are deemed second order contributors. As a result, large alterations in the F1-F5 fuel cycle or the vehicle cycle would not alter the GWP results. At this point the author can feel confident in the assumptions used throughout this study, as their significance to the overall results becomes apparent.

In comparison of each fuel type used, it becomes clear to see that the green electric and electric vehicles have the lowest impact towards GWP per person in the World and Denmark in 1990. The largest impacts are from the petrol and diesel vans. LPG vans contribute the least to GWP, per person, and the LFG-CNG van contributions are relatively low. However the difference between the largest and smallest contributors, with the exclusion of the electric vans, is small (46%) and, relatively speaking, all contributions to GWP are similar. The same applies to the HGVs with the LFG-CNG HGV contributing the least to the formation of GWP of the three vehicles under examination. The largest contributions are made by the buses, if however 30 people travelled daily by bus, it would be clear to see that the percentage contribution per person would be reduced from 588% to 19.6%. Making the contribution to GWP, per person, 4.75 times greater than an electric vehicle and 7.7 times less than a petrol van. The values presented in Figures 7.1-7.4 must not be interpreted the wrong way and it would be nonsensical to state that the use of a bus is of a major disadvantage to the contribution to GWP. The major contributor to GWP does in fact come from the use of the HGVs. These vehicles do not transport passengers and the percentage contributions in Figure 7.1 and 7.3 are the actual contributions made per vehicle, given the assumption that one driver is required per vehicle.

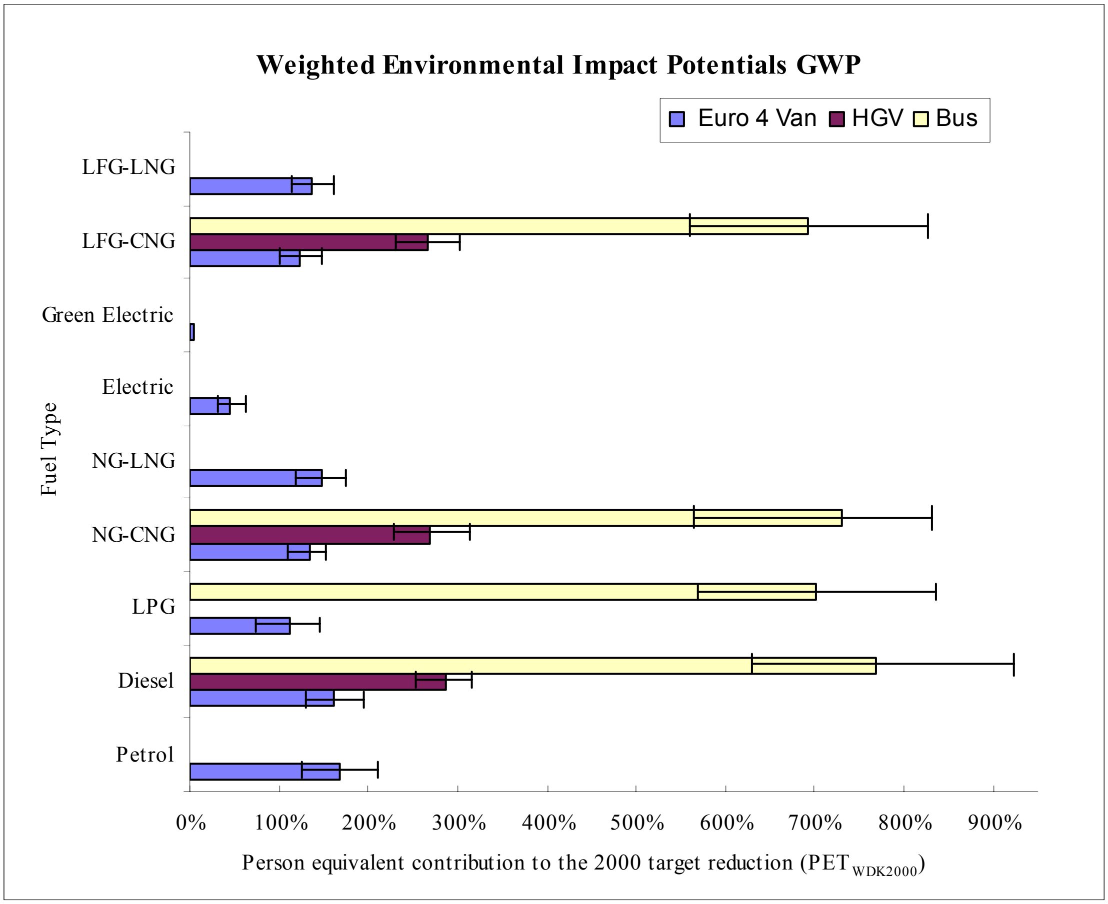
Figure 7.1 - Normalised Environmental Impact Potential for GWP with percentiles



It should also be noted that the results presented are for different driving cycles, speeds and operational characteristics, each can be seen in Appendix G. A user, when comparing vehicles, cannot compare like-with-like, as the operation of an inner city bus cannot be compared to the delivery cycles of a van or HGV on a suburban route. However the results do provide the user with a relative contribution made by each fuel type for each vehicle, which is one of the objectives of the study.

Once the results are normalised, they are able to provide information to the user on which contributions are large and small. One has already identified the largest and smallest contributors to GWP, per person, and in the case of the bus per vehicle carrying X number of people. However, identification of the relative impacts is insufficient and the results need to be weighted relative to targeted reductions. The EDIP method uses a ‘distance to target’ method in weighting, see EDIP **2** 535. The weighted results presented in Figure 7.2 are very similar to the normalised results, however they represent the targeted reduction percentages to GWP and provide a more accurate account of the individual and relative impacts of each fuel and vehicle combination. The weighted results convert the total normalised impacts into ‘real world’ reduction measures that were in place in Denmark during the 1990–2000 period. The use of a petrol van contributed to 169% of the targeted reductions set for the World and Denmark in the year 2000. If every person in the World owned a van of this type, operating under the conditions set by the simulation, it becomes clear to see that the 2000 target for GWP would never have been met. If however, each person operated and owned an electric van, the targeted reductions, which for Denmark were a 12% reduction in CO_2 between 1990-2000, would have been achieved, see example 2 in Chapter 6.

Figure 7.2 - Weighted Environmental Impact Potential for GWP with percentiles



The weighted results show that a diesel bus could have a significant person equivalent contribution to GWP of 926% and a 5% chance that this percentage could be higher, up to a fixed limit of 950%. However if 30 people used the bus this percentage would drop to 31%. These results have many implications for public services vehicles. Should a bus only be used during rush hour? Would there be less pollution for two persons to use their cars to travel to and from work in, rather than a bus with two occupants?

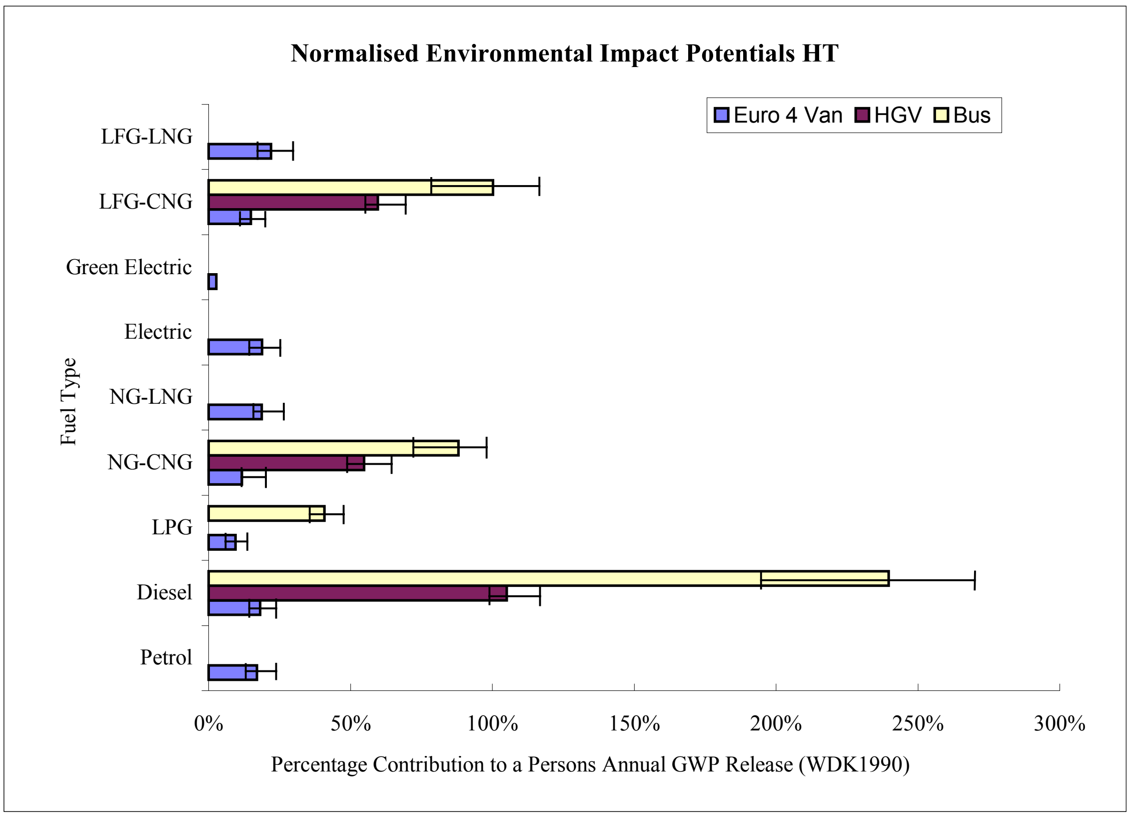
The results do show that the use of a HGV is of cause for immediate concern because there are no electric, or other less polluting, powered equivalents. Should a user view these results and identify the problem with the use of the vans, there is a solution with the purchase of electric vehicles to reduce GWP and HT. However, very few options are available for the HGV and the limited fuel choice limits any solution. The vehicles tested within the present study are of Euro 4 type with the highest emissions regulations, set for wide-scale European introduction in 2004. In the coming years there does not seem to be any immediate solution to the very real problem that exists for HGVs. Even with the use of ULSD the amount of pollutants exiting these vehicles is of cause for concern when assessing GWP and HT, as defined in the present study.

The results for HT differ from those shown in the GWP analysis. On review of Figure 7.1 and 7.3 some obvious differences occur. The NG-CNG and LFG-CNG buses have a similar impact to their equivalent HGVs. There is still a large difference between the diesel van, HGV and bus and the van life cycles contribute to HT on a similar scale. The reason why the gas buses are similar to the gas HGVs is due to the similarities in the levels of pollution, that contributes to HT, resulting from the life cycles of each vehicle. On a life cycle basis the NG-CNG HGV releases more SO_2, CO and PM than the NG-CNG Bus, which releases more NOx. Multiplying these absolute values by the equivalency factors for HT results in a larger contribution to HT from the bus in comparison to the HGV. This may seem strange given that the HGV releases more SO_2, CO and PM. Due to the fact that NOx has the largest equivalency factor of 8600 any increase is multiplied to a much larger value than say the equivalency factor for CO, which is only 830. This example highlights the important of the equivalency factors and the role they play in the calculation of HT and GWP.

Significant environmental benefits can again be seen with the use of electric vans and there is a clear separation between the benefits of electric vehicles in comparison to gas and liquid fuelled vehicles. For the vans the results for HT are similar to those of GWP in that the electric fuels are the lowest contributors and the liquid fuels are the highest contributors. There is also a lower percentage contribution per person required for HT in comparison to GWP, however the relative contributions are a little higher, with a diesel bus and HGV contributed over 13 and 6 times more towards HT than an equivalent diesel van.

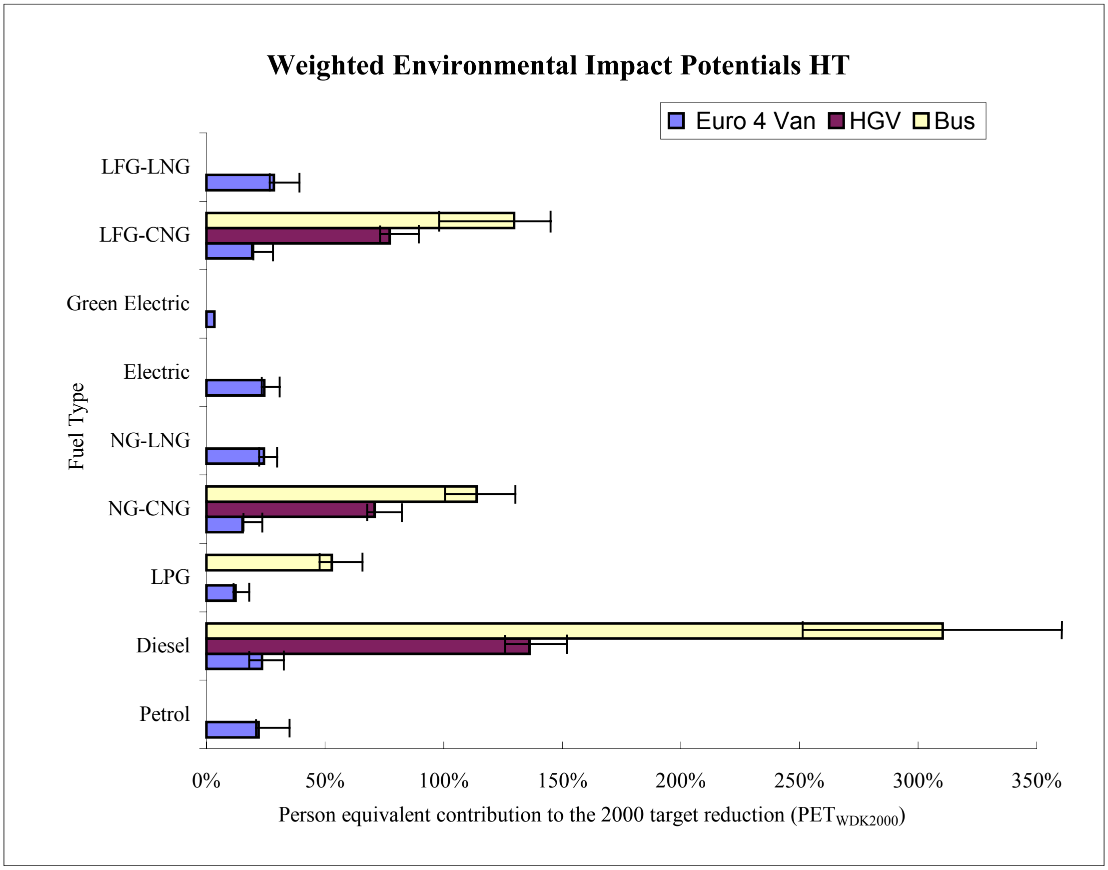
The percentiles show that in the case of HT there is a possibility of a HGV contributing the same to HT as a bus. This is an important result as it once again provides evidence of the impact of HGVs. Using the same simple calculation as for GWP, if 30 people used a bus the percentage contribution would drop from 237% to 7.9%, this would mean that on a per person basis the contribution to HT would be half that of a diesel van or equivalent to two and a half electric vehicles.

Figure 7.3 - Normalised Environmental Impact Potential for HT with percentiles



As before the normalised results only give an indication of the absolute and comparative values. For a more accurate and realistic 'real world' comparison the value are weighted as per the EDIP methodology. The results do not significantly alter but the percentage-targeted reductions are higher and a greater significance is placed on each fuel and vehicle combination.

Figure 7.4 - Weighted Environmental Impact Potential for HT with percentiles



Having identified the measures that are required in order to reduce the levels of GWP and HT to levels of acceptability for the World and Denmark, one can investigate further the actual variables that are of significant cause for concern. On identification any further research may wish to focus entirely on the variables that impact most of the life cycles of each fuel and vehicles combination. The variables are identified through an analysis of correlation coefficient.

7.5 Correlation Coefficient in @RISK

The graphs of correlation coefficient represent the sensitivity of each output variable to the input characteristics selected during the simulation. This identifies the most 'critical' inputs in the model. Once highlighted the user should concentrate on these when making decisions based upon the model. The choice of input variables is at the discretion of the user.

The correlation coefficient sensitivity analysis uses the Spearman rank correlation coefficient calculations, see Appendix Q. Within this analysis, the rank correlation coefficient is calculated between the selected output variable and the samples for each of the input variables. The higher the correlation between the input and the output, the more significant the input is in determining the output's value.

A coefficient value of 1 refers to a perfect positive correlation between the variables x and y, conversely a value of –1 refers to a perfect negative correlation between the two variables e.g. a perfect correlation (±1) means that the value of y is totally dependent on the particular x variable considered.

Figure 7.5 – Correlation Coefficient of CO_2 for a petrol van

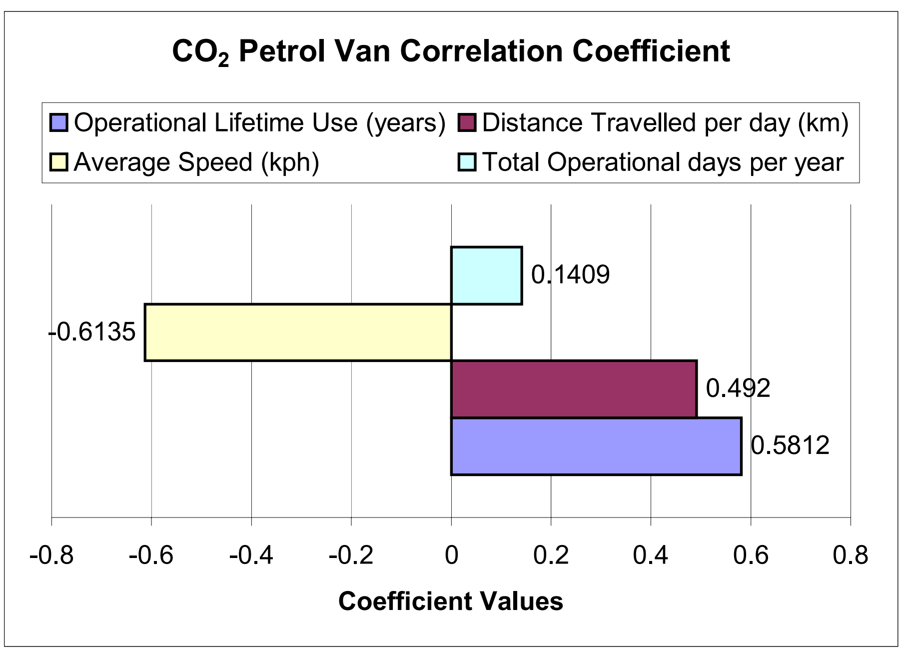


Figure 7.5 shows that the most critical variables, of those selected for simulation, see Appendix N, are average speed, operational lifetime use and distance travelled per day. All other variables, with the exception of CO, NOx and PM, are of little impact to the overall contributions to GWP and HT. The impacts of CO, NOx and PM are variable between each life cycle, however all affects are small in comparison of the overall life cycle results, see Appendix R.

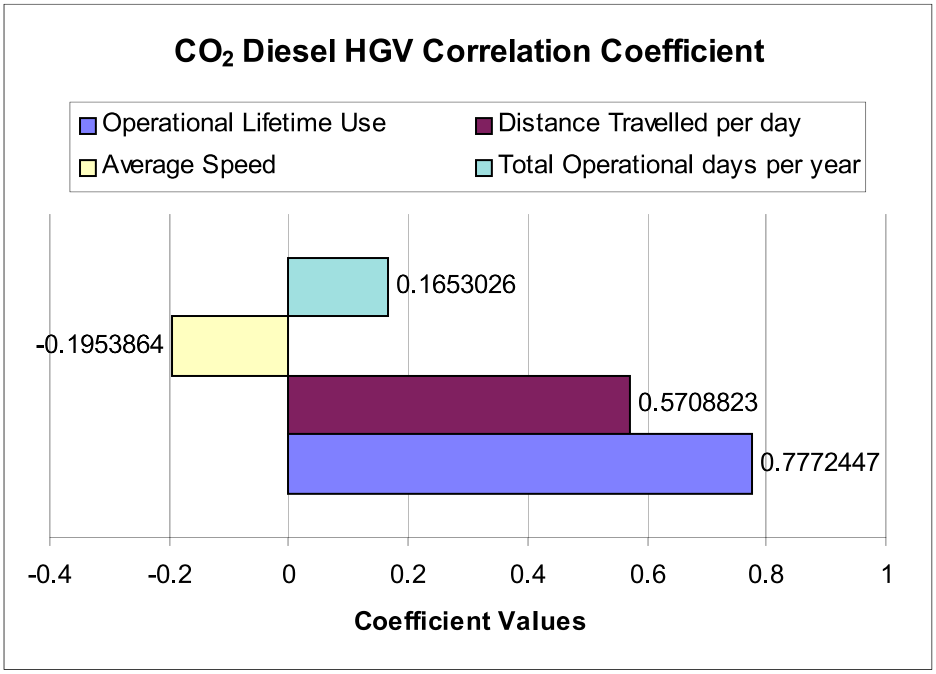
The three variables, speed, operational lifetime use and distance travelled have the largest contribution towards the generation of all the pollutants under investigation (CO_2, CO, NOx, NMHC, SO_2, CH_4 and PM) and the subsequent calculation of GWP and HT. All of these variables are used in the calculation of the emissions in the F6 stage of the life cycle for each van e.g. for simulation of a petrol van within @RISK a Beta (5,5) distribution was chosen for average speed, from a range between 10–30kph. These estimates are reasonable given the fact that a delivery van is operating in the inner city where average vehicle speeds would seldom go above 30kph or below 10kph. If the average speeds dropped below 10kph the van would be unable to make its daily deliveries. A triangular distribution was chosen for the variable, operational lifetime use, with a mean value of 15 years and minimum and maximum limits of 12 and 18 years respectively. On reflection, this distribution and choice of min/max values was correct, given that the majority of vans would not be economically viable to run after 15 years of operation and would generally be scrapped. The third variable of importance is that of distance travelled per day, again within the @RISK simulation an average value of about 130km per day was chosen with min/max limits of 100 and 160 km respectively with a beta (5,5) distribution chosen. On reflection this choice of distribution was correct; the distance travelled per day by a van would, on average, not drop below 100km and would not increase about 160km. In both cases the operational efficiency would not be adequate for any delivery or distribution operator.

A similar trend is found for each fuel, from petrol through to LFG-LNG, considered for use within the Euro 4 van; electric vehicles however are the exception to this rule, see Appendix R. The most significant stage in the analysis of the electric vehicles for GWP is from the lifetime use of the vehicle (0.98); a smaller, but significant contribution, is made from the variable operational days per year (0.24). For HT the most significant contributions are made, in rank order, from lifetime use, disposal and re-use, national transmission of electricity and operational days per year, see Appendix R.

It should be noted that these correlations result from the analysis of the van in the present study, using the distributions chosen for the simulations.

A HGV used for outer city urban road delivery was modelled with the variables listed in Appendix G. Results from the sensitivity analysis, see Figure 7.6, are very similar to the Euro 4 van. The most significant stages, in rank order, are operational lifetime use, distance travelled per day, average speed and total operational days. The same conclusions can be made for the HGV, although the average speed becomes less significant in the calculation of GWP and HT for the HGV in comparison to the van. This is due to the effect of speed against fuel consumption. In Appendix G, the speed against fuel consumption curve graph shows that a lot less fuel is consumed for the van travelling at the same speed as a HGV or bus, as one would expect; however the larger the fuel consumption (kmpg) the higher the emissions expelled from the vehicles exhaust.

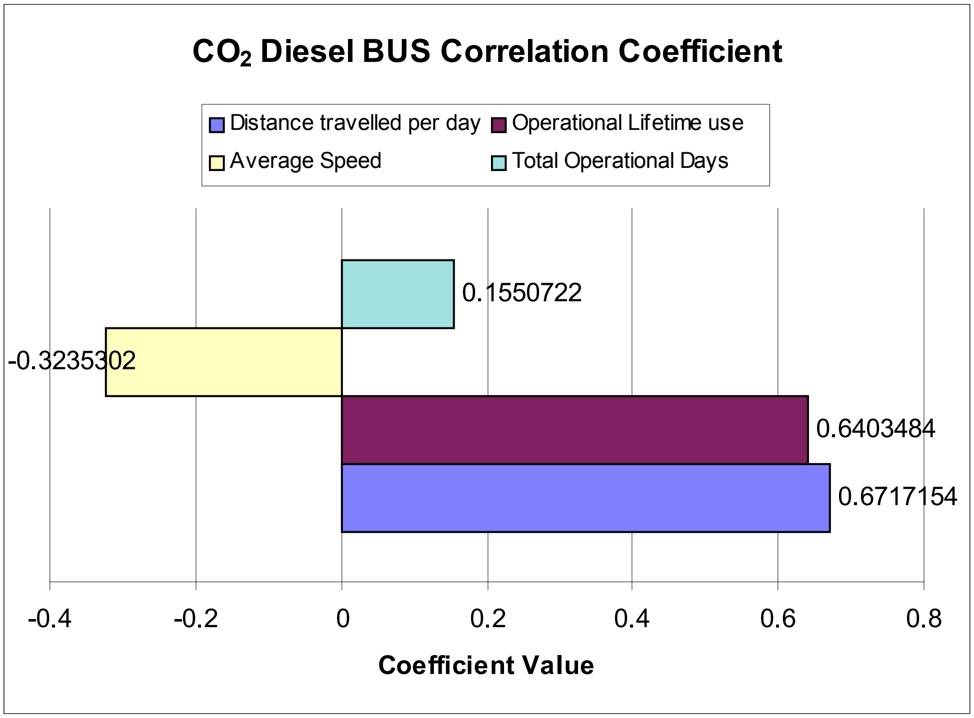
Figure 7.6 - Correlation Coefficient for a HGV



Similar coefficient values result from the NG-CNG and LFG-CNG life cycles, see Appendix R for actual results. As in the van cycles, CO (0.23), NOx (0.20) and PM (0.25) in the diesel F6 stage play a role in GWP and HT, however when compared to operational lifetime use (0.78) their contributions are minimal.

Slightly different results are drawn from the analysis of CO_2 from a diesel bus. The most significant results are ranked, distance travelled per day, operational lifetime use, average speed and total operational days. As can be seen in Figure 7.7 the distance travelled and operational lifetime use of a diesel bus are the most significant contributors to CO_2 and hence GWP. Of equal importance, they show that if the distance travelled per year or the lifetime use of a HGV was reduced the amount of CO_2 would reduce and the contribution to GWP would reduce. These results also show that if the total operational days were to be extended, the contribution to CO_2 would have less of an impact than that of increasing the distance travelled per day.

Figure 7.7 - Correlation Coefficient for a bus



Once again similar coefficient values are evident for the LPG and CNG cycles. Similarly levels of CO, NOx and PM play some role in the contribution to GWP and HT, see Appendix R.

The main differences between the van, HGV and bus correlation coefficient figures are the contributions made by average speed, operational lifetime use and total operational days. For the HGV and bus the average speed plays a less important role than the lifetime use and operational days. The lifetime use is reduced to 10 years from the 15 years of operation assumed for the van. Therefore one would expect a reduction in the contribution to CO_2 from operational lifetime use, however the lifetime use of a HGV or bus has a greater contribution to the formation of CO_2 than that of the van. This is due to the fact that if the average speed for the van is changed by a particular percentage (i.e 20kph to 30kph is equal to a percentage change of +50%), this change has a larger affect on the total CO_2 than a similar percentage change for the other input variables. In the case of the HGV and bus a 50% change in the total operational days per year has a greater contribution to the total CO_2 produced in comparison to a 50% change in the average speed.

7.6 Summary

Given that there was a wish to represent the random variation of key variables using probability distributions in which the probability mass is clustered around the mean and that there was no clear reason for introducing asymmetry, the choice between Triangular and Beta distributions is secondary. However, the Triangular distribution was used for lifetimes for largely qualitative reasons.

In the calculation of GWP and HT, the impact from each emission becomes much more apparent when it is multiplied by the equivalency factor to represent its true environmental impact e.g. CH_4 is 25 times more potent than CO_2 in the calculation of GWP.

When the results are subject to a further stage of normalisation and weighting the significance of the distributions is reduced further. The impacts are then assessed in comparison to a person-equivalent contribution. This provides a means of measuring the absolute and relative contributions each fuel and vehicle combination has on the environment. A clear distinction can be made with the various fuel and vehicle types, together with the relative and absolute impacts.

Identifying the most critical inputs in the model, shows the significance of each variable within each stage of the fuel and vehicle cycles. The average speed, lifetime use, distance travelled and operational days per year, play the most important parts in the calculation of GWP and HT, based upon the TRL UK Road Emissions database. With a different set of speed vs. emissions estimates and multiple equations, the most significant variables may differ from the ones identified in the present study. These variables alone have a greater contribution compared to any other variable within each life cycle.

Fleet operators, regional and local governments make most decisions based on fiscal and operational characteristics. The results presented in the Chapter are useful, however they become second order in relation to the procurement and operation of PSVs. If central Government opinion changed and a new 'carbon tax' or 'green tax' were to be introduced; the results of the simulation would become much more important. Any fleet operator could assess numerous vehicles that may or may not fit into a proposed 'green band' under a new taxation regime. The Life Cycle Emissions Model (LCEM) could be used as a predictor of the type of vehicle eligible for any Government backed funding or tax reductions for new or hybrid vehicles. A cost/benefit analysis could then be performed on the vehicles of interest and the uncertainty analysis would provide some measure of both the financial and environmental risks in the type of fuel and vehicle chosen by the operator.

With the present database, the uncertainty analysis has not indicated any one parameter that introduces a disproportionate degree of variability. This situation could change if, for example, the levels of non-traditional materials were to rise in the vehicle cycle as a consequence of the introduction of alternative fuels and power units having a greater degree of uncertainty attached to their toxic effects.