Can UK passenger vehicles be designed to meet 2020 emissions targets? A novel methodology to forecast fuel consumption with uncertainty analysis.

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Abstract

Vehicle manufacturers are required to reduce their European sales-weighted emissions to 95 g CO_2/km by 2020, with the aim of reducing on-road fleet fuel consumption. Nevertheless, current fuel consumption models are not suited for the European market and are unable to account for uncertainties when used to forecast passenger vehicle energy-use. Therefore, a new methodology is detailed herein to quantify new car fleet fuel consumption based on vehicle design metrics. The New European Driving Cycle (NEDC) is shown to underestimate on-road fuel consumption in Spark (SI) and Compression Ignition (CI) vehicles by an average of 16% and 13%, respectively. A Bayesian fuel consumption model attributes these discrepancies to differences in rolling, frictional and aerodynamic resistances. Using projected inputs for engine size, vehicle mass, and compression ratio, the likely average 2020 on-road fuel consumption was estimated to be 7.6 L/100 km for SI and 6.4 L/100 km for CI vehicles. These compared to NEDC based estimates of 5.34 L/100 km (SI) and 4.28 L/100 km (CI), both of which exceeded mandatory 2020 fuel equivalent emissions standards by 30.2% and 18.9%, respectively. The results highlight the need for more stringent technological developments for manufacturers to ensure adherence to targets, and the requirements for more accurate measurement techniques that account for discrepancies between standardised and on-road fuel consumption.

Keywords: Fuel consumption; energy use; vehicle emissions targets; uncertainty analysis; Bayesian; NEDC

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Highlights

- This paper introduces a Bayesian methodology to quantify new car fuel consumption.
- Model presents user with more realistic, on-road, fuel consumption estimates.
- Sources of NEDC uncertainty attributed to imprecise assumptions for resistances.
- Fuel consumption of average UK car projected to exceed 2020 emissions standards.

1 Introduction

The UK government is required to achieve an 80% reduction in national emissions by 2050, of which passenger vehicles contributed to 12.5% (73.3 $MtCO_{2\text{-eq}}$) in 2010 [1,2]. A sales weighted emission target was correspondingly imposed on vehicle manufacturers for 95 g CO_2/km by 2020 [3], all of which helped passenger vehicle emissions to decline by 22% between 2007-2013 [4]. These reductions have been largely achieved with modifications to internal combustion engine (ICE) vehicles [4], though our capacity rely on such design improvements for additional emissions reductions is largely uncertainty. Since no model is available to relate individual vehicle design changes to likely 'on-road' fleet fuel consumption, we are limited in about abilities to assess manufacturer's efforts to reduce emissions.

A particular source of ambiguity stems from the New European Driving Cycle (NEDC) [5], which is estimated to under-represent on-road passenger vehicle fuel consumption by approximately 20-25% [6]. Considering that the NEDC test is used to determine manufacturers' adherence to legislative standards, this failure has particular repercussions for the 2020 emissions targets that equate to fuel consumption ratings of approximately 4.1 L/100 km for Spark-Ignition (SI) vehicles and 3.6 L/100 km for Compression-Ignition (CI) [7]. Such NEDC testing discrepancies could allow for significant variations of up to 1.0 L/100 km (SI) and 0.9 L/100 km (CI) from real world fuel consumption, which must be considered when modelling manufacturer's adherence to fuel consumption targets.

This paper addresses two limitations of available top-down deterministic models that are used to quantify national transport energy consumption [8–10]. Firstly, the single point (i.e. deterministic) outputs from these models can be misleading to both academics and regulators, where underlying model structures and input variables are themselves subject to uncertainty. Secondly, current models are not designed to account for detailed vehicle design changes, as aggregate fuel consumption values are used to estimate annual fleet-wide energy demands. These limitations collectively hinder our ability to assess the influence of new national passenger vehicle policies and design changed on national fuel consumption. Recognising this, a new Bayesian methodology is presented in this paper, called the Cambridge Automotive Research Modelling Application (CARma), to estimate likely SI and CI fuel consumption of UK passenger vehicles from their inductive design inputs (i.e. vehicle mass, engine size and compression ratio). CARma is consequently designed to represent both NEDC and real-world driving cycles in its results, and is characterised by the following unique features:

1. *Hybrid Model Derivation* - CARma is formulated from both engineering and statistical principals that relate fuel consumption to vehicle fleet properties (engine size, compression ratio, vehicle mass and engine speeds).
2. *Prior Uncertainty Quantification* – Sources of uncertainty are categorised, and mitigation methods proposed. NEDC fuel consumption data is used to estimate uncertainties in the coefficients for the rolling resistance, aerodynamic drag, frictional powertrain loss and annual design improvements. These estimates are subsequently calibrated with open-source on-road fuel consumption data.
3. *Bayesian Model* – A Bayesian methodology is introduced to calibrate uncertain parameters, ensuring that combined information from NEDC and on-road datasets are incorporated into CARma's outputs. Results are presented as probability distribution functions.
4. *On-Road Fuel Consumption Estimation* – Stochastic passenger vehicle fuel consumption is estimated using both NEDC and real world data, allowing fleet-wide energy consumption to be uniquely linked with inductive vehicle design variables.

Having developed the CARma methodology, the model was used to quantify the likelihood of the average SI and CI vehicle, made available for sale in the UK, achieving its 2020 fuel consumption target (Section 4.4). Modelling uncertainties are similarly discussed in Section 4.2, before evolutionary projections for SI and CI vehicle mass, engine size and compression ratios are outlined in Section 4.3.

2 Background

2.1 Political Context

Environmentally sustainable growth is a cornerstone for the current UK government [11], though decarbonisation of the transport fleet is particularly difficult to achieve [12–14]. The King Review's recommendations on environmentally sustainable transport policies dismissed the existence of a single technology to reduce passenger vehicle emissions, though an emphasis on ICE vehicle development was recommend for near-term reductions [15,16]. Policies effecting UK transport emissions have henceforth avoided the promotion of one particular method to reduce passenger vehicle energy demands [17], instead choosing technological options that assume society's preferences will not change [18]. This landscape has defined how vehicle manufacturers primarily relied on ICE efficiency improvements to reduce new car emissions by 28% between 2001-2013, where the maximum contribution of ultra-low emission vehicles was just 1.3% in 2013 [4].

2.2 European Transport Models

Burgess et al. [19] reviewed the seven most prominent transport-policy models used to analyse European transportation networks, separating their methodologies into three categories; top-down equilibrium models, of which the PRIMES [20] and MoMo [21] models are prominent examples, bottom-up simulation models, such as the TRENDS [22] and TREMOVES [23,24] models and, transport network models, including the ASTRA [25], SCENES [26] and EXPEDITE [27] models. These methodologies, however, are not specific to a particular transport mode, and are unable to account for detailed passenger vehicle technology changes. A number of models have consequently been developed to specifically focus on the simulation of passenger vehicle fleets, all of which are characterised by their top-down (i.e. deductive) or bottom-up (i.e. inductive) methodologies.

Of those available deductive models, fleet-wide fuel consumption is effectively related to vehicle scrappage, propulsion system substitution [28–31] and design trade-offs [32–34], but the effects of detailed vehicle modifications are largely ignored. A number of inductive models have contrastingly been designed to relate bottom-up vehicle data to energy-use and emissions [31,35], though these models are themselves limited to extrapolate fuel consumption of an entire fleet from a small set of representative vehicles (e.g. typically <10 distinct vehicles used to represent the 35,000 distinct vehicle-models in the UK [36]). Such aggregation undervalues the true diversity of technologies at a national level, whilst the requirement for exhaustive engine map and vehicle resistance specification prevents them from being used to assess fleet-wide effects. Indeed, no model is available to specifically account for annual vehicle mass, engine size and compression ratio changes on national fuel consumption, despite an acknowledgement that such design modifications are the best means of reducing emissions in the near-term [15,16].

A deficiency of integrated bottom-up passenger vehicle models is particularly noted for the UK [18], where the majority of studies have focused on the analyses of the North American fleet. UK policy makers consequently rely on the disparate National Transport Models [8], Digest of UK Energy Statistics (DUKES) [9] and Energy Consumption UK (ECUK) models [37] to estimate national energy-use and emissions, despite the recognition that their top-down opposing methodologies converge to different conclusions [38]. Though the UK Transport Carbon Energy model was developed to account for this absence of integrated bottom-up packages [18], it too is unable to account for inductive ICE design modifications. Indeed, no available passenger vehicle model can account for detailed vehicle design changes or modelling uncertainties, despite being frequently used to inform policy makers on the optimum courses of action to take when developing policies [8–10].

2.3 Determinism of Available Vehicle Energy-Demand Models

Beyond their limitations to simulate effects of inductive design changes, present packages are equally hindered by their inability to represent influences of underling risk and modelling assumptions. Though simulation uncertainty is inherent to all scientific models and attributed to modelling inadequacies and ignorance, available transportation models have primarily embraced deterministic procedures. Indeed, just one of the available packages accounts for aggregate annual uncertainties about mean fleet fuel consumption [39], which itself is incapable of capturing detailed ICE details and specific to the North American market. Of those available UK transport fleet models [10,40,41], all are deterministic and characterised by their reliance on aggregate fuel consumption data. A new methodology is thus required to overcome the noted limitations in available vehicle energy demand models, where data and methodological uncertainties can be quantified and the effects of inductive vehicle design metrics assessed.

2.4 Sources of Uncertainty

The categorisation of modelling uncertainties is first required in vehicle simulation packages to ensure areas requiring risk mitigation are accurately identified. Several classification systems exist to distinguish between computer model uncertainties [42–44]. Among these, the Kennedy and O'Hagan scheme [44] is commonly used for statistical models. These uncertainties, and the measures adopted to mitigate them in CARma, are categorised as follows:

1. *Parameter Uncertainty and/or Observational Error* - Caused by a number of factors including insufficient data availability and inaccuracies in the NEDC testing process, parameter uncertainty can be managed by increasing the number of observations and using them to calibrate model inputs. For this study, open-source data was used to increase the sample size of fuel-consumption estimates [45], while Bayesian calibration allowed for improved parameter quantification.
2. *Model Inadequacy or Parametric Variability* - Attributed to over-simplification of systems that leaves unspecified variables, model inadequacy represents the difference between the true fuel consumption and the model estimates. This uncertainty cannot be completely eliminated due to the possibility of unknown unknowns, but its effects were mitigated in CARma by validating the statistical model with first-principal and statistical techniques.
3. *Aleatory Uncertainty* - Attributed to stochastic variability occurrin CARma is designed g within similarly defined homogeneous groups. For example, fuel consumption measurements can vary for identical vehicles tested under equivalent drive cycle conditions. Stochastic estimates were used to quantify model inputs and account for this underlying variability.

The NEDC test procedure for fuel consumption is a particularly influential source of modelling uncertainty, whose results are used to monitor the influence of current emissions policies [6]. The test is performed over a standard driving cycle, using representative vehicle for each available model, to advantageously provide a repeatable and comparable database of fuel consumption measurements. This assessment process, however, adversely provides manufactures an opportunity to optimise vehicle energy-use and emissions ratings to NEDC testing conditions. Indeed, a myriad of testing flexibilities are recognised to collectively cause deviances between NEDC and on-road fuel consumption and emissions of 21 ± 9% [6,28,46–49], many of which are listed below.

1. Acceleration patterns inaccurately represent on-road driving conditions [50]. For example, NEDC vehicles are stationary for approximately 20% of the test, which favours stop-start technologies.
2. Power and weight requirements of auxiliary systems are discounted (i.e. heating, sunroof and audio systems) [6], causing the true vehicle reference mass to be underestimated. Furthermore, air conditioning use is not included in NEDC tests, which has been shown to increase fuel consumption by up to 128% for extreme conditions [51].
3. A number of permissible flexibilities exist, including ambient test temperature, tyre specification, running-in periods, laboratory altitude, battery state-of-charge, reference mass, gear change schedule and the test track surface and grade [6]. Cumulatively, these flexibilities have been estimated to caused deviations in the order of 6-16% [52].
4. Mock et al. [46] note that certain modifications are allowed between NEDC and production vehicles, including engine control unit calibration and modification to tyre rolling resistance. Consequently, the potential for deviations between NEDC and on-road fuel consumption is further increased due to variations in the vehicles themselves.

2.5 Advantages of CARma

Recognising that available passenger vehicle energy demand models fail to both estimate uncertainty and account for evolutionary vehicle design changes, CARma was designed to stochastically estimate on-road fuel consumption for ICE vehicles sold in the UK. This Bayesian model uniquely provides the opportunity to quantify likely influences of detailed design changes on both individual-vehicle and fleet-wide fuel consumption, which no other passenger vehicle energy demand package is able to achieve.

CARma has several advantages over the available passenger vehicle models beyond its ability of relate bottom-up design metrics to vehicle fuel consumption. Its Bayesian approach advantageously foregoes the limiting requirement of other packages where data is often pre-selected and “cleaned” to remove outliers. Instead, CARma allows all data to be represented without bias and provides a natural means of representing parameter uncertainties, as initial assumptions can be updated with the acquisition of new data. This helpfully formalises the process of information acquisition, leading itself to the analysis of passenger vehicle fleets from other countries as new information becomes available.

3 Methodology

3.1 Data

CARma is designed to quantify the fuel consumption of UK SI and CI passenger vehicles using data from two sources - NEDC tests and open-source websites [45,36]. These data sources allowed for two separate models to be developed that relate physical vehicle characteristics to:

1. Rated NEDC fuel consumption in the NEDC Model (NEDC-M); and,
2. On-road fuel consumption in the On-Road Model (OR-M).

Both models were sequentially used to estimate fleet fuel consumption, where the NEDC-M was first employed to establish the prior uncertainties for model parameters. The prior distributions were subsequently calibrated with on-road fuel consumption data in the OR-M model, from which NEDC and on-road fuel consumption projections were developed. A detailed summary of data inputs and model results is presented in Section 3.2, Figure 1.

A dataset from CAP Consulting was used to specify the drivetrain, engine design and NEDC fuel consumption data of all 35,000 type-approval vehicles made available for sale in the UK since 2000 [36]. Open-source data consisted of 184,000 publically available on-road fuel consumption measurements collected from European users who each logged over 1500 km of vehicle distance travelled [45]. This selection criteria improves data integrity, yet the data's dependence on spatial location causes a bias towards continental European drivers whose driving patterns are different from those of UK drivers[1]. The Bayesian model, however, is setup to utilize new regional data when it becomes available. Consequently, parameter estimates can be updated with the acquisition of additional UK-specific data to reduce this spatial bias.

[1] The average vehicle kilometer travelled for a German citizen in 2002, for example, was 13,500 km [69] compared to 14,758 km for the average UK citizen [70].

3.2 Model Selection

The Bayesian methodology requires a statistical model of the form shown in Equation 1, where θ_i denotes the unknown parameters of the i^{th} term, and known variables are represented using β_i. First-principal derivation allowed for the inference of variables in each unknown parameter (θ_i).

$$\dot{m}_{\mathrm{f}} = \beta_1\theta_1 + \beta_2\theta_2 \ldots + \beta_i\theta_i + error \qquad (1)$$

3.2.1 First-Principal Model Selection

Indicated mean effective pressure (*imep* - a measure of usable work produced) was used to encapsulate both the break mean effective pressure (*bmep* - a measure of an engine's ability to produce work) and the frictional mean effective pressure (*fmep*- an indication of frictional losses within the drivetrain) of vehicles:

$$imep = bmep + fmep \qquad (2)$$

The *imep* was decomposed in Equation 3 to show that the total indicated work (W_{i}), normalized with respect to engine size (V_{d}), is dependent on the fuel mass flow rate ($\dot{m}_{\mathrm{f}}$), lower calorific value (Q_{LCV}) and engine efficiency ($\eta_{\mathrm{f,i}}$) [53]. Likewise, the *bmep's* normalised break work (W_{b}) was decomposed into break power (P_{b}), engine speed (N, which is represented as the difference between engine speed at maximum power and torque) and the number of crank revolutions for each power stroke per cylinder (n_{R}) in Equation 4.

$$imep = \frac{W_{\mathrm{i}}}{V_{\mathrm{d}}} = \frac{\dot{m}_{\mathrm{f}} Q_{\mathrm{LCV}} \eta_{\mathrm{f,i}}}{V_{\mathrm{d}}} \qquad (3)$$

$$bmep = \frac{W_{\mathrm{b}}}{V_{\mathrm{d}}} = \frac{\mathrm{P}_{\mathrm{b}} n_{\mathrm{R}}}{V_{\mathrm{d}} N} \qquad (4)$$

Additional inference of vehicle efficiency allowed for the incorporation of the compression ratio (r_c) into Equation 3, where A and γ were used as coefficients specific to the constant-volume (i.e. SI) and constant-pressure (i.e. CI) idealized heat addition processes [53]. This relationship is represented in Equation 5, where the compression ratio variables are incorporated into a simplified compression ratio term ($\eta_{\mathrm{f,i}} = f(r_\mathrm{c}) = Sr_\mathrm{c}$). The *imep* derivation was subsequently substituted into Equation 2, yielding the relationship presented in Equation 6.

$$imep = \frac{\dot{m}_\mathrm{f} Q_\mathrm{LCV} \eta_{\mathrm{f,i}}}{V_\mathrm{d}} = \frac{\dot{m}_\mathrm{f} Q_\mathrm{LCV}}{V_\mathrm{d}}\left[1 - \frac{A}{{r_\mathrm{c}}^{\gamma-1}}\right] = \frac{\dot{m}_\mathrm{f} Q_\mathrm{LCV}}{V_\mathrm{d}} Sr_\mathrm{c} \qquad (5)$$

$$\frac{\dot{m}_\mathrm{f} Q_\mathrm{LCV}}{V_\mathrm{d}} Sr_\mathrm{c} = bmep + fmep \Longrightarrow \dot{m}_\mathrm{f} = \frac{V_\mathrm{d}}{Q_\mathrm{LCV} Sr_\mathrm{c}}[bmep + fmep] \qquad (6)$$

Similarly, the substitution of the break power with road-loaded power under constant velocity in Equation 4 allowed for the inclusion of additional vehicle metrics (see Equation 7) [53]. These included vehicle mass (M_v), the coefficient of rolling resistance (C_R), acceleration due to gravity (g), vehicle speed (S_v), air density (ρ), the coefficient of drag (C_D) and vehicle frontal area (A_v).

$$bmep = \frac{P_\mathrm{b} n_\mathrm{R}}{V_\mathrm{d} N} = \frac{n_\mathrm{R}}{V_\mathrm{d} N}\left[C_\mathrm{R} M_\mathrm{v} g S_\mathrm{v} + \frac{\rho}{2} C_\mathrm{D} A_\mathrm{v} {S_\mathrm{v}}^3\right] \qquad (7)$$

Equations 6 and 7 were combined and compared with the required Bayesian statistical form in Equation 1. Variables for which data is unavailable are represented using the θ_i parameter and known variables (M_v [kg], V_d [cc], Sr_c, N [rpm], $Year$ [year], as shown in bold in Equation 8) are represented using the β_i parameters. Vehicle model year and error terms were further included to embody annual effects and model inaccuracies. The resulting model gives fuel consumption as a result of four θ_i parameters,

$$\dot{m}_{\mathrm{f}} = \theta_1 \underbrace{\left(\frac{\boldsymbol{M_{\mathrm{v}}}}{\boldsymbol{Sr_{\mathrm{c}}\,N}}\right)}_{\beta_1} + \theta_2 \underbrace{\left(\frac{1}{\boldsymbol{Sr_{\mathrm{c}}\,N}}\right)}_{\beta_2} + \theta_3 \underbrace{\left(\frac{\boldsymbol{V_{\mathrm{d}}}}{\boldsymbol{Sr_{\mathrm{c}}}}\right)}_{\beta_3} + \theta_4 \underbrace{(\boldsymbol{Year})}_{\beta_4} + \underbrace{e}_{\text{error}} \quad (8)$$

where, θ_1 represents $\underbrace{\frac{n_{\mathrm{R}} C_{\mathrm{R}} g S_{\mathrm{v}}}{Q_{\mathrm{LCV}}}}_{\text{Rolling}}$, θ_2 represents $\underbrace{\frac{n_{\mathrm{R}} \rho C_{\mathrm{D}} A_{\mathrm{v}} {S_{\mathrm{v}}}^3}{2Q_{\mathrm{LCV}}}}_{\text{Drag}}$ and θ_3 represents $\underbrace{\frac{fmep}{Q_{\mathrm{LCV}}}}_{\text{Friction}}$.

Finally, combined variable estimates ($\beta_1, \beta_2, \beta_3, \beta_4$) were normalized to their median 2000 value. This ensures all θ_i values have units of L/100 km and the error term represents the average fuel consumption when all parameters are set to zero. Variables were also centered about median values to ensure model convergence and increased accuracy, with normalized and centered values shown in the Appendix B of this paper.

3.2.2 Statistical Model Selection

The variables selected using the first-principal derivation where authenticated using statistical selection techniques, which ensures a fundamental understanding of CARma's both mechanical and statistical properties. Statistical parameter selection was initialised using a Variance Information Factors (VIF) stepwise selection process that eliminates multicollinearity amongst explanatory variables [54] based on coefficient of determination values (R^2) in Equation 9.

$$VIF_j = \frac{1}{1-R_j^2} \quad (9)$$

The j^{th} explanatory variable was regressed against all other explanatory variables (engine size, stroke, bore, cylinder numbers, rated power, rated torque, acceleration time, engine speeds at maximum power and torque, vehicle mass, compression ratios and capital costs) to establish a stepwise selection based on a VIF threshold of 10 (i.e. VIF $\geq$ 10 indicates variables are not independent) [54]. In this manner, all explanatory variables were eliminated expect for engine size (V_{d}), vehicle mass (M_{v}), compression ratio (Sr_{c}) and engine speeds at maximum rated power and torque (N). Using Mallow's C_p selection criterion [55], a model using all remaining explanatory variables was chosen as the best arithmetical form to achieve highest statistical significance. These statistical results justified the first-principal derivation in Equation 8, while the necessity for further transformation using a Box-Cox or equivalent function [56] was negated due to the model's adhered to the regression requirements of linearity, error independence and normality [57].

3.3 *Bayesian and Holt Methodology*

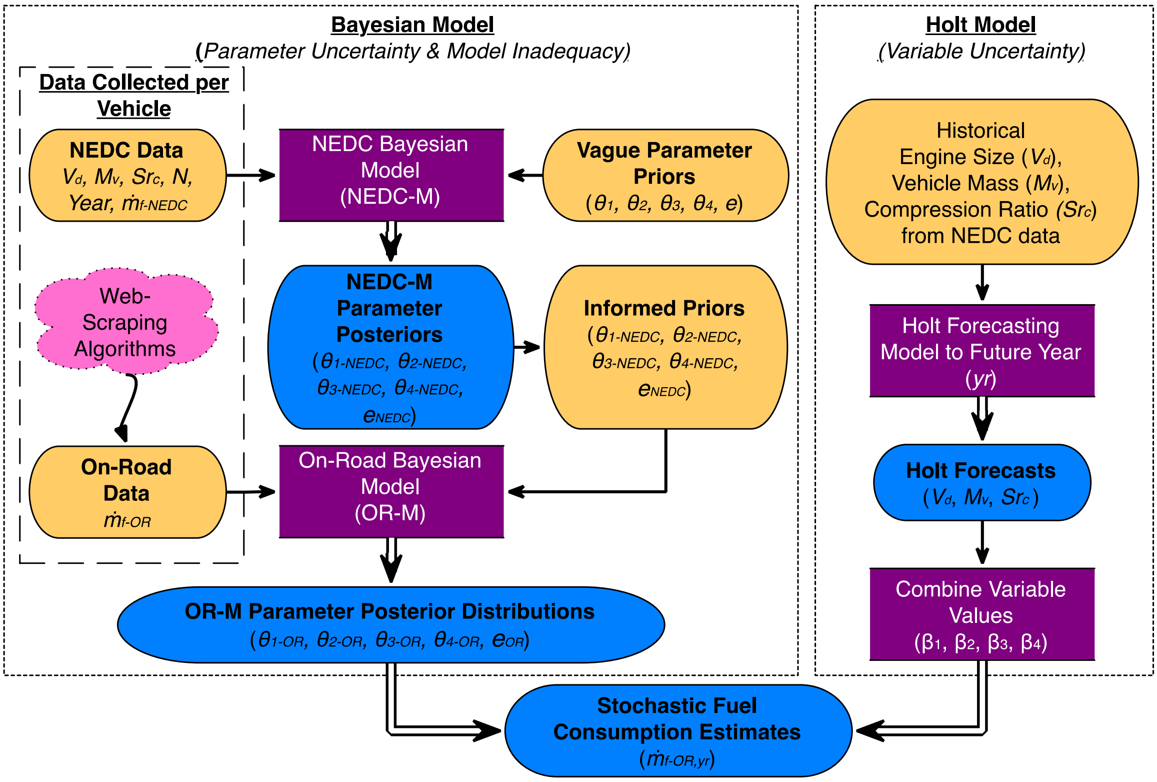

Figure 1: Schematic of CARma's structure depicting a Bayesian model (left) to determine rated and on-road fuel consumption relations and a Holt model (right) to forecast fleet metrics.

A summary of CARma's methodology is presented in Figure 1. Two models were used to account for different uncertainties, with (1) the Bayesian Model quantifying parameter uncertainty and model inadequacy; and (2) a Holt exponential smoothing model quantifying aleatory uncertainties using stochastic projections for vehicle design inputs (i.e. mass, engine size and compression ratio) [58]. Heterogeneous clustering was also performed by fuel type to reduce the variability caused by categorical dichotomies. Combined, these measurers mitigate the main identifiable sources of uncertainty (excluding model ignorance, which can only be reduced with a cumulative increase in scientific knowledge over time). Variable (i.e. Holt model outputs) and parameter (i.e. Bayesian model outputs) distributions were subsequently combined using Monte Carlo sampling to establish the final stochastic estimates for SI and CI fuel consumption.

For the NEDC-M and OR-M models, Bayesian Regression [59,60] was used to update uncertain model parameters that combine preceding knowledge with newly collected on-road data. This process is formally represented using the Bayes' formulation in Equation 10:

$$\underbrace{p(\theta|D)}_{\substack{Posterior \\ Distribution}} \propto \underbrace{p(D|\theta)}_{\substack{Likelihood \\ Function}} \cdot \underbrace{p(\theta)}_{\substack{Prior \\ Distribution}} \quad (10)$$

where, θ represents the vector of uncertain parameters, D represents fuel consumption data, and $p(\theta)$ represents the initial prior probability estimates for uncertain parameters based on NEDC data alone. Likewise, the statistical relationship among model variables and data is represented by a likelihood function $p(D|\theta)$, while $p(\theta|D)$ represents the posterior (calibrated) distributions of uncertain parameters that incorporate all available knowledge for fuel consumption (i.e. original NEDC and collected on-road data). As a result of the Bayesian Regression, the prior estimates of model parameters are updated with the information contained in the on-road fuel consumption data. Additionally, the posterior distributions of the model parameters are shown in Equation 10 to be proportional to the prior estimates and the likelihood, where the likelihood function quantifies how probable it is that the fuel consumption data is explained by the statistical model under the given set of uncertain parameters.

No prior estimates were available for the unknown parameters in the NEDC-M and vague priors were thus chosen. The posterior probability distributions ($p(\theta|D)$) for model parameters, obtained from the NEDC-M, were used as prior distributions in the OR-M. All results were developed using 50,000 Markov Chain Monte Carlo iterations in the Bayesian OpenBUGS software platform [61].

The posterior distributions inferred from this two-step Bayesian Regression represent the first-order uncertainty (i.e. the random variation around an average value) for each parameter within a sub-group of vehicles. Combining these posterior distributions with single value inputs for vehicle mass, engine size and compression ratio allows for the stochastic estimation of fuel consumption that accounts for model inadequacy and data uncertainty. The additional specification of the four input variables (β_i) as probability distribution functions incorporates second-order uncertainties into CARma, which stem from a lack of knowledge about the values of the input parameters themselves. These distributions were produced using the Holt exponential smoothing method [58], where the weighted average of past observations was used to forecast expected values to the year 2020. Weights were chosen to decline exponentially over time so that recent observations contribute to the forecasted estimate more than earlier observations. This technique is widely used for the development of national statistical forecasts [62] and provides the means of projecting future vehicle mass, engine size and compression ratios in CARma.

Finally, a note of caution is presented on the interpretation of derived parameter estimates, since the calibration of just four parameters causes other (uncalibrated) parameter uncertainties to be "lumped" into developed estimates. The selected calibration parameters should therefore be viewed as "pseudo-variables" that can cease to correspond to physically meaningful quantities. Though this approach is useful when developing fuel consumption forecasts from inherently uncertain input data (as is the intended function of this model), uncertainties due to ignorance are also partially lumped into the calibration parameters, which increases difficulty when interpreting a physical meaning from parameter estimates.

4 Results

4.1 NEDC Discrepancy and Model Validation

A comparison between the 35,000 NEDC and 184,000 on-road fuel consumption measurements in Table 1 shows that the mean on-road fuel consumption is 16.1% and 12.5% higher than rated NEDC estimates for SI and CI vehicles, respectively. On average, NEDC tests underestimate actual fuel consumption by 0.96 L/100 km for SI vehicles and 0.98 L/100 km for CI. Larger standard deviations (SD) are noted in the open-source on-road data due to a larger variation in drive cycles and user driving styles.

Table 1: Mean and standard deviation (SD) of NEDC and on-road fuel consumption for UK model years 2000-2011.

Propulsion System	NEDC Rated Fuel Consumption		On-Road Fuel Consumption		Discrepancy	
	Mean [L/100km]	SD	Mean [L/100km]	SD	Mean [L/100km]	SD
SI	5.95	1.22	6.90	1.48	0.96	1
CI	7.84	1.76	8.82	2.01	0.98	1.28
All	7.02	1.81	7.99	2.04	0.97	1.16

The form of the statistical model in Equation 8 was validated using 10-fold cross-validation to compare model estimates against separate test data [63]. For this process, NEDC data was partitioned into 10 equal subsamples, each of which were randomly split into two groups - 90% for model training and 10% for model testing. The 10 accuracy assessments were combined to give a measure of the model’s predictive performance using the mean squared error, which was estimated at 1.65. Results from this 10-fold cross validation are depicted in Appendix A, where modelled CARma estimates are shown to compare favourably against collected fuel consumption values. The statistical model form was also validated using linear regression, where the coefficients of determination were calculated to be 0.80 for CI vehicles (residual standard error of 0.65) and 0.82 for SI (residual standard error of 0.93).

4.2 Calibration of Model Parameters

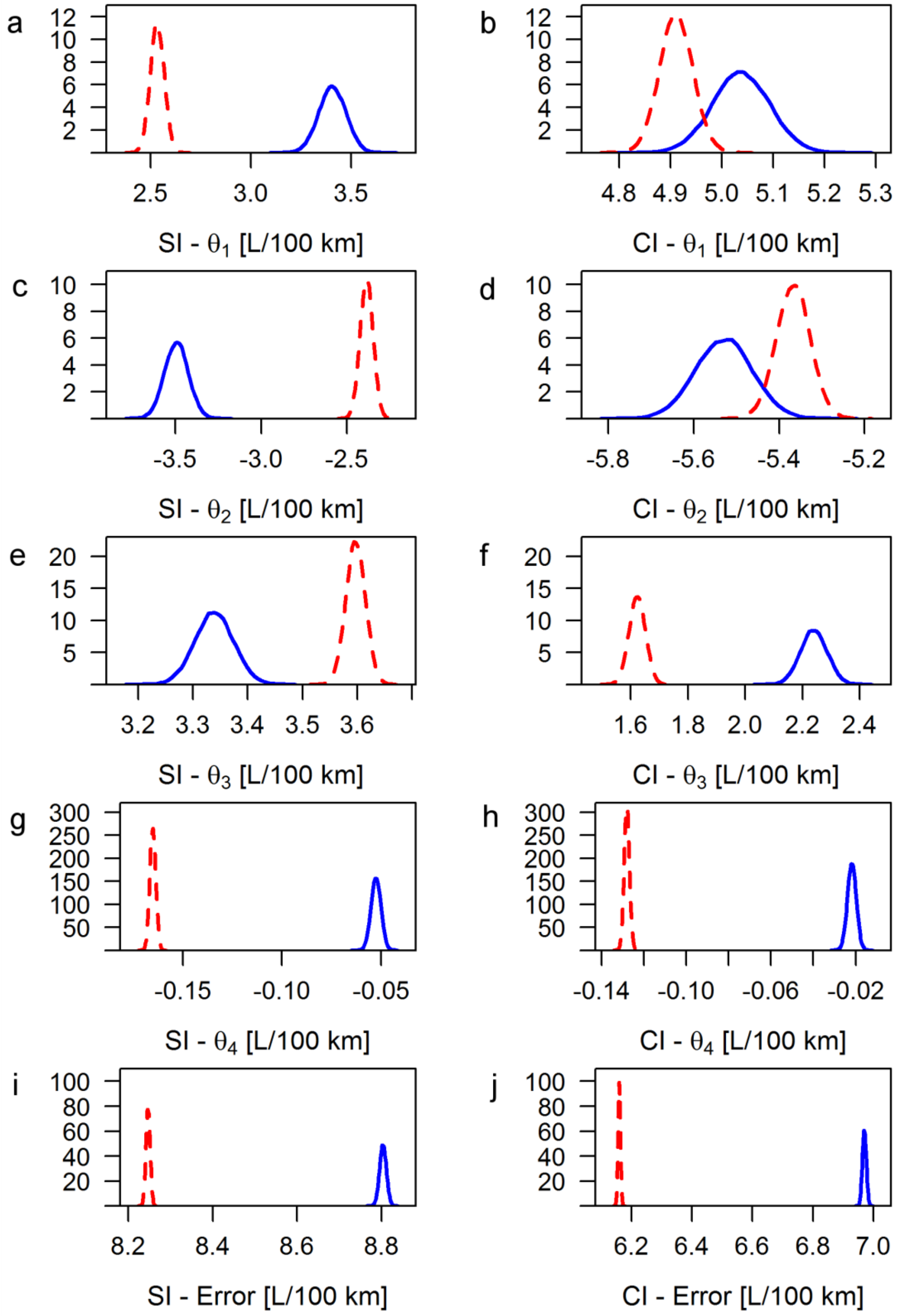

Figure 2: SI and CI prior (red dashed line for NEDC-M) and posterior density distributions (blue solid line for OR-M) for θ and error terms in units of L/100 km. Error terms represent average NEDC (prior) and on-road (posterior) fuel consumption when normalised model variables are set to zero.

Results from the Bayesian calibration process are shown in Figure 2 as prior and posterior distributions for the unknown model parameters[2] (*θ_1, θ_2, θ_3, θ_4, error*). These distributions are the primary outcomes from the calibration process and help to determine how the input variables influence fuel consumption under NEDC and on-road driving conditions. Larger absolute magnitudes indicate a greater influence on fuel consumption, while greater parameter variance represents more uncertainty around their expected values. The spread of uncertainties are noted to have increased for all parameters following the Bayesian calibration, indicating that variability within the NEDC is less than real-world drive cycle variability.

A comparison between the SI and CI distributions (see Equation 8) shows that on-road vehicles overestimate the θ_1 parameter by an average of 34.8% for SI vehicles and 2.6% for CI. As all θ_1 parameters are fixed other than C_r, these distortions can be thought of as the change in rolling resistance between the NEDC and on-road drive cycles, which can be achieved by over-inflating tires [64], reducing frictional losses [65], wheel realignment, and break adjustment (all of which are free parameters set by manufacturers during the NEDC tests) [52]. Similar trends are noted for the second group of unknown parameters (θ_2), in which the coefficient of drag term dominates. Here, aerodynamic drag is shown to have a greater influence on on-road fuel consumption compared to NEDC fuel consumption (on-road θ_2 is 46.6% lower for SI and 3.0% lower for CI), which may be caused by deviations between the average SI and CI vehicle coefficients of drag. Overall magnitudes of θ_2 parameter estimates are also lower for CI compared to SI vehicles, which indicates that the influence of the drag coefficient on fuel consumption is greater for CI, compared to SI, vehicles (mean CI prior is -5.37 L/100 km compared to -2.38 L/100 km for SI; mean CI posterior is -5.53 L/100 km compared to -3.49 L/100 km for SI).

[2] Prior and posterior distributions are represented as probability density functions (PDFs). These PDF's encapsulate the probability of a variable falling within a certain range, whose cumulative area is equal to one.

Opposing trends are shown for parameter θ_3 in Figure 3 e and f, implying that the NEDC overestimates frictional powertrain losses by an average of 7.8% for SI vehicles, but underestimate them by 32.3% for CI. Additionally, the magnitudes of NEDC-M and OR-M θ_3 values are higher for SI vehicles compared to CI (mean SI prior is 3.60 L/100 km compared to 1.62 L/100 km for CI), contrasting the results for the θ_2 term. Overestimation of frictional losses may be attributed to a higher number of trips running under low engine load conditions in the on-road dataset. Considering that 50% of European trips are known to be less than 3 km in length [66], the results may highlight an overrepresentation of the extra-urban driving cycle in the combined SI NEDC estimates. Nevertheless, the relatively higher mass and compression ratios of CI vehicles causes them to have increased *fmep* fractional losses compared to SI engines [67]. As the NEDC test is unable to account for such discrepancies when using a standardized test cycle, the differences in mean parameter estimates are likely attributed to such design differences.

A comparison between mean error terms shows average fuel consumption is higher for on-road vehicles when all parameter values are set to zero (8.80 L/100 km for on-road SI compared to 8.25 L/100 km; 6.97 L/100 km for on-road CI compared to 6.16 L/100 km). The influence of the vehicle model year parameter (θ_4) on SI and CI fuel consumption also reduced from -0.165 L/100 km yr^{-1} to -0.053 L/100 km yr^{-1}, and -0.128 L/100 km yr^{-1} to -0.022 L/100 km yr^{-1}, respectively, between the NEDC-M and OR-M models. This trend is attributed to the increased year-on-year optimization of vehicle designs to the NEDC standard, a practice that allows vehicle manufactures to maximize adherence to legislative emissions standards. The results imply that realistic OR-M vehicle design changes (θ_4) have a more limited influence on realistic fuel-consumption compared to NEDC estimates, which further undermines the accuracy of NEDC results.

Finally, complete formula showing mean parameter values for both NEDC-M and OR-M models are presented for SI (Equations 11 and 12) and CI vehicles (Equations 13 and 14). Mean prior and posterior values are shown for each θ_i parameter whilst, mean values for base year variables in 2000 ($\overline{\beta_{i,2000}}$) and across all years ($\overline{\beta_i} = \overline{\left(\frac{\beta_i}{\beta_{i,2000}}\right)}$) are presented in Appendix B.

$$\dot{m}_{\mathrm{f,NEDC-SI}}\left[\frac{\mathrm{L}}{100\ \mathrm{km}}\right] = \left\{\left(\frac{\beta_1}{\overline{\beta_{1,2000}}} - \overline{\beta_1}\right)\underbrace{2.53}_{\theta_1} - \left(\frac{\beta_2}{\overline{\beta_{2,2000}}} - \overline{\beta_2}\right)\underset{\theta_2}{2.38} + \left(\frac{\beta_3}{\overline{\beta_{3,2000}}} - \overline{\beta_3}\right)\underbrace{3.60}_{\theta_3} - \left(\frac{\beta_4}{\overline{\beta_{4,2000}}} - \overline{\beta_4}\right)\underbrace{0.165}_{\theta_4} + \underbrace{8.25}_{error}\right\}\left[\frac{\mathrm{L}}{100\ \mathrm{km}}\right] \quad (11)$$

$$\dot{m}_{\mathrm{f,OR-SI}}\left[\frac{\mathrm{L}}{100\ \mathrm{km}}\right] = \left\{\left(\frac{\beta_1}{\overline{\beta_{1,2000}}} - \overline{\beta_1}\right)\underbrace{3.41}_{\theta_1} - \left(\frac{\beta_2}{\overline{\beta_{2,2000}}} - \overline{\beta_2}\right)\underset{\theta_2}{3.49} + \left(\frac{\beta_3}{\overline{\beta_{3,2000}}} - \overline{\beta_3}\right)\underbrace{3.34}_{\theta_3} - \left(\frac{\beta_4}{\overline{\beta_{4,2000}}} - \overline{\beta_4}\right)\underbrace{0.053}_{\theta_4} + \underbrace{8.80}_{error}\right\}\left[\frac{\mathrm{L}}{100\ \mathrm{km}}\right] \quad (12)$$

$$\dot{m}_{\mathrm{f,NEDC-CI}}\left[\frac{\mathrm{L}}{100\ \mathrm{km}}\right] = \left\{\left(\frac{\beta_1}{\overline{\beta_{1,2000}}} - \overline{\beta_1}\right)\underbrace{4.91}_{\theta_1} - \left(\frac{\beta_2}{\overline{\beta_{2,2000}}} - \overline{\beta_2}\right)\underbrace{5.37}_{\theta_2} + \left(\frac{\beta_3}{\overline{\beta_{3,2000}}} - \overline{\beta_3}\right)\underbrace{1.62}_{\theta_3} - \left(\frac{\beta_4}{\overline{\beta_{4,2000}}} - \overline{\beta_4}\right)\underbrace{0.128}_{\theta_4} + \underbrace{6.16}_{error}\right\}\left[\frac{\mathrm{L}}{100\ \mathrm{km}}\right] \quad (13)$$

$$\dot{m}_{\mathrm{f,OR-CI}}\left[\frac{\mathrm{L}}{100\ \mathrm{km}}\right] = \left\{\left(\frac{\beta_1}{\overline{\beta_{1,2000}}} - \overline{\beta_1}\right)\underbrace{5.04}_{\theta_1} - \left(\frac{\beta_2}{\overline{\beta_{2,2000}}} - \overline{\beta_2}\right)\underbrace{5.53}_{\theta_2} + \left(\frac{\beta_3}{\overline{\beta_{3,2000}}} - \overline{\beta_3}\right)\underbrace{2.24}_{\theta_3} - \left(\frac{\beta_4}{\overline{\beta_{4,2000}}} - \overline{\beta_4}\right)\underbrace{0.022}_{\theta_4} + \underbrace{6.97}_{error}\right\}\left[\frac{\mathrm{L}}{100\ \mathrm{km}}\right] \quad (14)$$

4.3 Holt Projections

Projections for the engine size, vehicle mass and compression ratio of SI and CI vehicles were derived from an analysis of NEDC rated data from 2001 to 2011. Historical annual averages were used as inputs into the Holt exponential smoothing model, where known data is represented in Figure 3 using the red regression line and the Holt model is represented using the blue. This methodology allows an accurate representation of historical and irregular trends, and second-order uncertainties are shown to increase from 2011 to 2020 using a 95% normal predictive interval about mean forecasted values.

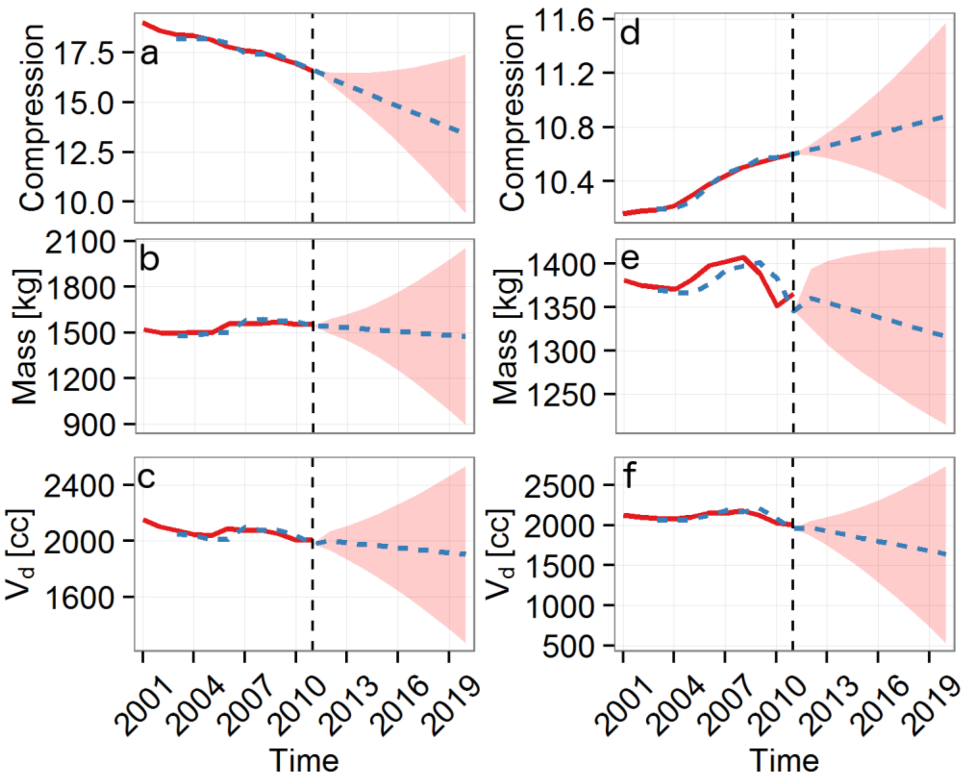

Figure 3: Holt forecasts (dashed blue line) and historical data (solid red line) for (a-b) compression ratio, (c-d) mass and (e-f) engine size of the average CI (left) and SI (right) passenger vehicle available for sale in the UK from 2011 to 2020.

An analysis of historical CAP data shows evolutionary changes in UK passenger vehicle designs that have helped improve fuel efficiencies over time. For CI vehicles, the average engine size reduced by 6.55% between 2001 and 2011 (2153 cc to 2012 cc), which helped to reduce fuel consumption. During the same period, average CI vehicle mass modestly increased by 2.43%, though a reduction from 1571 kg to 1553 kg is noted from 2009 onwards. For SI vehicles, average compression ratios increased from 10.2 to 10.6 across the decade as manufacturers endeavoured to increase fuel conversion efficiencies. Additional reductions in SI mass and engine size (-1.09% and 5.73%, respectively) also helped to improved efficiencies of SI vehicles.

Historical trends were projected using the Holt forecasts, with engine speeds at maximum power and torque assumed constant at 2011 averages (see Appendix B for values). The largest forecasted changes, relative to 2011 data, are for the compression ratio of CI vehicles and the engine size of SI vehicles that are correspondingly projected to decrease by 19.08% (16.56 to 13.40) and 18.39% (2007 kg to 1638 kg). Both trends are consistent with historical data and allow for the continued improvement of SI and CI environmental impact. Modest changes were projection for SI compression ratio (+2.64% to 10.88) and mass (-3.59% to 1317 kg), while forecasts for CI mass and engine size were more significant, at -4.96% (to 1476 kg) and -5.37% (to 1904 cc), respectively.

4.4 Forecasts for 2020 Fuel Consumption

The distributions of unknown model parameters (θ_i) and input variables (β_i) were combined using Monte Carlo factorial sampling to forecast the likely fuel consumption of the average SI and CI vehicle available for sale in 2020. These results are presented in Figure 4 as probability distribution functions, where the ordinate specifies the relative probability of the estimate, and the variance in fuel consumption is shown on the abscissa. Likely 2020 estimates for on-road SI fuel consumption were 7.60 L/100 km, with a 50% probability consumption between 7.22 and 7.98 L/100 km. Similarly, the expected on-road fuel consumption of the average CI vehicle was 6.44 L/100 km, where the 50% confidence interval was between 6.01 and 6.88 L/100 km.

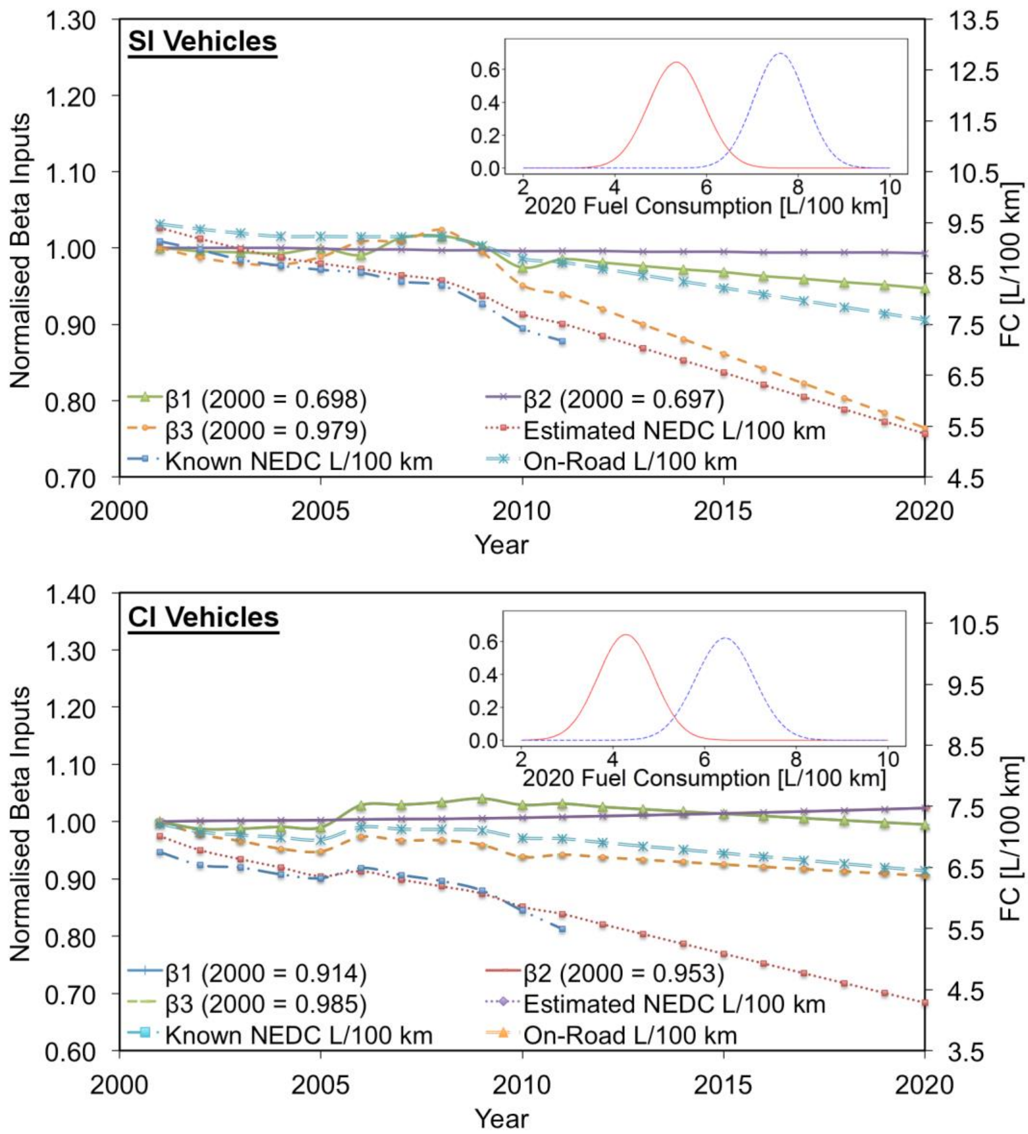

Figure 4: Main - Temporal projections for parameter inputs and NEDC fuel consumption for SI (top) and CI (bottom) vehicles. Inlay - CARma forecasts for the likely NEDC (red solid lines) and on-road (blue bashed lines) fuel consumption of the average SI (top) and CI (bottom) vehicle available for sale in 2020.

Comparing the projected 2020 on-road fuel consumption to 2011 averages (8.25 L/100 km for SI and 6.94 L/100 km for CI; NEDC ratings of 7.16 and 5.47 L/100 km, respectively), shows likely reductions in the fuel consumption of 7.9% (SI) and 7.2% (CI). These reductions are lower than those achieved from 2001 to 2011 (estimated using CAP data to be 22.0% for SI vehicles and 18.7% for CI), and indicate that the potential to improve fuel economy from evolutionary technological developments alone is diminishing. Furthermore, a 50% chance exists that the reductions in fuel consumption will be between 3.3% and 12.7% for SI vehicles and 0.9% and 13.4% for CI, when confidence intervals are considered.

Adherence to the fuel-equivalent emissions targets of 2020 is based on NEDC test results, and a direct comparison to CARma posterior forecasts (which account for on-road uncertainties) is not entirely appropriate. The NEDC-M distributions were consequently used to establish likely 2020 fuel consumption based on NEDC data alone, from which likely estimates of 5.34 and 4.28 L/100 km were derived for the corresponding SI and CI vehicle (see Figure 4). Even with this consideration, the average SI and CI vehicle was still expected to exceed its respective target by 30.2% and 18.9%. The results indicate that additional vehicle design changes, beyond those evolutionary developments considered in this study, may be required for vehicle manufacturers to adhere to their mandated sales weighted emissions targets. This study, however, excludes sale-weighted data and simply reviews the fuel consumption of the average available SI and CI vehicle. Consequently, the fleet averaged targets may still be achieved with the sale of smaller, lighter vehicles that compensate for the average technologies.

The exceedance of both SI and CI technologies to the 2020 NEDC goals highlights the extraordinary technological changes required by manufacturers to avoid fleet-weighted exceedance. CARma provides a novel method to attribute the differences between rated and on-road fuel consumption estimates to specific technological assumptions for the rolling, frictional, aerodynamic and annual efficiency gains. Indeed, the optimisation of vehicle designs to NEDC conditions is shown to over-represent annual reductions in fuel consumption by 310% of the on-road SI estimate and 580% the CI (see Figure 4). This has direct implications of the true fuel efficiency gains achieved by manufacturers, as 2020 on-road estimates exceeded 2020 rated values by 41.9% and 50.5% for SI and CI vehicles, respectively. NEDC limitations, however, are widely recognised by academics and regulators and the development of the Worldwide Harmonized Light Vehicles (WHLV) standard is currently underway to better predict exhaust emissions and fuel consumption under real-world driving conditions [68]. Once the WHLV standard is implemented, the Bayesian methodology will allow for new WHLV data to be included in the derived model, using CARma parameter posteriors from this paper as the priors in future work. Consequently, the accuracy of CARma fuel consumption estimates will increase, while differences between testing standards can also be quantified.

5 Conclusions

This paper introduces a new methodology to quantify the fuel consumption of the UK's light-duty vehicle fleet, where historical data has been used to project the likely energy-demands of the average SI and CI vehicle out to 2020. The proposed CARma model uniquely tracks the effects of inductive ICE-vehicle design changes on fleet-wide fuel consumption, while its ability to estimate uncertainties is similarly noted for its novelty. Discrepancies between NEDC and on-road fuel consumption were quantified, where the NEDC was shown to underestimate SI and CI fuel consumption by an average of 16.1% and 12.5%, respectively. A comparison between derived prior and posterior coefficients similarly revealed NEDC tests to underestimate the influence of aerodynamic losses and rolling resistances in both SI and CI vehicles. In particular, the optimisation of vehicle designs to the NEDC test conditions was shown to over-represent actual reductions in fuel consumption by an average of 310% of the on-road SI estimate and 580% of the CI.

Evolutionary SI vehicle design changes were forecast from 2011 to 2020 using a Holt exponential smoothing model, with engine size projected to fall by 18.4%, weight by 3.6% and compression ratio was projected to increase by 2.6%. Similar changes were forecast for the average CI vehicle, as engine size was predicted to fall by 5.5%, weight by 5.0% and compression ratio by 19.5%. Using future vehicle design forecasts as inputs in the CARma model, the average SI vehicle fuel consumption was estimated to be 7.60 L/100 km, with a 50% likelihood between 7.22 and 7.98 L/100 km. Likewise, the most likely estimate for the average CI vehicle was 6.44 L/100 km, with a 50% likelihood between 6.01 to 6.88 L/100 km. Both passenger vehicles exceeded their 2020 NEDC fuel equivalent targets by 30.2% and 18.9%, respectively. This indicates that evolutionary design developments alone are unlikely to allow for the required reductions in vehicle consumption to be achieved.

Finally, variability in the results highlights an underlying need to incorporate uncertainty when forecasting the influence of vehicle design changes on fuel consumption. The CARma model applies clustering to handle heterogeneity of SI and CI vehicles, whilst a Monte Carlo simulation was used to estimate the uncertainties about future vehicle design variables. As CARma is designed to utilise open-source fuel consumption data, the model can be easily adapted to quantify fuel consumption in other national vehicle fleets. Work is presently underway to allow CARma to be used in both fleet-wide and single vehicle projection studies, while the inclusion of fuel consumption ratings from additional testing standards can also be considered to improve the accuracy of parameter estimates. A true understanding of uncertainty provides a better appreciation of likely changes in fuel consumption out to 2020, and highlights the requirements for additional efforts to meet emissions targets.

6 Acknowledgements

NEDC data measurements were supplied by CAP Consulting. The authors are also grateful to the Energy Efficient Cities Initiative and the EPSRC (EP/F034350/1) for funding this work.

7 Nomenclature

Acronym	Definition
NEDC	New European Driving Cycle
SI	Spark ignition
CI	Compression ignition
CARma	Cambridge Automotive Research Modelling Application
ICE	Internal combustion engine
NEDC-M	New European Driving Cycle model
OR-M	On-road model
θ	CARma model parameter
β	CARma model variable
imep	Indicated mean effective pressure
bmep	Break mean effective pressure
fmep	Frictional mean effective pressure
Wi	Total indicated work
V_d	Engine size
$\dot{m}_f$	Fuel mass flow rate
Q_{LCV}	Lower calorific value
$\eta_{f,i}$	Engine efficiency
W_b	Normalized break work
P_b	Break Power
N	Engine Speed
n_R	Number of crank revolutions for each power stroke per cylinder
r_c	Compression Ratio
A	Coefficient distinguishing between idealised constant-volume and constant-pressure thermodynamic process
γ	Heat capacity coefficient of idealised constant- volume and constant-pressure thermodynamic processes
Sr_c	Simplified compression ratio
M_v	Vehicle mass
C_R	Coefficient of rolling resistance
S_v	Vehicle speed
ρ	Air density
C_D	Coefficient of drag

A_v	Vehicle frontal area
kg	Kilograms
cc	Cubic centimetres
rpm	Revolutions per minute
g	Acceleration due to gravity
VIF	Variance information factors
R^2	Coefficient of determination
$p(\theta\|D)$	Bayesian posterior distribution
$p(D\|\theta)$	Bayesian likelihood function
$p(\theta)$	Bayesian prior distribution
SD	Standard deviation
WHLV	Worldwide Harmonized Light Vehicles

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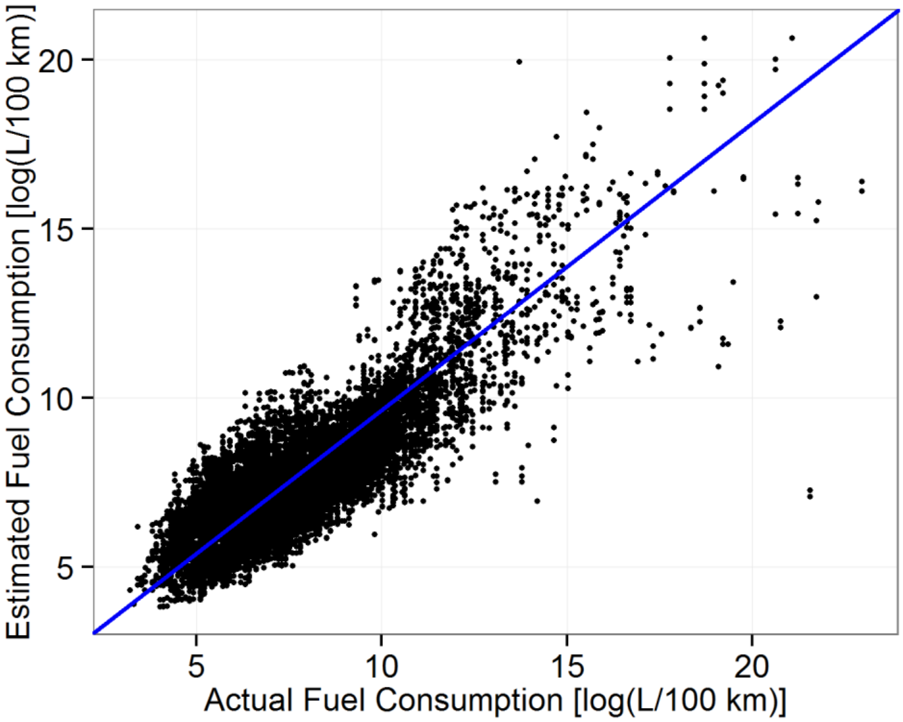
Appendix A



Comparison between measured and actual fuel consumption, using 10-fold cross validation of CARma. R^2 = 0.80 of CI and 0.82 for SI.

Appendix B

Normalised and centred variable values used in the NEDC-M and OR-M models.

Variable	SI	CI
$\overline{\beta_{1,2000}}$ [rpm kg^{-1}]	0.8246	0.8065
$\overline{\beta_{2,2000}}$ [rpm]	0.0005978	0.000509
$\overline{\beta_{3,2000}}$ [cc^{-1}]	2411	2306
$\overline{\beta_{4,2000}}$ [year^{-1}]	1	1
$\overline{\beta_1} = \overline{\left(\frac{\beta_\iota}{\overline{\beta_{1,2000}}}\right)}$	0.8939	0.9765
$\overline{\beta_2} = \overline{\left(\frac{\beta_\iota}{\overline{\beta_{2,2000}}}\right)}$	0.9372	1.014
$\overline{\beta_3} = \overline{\left(\frac{\beta_\iota}{\overline{\beta_{3,2000}}}\right)}$	0.9055	0.9427
$\overline{\beta_4} = \overline{\left(\frac{\beta_\iota}{\overline{\beta_{4,2000}}}\right)}$	6.879	7.961
Engine Speed – Maximum Torque [rpm]	3125	1748
Engine Speed – Maximum Power [rpm]	5786	3923