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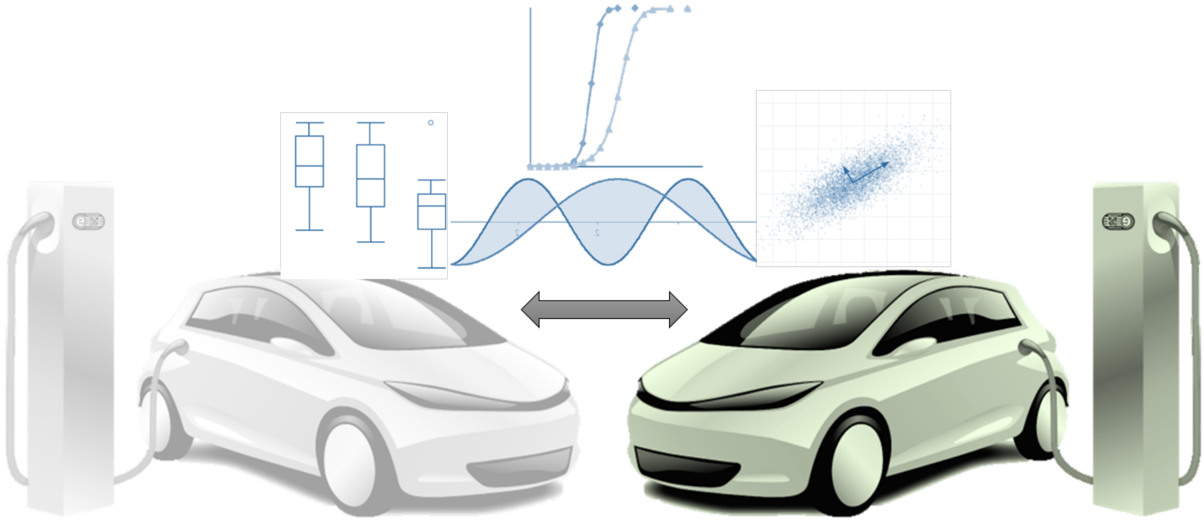

Validation of Virtual Vehicles

Master's thesis in Automotive Engineering

AKHIL KATHRIKOLLI NEELAKANTA
SAKETH RATAKONDA

Department of Mechanics and Maritime Sciences
CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2018

Master's thesis 2018:92

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Akhil Kathrikolli Neelakanta
Saketh Ratakonda

Department of Mechanics and Maritime Sciences
Division of Combustion and Propulsion Systems
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Akhil Kathrikolli Neelakanta
Saketh Ratakonda

Supervisor: Mikael Lilja, Volvo Car Group
Examiner: Sven B Andersson, Chalmers University of Technology

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Chalmers University of Technology
SE-412 96 Gothenburg

Cover: BMW i3 charging illustrated against model and system, being correlated using statistics, Image courtesy: Electric vehicle Car Battery charger BMW i3 Charging station - Parking Sensor.

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Abstract

This Master thesis work, performed at the Vehicle Energy Efficiency department at Volvo Car Group, presents a methodology to validate simulation models with reference to test rig data. *VSim*, a complete vehicle simulation tool, consists of various component models that work in unison to replicate energy flows in a vehicle and come up with performance metrics. There is a need to validate these models and to subjectively and objectively determine how well these models emulate the energy flows in real world systems.

Subjective and Objective validation methods were devised based on the literature survey, and implemented on two power source components in *VSim*, the High Voltage Battery and Combustion Engine. Error plots and box plots were used to analyse the models subjectively, while the Russell's error measure and the PCA-Area metric method were utilised for determining objective validation numbers. Based on these plots and numbers, a general analysis was done showing specifics about the correlation and the relevance of the validation metrics when related to the plots.

The analysis of the results showed that the validation code provides metrics that can help the model developer analyse the errors between simulation and test. The objective measures interpret the behaviour of the output signals and their differences quite well, and correspondingly reflect the trends seen in the subjective plots. This analysis aims at providing feedback to the model developers at Volvo Car Group in order to perform an update where needed in the model. Finally, certain improvement areas in the methodology were highlighted to be researched for future work.

Keywords: Validation, Energy flow, Simulation, Models, Correlation, Box plots, Russell's error measure, Principle Component Analysis, Area Metrics.

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Firstly, we would like to thank our guide and supervisor, Mikael Lilja, for his productive ideas and continuous inputs. Those have helped us shape our methodologies and give an overall solid structure to our work here at Volvo Cars. The acknowledgement extends to the entire *VSim* development team for their support in making us understand our intent in a better way, by sharing with us their expertise in the simulation software. Special thanks to the team manager, Jonas Henningson, for his support throughout the thesis tenure.

A lot of our thesis work involved interactions with the component owners and test rig engineers for the components that were validated. We would like to thank these representatives from the High Voltage battery and Combustion engine teams, for their timely provision of data and patient attitude facilitated us in carrying out the tasks in an orderly fashion with least idle time.

We would also like to send out our deepest gratitude to our guide and supervisor at Chalmers University, Sven Andersson. His continuous support and valuable inputs from beyond the gates of Volvo Cars have helped us in performing this thesis in a smooth manner.

Lastly, we would like to thank our families and friends from all around the world for their undying motivation, helping us in achieving each milestone with optimism.

Akhil Kathrikolli Neelakanta & Saketh Ratakonda

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1
Introduction

1.1 Background

The use of virtual simulations to design, understand and evaluate a concept is growing to make the product development process more efficient. Using virtual simulations to analyse the behaviour of the physical system has its own advantages. Firstly, virtual simulations prove to be more time and cost efficient when compared to real world testing of a system. Secondly, virtual simulations are done usually during the design phase of the project, which helps in making design decisions at an early stage based on the analyses. Moreover, it is sometimes seen that simulations of complex systems is quite possible in a low cost and low risk environment, given sufficient computational power. These complex systems may not be replicated well enough (or could be unsafe to do so) in real world situations (weather forecasting using supercomputers[1], for example).

These advantages make way for applying virtual simulations in the automotive industry. The definition of "vehicle model" has shifted from the sole-manufactured expensive prototype in the early 90s to a computer representation that can be simulated for certain scenarios[2]. For instance, Vehicle simulations facilitates analysing performance of a vehicle with different powertrain options, which would be time and resource consuming in the case of field testing. Not just vehicle specifications, but also environmental variables that influence the on-road driving can be controlled, for instance, in driving simulators[3].

Simulations, however, do not always recreate every test/system behaviour faithfully. For the process to be efficient, the virtual tools and models used must be reliable and accurate in representing the physical system. This calls for the need to validate the models used by comparing them to results obtained from physical tests, hence by emulating the test conditions in the virtual environment. This aims to increase the virtual model's confidence and assist in making them as representative of real conditions as possible.

Validation of virtual models is thus finding its ground in the industry, and correspondingly, costs are involved. Iterations for model improvements are done by validating the model at each step. This results in achieving higher confidence levels for the model at every iteration, and the cost involved also tends to increase. Also, the value of the model to the user increases. Thus, instead of achieving 'absolute' validity, industries aim at achieving certain level of confidence based on the investment and time (which varies similar to cost), and of course, the user value desired. Figure 1.1 illustrates this relation[4].

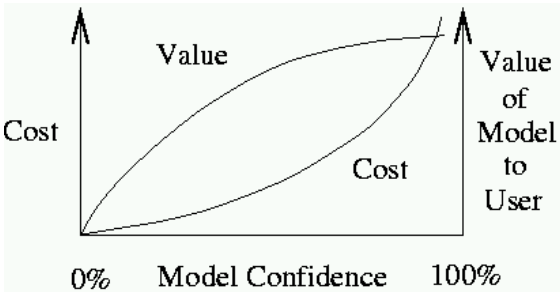


Figure 1.1: *The effect of desired model confidence on model value and incurred cost[4]*

Numerous validation methodologies are adopted in research and industry, and the choice depends on various factors. Jack P.C. Kleijnen (1999), in his paper on Validation of models[5], states that validation techniques can be used based on the availability of data - either no real data available, only output data available or both input and output data available. In this thesis work, we deal with the third kind, since both input and output data are available (trace-driven simulation). This case directs to validate models using the scatter plots, and creating the regression line to calculate its slope (this is a widely used technique to visually and numerically analyse model behaviour). Although trace-driven simulations has all input and output data for validation, there are some errors from the experimental data that the validation methodology must consider. It must consider the random errors and the correlation bias errors in the test data if possible, and also the uncertainty due to lack of experimental measurement[6].

Lastly, considering we are dealing with *validation* specifically in this thesis, we must note the difference in the meaning of the terminologies *Verification* and *Validation* (V & V). The guide for verification and validation of computational fluid dynamics simulation[7] defines verification and validation as follows

"Verification is the process of determining that a model implementation accurately represents the developer's conceptual description of the model and the solution to the model."

"Validation is the process of determining the degree to which a model is an accurate representation of the real world from the perspective of the intended uses of the model."

Hence, model verification deals with ensuring the developer's conceptual description of the model is rightly implemented and programmed or modelled in the computer simulations. Meanwhile, model validation deals with ensuring how accurately the

model simulates the real world phenomena with respect to its intended domain of application.
A clear illustration of validation and verification in the model development process is given by Figure 1.2, as proposed by Robert Sargent(1998)[8]. The *problem entity* (system) represents the real world phenomenon, the data from where is used to *validate* the *computerised model*. *Verification* is making sure the computer programming and implementation of the conceptual model is correct[4]. In this thesis, we deal with comparing the behaviour of the computerised model with that of the system, mentioned as *operational validity* in Figure 1.2.

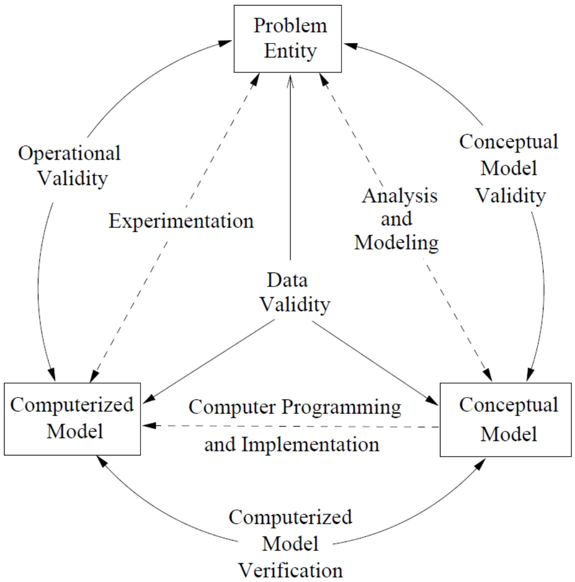


Figure 1.2: *Illustration of Verification and Validation in Modelling process[8]*

1.2 Problem statement

Given the background on virtual simulations in the automotive industry and the validation of those models, there is a requirement to device a generic validation methodology. The intention was to come up with validation metrics that give a perspective on the fidelity of the model, both subjectively and objectively.

Volvo Car Group uses an in-house developed tool (based on MATLAB and Simulink) called *VSim* for complete vehicle simulations. The tool simulates the energy flows in the complete vehicle and is used to, for example, predict the fuel consumption, analyse the vehicle performance and for component dimensioning. All simulations in *VSim* intend to simulate correct energy flows in the system. To make the *VSim* tool more accurate and reliable, there is a need to validate the component models used in order to understand how accurately they simulate the real world scenarios.

Moreover, there are components such as the High Voltage Battery that are used in HEVs and BEVs, and are comparatively newer technologies in the market, hence there is a lack of data for validation. Thus, another driving factor for the thesis is also the need to validate these components (preferably those involved in HEVs and BEVs) in *VSim*.

1.3 Objective

The objective of this thesis work is to answer the research question - *What are the appropriate techniques to validate a virtual model of a component*?

Thus, we aim at coming up with a Validation methodology that performs subjective and objective analysis to determine the fidelity of different models with real world behaviour.

1.4 Deliverables

In this thesis, we look to

- Deliver a generic validation function giving different validation metrics that can be used to validate the components in *VSim*.
- Implement the developed methodology on prioritised vehicle components and assess the performance of the methodology by showing how well the metrics illustrate the behaviour of the model with reference to that of the real system.

1.5 Limitations

There were some limitations on the thesis, which were the considerations that falls beyond the scope of the work done:

- The errors in the test data is a vital factor that tells how well the validation metrics translate the fidelity of the model. This thesis does not consider the errors and compensate for errors associated with test data received.
- The test data used to validate the models are obtained from tests that were already performed. This thesis does not define test procedures that covers all operating regions in the intended domain of application. Defining test procedures is better to be used in validation since the validation metrics obtained tell about the fidelity of the model in all the intended operating regions.

2
Theory

The foundation of the thesis is based on various theories concerning modelling and its validation, which were supported by the literature study done. The following sections explore the physics and mathematics that were involved in achieving the results.

2.1 Energy flow in a vehicle - Bond graph modelling

Bond graph modelling is a multi-domain modelling technique that is used to model and simulate mechatronic systems. Here, the domains under consideration can be mechanical, electrical and/or thermal. The bond graph is a graphical representation of how energy flows in a system[9][10]. A modelling technique where energy is the exchange variable is specifically considered in this case. Hence, the two co-variables used here are called *effort* and *flow*. For instance, voltage, pressure and force are effort variables, while current, coolant flow rate and velocity are the flow variables. Hence, each domain of energy flow will have the corresponding effort-flow pair. This energy exchange takes places through interfaces called energy ports. Also noteworthy are the two types of models considered in energy flow bond graph modelling, which are the *energy sources* (generate the energy - provide system inputs) and *energy transfer elements* (transfer energy through energy ports between models and sometimes from one form to another, also incurring losses)[11].

The energy transfer in *VSim* is based on Bond graph modelling, where energy flow forms the basis of modelling. The bond graph applied for the complete vehicle model is illustrated in Figure 2.1. Note the signals in opposite directions (effort and flow). The *flow* signals are based on physical quantities representing the load demand from the road (such as wheel input/output speed, transmission input/output speed, battery input current). The *effort* signals are physical quantities that cater to the demanded load, i.e., represent the effort required to put the system into action (wheel input torque/output tangential force, transmission input/output torque, battery output voltage). Respective products of the effort and flow signals give the power flow (for example, mechanical - *torque*angular velocity* or *force*linear speed*, electrical - *voltage*current*). These energy flow paths (through the energy ports) are referred to as Power bonds in *VSim*.

Figure 2.1 shows an example of a vehicle with two power sources, which are the energy sources in the Energy transfer model terminology, while the components represent the Energy transfer elements, with some energy losses[11].

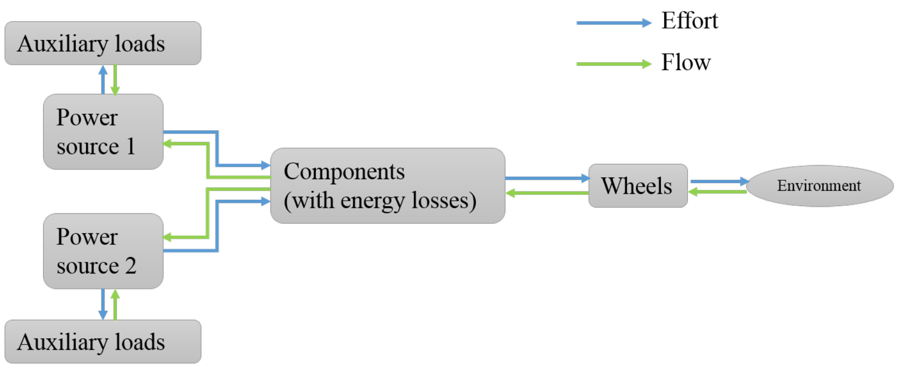


Figure 2.1: *Representation of energy transfer in a complete vehicle simulation (with two power sources)*

2.2 Model validation - Statistical methods

The validation methodology adopted consists of **Subjective analysis** and **Objective analysis**. Subjective analysis consists of visual illustrations and plots to give a more subjective assessment of the validation results. Objective analysis has a statistical and mathematical approach and aims to achieve validation metrics in the form of numerical values.

2.2.1 Subjective Analysis

In order to visually assess the error between test and simulation data, *Box plots* have been adopted to show the error distribution over the test period.

2.2.1.1 Box plots

Box plots are a method of indicating the distribution of the data using the five number summary: minimum, first quartile, median, third quartile and maximum[12]. They are used as visual representation of distribution of the error between the test signal and the simulation output signal. The representation of box plot is shown in Figure 2.2.

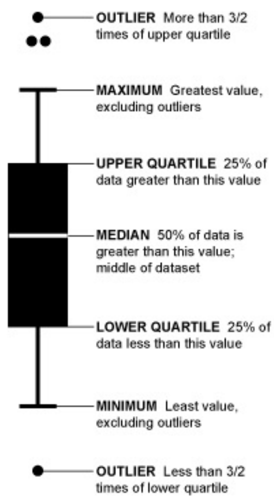


Figure 2.2: *A detailed description of Box plots*[13]

The rectangular box in the Figure 2.2 indicates the inner quartile range, spanning from the first quartile to the third quartile. The line in the inner quartile range indicates the median. The minimum and maximum are at 1.5 times inner quartile range from the lower quartile and the upper quartile respectively, these regions are called whiskers. All the points outside whiskers are called outliers.

2.2.2 Objective Analysis

In order to validate the models objectively, we have come up with two methods based on our literature study. These methods look to produce objective numbers that describe how well the model behaves compared to rig tests, thus works as an objective validation metric.

2.2.2.1 Russell's Error Measure

Russell's error measure is a method used to quantitatively compare time history signals of the simulation and experimental test results. It provides magnitude and phase errors for each individual simulation output signal and corresponding test signal, and combines them to give overall comprehensive error[14]. The magnitude (M), phase (P) and comprehensive (C) error are given by equations 2.1, 2.2 and 2.3 respectively.

$$M = sign(\psi_{AA} - \psi_{BB}) * log_{10}(1 + |\frac{\psi_{AA} - \psi_{BB}}{\sqrt{\psi_{AA} * \psi_{BB}}}|) \tag{2.1}$$

$$P = \frac{1}{\pi} * cos^{-1}(\frac{\psi_{AB}}{\sqrt{\psi_{AA} * \psi_{BB}}}) \tag{2.2}$$

$$C = \sqrt{M^2 + P^2} \tag{2.3}$$

where,

$$\psi_{AA} = \frac{\sum_{i=1}^{N} a_i^2}{N}, \psi_{BB} = \frac{\sum_{i=1}^{N} b_i^2}{N}, \psi_{AB} = \frac{\sum_{i=1}^{N} a_i b_i}{N} \tag{2.4}$$

a_i and b_i represents the test signal and simulation output signal values at each time instant respectively and N represents the total number of such data points.

The magnitude error indicates the relative difference between the magnitudes of the test signal and the simulation output signal. The magnitude error is fairly well bounded and on the same scale as the phase error. The physical interpretation of the magnitude error is $S_1 \approx 10^M * S_2$, where S_1 represents the test signal and S_2 represents simulation output signal. The phase error represents the difference in phase between the signals, independent of the magnitudes. The phase error varies from 0 to 1. 0 represents the signals are in phase, while 1 represents the signals are out of phase[15]. The magnitude and phase errors are combined to obtain the comprehensive error.

2.2.2.2 Principle Component Analysis (PCA) - Area metric

The PCA-Area metric method is used to analyse models where more than one output have to be considered (multivariate analysis). The approach considered here, based on the method proposed by Luyi Li and Zhenzhou Lu on multivariate analysis[16], involves converting the time series model outputs into principle components. The resulting Principle components(PCs) are thus linearly uncorrelated with each other, obtained through orthogonal transformation of the original output variables.

The algorithm used here to obtain the PCs is the Eigenvalue decomposition of the variance-covariance matrix. Consider a model with p output variables $d_1, d_2, d_3 ... d_p$, each containing N observations or data points. If we have the output variable matrix as $Y \epsilon [N, d]$ (where $d = [d_1, d_2, d_3, ..., d_p]$), Y_c is the matrix obtained from mean centering and normalising the outputs(columns of Y). The variance-covariance matrix of Y_c (VC_{Y_c}) is obtained as

$$VC_{Y_c} = \frac{1}{N} {Y_c}^T Y_c \tag{2.5}$$

Consider $\lambda_1, \lambda_2, \lambda_3, ... \lambda_p$ as the eigenvalues obtained from the VC_{Y_c} matrix, and $\phi_1, \phi_2, \phi_3, ..., \phi_p$ as the corresponding eigenvectors. Then, the p PCs are given as

$$PC_k = Y_c \phi_k \tag{2.6}$$

where $k = 1, 2, 3, ..., p$.

From the original output matrix Y, we now have the Principle component matrix PC (both Y and PC matrices are of the same dimensions, the original output columns have just undergone a transformation). The PCs can be found for both the simulation and test data, and the next step is to perform area metric on the corresponding outputs of simulation and test.

This is done by finding the difference in area between the *cumulative normalised* PC plots. Consider the area difference values to be $A_1, A_2, A_3, ..., A_p$. Also considered is another factor called the Contribution Rate(CR), which is a PCA weighing factor and determines the contribution based on the output variability, given as

$$CR_k = \frac{\lambda_k}{\lambda_1 + \lambda_2 + \lambda_3 + ... + \lambda_p} \tag{2.7}$$

where $k = 1, 2, 3, ..., p$.

In order to obtain the Overall validation metric (OVM) from the PCA and Area metric, the area differences are multiplied with their corresponding CRs (obtained from equation 2.7), and this term is normalised to the length of the data (number of observations N) available, as shown in equation 2.8. This normalising to N makes sure that this method is generic in the sense that it can be applied to test data of any number of data points, the OVM can still be comparable between two different simulations/components.

$$OVM = \sum_{k=1}^{p} \frac{A_k * CR_k}{N} \tag{2.8}$$

The method to find A_k used here deviates from the one used in the original reference literature[16], where the area difference is found by comparing the Cumulative Distribution Function (CFD) of the polynomial curves of the simulation and test data, and integrating the difference polynomial between $-\infty$ to ∞. This is replaced here by normalising both the X and Y axes (between 0 and 1) and calculating the area difference between the cumulative curves.

2.2.2.3 Energy Validation Metric (EVM)

Apart from the Overall Validation Metric (OVM) determined, another objective metric called Energy Validation Metric (EVM) is obtained, which basically utilises the same method (Area metric) to determine the error in calculating energy flow from a component. Since here we shall be considering one "output", PCA step is eliminated, and the Area metric is determined between the output power plots ($Power = Voltage*Current$ for electrical energy flow, $Force*Speed$ for mechanical energy flow, and so on) of the simulation and the test. Thus, similar to equation 2.8, we have the relation for the EVM as

$$EVM = \frac{A_e}{N} \tag{2.9}$$

where, A_e is the absolute area difference between the simulation and the test power plot (indicating energy flow correlation). Note that like the OVM, the EVM is also normalised by N again to make the method generic.

Overall values for multiple tests - In case of multiple tests of the same type performed (giving us a higher confidence in the results), all of the above metrics have to be averaged to give an overall value. For this, the **Mean** and the **Standard deviation** (SD) were employed. The mean gives an idea of the average value of multiple metric values obtained from multiple tests, while the SD talks about the spread/deviation of the values from the mean. The standard deviation gives additional information in cases when the mean does not convey enough information (for instance, if the mean of many metric values was zero, even though some of the metric were non-zero values, the standard deviation conveys how much the other values deviate around zero).

3

Methods

The concepts discussed in chapter 2 are used to validate the model. Each method used has a specific purpose and conveys specific information about the model which will be discussed further in this Chapter, indicating the fidelity of the model being validated. The validation methodology employed consists of **Subjective Analysis** and **Objective Analysis**.

3.1 Validation methodology

3.1.1 Subjective Analysis

Subjective analysis consists of visual illustrations and graphical displays to give a more qualitative assessment of the model. In subjective analysis the simulation output signals are compared with corresponding test signals, to assess the fidelity of the model. One method employed is **Error Plots**. They are graphical representation of the simulation output signal and corresponding test signal with respect to time and the error between them.

Box Plots are used to visually represent the error between the simulation output signal and corresponding test signal over time. Box plots here are used to analyse the error between the signals, even though the signals are dependent on the previous time step.

3.1.2 Objective Analysis

In objective analysis, quantitative metrics are obtained to validate and indicate the fidelity of the model. The **Russell's error measure, Overall Validation Metric** and **Energy Validation Metric** discussed are used to validate the models objectively. A simulated model, as discussed, can have multiple outputs. To quantify how well each individual output is predicted with respect to corresponding test signal, **Russell's error measure** is adopted.

To validate the model as a whole considering all the necessary model outputs, **Overall Validation Metric** obtained from PCA-Area metric is used. It considers all the necessary model outputs of the *VSim* models and test data, and arrives at a single OVM for the model, irrespective of number of outputs and data points.

The **Energy Validation Metric**, which was also discussed, is used for validating the model based on energy. The EVM considers only the signals contributing to the energy flow for validation of the model.

3.2 Model Validation

The methodologies discussed in section 3.1 were applied to components High Voltage Battery and Combustion Engine. The decision to chose these two models was done analytically by running complete vehicle simulations on different vehicle architecture models and calculating the relative power loss in the components with respect to the complete vehicle power loss. In addition, an extra weighing factor was given to the component priority if the component was a power source. And, the availability of test data was considered as a factor, without which validation was not possible. From this study, the **High Voltage Battery** and the **Combustion Engine** were the top two priority components (quite intuitively as both are power sources).

3.2.1 Generic Validation Function

A generic function was developed in MATLAB, to accept the results from simulation and output the metrics. The inputs to the function are simulation results which contain simulation output signals and corresponding test signals. The outputs are the subjective and objective metrics discussed. This function developed is generic, which accepts any number of inputs (which are outputs from the simulation model), any number of data points in a test and any number of similar tests on the same component and provides the metrics.

3.2.2 High Voltage Battery

The High Voltage (HV) Battery was one of the important components to validate since it is a power source in a vehicle, and has considerable relative power loss.
The test data against which the *VSim* battery model had to be validated was obtained from the Battery test rig at Volvo Cars. Although we were unable to order predefined test to cover all operating regions of the battery (due to the non-availability of test rig), we were provided with data from tests that were already performed at the rig. The data available was for 3 test types given, namely,

Discharge test - In this test, a constant current demand was made from the battery, followed by the current demand cut-off as a cooldown period as noticed in Figure 3.1. Thus, for the model, the same current signal from the test rig is given into the input port. The discharge ideally results in a constant reduction in the *SoC* value.

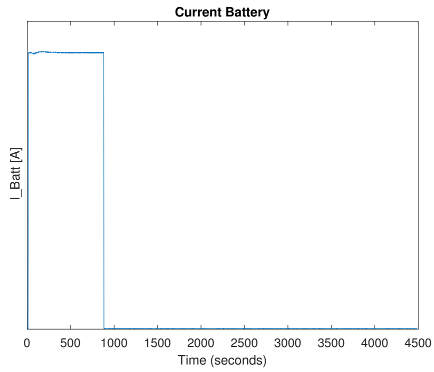


Figure 3.1: *Current input for the discharge test*

Fast charge test - This test involves increasing current demand in steps, where a certain amount of current demands are made for a given duration at each current level as shown in Figure 3.2, which is given as input to the simulation model. This is gradually charging the battery, as opposed to the constant current charging. This test ideally results in a gradual increase in SoC value.

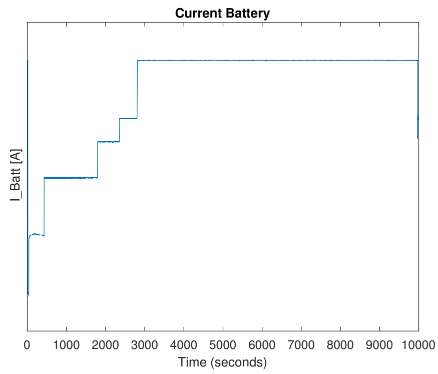
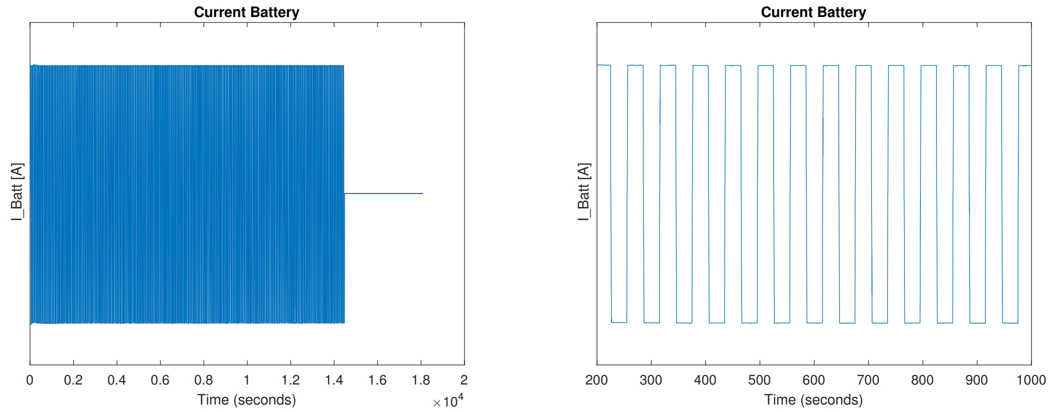


Figure 3.2: *Current input for the fast charge test*

Cooling homogeneity test - In this test, the current fluctuates between the same negative and positive values in a cyclic manner, followed by a cooldown period of zero current demand as shown in Figure 3.3a. Figure 3.3b can be referred to get a clear picture of the current behaviour, showing a certain section of the test. This test is more dynamic compared to the other two tests. While the discharge and fast charge test data was for one test each, we received data from 11 cooling homogeneity tests, each test varying by the input conditions such as rate of coolant flow and current level. Out of the 11 test, only 9 were considered for model validation as two tests had very noisy coolant flow rate signals.



(a) **(b)**

Figure 3.3: *(a)Current input for one of the cooling homogeneity tests, (b)One section of the current input in detail showing the current fluctuations*

The HV Battery component in *VSim* having same configuration as the HV Battery for which test data was obtained, was simulated. The HV Battery component has certain number of inputs ports, to which signals from the test data was fed. The model was simulated for each test, and the outputs derived from the model were then compared with the corresponding test signals obtained from the test rig, and stored in a file. And the stored data was used to analyse and interpret the fidelity of the model using validation methodologies discussed. This was done with the help of the generic MATLAB function developed. Hence, a fair comparison of the model behaviour and the real world system behaviour for the same input conditions was made.

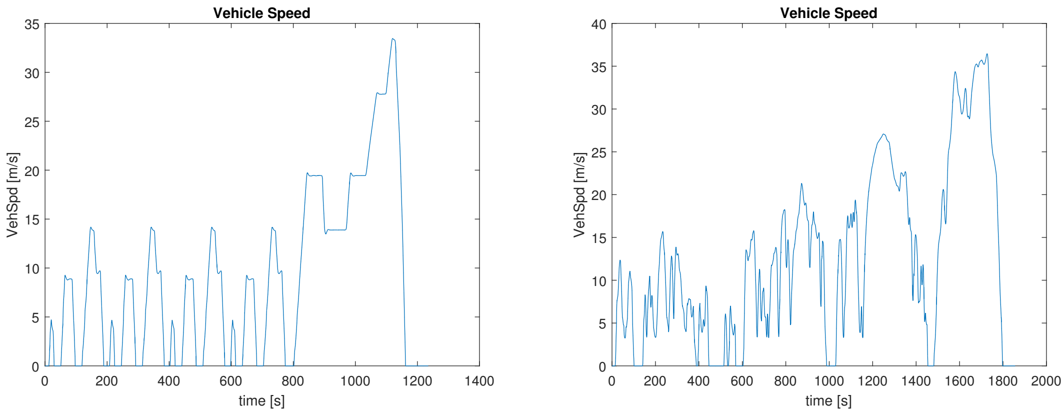
Considering that the domain of the model's intended applicability lies in analysing energy flows, three outputs of the model are given importance and considered for model validation, namely, the *State of Charge (SoC)*, *Temperature* and *Voltage*.

3.2.3 Combustion Engine

The Combustion Engine had the highest relative power loss and since it was a power source as well, it was an important component to be validated. The test data for combustion engine was obtained from FPD test rigs at Volvo Cars. FPD test rig is a Hardware in the Loop (HiL) system where the test object is the combustion engine, and it simulates the vehicle components not installed in the test rig. As in the case of HV Battery, due to the non-availability of test rigs, we utilised test data that was already available from the FPD test rigs.

For validation of the combustion engine model against the test data, the combustion engine plant along with combustion engine controller was considered in *VSim*, having the same specifications as the engine for which test data was obtained. The combustion engine plant model requires actuators signals fed back by the controller, hence the controller is simulated along with the plant.

The test data was obtained for two test under the **NEDC** (New European Driving Cycle) and one test under the **WLTP** (Worldwide harmonised Light vehicles Test Procedure) driving cycles, and combustion engine model was validated for the obtained test data. The velocity profiles for the driving cycles are shown in Figure 3.4.



(a) **(b)**

Figure 3.4: *Velocity profiles of the NEDC and WLTP driving cycles*

Certain necessary input signals such as brake pedal position, coolant flow rate in the engine and torque from starter motor were unavailable for setting up the combustion engine model simulation. It was necessary to mock the unavailable signals, similar to the test environment and provide it to the model to be able to simulate. A similar vehicle was setup in *VSim* as the vehicle used in test environment and simulated for the same driving cycles. The required signals were then mocked from this simulation and provided it to the combustion engine model as a input, along with other test signals as inputs to simulate the combustion engine model. The simulations results were used to analyse the fidelity of the model using the validation methodologies discussed. The outputs considered based on the model's intended purpose of simulating energy flows are *Torque delivered*, *Temperature of the coolant* and *Fuel Mass Flow Rate*.

4

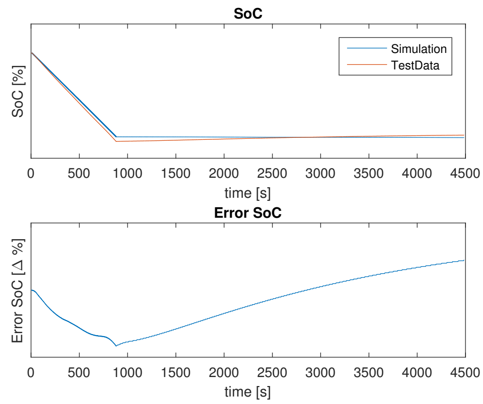
Results

4.1 Validation of High Voltage Battery Model

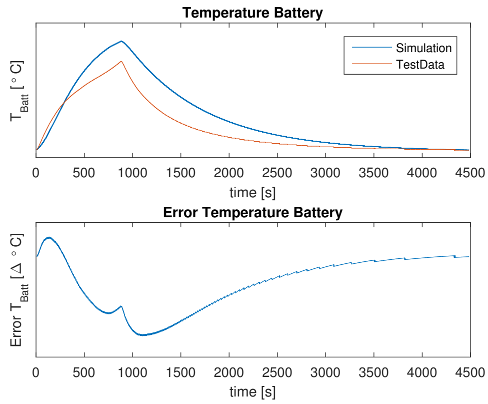
The following sections present the results obtained from the simulation run on the High Voltage battery, and the correlation of the outputs with corresponding test data to obtain the validation metrics.

4.1.1 Discharge test

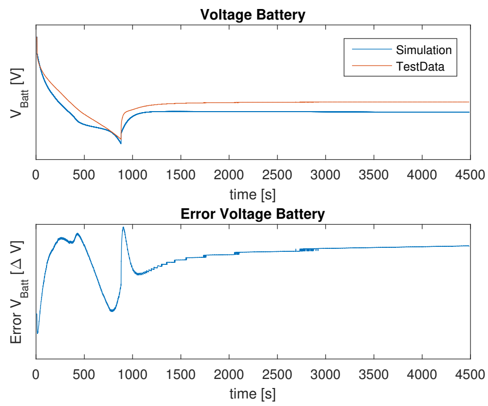
Figure 4.0 shows the results obtained from the discharge test performed on the HV Battery.



(a)



(b)

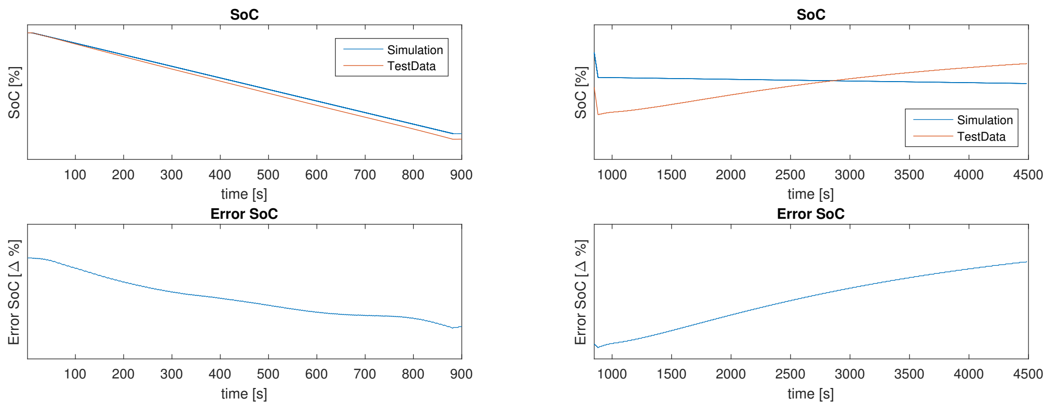


(c)

Figure 4.0: *Discharge test - comparison between simulation and test data - (a)State of Charge(SoC), (b)Temperature, (c)Voltage*

The State of Charge (SoC) behaviour can be analysed from Figure 4.1. As anticipated from a constant current demand on a battery, the SoC gradually decreases until the current demand lasts. However, few anomalies can be seen between the Simulation and test data.

The region of gradual descent in the SoC (approximately between 10 to 900 seconds) is overestimated (lower slope) in the simulation model, i.e, estimates a slower discharge rate, as illustrated in Figure 4.1a. Also, during the second part of the test, the cooldown section, the battery in the rig appears to self charge slightly, showing a slow increase in the SoC, while the model shows a very slow drop in the SoC, owing to the almost zero current demand. This behaviour is illustrated in Figure 4.1b.

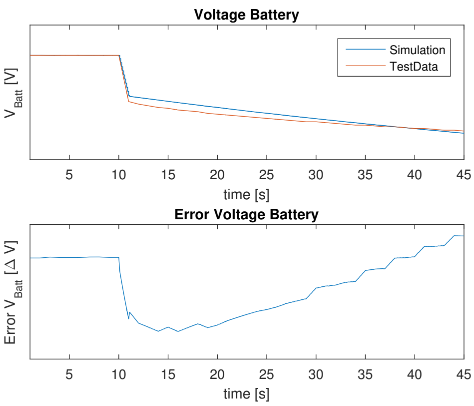


(a) **(b)**

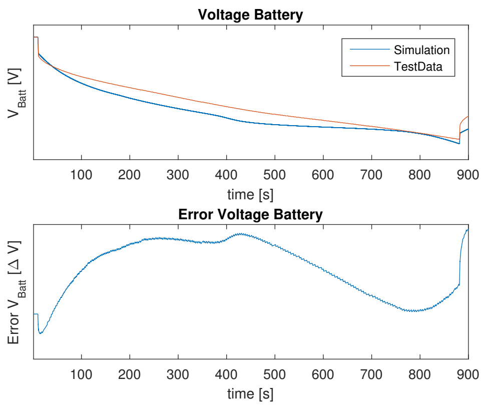
Figure 4.1: *SoC for the Discharge test - detailed illustration of the differences*

The Voltage behaviour is illustrated in Figure 4.2. Compared to the SoC, the voltage plot of the model follows the test data much better. Moreover, there is a sudden dip in voltage at the start of the discharge. This phenomenon is captured

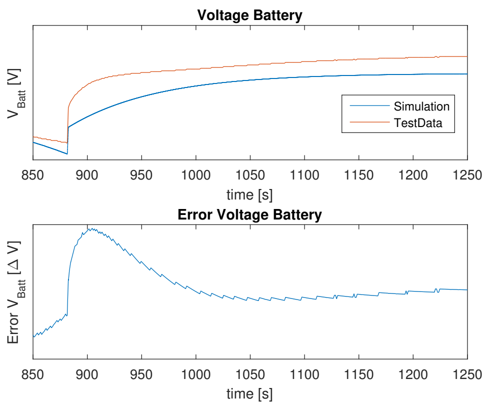
quite well by the model, as seen in Figure 4.2a. After the initial dip, the voltage reduces gradually, which depends on the current drawn and the resistance of the battery. This section is underestimated throughout by the model, as seen in Figure 4.2b.
The voltage suddenly rises at the end of the discharge. However, the levels of this voltage rise does not match well between the simulation and test data, as seen in Figure 4.2c. After this region, there is an almost constant error between the simulation and test values. This can be seen again in Figure 4.2c.



(a)



(b)



(c)

Figure 4.2: *Voltage for the Discharge test - detailed illustration of the differences*

The Temperature varies as shown in Figure 4.1b. The correlation in temperature keeps decreasing as the battery heats up rapidly due to a constant high valued current demand. But as the cooldown period starts, the error keeps reducing and the end state depicts more or less the same value between the simulated and test data values. Overall, the simulation model over estimates the temperature, and the maximum overestimation is seen right at the beginning of the cooldown period.

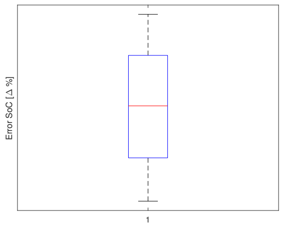
The **Box plots** for the discharge test signals can me seen in Figure 4.3. The error in SoC (Figure 4.3a) is distributed symmetrically about the median, which is located in the negative region, in case of the discharge test. This is owing to the explanation provided and noticed from the Figures 4.1a to 4.1b, in the initial discharge region the simulation overestimates the SoC and towards the end of cooldown region the simulation underestimates SoC. The major part of inner quartile region and whiskers are present in the negative region, indicating the SoC overestimated for major part of the test.

From the Figure 4.3b, it can be noted that the inner quartile is concentrated for the error in voltage. It indicates there are many error data points concentrated in one region during the test. As explained, this can be noticed from the Figure 4.2c in the long cooldown stage of the test. Also, the voltage is underestimated by simulation during this period, leading to the presence of inner quartile region in the positive region. And the Figure 4.3b also shows presence of many outlieres, which indicates the error in voltage varies to a large extent during the test as seen in Figure 4.0c, the large variation is mainly present in discharge stage of the test.

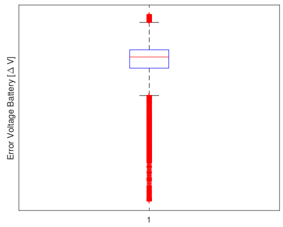
Similar to the box plot for voltage, there is large variation for error in temperature which can be noticed in the Figure 4.1b. The median is not symmetrically present in the inner quartile region, which indicates the error data points from median to upper quartile is more concentrated as can be inferred from the Figure 4.1b. The major part of inner quartile region and whiskers are present in the negative region, indicating the temperature is overestimated for major part of the test.

The results obtained from using the **Objective analysis** methods (Russell's error measure and PCA-Area metric method) are summarised into Table 4.1. From the magnitude of **Russell's error measure** of SoC and temperature, it can be noticed they are negative, indicating they are overestimated for major part of the test and the magnitude error of voltage is positive, indicating it is underestimated as inferred from respective box plots(Figure 4.3), and also the error plots(Figure 4.0). As is evident from all the plots, the temperature shows the lowest level of correlation, while the voltage shows the highest, as reflected in the Comprehensive errors for the 3 outputs.

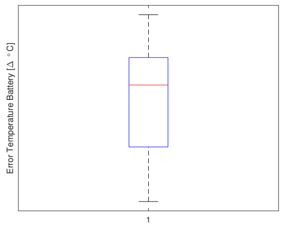
The OVM and EVM metrics are as shown in Table 4.1. The **OVM** shows a high (relatively higher, as will be seen further) value. As seen for Figure 4.0, there is significant area difference between the simulation and test plots, especially for the temperature and voltage. Since the Contribution rates are comparatively much higher for the temperature than for the SoC and voltage, the OVM returns a higher value, showing a comparatively poor level of overall correlations. The **EVM** shows an intermediate value (which is worse by a very small amount than the fast charge test, but much better than the cooling homogeneity test, as will be further seen), where the correlation in only the voltage plays a factor in determining how well energy flow is captured.



(a)



(b)



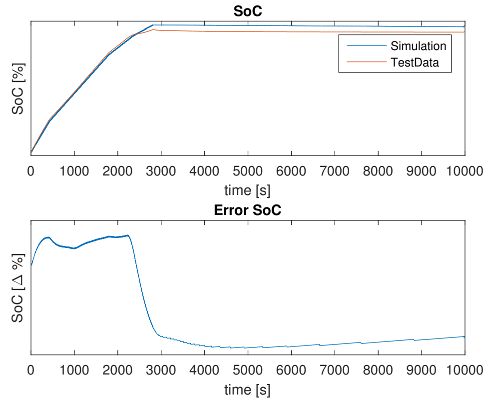
(c)

Figure 4.3: *Box plots for the Discharge test - (a)State of Charge(SoC), (b)Voltage, (c)Temperature*

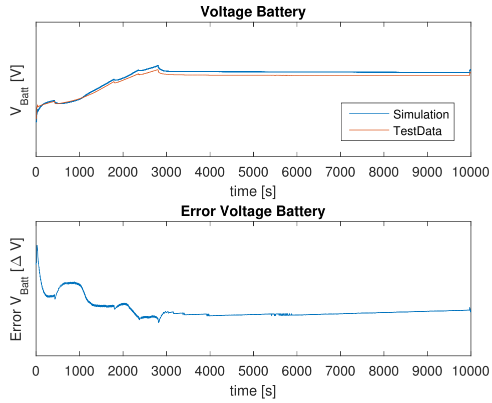
Table 4.1: Objective analysis of discharge test

Russell's Error Measure			
	Magnitude	Phase	Comprehensive
SoC	-0.0243	0.0196	0.0312
Temperature	-0.0560	0.0174	0.0587
Voltage	0.0165	0.0016	0.0166
Overall Validation Metric			
0.0622			
Energy Validation Metric			
0.0138			

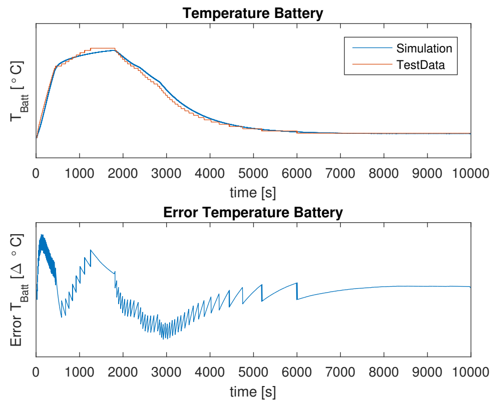
4.1.2 Fast charge test



(a)



(b)



(c)

Figure 4.4: *Fast charge test - comparison between simulation and test data - (a)State of Charge(SoC), (b)Voltage, (c)Temperature*

Figure 4.4 shows the results obtained from the fast charge test (described in section 3.2.2) performed on the HV Battery.

The State of Charge (SoC) behaviour can be analysed from Figure 4.4a. The SoC is slightly underestimated by the model during the fast charge period. However, it is seen that the battery in real world conditions do not reach as close to 100 % SoC, but the model predicts a final state which is closer to 100 %. This is clearly seen in Figure 4.5.

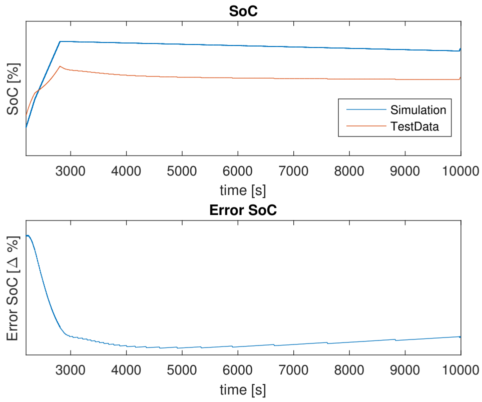
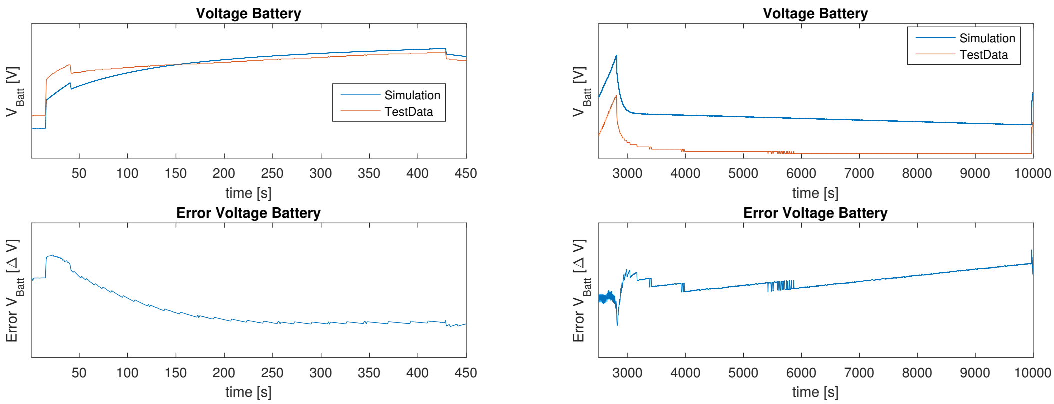


Figure 4.5: *SoC for fast charge test - depiction of SoC error after fast charge ends*

The Voltage behaviour is illustrated in Figure 4.6. The model voltage is very well correlated with test data, except for few regions. The initial peak in voltage occurs when a battery suddenly begins to charge. This phenomenon is underestimated by the model, but is very slightly overestimated during the charging period. This is illustrated in Figures 4.6a and 4.6b.



(a) **(b)**

Figure 4.6: *Voltage for the Fast charge test - detailed illustration of the differences*

The Temperature behaviour is shown in Figure 4.4c. It is seen that the model follows the test data much better that it did for the discharge test (refer Figure 4.1b). Discharge test is a direct constant current demand of high value, while fast charge involves current supply at shorter intervals and hence has more gradual dynamics. Thus the thermal model follows the test data better during slow load demand changes, as compared to high load demand at a quicker pace.

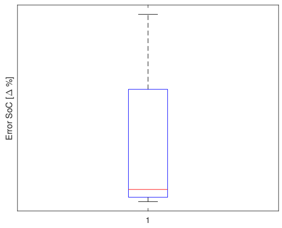
The **Box plots** for the signals in the Fast charge test is shown in Figure 4.7. From the Figure 4.7a it can be seen that the error distribution for SoC is skewed. The Figures 4.4a and 4.7a indicate that the error is concentrated from the lower quartile to the median, this is due to the nearly constant error present after fast charge period. From the Figure 4.7a it can also be noticed the entire inner quartile region is present in the negative region, stating the SoC is overestimated for major part of the test by the model.

Similar to the discussion on box plot for voltage in case of the discharge test, it can be noticed in the Figure 4.7b the inner quartile region is concentrated, because of many error data points present in one region of the test, this is after the fast charge period. But in this case, the inner quartile region is present in the negative region, unlike discharge test. This indicates the voltage is overestimated for the major region of test. The presence of many outliers is due to large variation of voltage noticed in the fast charge period.

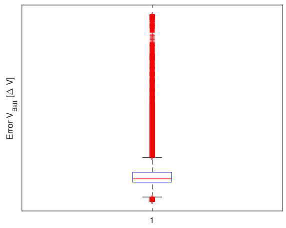
Since, the temperature is predicted very well by the model for the fast charge test, the magnitude of variation in error for temperature is much smaller. The median is close to zero and not symmetrically present in the Figure 4.7c, indicating the inner quartile is region is skewed and present more in the negative region.

The results obtained from using the **Objective analysis** methods are summarised into Table 4.2. From the magnitude errors or **Russell's error measure**, it can be inferred all the outputs are overestimated by the model, as noticed from box plots. As it is evident from the plots in section 4.1.2, the SoC shows the lowest level of correlation, while the temperature shows the highest, as reflected in the Comprehensive errors for the 3 outputs.

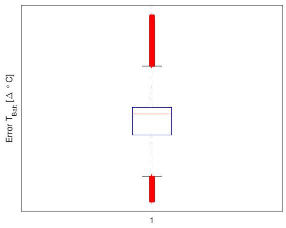
The OVM and EVM metrics are as shown in Table 4.2. It is seen that both the factors are lower than those of the discharge test. The increase in correlation in the temperature and voltage accounts for this. Also, the Contribution Rate of the temperature is much higher compared to the other two signals (higher imbalance than for the discharge test), hence the considerably poor correlation in SoC is not given much weightage, further lowering the **OVM** value. The **EVM** is much lower compared to the discharge test (and the cooling homogeneity test, as seen further), since the voltage correlation is much better here.



(a)



(b)



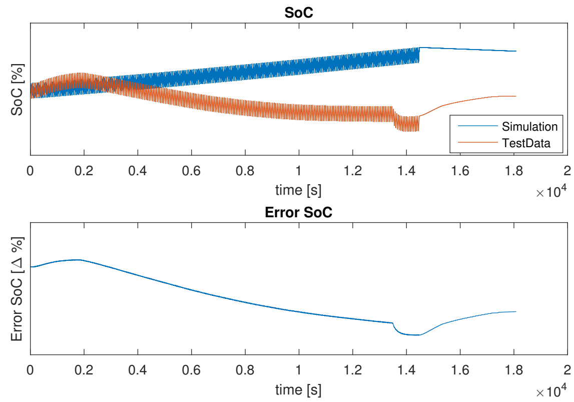
(c)

Figure 4.7: *Box plots for the Fast charge test - (a)State of Charge(SoC), (b)Voltage, (c)Temperature*

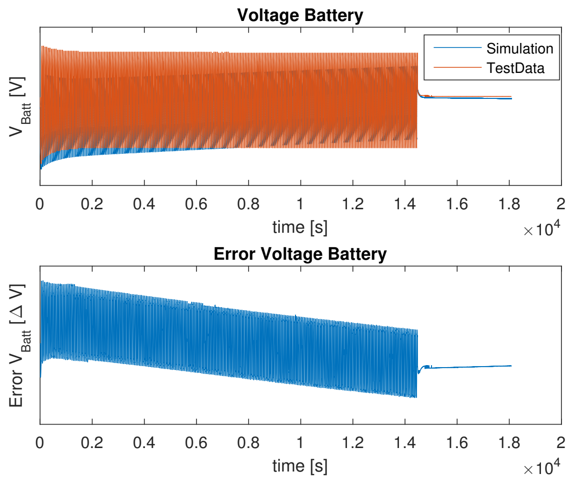
Table 4.2: Objective analysis of Fast charge test

Russell's Error Measure			
	Magnitude	Phase	Comprehensive
SoC	-0.0243	0.0057	0.0249
Temperature	-0.0008	0.0015	0.0017
Voltage	-0.0070	0.0011	0.0071
Overall Validation Metric			
0.0076			
Energy Validation Metric			
0.0026			

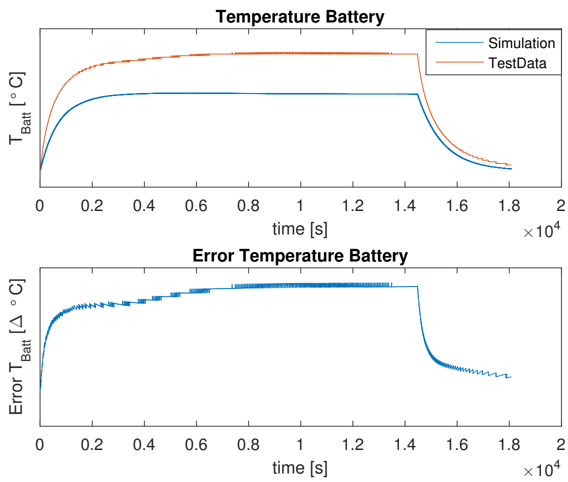
4.1.3 Cooling homogeneity



(a)



(b)



(c)

Figure 4.8: *Cooling Homogeneity test - comparison between simulation and test data - (a)State of Charge(SoC), (b)Voltage, (c)Temperature*

Figure 4.8 shows the results obtained from one of the cases of the Cooling homogeneity tests (described in section 3.2.2) performed on the HV Battery.

The State of Charge (SoC) shows the least correlation amongst the 3 outputs, with simulation values overestimated throughout, and the difference keeps increasing over time (refer Figure 4.8a). The test data shows a small sudden dip in SoC during the last 1000 seconds of the current fluctuation, which is not reflected in simulation (refer Figure 4.9). The difference very gradually reduces after end of current fluctuation, but the final state still shows considerable differences in the SoC values.

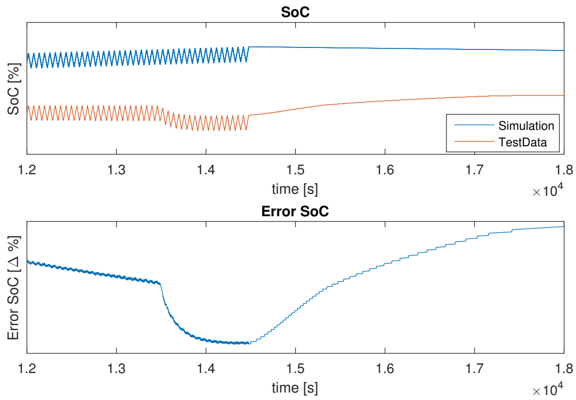


Figure 4.9: *SoC from Cooling homogeneity test - depiction of differences during the last section of the current fluctuation*

The Voltage correlation increases over time, where the simulation value is underestimated throughout. Thus, the conversion of current input into voltage output is not very representative, but reaches more towards real world value over time. After the end of current fluctuation, the correlation is higher. This behaviour can be seen previously from Figure 4.8b and the increasing correlation can be seen for a particular region in Figure 4.10. In comparison, the voltage has the highest correlation in this test.

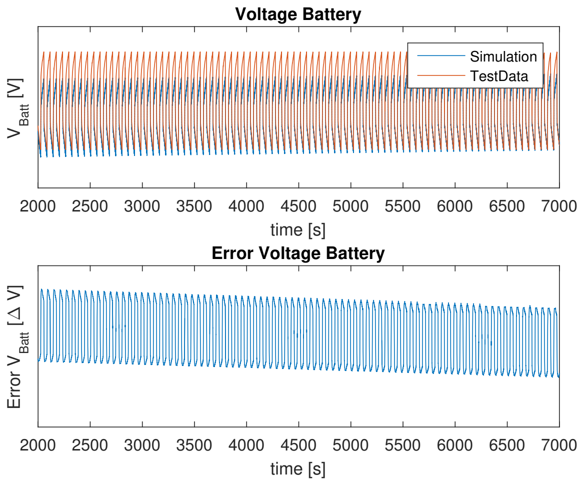


Figure 4.10: *Voltage from Cooling homogeneity test - depiction of decreasing model underestimation*

The Temperature in the simulation is overall underestimated, following a similar trend as voltage. But after end of current fluctuation, the difference non-linearly reduces towards zero. This can be noticed in Figure 4.8c.

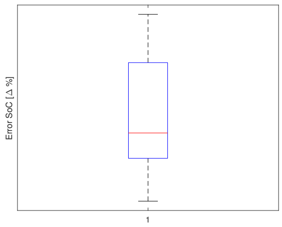
The **Box plots** for the signals in the Cooling homogeneity test is shown in Figure 4.11. As discussed, the simulation overestimates the SoC for the most part of cooling homogeneity test. Hence the inner quartile of the box plot shown in the Figure 4.11a is completely in the negative region. The error does not vary to a large extent as well, which can be inferred from the absence of outliers in the Figure 4.3a. In this case, the error data points is skewed and concentrated from lower quartile to median region.

The error in voltage varies largely during the entire cooling homogeneity test, but the variation is repetitive, hence there are no outliers in the box plot for error in voltage as seen in 4.11b. Since the voltage is underestimated throughout, the inner quartile is present on the positive region. And since the simulation predicts the voltage better with time, which can be noticed in Figure 4.8b the error data points are concentrated from lower quartile to the median.

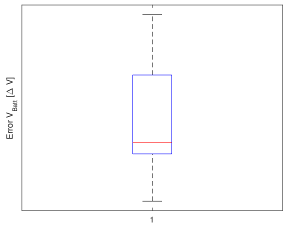
Similar to the voltage, the temperature is underestimated throughout, hence the inner quartile is present in the positive region. The variation for error in temperature is large and this can identified from the outliers present in the Figure 4.11c. Also, the outliers are present below the lower whiskers, indicating that the extreme error data points are present only one side of the median.

The results obtained from using the **Objective analysis** methods are summarised in Table 4.3. From the results, the magnitude errors of **Russell's error measure**, it can be inferred that the SoC is overestimated, the voltage and temperature outputs are underestimated by the model, as observed from box plots and error plots (Figures

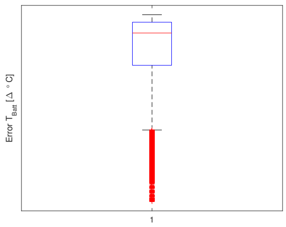
4.11 and 4.8 respectively). As is evident from the plots in section 4.1.3, the SoC shows the lowest level of correlation, while the Voltage shows the least, as reflected in the Comprehensive errors for the 3 outputs.
However, this is the result from one of the 9 tests. By looking at the results from the other tests, the voltage is the best correlated in all the tests, while the worst correlation is taken over by SoC sometimes, and temperature otherwise. A summary of the mean and standard deviations of the metrics considering all 9 tests is shown in Table 4.4.
From the validation numbers, it is seen that the averaged **OVM** is higher than that of discharge test and much higher than the fast charge test. The Contribution rate in this case weighs heavily towards the SoC, and also considering the large area difference between the simulation and test plots for SoC, shoots up the SoC, as noticed in Tables 4.4 and 4.4. Moreover, the energy flow correlation is very low for the Cooling homogeneity tests, which is reflected in the **EVM**, which is the highest of the three tests.



(a)



(b)



(c)

Figure 4.11: *Box plots for the Cooling homogeneity test - (a)State of Charge(SoC), (b)Voltage, (c)Temperature*

Table 4.3: Objective analysis of cooling homogeneity test 1

Russell's Error Measure			
	Magnitude	Phase	Comprehensive
SoC	-0.1244	0.0362	0.1295
Temperature	0.0628	0.0078	0.0633
Voltage	0.0059	0.0028	0.0065
Overall Validation Metric			
0.0972			
Energy Validation Metric			
0.1532			

Table 4.4: Objective analysis of multiple cooling homogeneity tests (averaged)

Russell's Error Measure						
	Magnitude		Phase		Comprehensive	
	Mean	SD	Mean	SD	Mean	SD
SoC	0.0144	0.0713	0.0185	0.0070	0.0682	0.0321
Temperature	0.0444	0.0179	0.0074	0.0027	0.0450	0.0180
Voltage	0.0059	0.0014	0.0024	0.0006	0.0063	0.0015

Overall Validation Metric	
Mean	SD
0.0722	0.0144

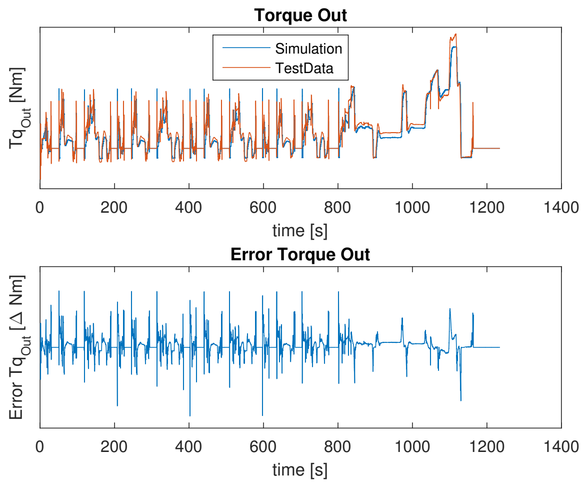
Energy Validation Metric	
Mean	SD
0.1615	0.0196

4.2 Validation of Combustion Engine Model

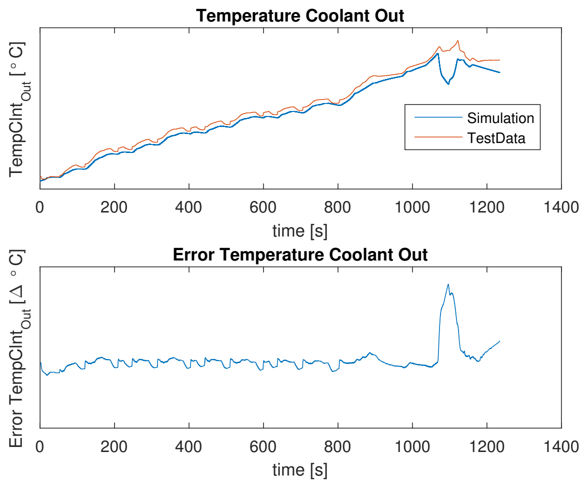
The following sections show the results obtained from simulations of the Combustion engine model for the NEDC and WLTP tests and its correlation with the test data, giving the validation metrics.

4.2.1 NEDC test

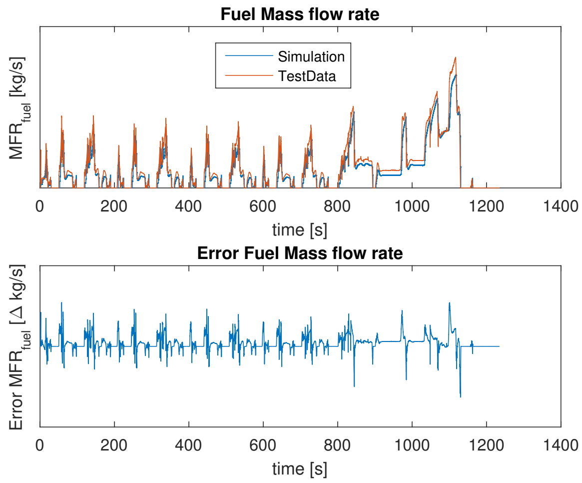
The results obtained for the combustion engine model, from simulating the model for the NEDC test data acquired (described in section 3.2.3) are presented below.



(a)



(b)



(c)

Figure 4.11: *NEDC test - comparison between simulation and test data, (a)Torque delivered, (b)Temperature of Coolant, (c)Fuel Mass Flow Rate*

The torque delivered by the simulation model and the comparison to test data can be observed from Figure 4.12a and detailed illustrations for analysis can be observed from Figures 4.12a and 4.12c. It can be noticed that there is a phase difference between the simulation and test results. From the Figure 4.12b, it can be noticed engine starts at t = 213s, 251s and 320s. When the engine starts, there is a difference in torque delivered by the engine. The torque from starter motor is mocked(as discussed in section 3.2.3) and provided to the combustion engine simulation model, the mocked torque induces errors in torque delivered by the engine when the engine starts, increasing the discrepancies further between simulation and test data. For the extra urban driving cycle region of NEDC, it can be noticed that the torque delivered the phase difference still persists as seen in Figure 4.12c. The torque is underestimated for the most part of the test. Fuel Mass Flow Rate comparison follows similar trend as torque delivered, that is there is a phase difference between simulated and test signal and it is underestimated for the most part of the region.

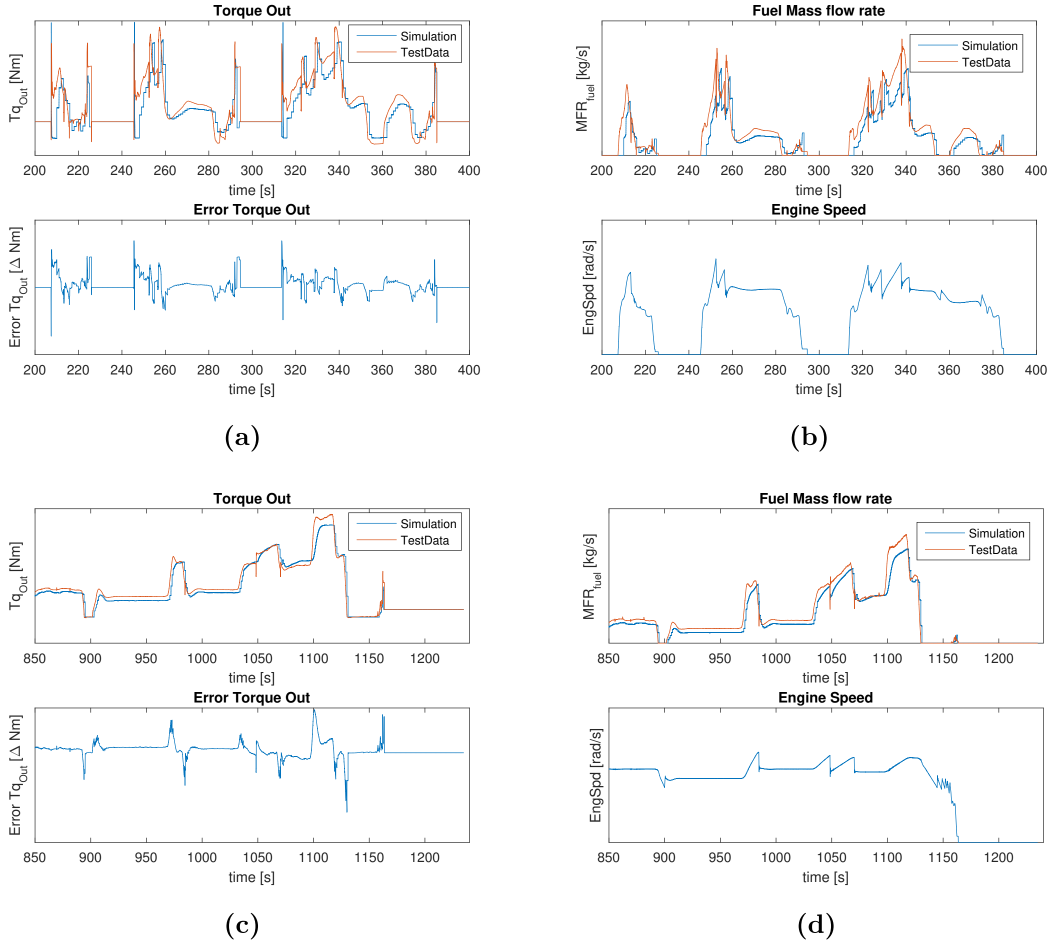


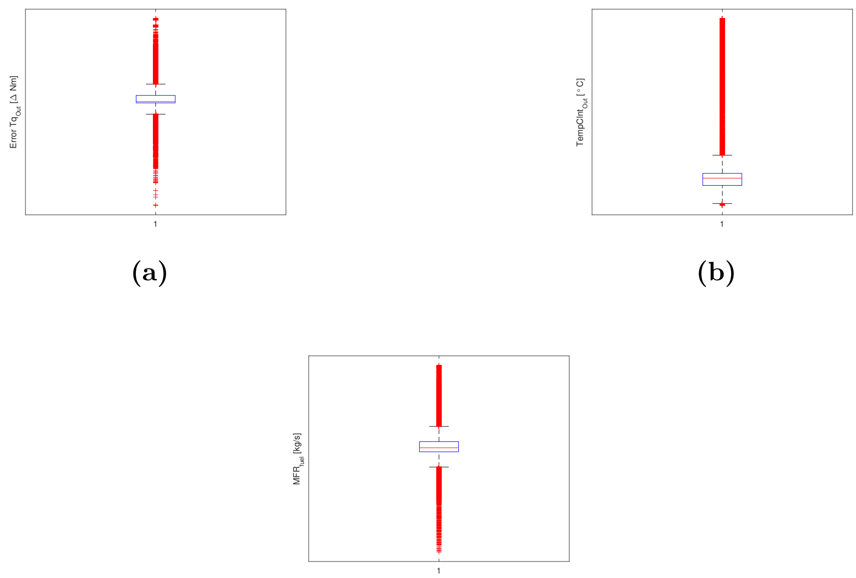
Figure 4.12: *Torque, Fuel Mass Flow Rate and engine speed for the NEDC test - detailed illustration of the differences*

The comparison of temperature of coolant can be seen in 4.12b. The coolant flow rate was one of the mocked signals, and this induces some errors in the simulation results. The temperature is underestimated for major part of the test. The test data indicates drop in temperature levels when the vehicle is at standstill, which can be noticed in the error plots as negative peaks during standstill. This indicates the cooling of the engine during standstill isn't captured well. Also, there is a large error in temperature of coolant towards the end of driving cycle which reduces the correlation and increases the errors in metrics.

The **Box plots** for the simulation output signals are shown in Figure 4.13. From Figure 4.13a it can be noticed there are many outliers present. This is due to large variations in error of torque as noticed in 4.12a. The median and inner quartile region is close to zero, but the magnitude of variation in error is large. The variation of error is large even for the temperature and the mass flow rates. The temperature and fuel mass flow rate Figures 4.13b and 4.13c show presence of outliers, indicating variations of error. The temperature and MFR are underestimated for most part of the test as discussed and this can be observed from the presence of inner quartile regions in the positive side, in the Box plots.

The results of **Objective analysis** methods are shown in Table 4.5. As inferred from the Box plots, due to large variations of error, the **Russell's error measures** are high. The magnitude error is positive for Russell's error measure, indicating the signals are underestimated as observed from box and error plots. The lowest correlation is seen in the torque delivered, and the highest correlation is in temperature of coolant, as observed from the comprehensive errors.

The OVM and EVM metrics are shown in Table 4.5. The **OVM**, is comparatively lower than the battery model for Discharge and Cooling homogeneity test. This is due to the fact that OVM measures the area difference between the plots, which are normalised. Hence OVM gives an idea of the shape of the area difference (the trend in which the simulation plot follows the test plot), which is followed much better for the Combustion engine NEDC test compared to the HV Battery. The Contribution rate weighs more towards the Coolant temperature, and its bad correlation contributes further to the OVM. The **EVM** is lower than the Cooling homogeneity test in the battery model. The mean and standard deviation of the objective metrics obtained for the two NEDC tests is shown in Table 4.6.



(a) **(b)** **(c)**

Figure 4.13: *Box plots for the NEDC test, (a)Torque delivered, (b)Temperature of Coolant, (c)Fuel Mass Flow Rate*

Table 4.5: Objective analysis of NEDC test 1

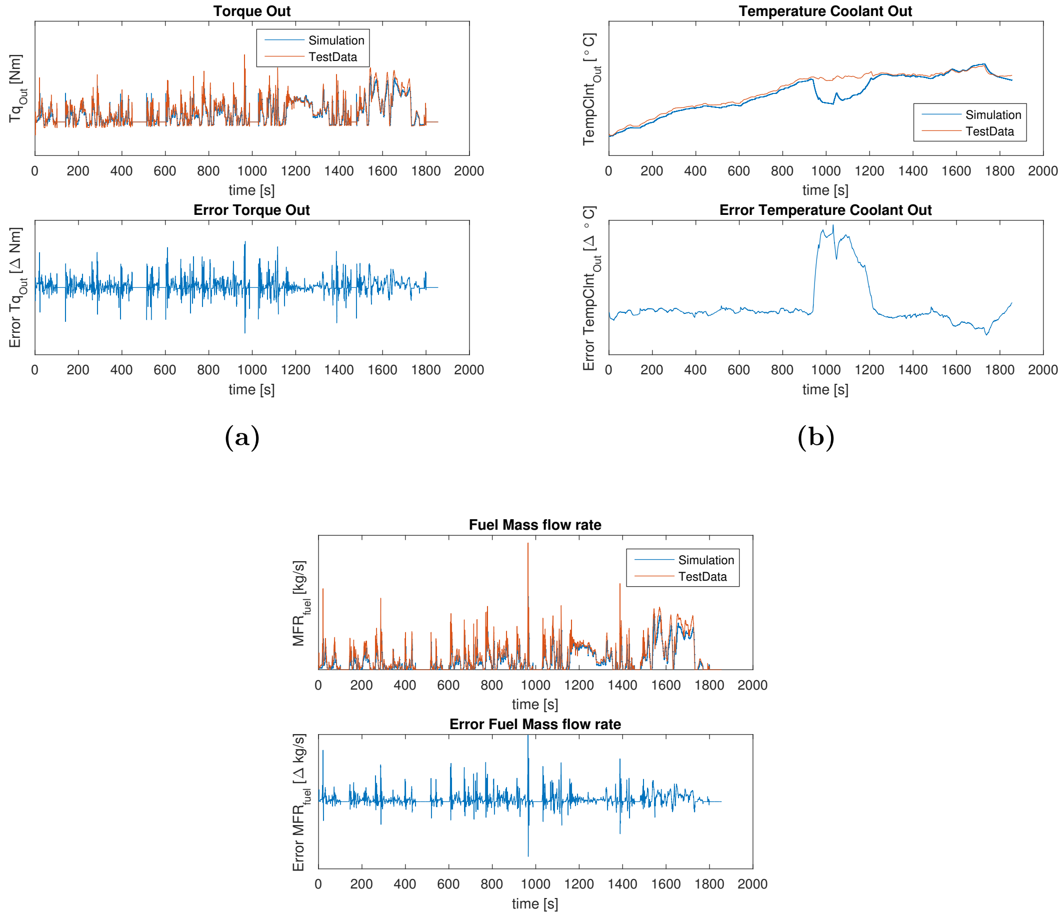
Russell's Error Measure			
	Magnitude	Phase	Comprehensive
Torque	0.0796	0.1044	0.1313
Temperature of Coolant	0.0397	0.0118	0.0414
Fuel mass flow rate	0.1175	0.0756	0.1397
Overall Validation Metric			
0.0166			
Energy Validation Metric			
0.0934			

Table 4.6: Objective analysis of NEDC test(averaged)

Russell's Error Measure						
	Magnitude		Phase		Comprehensive	
	Mean	SD	Mean	SD	Mean	SD
Torque	0.0756	0.0041	0.1035	0.0009	0.1282	0.0031
Temperature of Coolant	0.0445	0.0048	0.0115	0.0003	0.0459	0.0045
Fuel mass flow rate	0.1152	0.0023	0.0759	0.0003	0.1380	0.0017
Overall Validation Metric						
Mean			SD			
0.0126			0.0041			
Energy Validation Metric						
Mean			SD			
0.0922			0.0013			

4.2.2 WLTP test

The simulation of combustion engine model was run for WLTP tests, the results obtained are discussed below. The error plots are shown in Figure 4.14.

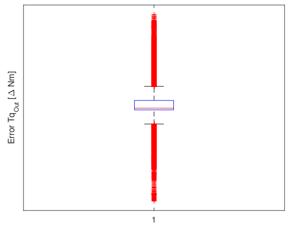


(a) (b)

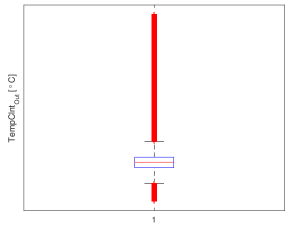
(c)

Figure 4.14: *WLTP test - comparison between simulation and test data, (a)Torque delivered, (b)Temperature of Coolant, (c)Fuel Mass Flow Rate*

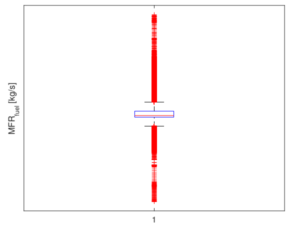
Similar to the NEDC test, the there is a phase difference in WLTP test for torque delivered and fuel mass flow rate, the temperature is not predicted well by the model during a region of test. The box plots illustrated in Figure 4.15. It can be noticed from box plots that the magnitude of variation of outputs and inner quartile regions in WLTP tests is larger than NEDC tests. This results in higher comprehensive error in Russell's error measure as noticed in Table 4.7. The **OVM** and **EVM** are higher in case of WLTP tests when compared to NEDC tests as seen in Table 4.7. The OVM from WLTP test similar to NEDC test is higher that fast charge test and comparatively lower than discharge and cooling homogeneity test of battery model. The Contribution rate weighs more towards the badly correlated Coolant temperature, more than that for the NEDC test, hence the OVM is a bit higher than that for the NEDC tests. The EVM is lower only when compared to cooling homogeneity test of the battery model.



(a)



(b)



(c)

Figure 4.15: *Box plots for the WLTP test, (a)Torque delivered, (b)Temperature of Coolant, (c)Fuel Mass Flow Rate*

Table 4.7: Objective analysis of WLTP test 1

Russell's Error Measure			
	Magnitude	Phase	Comprehensive
Torque	0.1227	0.1276	0.1771
Temperature of Coolant	0.0501	0.0310	0.0589
Fuel mass flow rate	0.1753	0.1194	0.2121
Overall Validation Metric			
0.0183			
Energy Validation Metric			
0.1353			

5
Discussion

The results obtained from implementing the validation code on the two power source components help us judge the performance of the methodology used. Even though the number of outputs considered in both the cases were the same, the kind of tests performed were varied for both the components, which gives us a broad perspective to discuss the behaviour of the signals and the validation code.

5.1 Signal behaviour

From the simulations of various test cases, some interesting behaviours of the signals can be noticed.

From the discharge and the fast charge tests for the HV Battery, we notice that the **current inputs** change differently. For the discharge test, it a constant current demand of a high value, while in the fast charge test, the current charges in gradual steps (observed respectively from Figures 3.1 and 3.2). This affects the **temperature changes**, where the maximum error for the discharge test is about three times that of the fast charge test (due to the sudden high current demand in discharge test compared to the gradual change in current in the fast charge test). The higher dynamics of the discharge test is not well handled by the simulated temperature, which shows worse correlation with test data when compared to the temperature correlation for fast charge (which is reflected finally in the OVM).

All three tests for HV battery are devised to have a "cooldown" phase, i.e., the **signals are logged** for sometime even **after the actual experiment** with the changing input current has ended. This has an effect on the validation metrics as considerable amount of poor correlations can be observed during this cooldown phase (especially for the discharge and fast charge tests). Hence, if the tests are redefined to have only the dynamic section and remove the cooldown phases, the metrics would give different interpretations.

In the cooldown phase of the fast charge test, it is seen that the simulation values for **SoC** reach closer to 100%, whereas in reality, it is not as **close to full charge** (as discussed in section 4.1.2). This is probably due to the **lack of controller** for the HV battery for the simulation. The charge and discharge limits are set for the battery in order to maintain a longer battery life cycle.

From the model structure of the HV Battery, it is seen that the **SoC** is logged as an **output signal**, calculated each simulation step using values of current and reference cell charge (The initial SoC is set as an initial condition in the simulation and further values of SoC are calculated at each time step and given as an output). However, the SoC is considered more as an input in real world phenomenon.

For the Combustion engine, we see that 3 input signals, which were not available from test data, was mocked in the simulation (Brake pedal position, coolant flow rate and starter motor torque). An important consideration is that the **mocked signals** may not be representative of the actual signals in the test environment and may **induce some errors** in validation of the combustion engine model. The starter motor torque, for instance, induces errors in torque delivered by the engine when the engine starts, increasing the discrepancies further between simulation and test data.

5.2 Metric behaviour

Metrics and their interpretations - In subjective analysis, we qualitatively asses the direction of poor correlation between simulation output signals and corresponding test signals and also, based on the variation of error, if the model is performing reasonably well. Knowing how well individual simulation output signal is predicted by the model, will help the model developer identify the subsystems in the model which needs attention and focus to improve the model as a whole. **Error plots** are used to identify which simulation output signals are being predicted well by the model. They are useful in analysing different phases of the test, and identifying phenomena and regions where the model captures the physical system well. The **Box plots** qualitatively represent how well the simulation output signal is being predicted by the model, like error plots and the analysis from box plots supplements the quantitative results obtained from Russell's error measure. The **Box plots** also provide variation of error for the entire test, and based on the magnitude of variation of the error, we can subjectively analyse if the model is performing reasonably well.

The objective metrics quantitatively indicate how well the model is performing. **Russell's error measure** apart from indicating the direction of poor correlation like box and error plots, it also gives measures for the errors. Higher the magnitude, the phase and the comprehensive error measures, lesser the correlation. Russell's error measure provides information about individual signal, but does not quantify the fidelity of the model as a whole, i.e., it is not a multivariate analysis(does not consider the simultaneous effect of all the outputs of the model). To overcome the shortcoming of Russell's error measure, **OVM** is used. OVM is a generic metric, and can be compared for different tests or different models to analyse how the model behaves and represents the real physical system. The **EVM** considers only the signals contributing to energy flow where as the OVM consider all the necessary outputs for validating the model. EVM would indicate the correlation in energy between the physical system and virtual model. Since *VSim* mainly deals with energy flows and losses between the components, this would be an important metric. Similar to OVM, this is a generic metric and can be used to compare results from different tests and models to validate the model based on energy flow.

Trends between the OVM and EVM - Extending on the previous point of EVM, it is evident that the trends between the OVM and EVM can be different, i.e., a component with higher value of OVM can have a lower value of EVM and vice versa. This opposing trend can happen when the OVM gives a *higher weighing factor* (Contribution Rate CR) to an output signal which is *not involved* in energy flow calculation equation (such as temperature, fluent flow rate, etc.). However, we see that for the two components considered in this thesis, the OVM and EVM follow the same trend.

Relative measure of correlation - Having mentioned about OVM and EVM, we notice that both these values are relative measures, and *not absolute*. Both the area metric factors have a defined minimum value, i.e., $OVM = EVM = 0$ for a perfect correlation (areas between the simulation and test plots = 0). However, there is no definite number for the "worst" correlation, since the metric keeps increasing indefinitely with increasing area difference. This implies that the single component alone cannot have a *good* or a *bad* OVM or EVM, but can have a *better/worse* OVM or EVM relative to another component.

Basis for weighing outputs in OVM - With respect to the Contribution Rates (CRs) in the OVM metric, another anomaly can be noticed. We see that the CRs are based on the *variability of the output signals*, implying that an output with the highest variance gets a higher weighing factor. Here, the PCA method weighs outputs by recognising "hidden patterns" in the data set[17]. However, this may sometimes suppress information that may be relevant (for instance SoC is given very low weighting factor in fast charge, even though the poor correlation may have considerable impacts on the credibility of the model). Thus, the basis for calculating Contribution rates may have to be reconsidered.

Difference between OVM and Russell's measure - A difference in the interpretation of results is also noticed between OVM and Russell's error measure. By definition, OVM is meant to interpret the overall *difference in the area* of the normalised PCs, while the Russell's error measure interprets the *error values lumped* together. In fact, the theory behind Russell's measure shows the error calculated as the *ratios* of the simulation and test data points added-up (refer section 2.2.2.1), while the OVM calculates the area of the *shape* between the respective cumulative principle component curves.

Application of Principle Component Analysis (PCA) - Generally in data analysis, performing PCA serves to extract the relevant information (largest variability) in order to remove the redundant information. However, for the models that we have validated in this thesis, we consider 3 outputs for both, and we wish to consider all of them as important for assessing the performance of the component. Thus, here we do not eliminate any outputs in PCA, but only weigh them using CRs by their variances (using their eigen values).

Influence of phase on magnitude in Russell's measure - In the current method of quantifying the magnitude and phase errors in Russell's error measure, the presence of phase difference influencing the magnitude error is not accounted for. To reduce the influence of phase difference on magnitude, the global phase difference can be identified in terms of time steps and one signal can be shifted by the identified time steps. The shifted signals will still have local phase difference which can be further reduced by employing dynamic time warping method. Then the magnitude error can be calculated, which is not influenced by phase difference[14].

Errors in test data unaccounted - The validation methodology developed doesn't take into account the errors from the measurement in the test data. Non-trustworthy data may not be appropriate to compare with simulation results, as the results may underestimate or overestimate more than the actual differences in signals.

Specific variant of models - The battery model or combustion engine model validated was of one specific variant for which test data was procured. The metrics talk about fidelity of one variant. Models of different variants (defined by different parameters), say a Combustion engine of a sedan car compared to an engine of a heavy duty truck, may have different behavioural characteristics, and the Validation code may give different results. Applying the code to different model variants will also help in verifying its generic nature, and can be observed how the metric behave for different cases.

6
Conclusion

From the mathematical approaches made in devising validation methodologies, we have a generic validation code that can validate energy flow models in *VSim*. This validation can be done on models that have any number of outputs, and for test cases with any number of data points. The outputs considered can be of different physical units. This code was implemented by comparing the output signals of both the simulation and test, resulting in the metrics obtained for the two power source components.

The numbers from the objective metrics well reflect the trends noticed from the subjective plots. The different objective metrics (Russell's measure, OVM, EVM) are able to convey different aspects of the model behaviour, and is consistent with the observations made from the Error and Box plots.

Finally, we see that there are few areas of improvements with respect the objective analysis that can be made in order to illustrate the correlation better, which can be a scope for future research beyond this thesis.

7 Future scope

A few observations were made, which can be taken up as tasks for future development on this topic, beyond the scope of this thesis.

The energy validation metric can be split into three metrics, one for mechanical, one for electrical and one for thermal energy flow. This given a more diverse impression of the model, saying how well it replicates each type of energy flow.

The validation code needs to verified by giving dummy inputs for which the validation metrics is known. Extreme cases as dummy signals can help verify the authenticity of the methodology, and also help determine the metric value for the "worst case scenario".

The test data obtained here were obtained from tests already being done. It would be a vital future task to develop a test code that defines test cases that covers all the operating regions of each component in its intended domain of application. This would depend on the availability of the test rigs to order the tests.

By working on the above mentioned improvements, this methodology can be further used to validate other component models in *VSim*, including components that deal with mechanical, electrical and thermal energy flows, or a combination of all these.

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