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Objective Based Modelling and Simulation within a Context of an Electric Vehicle Development Program

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Abstract

Modelling and simulation have become inseparable activities in any applied science or engineering research and development endeavour. The nature of inseparability is even more evident in the case of the automotive industry. Adding to the modelling complexity are the electric vehicles with a rich interplay of previously well demarcated disciplines of electrical-electronics engineering and mechanical-automotive engineering (and to a lesser extent chemical engineering). A traditional internal combustion engine vehicle development program has very well segmented and well defined set of modelling and simulation activities. The modelling and simulation tools used are mature and have been tested and proven. However, an electric vehicle program often suffers if a decision to pursue the traditional approach is accepted. The complex interplay of different disciplines, the lack of expert/mature modelling and simulation tools and constantly changing landscape of electric vehicles tend to keep the electric vehicle modelling and simulation groups small, esoteric and often lacking in direction. In this work we define three guiding principles for a modelling and simulation group in the context of an electric vehicle development program. The interaction between three connected but dissimilar facets of modelling and simulation, i.e., vehicle level simulation, sub-system level modelling and simulation and model inspired in-vehicle algorithms are explored based on objectives that are defined before the start of the modelling and simulation exercise. The importance of finding the right common thread, model fidelity and continuous learning are discussed.

Keywords: Modelling, Simulation, Electric Vehicles, Electric Vehicle Development Program, Guiding Principles

1 Introduction

Modelling and simulation has been used for prediction, optimization and virtual experimentation for the past four to five decades, successfully, in the automotive industry. Topics ranging from determining the optimum vehicle shape with a goal of reducing the vehicle's aerodynamic drag [1] to vehicle mechanical systems that optimize vehicle suspension [2] have been tackled comfortably and effectively using modelling and simulation tools.

Before we embark on the title topic it is important that we distinguish between the terms 'modelling' and 'simulation'. Modelling is defined as a mathematical construction or description of a physical system. Models can be used for prediction or analysis. Simulation is defined as an experiment of a test case on the available mathematical models [3]. Simulation activities usually follow the modelling activities. Modelling typically requires in-depth technical domain expertise while many simulation activities do not require in-depth technical domain expertise (this is especially true while using off-the-shelf simulation software). In many programs, modelling and simulation are done concurrently and in many instances are defined as one activity in the vehicle development program.

As described previously, there are many simulation tools that are available off-the-shelf for various aspects of vehicle design and analysis. For example, Altair Hyperworks(R) is used specifically for Computer Aided Engineering (CAE) activities [4]. This specialized tool is used in car programs to simulate effects of stress, fluid structure interactions, etc. Many times it is important to also have models developed in-house. This not only reduces the dependence on external software but also increases the IP value of the company. Developing vehicle preliminary requirements is one such activity where in-house specialised models play an important role in the vehicle development program. In-house models also form the link between objectives, model fidelity and tools used within a vehicle development program.

Modelling and simulation has also become a complex activity with different fidelity levels or hierarchies of complexity. Going with the theme of the paper it is obvious that the objective of the modelling exercise would define the complexity or fidelity of the models used. It is common practice that vehicle level models are relatively low-fidelity and specific subsystem models are moderate to high fidelity. Again, the objectives of the vehicle development program and the modelling and simulation activity define the scope of fidelity. A rigorous discussion on the philosophy and trade-offs between different model fidelity is presented in section 3.2.

With the resurgence of electric vehicles, the interaction between the electrical systems and the mechanical systems has become much more complex and the domain of modelling and simulation has blurred previously well demarcated disciplines. The understanding and ability to predict the behaviour of the interplay of battery dynamics, electric motor/drive system dynamics and vehicle dynamics has become important in developing better and more efficient electric vehicles. In this work we look at modelling and simulation from three different facets, i.e., vehicle level simulation, sub-system level modelling and simulation and model inspired in-car algorithms and try to collate and define a set of guiding principles for a modelling and simulation group within a context of an electric vehicle development program.

2 Electric Vehicle Development Program:

As with any typical vehicle development program, the electric vehicle development program consists roughly of the following activities in a similar order as seen in Table 1.

Table 1.: Stages in a car development program

Stage No.	Stages/Phases
1	User/Market requirement studies
2	Concept design
3	Feasibility study
4	Concept Prototype build
5	First builds (alphas)
6	Second builds (betas)
7	Testing, validation and homologation
8	Pre-production

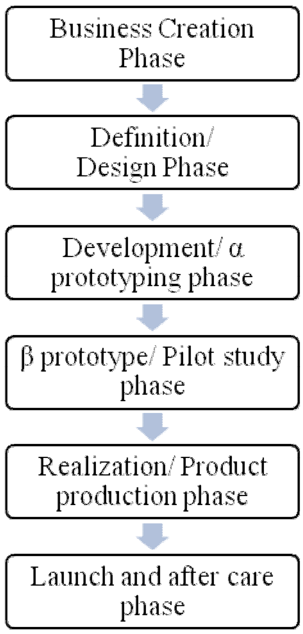

Figure 1.: Stages in a car development program

The different stages are depicted in Figure 1. With the introduction of the concept of systems engineering, methods and processes for machine development have become much more streamlined and efficient. Figure 1 depicts the major milestones in the Mahindra Reva Car Creation Process

(RCCP) of our in-house vehicle creation program. The various stages depicted in figure 1 have different aspects of modelling and simulation associated with it. Each of the stages uses different Modelling and simulation activities, i.e., statistical, technical, techno-commercial, etc...

Stage 1 - User/Market requirement studies: Usually, statistical models are used to account for the current user demands, motivations and usage patterns to arrive at possible configuration of vehicles that might meet market or customer requirements. Although this stage does not require technical/engineering models, this stage provides the basis for most of the objectives that are passed down to the design phase. Top level vehicle specifications may be arrived at in this stage. In an electric vehicle program, models used in this stage may be of relatively low fidelity and use standard statistical tools. This stage also forms the interface between the research and development teams and the marketing/customer care teams. Some of the important parameters that are fed into stage 2 are expected range, speed and overall target cost of the vehicle to be designed.

Stage 2 – Concept Design: This stage forms the bulk of the modelling and simulation activities. In an electric vehicle program this stage can be further divided into three categories (facets) that form the core of this article, i.e., vehicle design, subsystem design and in-vehicle algorithm designs.

- The vehicle design phase involves virtual feasibility, component sizing simulations and virtual validation activities that have inputs from stage 1, i.e., user/market requirements. Models in this stage can vary from low-fidelity to high-fidelity based on specific objectives. For a discussion on model fidelity the readers are directed to section 3.2.
- The second facet is vehicle sub-systems and their interactions. In an electric vehicle there are three main sub classifications, i.e., mechanical sub-systems, electrical subsystems and energy storage subsystems. It can be argued that the energy storage subsystem could be listed under electrical sub-systems but a clear demarcation allows for a robust understanding of the energy storage systems (it is noted that the system can be an energy conversion system as well, for example, fuel cells). Models in this phase tend to be moderate to high in fidelity. Objectives range from characterization to understanding fundamental physics of operations for extracting the most out of these sub-systems. It is interesting to note that based on the objective sub-system models can find their way into the vehicle level models and in-vehicle algorithms. Again, for a discussion on model fidelity readers are directed to section 3.2.
- The third facet is in-vehicle algorithms. In-vehicle algorithms find application from vehicle functioning, monitoring and safety. Most of the algorithms that form the functioning part are inspired either in part or in full from sub-system models.

Stage 3 – Feasibility studies form a very important part of any vehicle development program more so for an electric vehicle program. The studies, traditionally, are done as pre-alpha builds but of-late the use of virtual feasibility/validation have become more prevalent. Feedback from this stage is considered critical for the success of any vehicle program.

Stage 4 – Concept prototypes can be either virtual or vehicle builds. In the case of virtual prototypes, the interaction of subsystems and their effect on the vehicle are usually assessed. The topic of virtual prototyping of the electric vehicles are still quite nascent.

Stages 5 & 6 – The alpha and beta builds are dominantly hands-on building of vehicles with input from the initial stages. Feedback from these stages forms an excellent base for continuous learning for the modelling and simulation activities. The nascent nature of the electric vehicle technology provides excellent opportunities for learning and in turn improvements to the design. Section 3.3 attempts to describe this process in a little more detail.

Stage 7 – In any vehicle development program, the testing, validation and homologation forms the most expensive, time consuming and labour intensive set of activities. Subsystem models can be tested and validated virtually as a result of which time, cost and labour can be reduced. The model fidelity of subsystems in such cases needs to be moderate to high.

Typically, modelling and simulation efforts start as part of the feasibility study. In recent years it is also common to perform simulations at the concept design and market requirement activity stages. Feedback from various phases after the feasibility study activity into the modelling and simulation activity has also become common place.

3 Guiding Principles:

The following three guiding principles are arrived at after a lot of iterations and feedback.

3.1 Principle-1.: Different Goals, Common threads:

We look at three different facets that serve different end goals but they also share common threads: 1. Vehicle level simulation, 2. Electric Vehicle sub-system modelling and simulation and 3. In-car algorithms derived or inspired from modelling and simulation results. Figure 1 depicts the overlapping nature of the three facets.

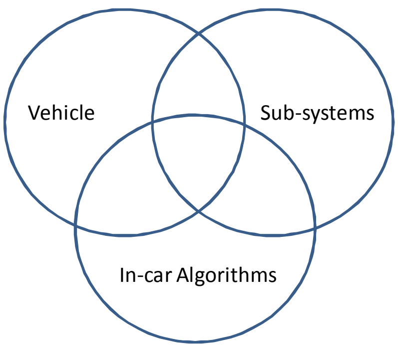

Figure 2.: Figurative description of the overlapping nature of levels of modelling and simulation in a vehicle.

Vehicle level simulations or vehicle performance simulators are top level simulations that are required to create a benchmark value for the vehicle specifications. Vehicle specifications may include range, top speed, acceleration, battery sizing, etc. Most of the vehicle level simulations are based on simple physics and tend to be relatively low-fidelity. A variety of vehicle simulators for both electric and hybrid electric vehicles are available in the market; examples of industry benchmarks would be Autonomie [5] (formerly, PSAT) from Argonne National Labs and Cruise [6] from AVL. Mahindra Reva also uses an in-house developed graphical block vehicle level simulator on the Matlab-Simulink platform [7].

Sub system modelling and simulation very often require detailed models and often predict combinations of complex physical phenomena. A good example for an electric vehicle sub-system is the battery and the battery management associated with them.

In-car algorithms can vary in functioning complexity depending on the available computing power on-board. Most often they are simplifications or linearization of sub-system models. An example of algorithms derived or inspired from sub-system models is the State-of-Charge algorithm. Figure 3 depicts a start-to-end objective based activity. The common threads most often are the objectives set forth by the vehicle development program and the goals vary based on the complexity of the models used. This leads us to the next section.

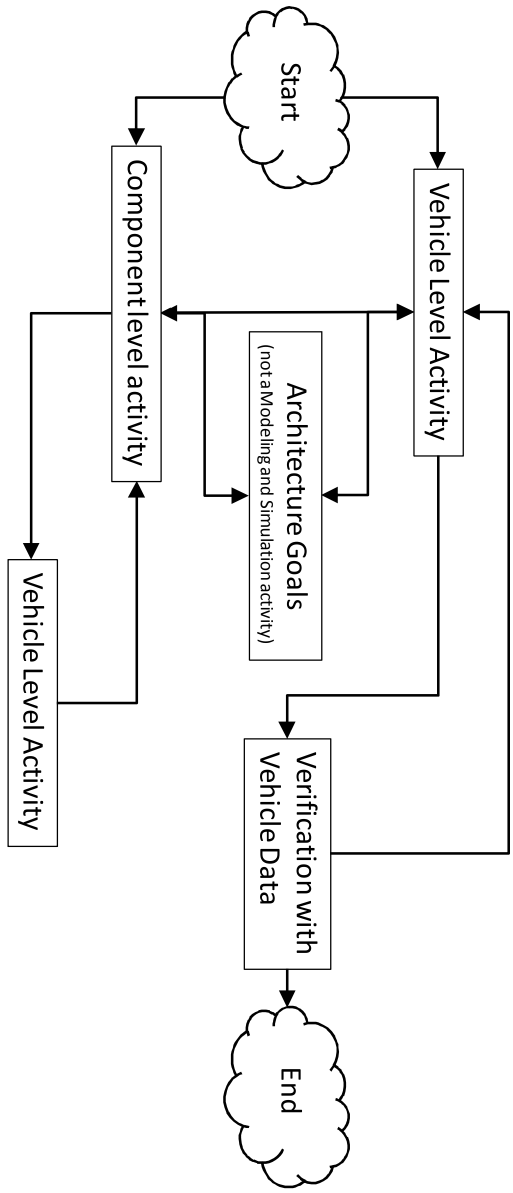

Figure 3.: Flow chart depicting Start-to-End activity based on defined objective.

3.2 Principle-2.: Model Fidelity, less is more or more is not enough?

A topic of deliberation in the field of modelling and simulation, trade-offs associated with results from models with different levels of fidelity form the basis for this section. It is important to have models of varying degrees of fidelity to serve different objectives, usually fundamental physics based models and component level models tend to be of higher fidelity than system level models. For an exhaustive list of modelling and simulation definitions the readers are directed to a review by Prof. Tuncer Oren [8]. It is proposed to adopt a balanced approach with respect to model fidelity during the modelling and simulation activity in an EV development program in light of the objectives defined. Figure 4 proposes a generic method to decide model fidelity for different objectives.

Most academic and scientific research has gone into quantifying errors and uncertainties in model prediction [9-11] focusing solely on how good the accuracy of the model is. In his book, introduction to physical system modelling [12], Prof. Peter E. Wellstead classifies models into, intuitive models, simulation models, dynamic models and actual system models based on their decreasing order of approximation. Simulation models are used for empirical investigation of properties and dynamic models are used for control analysis and design. Using Prof. Wellstead's classification we then organize our objectives into two categories, 1. Property investigations, 2. Control analysis and design. Having established an objective and its classification, we now narrow down the fidelity of the model. This would be an easy task if we had one model to use but it is becoming increasingly prevalent to have at our disposal multiple models with varying levels of fidelity. A decision making framework for management of models needs to be in place.

The aircraft industry uses one such framework called AMMO or Approximation and Model Management Optimization [13]. Usually used for design optimization, AMMO is a framework that maximizes the use of lower-fidelity, cheaper models in iterative procedures with occasional, but systematic, recourse to higher-fidelity, more expensive models for monitoring the progress of design optimization. The main objective of AMMO is therefore reducing the computation time while making sure that the design is optimized and error free. It is of importance to note that the aerospace and aircraft industries have tighter tolerances when compared to the automotive industry.

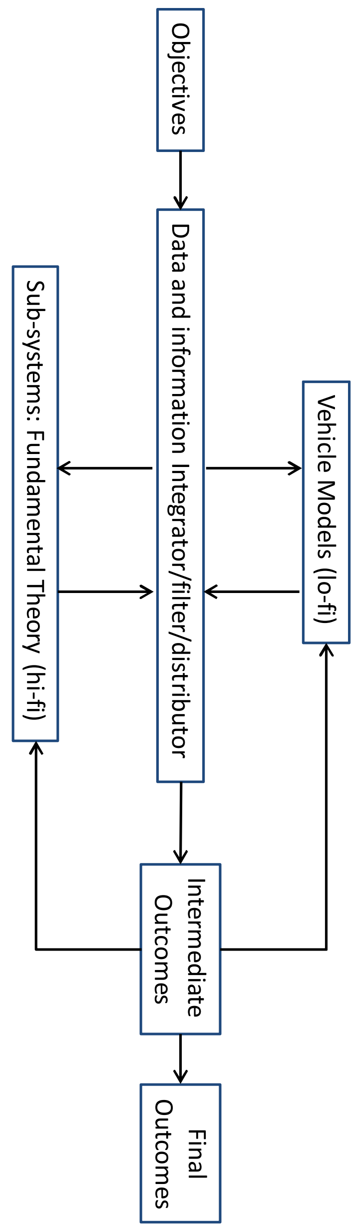

Figure 4.: Generic method to decide model fidelity.

For the automotive industry one is referred to the reviews by Massimiliano Gobbi and co-workers [14,15]. They categorize objectives for optimum design of vehicle and vehicular sub-systems as follows:

1. Vehicle System Dynamics
2. Powertrain Design
3. Internal Combustion Engine Design
4. Active Safety and Ride Comfort

5. Vehicle System design and lightweight structures
6. Integration of vehicle electronic controls.

We modify this set of objectives proposed by Gobbi and co-workers for an electric vehicle program as follows:
1. Vehicle System Dynamics
2. Drivetrain Design: Motor, gearbox and drive related electronics
3. Energy Storage Systems: Batteries, Fuel Cells
4. Active Safety and Ride Comfort
5. Vehicle System Design and Lightweight Structures
6. Integration of Vehicle Electronics Controls

Analytical Target Cascading is used in the automotive industry in product development with a systematic effort to propagate the desired top-level system design targets to appropriate specifications for subsystems and components in a consistent and efficient manner [16]. Elsewhere trade-off models for multi-attribute system level decision making is presented [17]. Combining work of Wellstead and Gobbi we reformulate figure 3 as follows:

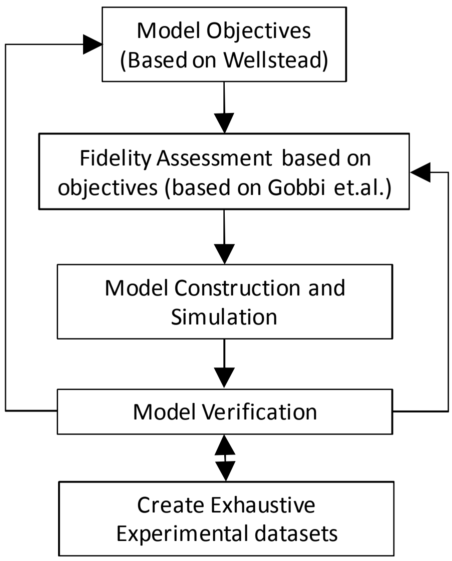

Figure 5.: Reformulation of the generic method shown in figure 4.

In figure 5, the activity of model verification is the next topic of discussion. Apart from the model management part, tremendous amount of work has also gone into model order and fidelity reduction without sacrificing accuracy of the models. For example, work by Subramanian and co-workers [18], Seshadri and co-workers [19], Moura and co-workers [20] on Lithium Ion battery electrochemical model reformulation throws light on the importance of having different model fidelities for different objectives. Models are only as good as their accuracy which brings us to the discussion in the next section.

3.3 Principle-3.: Adapting and continuous learning:

As more data is made available, especially, from long term testing it is important to subscribe to a view of continuous improvement to the models. Improvements, among other things, include adding new physics features or removing features that are otherwise proving redundant. A judicious call and filtering mechanism needs to be built in to the feedback process such that relevant and important information and ideas are captured and represented by the models.

In our opinion and practice these models have three underlying aspects that need to be considered when it comes to adapting and continuous learning, they are:

1. The models need to be modular in nature. A plug-and-play architecture needs to be subscribed to.
2. A motif of continuous improvement of models as a result of availability of more specialized datasets needs to be in place. The improvements can be both for low-fi and hi-fi models and can separately make the model generic or specific.
3. The model backbone needs to be future proof. This means that activities like confirmation to emerging standards, physics, etc. will need to be easily incorporated.

In the previous section, we briefly mentioned about the model validation and verification. The expected outcome of the validation and verification process is the quantified level of agreement between experimental data and model prediction, as well as the predictive accuracy of the models [21,22]. By definition, verification is the process of determining that a model implementation accurately represents the designers' conceptual description of the model and the solution to the model. By definition, 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. It is of critical importance therefore that the data sets being used to validate the models also vary in their fidelity. For example, vehicle level data would form a very abstract layer of data with the number of unknown parameters being quite large. A low-fi model may not pass validation with this data set and would therefore necessitate a high fidelity model. It is of interest to note that most model validation and verification is done with very abstract data with varying parameters. This brings about the important aspect of model uncertainty [23]. Uncertainty can be caused by many factors including: initial conditions, level of fidelity, numerical accuracy, multi-scale phenomena, parametric settings, etc. Clearly, as in the previous section, a well defined objective will reduce the uncertainty levels in the models.

4 And finally ...

Figure 6 shows a formalism of the ideology proposed in the paper.

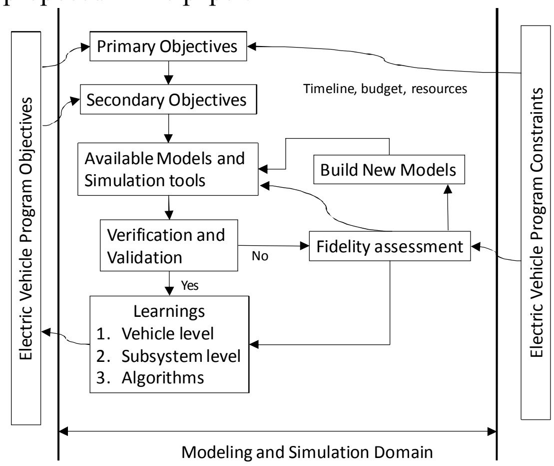

Figure 6.: Flow chart formalism of the Ideology presented in the article.

When looking at the domain of modelling and simulation, it is obvious that in an electric vehicle program one has to have clear set objectives. It is also important to note that the activity of modelling and simulation often intersects the vehicle domain, sub-system domain and could inspire in-vehicle algorithms. This intersection of domains causes goals to be multifaceted with a common thread. A philosophy of objective selection is provided herein where one could navigate the maze of model fidelity. The important activity of model validation and verification forms the core of a vehicle programs' success in the field, it also forms the crucial link between the virtual experimentation and the real world. Electric vehicle programs are still quite naive in maturity when compared to regular vehicle development programs. The current work aims to 'stitch together' the loose ends in the simulation framework for electric vehicles and formulate a cohesive approach directed at achieving the objectives.

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