A New Type of Metamodel for Longitudinal Dynamics Optimization of Hybrid Electric Vehicles

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1 Introduction

Optimizing the efficiency and performance of vehicles is an important task in automotive engineering. Several factors determine the efficiency of conventional vehicles like engine size, fuel consumption characteristics, gearing, exhaust after-treatment, and aerodynamics. For Hybrid Electric Vehicles (HEVs) the situation is even more complex as further components like electric machines and batteries need to be considered. These enable a HEV to operate in different modes like combustion drive, electric drive, parallel operation of the engines, and several more. The activation of the modes during driving is governed by an operation strategy which responds to internal and environmental factors according to parametrized rules.

When optimizing HEV models , one has to rely on computer simulation to test different parameter configurations. In this work we consider longitudinal dynamics simulations where the performance of a HEV model is simulated on a given driving cycle. Driving cycles define a time series where for each point in time a target velocity is specified. The vehicle is then simulated to match the target velocities while its performance criteria are measured, e.g. fuel consumption or green house gas emissions. Standardized driving cycles are highly relevant for determining official fuel consumption ratings, like the "New European Driving Cycle". Often heard critic concerning the standardized cycles concern their limited generalizability for real life usage. Therefore evaluating the performance of a vehicle on a larger set of real life driving cycles would be beneficial.

Depending on the accuracy of the simulation model, the simulation times usually range from several seconds to many minutes (up to 20 minutes in tested scenarios) s.t. a long time is spent for evaluating the objective function for each candidate solution. To overcome these limitations, metamodels can be used as approximation for the time-intensive simulations. Common metamodels are regression models fitted to a simulation, like Generalized Linear Models, Artificial Neural Networks, Support Vector Machines, or Regression Trees, which are created to predict a performance measure of the simulation. Approaches for optimization of HEV models with metaheuristics and further references are given in [1], and [2].The following concepts build upon the results for time-progressive learning ensembles (TPLE) in [1]. The results indicate that the decomposition of driving cycles into smaller parts, creating metamodels for each, and sequential evaluation is promising.

2 Bottom-Up Metamodels

Typically metamodels suffer from a reusability issue. A metamodel $\varphi_D : \mathcal{P} \to \mathbb{R}$ is created from a training set $T = \{(\boldsymbol{p}, r) \mid \boldsymbol{p} \in \mathcal{P}, r = \Omega_D(\boldsymbol{p})\}$, where $\mathcal{P}$ is the search space of the simulation and r is some performance measure of a configuration $\boldsymbol{p}$ for the simulation Ω_D of some driving cycle D. This is an example of a top-down approach to metamodelling which requires the collection of a large set of expensive simulation results for a specific cycle D. In this mindset it is hard to generalize a model to an arbitrary driving cycle or even just a set of prespecified cycles, as most of the acquired training data is valid for D only.

Therefore we propose a new bottom-up approach to metamodelling where the metamodel φ is built from the simulation results for a set of multi-purpose scenarios $\mathcal{S}$. A scenario s is a small building block of a driving cycle defined by a start velocity, end velocity, duration, and environmental settings. Each scenario is then simulated with different settings for the configuration $\boldsymbol{p}$, all operation modes m, and initial values for internal signals $\mathcal{I}$. The output set $\boldsymbol{o}$ of performance measures and internal signals, which are relevant to the operation strategy $\mathcal{A}$, are recorded at the end of each simulation. Consecutively, scenario models $\varphi_s^m : \mathcal{P} \times \mathcal{I} \to \mathbb{R}$ are built, generalizing the recorded scenario training data. The obtained scenario models can then be (re-)used for different purposes.

Beside others, an obvious use case is to build a metamodel φ_D for a specific driving cycle D. To this end the driving cycle is rebuilt by a sequence of n scenario models φ_{s_i} as close as possible. The operation mode m_i can not be determined in advance, but only while evaluating φ_D for a specific configuration $\boldsymbol{p}$. The evaluation of φ_D proceeds by recursively invoking the operation strategy $\mathcal{A}(\boldsymbol{o}_{i-1}) = m_i$ with the output set $\boldsymbol{o}_{i-1} = \varphi_{s_{i-1}}(\boldsymbol{p}, \boldsymbol{o}_{i-2})$ of the last scenario to determine the operation mode m_i of the next scenario. Subsequently $\varphi_{s_i}^{m_i}(\boldsymbol{p}, \boldsymbol{o}_{i-1})$ is evaluated to determine $\boldsymbol{o}_i$. The metamodel for the reconstructed cycle can then be evaluated as $\varphi_D(\boldsymbol{p}) = \varphi_{s_n}^{\mathcal{A}(\boldsymbol{o}_{n-1})}(\boldsymbol{p}, \boldsymbol{o}_{n-1})$.

How scenarios should be chosen to reach a high level of accuracy across different driving cycles as well as to limit computation times is an open issue.

References

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