Automotive Vehicle Launch Optimization based on Differential Evolution Approach for Increased Driveability

Markus Bachinger\(^{(1)}\), Bernhard Knauder\(^{(1)}\), Michael Stolz\(^{(2)}\)

\(^{(1)}\) Kompetenzzentrum
Das Virtuelle Fahrzeug Forschungsgesellschaft mbH
8010 Graz, Inffeldgasse 21/A/I
markus.bachinger@v2c2.at

\(^{(2)}\) AVL List GmbH
8020 Graz, Hans-List-Platz 1
michael.stolz@avl.com

Abstract
An important target for automated transmission development is driveability during the launch process of a vehicle. For transmissions using launch clutches the friction energy has to be considered to avoid thermal breakdown.

The launch process is controlled by electronic control units containing functions tunable by parameters. Optimizing those parameters can be time-consuming when testing on a real vehicle. Using a simulation model as input for evaluation of the objective function can lead to significant cost savings as well as shorter development time in automotive applications.

In this work we contribute a lean mathematical model of a vehicle’s drivetrain tailored for optimization of the launch process. The model includes combustion engine, inertias, clutches, flexible shafts and control algorithms for engine and clutches.

The two design parameters clutch closing time and scaling factor for clutch slip speed are chosen to optimize the objective function taking into account driveability and clutch friction energy. As the objective function is nonlinear and not even continuous, we propose using a DE approach, which does not require the knowledge of the objective function’s gradient. To further improve optimization results a surrogate objective function is built using a radial basis function approach.

Found optimal parameters for clutch closing time and scaling factor for clutch slip speed shall be applied to a prototype vehicle as initial parametrization. Within this paper a realistic launch simulation with optimized parameters is shown. Furthermore the suitability of a DE approach for the given task is demonstrated.

Keywords: Differential Evolution, Vehicle Launch, Optimization, Surrogate-based analysis and optimization.

1 Introduction
Advancing electrification of drivelines in automotive industry leads to new potentials in order to satisfy customer demands regarding performance and comfort aspects. A large variety of different hardware configurations results in increased requirements for the vehicle control system. Modern control systems contain complex algorithms responsible for the coordination of several actuators within the propulsion system. One big issue here is to find a suitable parameter set for those control mechanisms. In order to find an optimal adjustment of the control system several optimization techniques have to be taken into account. Since different driving situations require different control algorithms also the optimization procedures for those need to be selected in a suitable way.

A very special problem in vehicle adjustment is the setup of the launch process. This is a very sensitive topic because especially at vehicle launch the driver is usually very attentive and recognizes unwanted jerks immediately. Automotive engineering spends lots of effort on this topic in order to design their product to customer satisfaction. Several industrial suppliers provide the market with driveability assessment tools [1]. These tools support development departments in adjusting the control system properly on one hand side during vehicle calibration on the test track (using prototype vehicles) and on the other hand side to find a suitable pre-calibration using simulation environments. Characteristic signals such as vehicle velocity, accelerations, performance etc. serve as input signals for driveability assessment tools in order to be able to rate the driveability of a vehicle.

Target of the work presented within this paper is the optimization of the launch specific parameters using the differential evolution (DE) technique as published in [2]. Since we focus a multi criteria objective function an optimization procedure delivering a quantity of feasible parameter sets is implemented.
With a global understanding of the impact, the user can select the most suitable parameter set. The cyclic optimization procedure is implemented according to Fig.1.

The simulation environment contains the maneuver controller, the control unit for the vehicle plant (in this work the transmission control unit - TCU) and the vehicle plant model itself. Further description is presented in section 2. The objective function considers information given by the simulation environment and is specifically tailored for the vehicle launch process. Section 3 describes this objective function and the parameter space taken into account for the multi-objective optimization. The implementation of the optimization algorithm is presented in section 4. Due to the problem class the differential evolution algorithm is expected to deliver a good performance. In order to speed up the optimization process, also a surrogate-based analysis and optimization (SBAO) extension is implemented and compared to the plain algorithm.

2 Simulation Environment

Fig.2 depicts the simulation environment used within this work. A double clutch transmission (DCT) system serves as a base of this application. In order to realize an automated driveline control, the transmission control unit is designed in a way capable to control several actuating devices. The inputs from the driver (acceleration pedal, brake pedal, gear lever) are time dependent signals, which define the investigated maneuver. Since with this setup no feedback from vehicle to driver is allowed, no specific driver model is needed and the simulation results are not additionally influenced by possible driver-vehicle-interaction. Transmission control unit and vehicle plant model are interconnected via a closed loop system.

2.1 Plant model

For demonstration purposes a dynamical vehicle simulation model is implemented. Since the quality criteria for a launch process involves mainly the longitudinal dynamics of a vehicle, the implemented model is focused on these. For simulation the following components have been implemented: engine, clutch, gearbox, axles, wheels and vehicle. The main principle of the models is described in [3][4], an overview of the system modelled is shown in Fig.3.
all rotating elements from the engine and the primary clutch sides (e.g., flywheel, pressure plates). Odd and even path of the double clutch transmission model are composed equally. For launching only the first gear, which is arranged on the odd path, is relevant. Therefore only the odd path is described here. \( T_{\text{Cl,o}} \) represents the demanded clutch torque which results from the clutch actuating pressure controlled by the TCU. The inertia of the secondary side of the clutch is denoted by \( J_{2,o} \).

An electric motor is coupled to the gearbox input shafts via a planetary gearset. Besides its primary function of propulsion support in a mild hybrid vehicle the electric motor is used electric synchronization of the drive shafts for gear shifting. \( T_{\text{mot}} \) is the torque provided by the electric motor. However the electric motor is not used as launching support in the available control algorithm. Therefore its function and connection properties to the drivetrain via the planetary gearset will not be discussed further within this paper.

![Figure 3: Model of mechanical components of a double clutch drivetrain comprising inputs for torques of combustion and electrical engine as well as clutch torques and vehicle resistance.](image)

The friction between even (outer) and odd (inner) shafts and between outer shaft and housing is represented as \( d_{o,e} \) respectively \( d_{a,e} \). In order to consider the shaft oscillations a spring \( k_{1,o} \) and a damper \( d_{1,o} \) is included in the model. The transmission itself is realized via dog clutches \( b_{1,o} \), which can either be engaged or disengaged. Synchronization of the drive shafts has to be performed externally (via electric motor) as any speed difference on the dog clutches will result in an engagement impulse on the drivetrain. Currently active transmission ratios of the selected gears are designated as \( i_{o} \) respectively \( i_{e} \). \( J_{3} \) contains the concentrated inertias of all rotating elements which are located between side shafts and dog clutches \( b_{1} \) of the gear box. Furthermore concentrated backlash \( b_{2} \) and spring and damping coefficients \( k_{2} \) and \( d_{2} \) of those parts are considered in the model.

The inertia of the driven wheels is represented by \( J_{4} \). \( T_{\text{drv}} \) consists of the corresponding parts of braking torque \( T_{\text{brk}} \) and rolling resistance \( T_{\text{roll}} \) for the driven wheels. The inertia \( J_{5} \) is made up of the inertias of the undriven wheels and the vehicle itself. \( T_{\text{veh}} \) is composed of the corresponding parts of braking torque \( T_{\text{brk}} \) and rolling resistance \( T_{\text{roll}} \) of the undriven wheels on one hand side but contains also the incline resistance \( T_{g} \) and the aerodynamic resistance \( T_{\text{drag}} \) of the whole vehicle on the other hand side. The damping element \( d_{3} \) represents the coupling element between vehicle and driveline (chassis).

The following system of equations (1) to (6) describe the system behaviour in case of a slipping clutch
which represents the standard case during launching:

\[ J_{1} \dot{\varphi}_1 = T_{\text{eng}} - T_{\text{Cl},o} - T_{\text{Cl},e} \]
\[ J_{2,o} \dot{\varphi}_{2,o} = T_{\text{Cl},o} + T_{\text{mot},o} - b_{1,o}k_{1,o}(\varphi_{2,o} - i_o \varphi_3) - b_{1,o}d_{1,o}(\dot{\varphi}_{2,o} - i_o \dot{\varphi}_3) - d_{G,o} \dot{\varphi}_{2,o} \]
\[ J_{2,e} \dot{\varphi}_{2,e} = T_{\text{Cl},e} + T_{\text{mot},e} - b_{1,e}k_{1,e}(\varphi_{2,e} - i_e \varphi_3) - b_{1,e}d_{1,e}(\dot{\varphi}_{2,e} - i_e \dot{\varphi}_3) - d_{G,e} \dot{\varphi}_{2,e} \]
\[ J_{3} \dot{\varphi}_3 = i_o b_{1,o}k_{1,o}(\varphi_{2,o} - i_o \varphi_3) + i_o b_{1,o}d_{1,o}(\dot{\varphi}_{2,o} - i_o \dot{\varphi}_3) + i_e b_{1,e}k_{1,e}(\varphi_{2,e} - i_e \varphi_3) + i_e b_{1,e}d_{1,e}(\dot{\varphi}_{2,e} - i_e \dot{\varphi}_3) - b_{2}k_2(\varphi_3 - \varphi_4 - \varphi_{34} \text{sgn}(\varphi_3 - \varphi_4)) - b_2d_2(\dot{\varphi}_3 - \dot{\varphi}_4) \]
\[ J_{4} \dot{\varphi}_4 = b_{2}k_2(\varphi_3 - \varphi_4 - \varphi_{34} \text{sgn}(\varphi_3 - \varphi_4)) + b_2d_2(\dot{\varphi}_3 - \dot{\varphi}_4) - d_3(\dot{\varphi}_4 - \dot{\varphi}_5) - T_{\text{drv}} \]
\[ J_{5} \dot{\varphi}_5 = d_3(\dot{\varphi}_4 - \dot{\varphi}_5) - T_{\text{veh}} \]

Note that for the sake of simplicity the torque coming from the e-motor is assumed to be zero for the vehicle launch process.

### 2.1.2 Clutch states

Since the driveline has 2 clutches, 4 different states of activation have to be distinguished.

- Slip: Clutches of even and odd path’s slipping
- Stick-odd: Clutch of even path slipping, Clutch of odd path sticking
- Stick-even: Clutch of even path sticking, Clutch of odd path slipping
- Stick: Clutch of even and odd path sticking

The vehicle launch process itself only involves two of these states. It starts at vehicle standstill where the primary clutch side rotates with engine speed and the secondary side isn’t rotating at all. Due to this difference of rotational speeds the clutch state is identified as *slipping*. In order to launch the vehicle in a standardized way, the first gear, which is part of the odd path of the driveline, is assumed to be engaged at the beginning. \( T_{\text{Cl},o} \) is now increased from zero to a certain level in order to transmit propulsion torque from the engine to the wheels. Depending on the amount of available engine torque \( T_{\text{eng}} \) and the clutch torque request \( T_{\text{Cl},o} \), an acceleration of the vehicle takes place.

During this process the rotational speeds of primary and secondary clutch sides are converging. The state of the clutch is considered to be *sticking* (in this case stick-odd) when the rotational speed difference between the clutch plates is zero and the transmitted torque is lower than the clutch torque.

On sticking clutch state, eq. (1) and eq. (2) are replaced by:

\[ (J_1 + J_{2,o}) \dot{\varphi}_1 = T_{\text{eng}} - T_{\text{Cl},e} + T_{\text{mot},o} - b_{1,o}k_{1,o}(\varphi_{2,o} - i_o \varphi_3) - b_{1,o}d_{1,o}(\dot{\varphi}_{2,o} - i_o \dot{\varphi}_3) \]
\[ - d_{G,o} \dot{\varphi}_{2,o} - d_{G,e} \dot{\varphi}_{2,e} \]
\[ \dot{\varphi}_{2,e} = \dot{\varphi}_1 \]

Eq. (7) combines engine and clutch inertias for sticking and (8) sets both angular accelerations of engine and clutch parts equal. (During launching \( b_{1,o} \) is engaged.)

### 2.2 Vehicle Launch Process

A typical vehicle launch process for the specific control topic is depicted in Fig.4. In the upper graph the requested clutch torque \( T_{\text{Cl},u} \text{Req} \) and engine torque demand \( T_{\text{Eng,Dmd}} \) are shown. \( T_{\text{Eng,Dmd}} \) during launching only results from driver demand and engine idle speed control. \( T_{\text{Cl},u} \text{Req} \) during launching is controlled to close the clutch up to \( T_{\text{Eng,Dmd}} \) by a ramp and to exceed \( T_{\text{Eng,Dmd}} \) depending on the slip speed of the clutch plates. As soon as the clutch sticks \( T_{\text{Cl},u} \text{Req} \) is increased slightly tracking the torque of \( T_{\text{Eng,Dmd}} \) in order to keep the clutch sticking but to allow damping of high transient shocks.

The next graph contains the corresponding shaft speeds for the primary side \( n_{\text{Eng}} \) (engine side) and
Figure 4: Reference clutch torque request $T_{\text{Clu Req}}$ signal for vehicle launch process. Secondary clutch side speed $n_{\text{Clu}}$ converges towards engine speed $n_{\text{Eng}}$ when clutch is closing.

the secondary side $n_{\text{Clu}}$ of the clutch system. $T_{\text{Eng Dmd}}$ represents the maximum torque capacity of the internal combustion engine at the current operating point scaled by the drivers demand defined via the acceleration pedal position $\alpha_{\text{acc}}$. The standardized excitation by $\alpha_{\text{acc}}$ is shown in the lower graph. $T_{\text{Clu Req}}$ in this figure is the requested clutch torque of the odd drivetrain path, which can be induced by applying force to the actuating system of the clutch. This force is commanded by e.g. the transmission control unit (TCU).

Rising $T_{\text{Eng Dmd}}$ here implies the beginning of the vehicle launch process, which can be detected at approx. second 3.2. Engine speed control is applied then with a target speed depending on the driver’s acceleration request represented by the accelerator pedal. Just a few moments later, when the requested clutch torque increases above zero the closing procedure of the clutch starts in order to transmit torque from the engine to the wheels. Some jerks on the secondary side of the clutch ($n_{\text{Clu}}$) are reflecting the system behaviour of the vehicle and the powertrain on the secondary side. Hence the vehicle starts to accelerate (approx. second 3.8). While the requested clutch torque stays below the demanded engine torque, only a very small influence of the acceleration can be detected in the engine speed $n_{\text{Eng}}$. When $T_{\text{Clu Req}}$ exceeds $T_{\text{Eng Dmd}}$ at approx. second 3.9 a significant drop of $n_{\text{Eng}}$ happens because the engine can not provide enough torque to stabilize its rotational speed. After approx. 5.4 seconds the speeds $n_{\text{Eng}}$ and $n_{\text{Clu}}$ are identical. Here the vehicle launch process is theoretically completed. In order to detect unwanted system behaviour after this point which is caused by the launch process, the observation window for quality rating is extended by some amount of time.

3 Optimization problem

The goal of performed optimization is to find optimal solutions for the objective function. Since the investigated objective function is not a scalar value but a vector of different conflicting objectives the problem is a multi criteria optimization. A simple way to get rid of the multi criteria objective function is to introduce weights and form a single objective function. However this leads to the question how to find a good weighting.

A different strategy, which offers choosing out of a big set of unweighed solutions is searching for the pareto optimal solutions, where the definition of the weighting can take place after the optimization.
The set of pareto optimal solutions contains solutions that do not dominate each other. A solution is said to dominate another one if it generates lower values (in case of a minimization problem) in all objective function parts. After optimization the user is able to analyse the returned pareto set of solutions. This procedure enables globally judging the influence of changing design variables on the multiple objectives.

### 3.1 Objective function

Control algorithms implemented in the transmission control unit are rather complex and may contain switching mechanisms which lead to rather different behaviour at nearly same conditions (strongly non-linear behaviour). Objective functions based on this may become non-smooth. In this case the derivative of the objective function is unknown, and there may be locations in parameter space where the derivative is not defined. As already mentioned before, the target of this work is to optimize the control algorithm parameters for the vehicle launch process. Therefore the simulation environment is extended by a benchmarking system rating the simulation results. Two indicators are taken into account:

\[ D(x) \] representing a rating of driveability. Calculation mainly considers vehicle acceleration and speed and reflects the quality of the launch process. The value is derived using an industrial driveability assessment tool [1].

\[ E(x) \] quantifying the energy input into clutch, which increases the clutch heat during the launch process.

The overall objective function \( J(x) \) containing both presented optimization objectives (\( D_N \) and \( E_N \) are constant scalar factors used for normalizing) is defined as:

\[
J(x) = \begin{bmatrix} j_1, j_2 \end{bmatrix}^T = \begin{bmatrix} D(x) / D_N, E(x) / E_N \end{bmatrix}^T, \quad x \in \mathbb{R}^2
\]  

(9)

### 3.2 Optimization parameters

Calibration of the control algorithm governing the launch process involves two parameters: \( x_1 \), a factor for closing ramp steepness of the clutch and \( x_2 \), a factor for clutch torque exaggeration.

Fig. 5 depicts variations of \( x_1 \) and \( x_2 \) during vehicle launch and their influence to the simulation results.

\[ \text{(a)} \text{ Variation of optimization parameter } x_1 \quad \text{(b)} \text{ Variation of optimization parameter } x_2 \]

**Figure 5:** Torque graph depicting clutch torque request signal (\( T_{\text{CluReq}} \)) for different optimization parameters \( x_1 \) (clutch closing ramp) and \( x_2 \) (clutch clutch torque exaggeration)
The variation of the closing ramp of the clutch is shown in Fig. 5a. The solid black line represents the simulation at $x_1=1$. An exemplary variation of $x_1=0.5$ is drawn with the dashed dark grey line showing a decreased steepness of the requested clutch closing torque $T_{CluReq}$. The solid gray signal line corresponds to the demanded engine torque $T_{EndDmd}$ and serves for orientation of the viewer.

In Fig. 5b the variation of the clutch torque exaggeration is shown. The solid black line shows an exaggeration of $T_{CluReq}$ over $T_{EndDmd}$ depending on the clutch slip speed for the case of $x_2=1$. For less clutch torque exaggeration the optimization parameter $x_2$ was set to $x_2=0.4$ to exemplify this variation. This behaviour is represented by the dashed dark grey line.

4 Optimization algorithm

The optimization problem for the investigated case can be summarized:

$$\begin{align*}
\min_{x} & \quad J(x) \\
\text{s.t.} & \quad x_{\text{min}} \leq x \leq x_{\text{max}}
\end{align*}$$

(10)

Due to the properties of the optimization problem discussed above a stochastic optimization algorithm is selected for solving. Since the evaluation of the objective function is rather costly in terms of computing time, a so called greedy algorithm the differential evolution (DE) algorithm is used [5][2].

4.1 Surrogate-based Analysis and Optimization

Investigations on further saving computing time by reducing the needed function evaluations lead to surrogate-based analysis and optimization (SBAO) methodologies as described in [6][7]. The main idea is to additionally use a surrogate function in the optimization process. This surrogate function is not as precise but can be computed with much less computational effort.

Different approaches have been proposed in literature to build the surrogate function based on known evaluations of the real objective function. A very commonly used approach is based on radial basis functions (RBF). Within this work an extended RBF approach is used as proposed in [8]. In the following the calculation scheme is shortly summarized. For each dimension of the objective function a separate surrogate model is generated. The $k$-th coordinate $j_k(x)$ of the objective function $J(x)$ is denoted with $\hat{j}_k(x)$ and can be calculated by:

$$\hat{j}_k(x) = \sum_{i=1}^{N} \lambda_i \Phi_i(||x - x_i||) + \sum_{i=1}^{M} a_i \Theta_i(x)$$

(11)

Within (11) the number of basis function centers with corresponding coordinates $x_i$ is $N$. The number of polynomial components is $M$. $\Phi(r)$ denotes the so called kernel function, which in the presented work is a Gaussian kernel function with

$$\Phi(r) = e^{(-c^2 r^2)}$$

(12)

where $r$ is the euclidean norm of the distance between a point in parameter space to a kernel center point. The free parameter $c$ has to be tuned dependent on the scale of the parameter space and the distance between the kernel centers. The weights $\lambda_i$ have to be derived during a fitting step explained later on. As an extension low order polynomial functions of the type

$$P(x) = a_0 + a_1 x_1 + a_2 x_2 + a_3 x_1^2 + a_4 x_2^2$$

(13)

are added. Eq.(13) can be written in a shorter notation

$$P(x) = \Theta(x) \mathbf{a}.$$
In the current work $\Theta(x)$ was set to

$$\Theta(x) = [1, x_1, x_2, x_1^2, x_2^2].$$

(15)

The corresponding vector of parameters $a$ has to be calculated during a fitting step, which is shortly explained in the following. Based on the known evaluations $j_k$ at the coordinates $x_i$ the vector of weights $\lambda$ and the vector of polynomial coefficients $a$ can be calculated by solving the following linear system [8]:

$$\begin{bmatrix} \Phi & \Theta \\ \Theta^T & 0 \end{bmatrix} \begin{bmatrix} \lambda \\ a \end{bmatrix} = \begin{bmatrix} j_k \\ 0 \end{bmatrix}, \quad \Phi \in \mathbb{R}^{N \times N}, \ \Theta \in \mathbb{R}^{N \times 5}, \ \lambda \in \mathbb{R}^N, \ a \in \mathbb{R}^5, \ j_k \in \mathbb{R}^N$$  

(16)

This results in one set of weights, parameters and kernel centers for each surrogate model interpolating one of the objective functions dimensions. As proposed in [9] solving can be done in a progressive way to reduce the computational effort. The interested reader is referred to [8] for further detail about RBFs.

![Objective function $j_1$ over parameter space](a)

![Objective function $j_2$ over parameter space](b)

Figure 6: Surrogate functions plotted together with objective function evaluations (○) and pareto-front samples ♦.

In Fig.6 both surrogate functions are plotted together with the function values of the objective function and the function values form the pareto front. Fig.7 lists the steps of the used surrogate based optimization approach.

| (A) | Generate initial screening point distribution for surrogate function. |
| (B) | Evaluate on objective function and generate pareto front. |
| (C) | Fit surrogate function based on known evaluations |
| (C1) | Run DE on surrogate with increased number of #: individuals, allowed function evaluations and pareto archive size. |
| (C2) | Extract points from surrogate pareto front that dominate the pareto front, and choose a subset of candidate points out of these. |
| (D) | Evaluate new candidates on objective function and add to pareto front if feasible. |
| (E) | Find the biggest gap in pareto front and generate new screening points. |
| (F) | Continue at (B) until termination criteria is met. |

Figure 7: Surrogate based optimization (SBAO) approach used in this work.
To be able to construct a surrogate model some initial evaluations of the objective function have to be performed (A). In literature this procedure is called screening [10]. Since extrapolation is always dangerous, most of the initial screening points have been chosen to be on the limits of the parameter space. Next (B) the objective function is evaluated at the screening points. In step (C) the surrogate model is generated and optimized in step (C1) using a DE algorithm. The number of individuals for the surrogate optimization can be chosen higher compared to the non surrogate approach to get a better parameter space exploration. Step (C2) is most important for improving the performance. The strategy is to get high potential candidate points to extend the existing pareto front. Only points that extend the existing pareto front (assuming the surrogate model estimates are perfect) are of interest. From this set of points again only the ones are chosen, which extend the pareto front at the borders or at locations with few points in the neighbourhood. In step (D) the selected candidates of the surrogate step are evaluated on the objective function and the pareto front is updated. To further improve the surrogate model additional screening points are selected and evaluated (E). A new loop beginning in (B) is started if the termination criteria is not met otherwise optimization finishes.

4.2 Application of optimization method

Two different approaches were used to solve the optimization problem. A pure DE approach and a surrogate based approach using DE to optimize the surrogate model.

Fig. 8 shows the results for a typical run at 48 allowed function evaluations on the objective function. In the plotted example run the resulting pareto front of solutions produced by the two approaches are once plotted in the objective space and once in the parameter space. To better identify which set of parameters corresponds to which objective function value, the pareto solutions are indexed. Within the plots it can be seen that the surrogate based approach was able to deliver 15 pareto members and the pure DE approach delivered 10 pareto members. Both pareto fronts contain members, which might dominate pareto members of the other approach.

Figure 8: The pareto front for pure DE and a surrogate based DE is plotted in objective as well as in parameter space. Both algorithms used 48 function evaluations to evolve.

From a runtime point of view, the surrogate approach needs more overall computation time due to the surrogate fitting and the additional inner optimization steps. In the investigated case evaluating the cost function was the major time consuming task. The surrogate approach needed 152 seconds and the
pure DE approach needed 118 seconds to solve the optimization task including simulation and objective function evaluation on an i7 intel PC. Finally Tab.1 summarizes used parameters.

Table 1: Used parameters (according to [2]) and results for one example run

<table>
<thead>
<tr>
<th>Approach</th>
<th>Function Evaluations</th>
<th>Pareto members</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>DE</td>
<td>48</td>
<td>10</td>
<td>de/best/1/bin, (NP = 6), (CR = 0.6), (F = 0.6)</td>
</tr>
<tr>
<td>SBAO DE</td>
<td>48</td>
<td>15</td>
<td>de/best/1/bin, (NP = 30), (CR = 0.6), (F = 0.6), (\beta = 0.1)</td>
</tr>
</tbody>
</table>

5 Results

Target of the task was to generate a big quantity of suitable parameter sets for the user selection using few function evaluations. Based on the resulting pareto front of provided parameter sets in Fig.8a set \(x_2 = [0.4108, 0.1716]^T\) from the SBAO DE run has been chosen for the final application with a corresponding objective function value of \(J(x_2) = [-0.7211, 0.6335]^T\). At this set from application point of view a good trade off between the competing objectives exists, since at this point only few additional improvement of the driveability is possible at rather big drawbacks in terms of higher energy input into the clutch.

Fig.9 depicts the results of the simulation using the described parameter set. The shaft speeds for the primary clutch side \(n_{Eng}\) and for the secondary clutch side \(n_{Clu}\) are shown in the upper graph. In order to get a rough idea about the quality of the resulting vehicle launch process, the vehicle acceleration \(a_{veh}\) which is an important indicator for driveability benchmark and the energy input into the clutch \(E_{Clu}\) are depicted in the middle. The lower graph then shows the standardized excitation by \(\alpha_{acc}\) which represents the acceleration demand by the driver during launching.

Figure 9: Simulation result on base of the selected parameter set depicting shaft speeds and vehicle acceleration respectively clutch energy input.

From a point of view of dimensioning the clutch the application of energy into the clutch during the launch process \(E_{Clu}\) is a very important criteria. The pareto front for the launch process can be
used for dimensioning, since even clutch systems that allow application of higher friction energy (i.e. bigger clutches) than needed for parameter set $x_2$ cannot improve the driveability in a reasonable way. Nevertheless it has to be considered that optimization results were shown for the specific control algorithms available and for a specific driver’s launch demand, which is represented by the acceleration pedal value $\alpha_{acc}$. For clutch system design besides other criteria for dimensioning all applicable launch processes have to be considered.

6 Discussion

Within the investigated use case, the optimization algorithm using the surrogate approach provides a bigger variety of pareto solutions when allowing rather few function evaluations (48). For a bigger number of allowed function evaluations (app. 120) both DE and surrogate based DE performed approximately equally. One of the reasons may be the special configuration of the pareto points within the parameter space, which is beneficial within the mutation step of DE.

The optimization results in Fig.9 show significant improvements in the objective functions - namely driveability and friction energy in the launch clutch - which were evaluated on the drivetrain model described in section 2. The results may be used as base parameterization of the control algorithms for testing on the real drivetrain. The quality of these base parameter values depends on the quality of the drivetrain model. The resulting achievable driveability shows some potential for further improvement by adapting the launch control algorithms and repeating the optimization problem on new parameters.

7 Conclusions and Outlook

The use case of finding parameters that govern the launch process of a transmission control unit was successfully solved using stochastic optimization. Using a surrogate objective function could further improve the results in the tested case permitting very few function evaluations. By this a bigger variety of pareto solutions at few allowed objective function evaluations could be generated.

The specific control algorithms for launching are planned to be adapted to an improved strategy probably resulting in an optimization problem with a higher number of parameters. The authors are convinced that the optimization algorithm using a surrogate approach for that adapted use case will show even higher benefit. Besides optimization parameters, objective function and control algorithms also the quality of the drivetrain model influences the optimization result, which is also planned to be subject of further investigations.

Future investigations will be made extending dimensionality of parameter and objective function spaces. Also surrogate model approaches other than RBFs (e.g. local linear model tree LoLiMoT approach) will be a field of future research.

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