Parameter Identification for Simulation Models by Heuristic Optimization

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ABSTRACT:

In this publication we describe a generic parameter identification approach that couples the heuristic optimization framework HeuristicLab with simulation models implemented in MATLAB or Scilab. This approach enables the reuse of already available optimization algorithms in HeuristicLab such as evolution strategies, gradient-based optimization algorithms, or evolutionary algorithms and simulation models implemented in the targeted simulation environment. Hence, the configuration effort is minimized and the only necessary step to perform the parameter identification is the definition of an objective function that calculates the quality of a set of parameters proposed by the optimization algorithm; this quality is here calculated by comparing originally measured values and those produced by the simulation model using the proposed parameters. The suitability of this parameter identification approach is demonstrated using an exemplary use-case, where the mass and the two friction coefficients of an electric cart system are identified by applying two different optimization algorithms, namely the Broyden-Fletcher-Goldfarb-Shanno algorithm and the covariance matrix adaption evolution strategy. Using the here described approach a multitude of optimization algorithms becomes applicable for parameter identification.

1 INTRODUCTION

Simulation models are used for describing processes and systems of the real world as closely as possible, analyzing and predicting system behavior, and testing alternatives for the original system's design or parametrization. Dynamical, technical systems are often modeled using differential equation systems; usually, first appropriate equation systems are defined, and afterwards their parameters are adjusted so that the resulting set of equations resembles the modeled system as closely as possible.

In this context, parameter identification is the identification of the best parameter values for a simulation model [1,2] that has to be adapted to the concrete circumstances of the modelled system in order to match the real world as exactly as possible. These adaptations are necessary simply because otherwise the predictions of the simulation model would be inaccurate. For example, the friction coefficients of a cart vary depending on the surface it is moved on and have to be adapted for the respective simulation model. The only prerequisite of this parameter optimization approach is that the structure of the simulation model has to match the system which is modelled; if not any adaptation to the real system would certainly fail, regardless of the effort used for parameter optimization.

We here investigate whether and to what extent heuristic optimization methods can be used for identifying parameters of systems by optimizing parameters of simulations. As we see in the empirical part of the paper, this is possible – which indicates that the here discussed approach for simulation-based optimization is applicable for various kinds of systems.

2 PARAMETER IDENTIFICATION

The parameter identification process using simulation models is illustrated in Figure 1. The optimization algorithm controls the overall workflow and triggers the associated simulation whenever necessary. A possible solution candidate (usually a set of parameters) is passed to the simulation which then returns the outcome of the concrete simulation model executed with the provided parameters. The outcome of the simulation model is then aggregated into a quality value to allow the assessment of the solution candidate and is returned to the optimization. This quality value expresses the accordance between the outcome of the simulation model with the currently used parameter values and the measurements observed in real world. In many cases the sum of deviations at predefined time steps is calculated and used as quality value. The optimization generates new solution candidates (which are again evaluated by the simulation) and tries to minimize/maximize the objective function. If the simulation model contains stochastic elements, the returned quality has to be seen as a random variable and often multiple simulation runs with the same parameter set have to be executed to estimate the expected quality accurately.

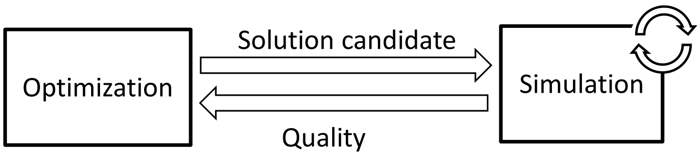

Figure 1. Schematic representation of the parameter identification process for simulation models.

Optimization algorithms often use simulation models when, for example, a closed-from representation of the objective function is not feasible due to complex stochastic elements or dynamic interactions. In this context the application of heuristic optimization algorithms has been proven fruitful [3,4].

2.1 Heuristic Optimization Algorithms

In general, heuristic algorithms are designed to find solutions for optimization problems with limited knowledge and time. Such methods have the advantage that they can be used when a problem cannot be solved analytically due to its size or complexity [5].

In the context of real-valued parameter identification the challenge is to find parameter values so that the predicted state variables of the simulation correspond to actually measured values as closely as possible. Thus, the optimization routine used to identify parameters of the system (i.e., to optimize the parameters of the simulation model) has to execute the simulation and compare the predicted and the actual values. This information is used to assess the quality of the parameter combinations created and for guiding the algorithm's evolutionary process.

This approach is independent of the type of simulation model and simulation framework, and therefore can be used for various simulation models; any algorithm that is able to handle solution candidates encoded as real-vectors could be used to solve such parameter identification problems.

2.2 Coupling of HeuristicLab with Simulation Frameworks

The HeuristicLab framework [6] provides several algorithms which are suitable for parameter identification of simulation models: genetic algorithms, evolution strategies, simulated annealing, etc. The use of optimization algorithms provided by HeuristicLab for parameter identification has been enabled by implementing a layer that handles the communication with the targeted simulation environment. Most simulation environments already provide multiple possibilities to couple them with external applications and to programmatically utilize their functionality. The technologies for such a coupling range from direct calls to specialized application programming interfaces (API), the component object model (COM) for inter-process communication, or web services. A drawback is that this coupling, regardless of the utilized technology, is specific to the targeted simulation environment. However, such a layer can be implemented in a generic way which allows the execution of arbitrary commands instead of running a specific simulation model and hence its reusability is ensured.

We have implemented a layer for the communication between HeuristicLab and Scilab [7] and HeuristicLab and MATLAB [8]. Both of these frameworks were originally designed to perform numeric computation and provided specialized components which ease the development of continuous simulation models. Based on these layers we have developed a real-vector encoded parameter optimization problem, where solution candidates are encoded as real-vectors, and the quality of a solution candidate is evaluated by a script in the programming language of the target simulation environment. Hence, not only parameter identification of simulation models can be performed, but any optimization problems, for which the quality of a solution candidate is calculated by a numeric computation framework, can be solved in this way.

An exemplary optimization problem, which tunes the coefficient of a polynomial is depicted in Figure 2. Here, the quality of a solution candidate is calculated by the encapsulated Scilab script as the average absolute error calculated at ten positions. Besides the quality function the problem also defines the name of the parameters and the quality variable, the problem size or dimension, the bounds for the solution candidate (minimum and maximum value for each variable), and whether the quality value should be maximized or minimized.

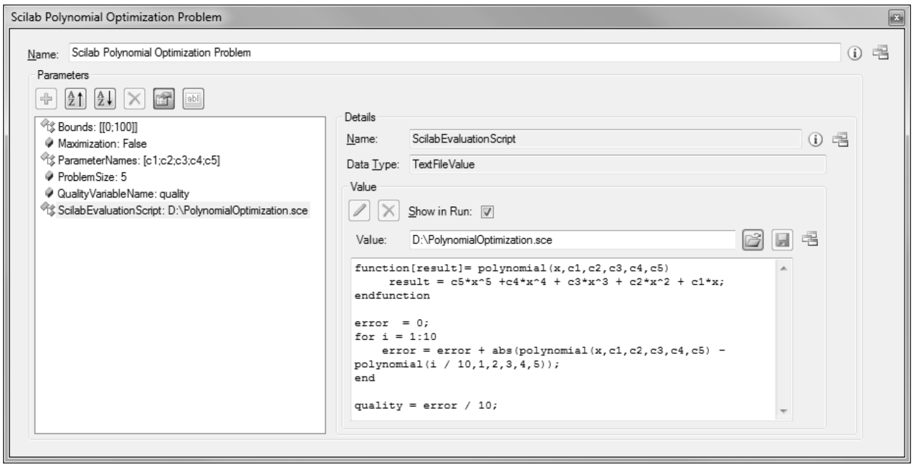

Figure 2. Screenshot of a five-dimensional Scilab parameter optimization problem in HeuristicLab.

3 USE CASE - ELECTRIC CART SIMULATION

The well-known cart system with an electric motor was used as a reference application to test the suitability and effectiveness of the described approach. A certain voltage was applied to the cart's motor and the resulting movement was tracked. Furthermore, a system model in terms of differential equations (given in Equations 1-4) was developed and implemented in both simulation frameworks Scilab and MATLAB. Every parameter and state variable of the simulation is known, except the mass of the cart (m_1), the linear friction coefficient (d_1) and the static friction coefficient (F_C), which have to be identified by the optimization process based on a known current (u_A) and measurements of the position (x) of the cart.

$$x' = v \tag{1}$$

$$v' = -\frac{\mathrm{d}_1}{\widetilde{m}}\, v - \frac{1}{\widetilde{m}}\, F_C \operatorname{sign}(v) + \frac{k_m n}{r\, \widetilde{m}}\, i_A \tag{2}$$

$$i_A{}' = -\frac{k_m\, n}{L_A\, r}\, v - \frac{R_A}{L_A} i_A + \frac{u_A}{L_A} \tag{3}$$

$$\widetilde{m} = m_1 + J_A \left(\frac{n}{r}\right)^2 \tag{4}$$

The response of the simulation model in terms of the cart's position and velocity for three different combinations of the parameters to identify is shown in Figure 2. "Original Model" shows the response with the correct values for the mass and the two friction coefficients, whereas "Model with increased mass" shows the response with a higher mass (slower acceleration and slow down) and “Model with increased friction” shows the response with higher friction coefficient (constant offset in position and velocity).

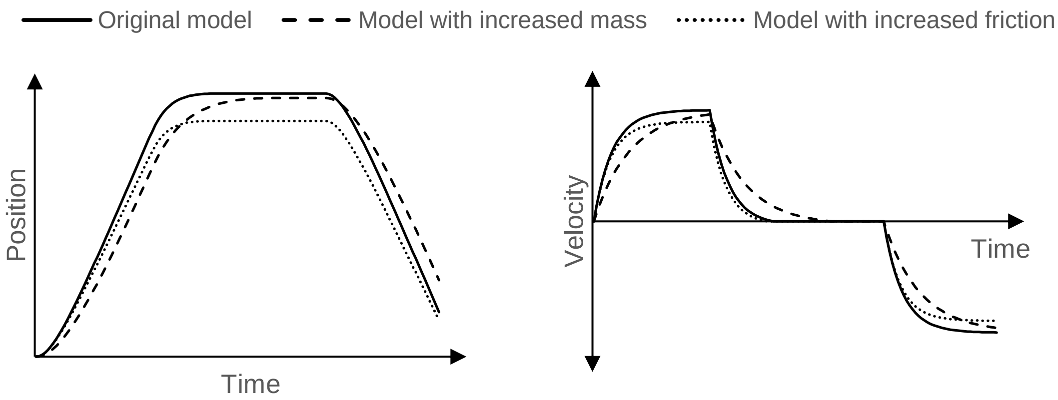

Figure 3. The response of the simulation model with the correct parameter values, with an increased mass and with increased friction coefficients in terms of the cart’s position and velocity.

We have applied a limited memory variant of the Broyden–Fletcher–Goldfarb–Shanno algorithm (LM-BFGS) [9] and the covariance matrix adaption evolution strategy (CMA-ES) [10] on this parameter identification problem and performed 50 repetitions of each algorithms, where the number of simulation model evaluations has been limited to 1000. The correct parameter values for this experiment were 1.5 for the mass, 1.0 for the linear friction and 0.5 for the static friction and the quality of a proposed parameter set has been calculated as the average absolute error in the cart’s position. An algorithm execution is considered successful, if all three parameters were identified with a tolerance of 10^{-2}. The detailed results in terms of the number of success full runs, the obtained quality and the identified parameter values are reported in Table 1.

Table 1. Results of 50 repetitions of the optimization algorithms (average ± standard deviation). Successful runs denotes the number of times the correct parameter values have been identified, quality the average absolute error in the cart’s position and the other rows the identified parameter values.

Results	LM-BFGS	CMA-ES
Successful runs	13 / 50	47 / 50
Quality ($\mu \pm \sigma$)	0.043 ± 0.055	0.000 ± 0.000
Mass (m_1, target 1.5)	1.499 ± 0.007	1.500 ± 0.000
Linear friction (d_1, target 1.0)	0.968 ± 0.472	1.000 ± 0.004
Static friction (F_C, target 0.5)	0.516 ± 0.199	0.500 ± 0.002

The best result on this parameter identification problem with respect to the obtained quality and the number of successful runs have been obtained by the CMA-ES. The explanation is that the CMA-ES uses multiple parameter sets simultaneously, whereas the LM-BFGS optimizes one single parameter set iteratively and therefore, the CMA-ES is less likely to get stuck in a local optimum. The performance of the LM-BFGS could be easily improved by incorporating multiple restarts of the algorithm, but this would have exceeded the number of simulation models evaluations and resulted in an unfair algorithm comparison.

4 CONCLUSION

In this publication we have presented a generic parameter identification approach using simulation models and heuristic optimization algorithms. We have demonstrated its suitability to identify the parameters of an electric cart system by applying two optimization algorithms. The advantage of this approach is that existing simulation models implemented in either Scilab or MATLAB and optimization algorithms provided by HeuristicLab can be reused. Furthermore, no information about the concrete simulation model is needed as the only information exchanged is a set of parameters generated by the optimization algorithm and its quality value calculated by the simulation model. Therefore, a whole new range of optimization algorithm becomes applicable to parameter identification. In the exemplary use-case the best results have been obtained by the CMA-ES algorithm, which further highlights the usefulness of heuristic optimization methods for parameter identification.

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