Control and Optimization of FES-Cycling with Differential Evolution: A Computer Model-based Study

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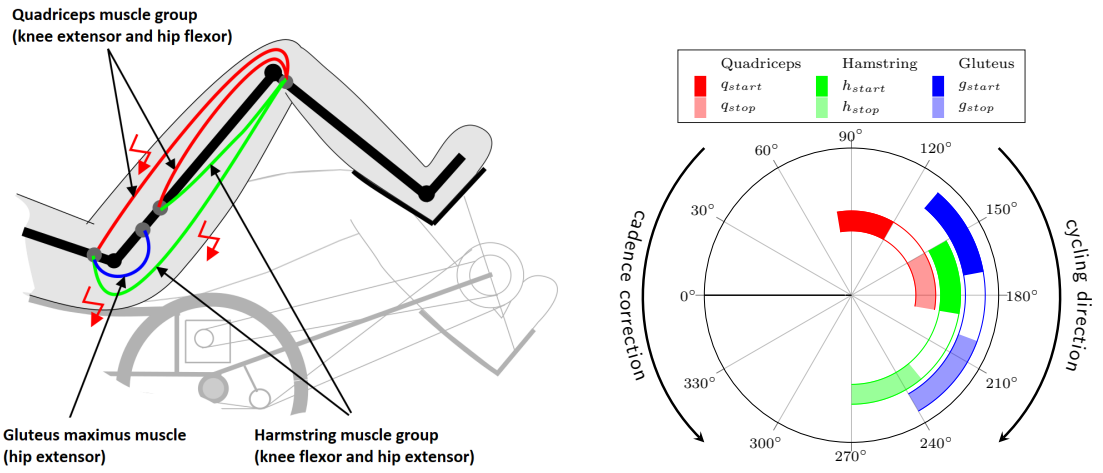
Abstract

An objective function with the intention to evaluate the effectiveness of FES cycling is defined. To optimize this function a heuristic control strategy that relies on the global function optimizer Differential Evolution (DE) is presented. In this approach the timing of the muscle stimulation is changed by DE. To evaluate, how effective DE can optimize this problem domain a FES cycling computer model is used. Results show that the online optimization takes between 15 min and 40 min of cycling. A comparison of the stimulation intensity showed that the optimised FES cycling shows a $9,6\%$ reduction. This saving might enable longer FES cycling therapies.

1 Cycling by Means of Functional Electrical Stimulation

The Functional Electrical Stimulation (FES) is a special form of neuromodulation, which stimulates the neural interface via electrical pulses. One of it's many applications is FES cycling. FES cycling is intended for patients with central neurological impairments that partially or completely paralyse the lower limbs. For example an individual with paraplegia due to spinal cord injury can cycle by means of FES stimulation. This is achieved by stimulation of the large leg actuating muscles in such way, that the resulting muscle contraction leads to a positive drive torque at the crank. Most FES cycling therapies are carried out on specialised stationary ergometers with the FES stimulation

applied via surface electrodes [6, pp.395-402].



(a) Stimulated muscle groups (source:[13])

(b) Exemplary stimulation pattern for the muscles of the right leg

Figure 1: Stimulated muscles and stimulation pattern. If the crank angle is in between the ranges defined by the stimulation pattern, the corresponding muscle gets stimulated.

The three most commonly stimulated muscle groups in FES cycling are displayed in Figure 1(a). Most control strategies for FES cycling map a stimulation pattern over the crank shaft angle. For every stimulated muscle group the stimulation pattern defines ranges for effective muscle stimulation. An exemplary stimulation pattern for the right leg can be seen in Figure 1(b). In most classic control strategies the stimulation pattern is predefined and static. Only a cadence correction shifts the stimulation pattern forward in time to counteract the rising influence of muscle contraction latency with rising cadence. In this study the start and stop angles of the stimulation are variable within a 40° range and are optimized with respect to an objective function.

1.1 The Possible Benefits of Differential Evolution in FES Cycling

The medical benefits of FES cycling have been subject to many clinical studies. The physical exercise enabled by FES cycling primarily prevents secondary medical complications [9, 5, 1, 3]. Key to a successful training is the ease-of-use and the intensity of training. In comparison with the cycling of able-bodied persons the FES cycling's power output and efficiency is significantly lower [2].

One way to improve the efficiency and power output of FES cycling is to find better control strategies. Control strategies for FES cycling face numerous challenges. The plant of the control system, i.e. the patient-bicycle/ergometer system, changes with respect to the day to day condition of the patient, as well as the varying mechanical set-up. Fatigue of the patient also plays a significant role. Thus the system plant is heavily time variant. The optimal cycling movement itself is complex and still object of research. Additionally actuating muscles or nerves with FES is non-linear. In sum, all properties are too complex

for a precise mathematical description. Nevertheless, a good control strategy should be able to optimize the training effect while delivering stable results without human intervention. A heuristic control strategy relying on Differential Evolution (DE) as a global function optimizer may be one possibility to fulfill these requirements.

2 Control Strategy

A heuristic **control strategy** that can optimize FES cycling with respect to a given objective function is shown in Figure 2. Here Differential Evolution (DE) is implemented in such way, that it can change the stimulation pattern during cycling.

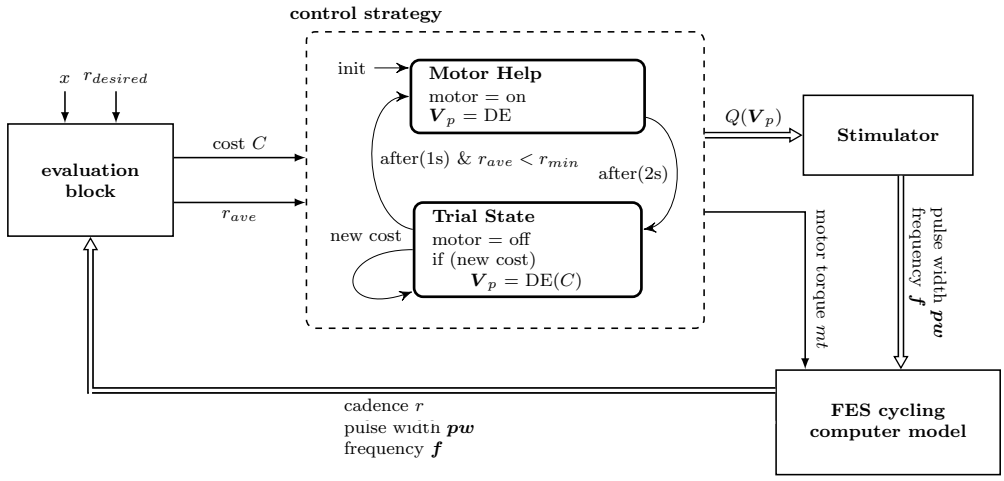


Figure 2: State based control strategy relying on differential evolution

The **control strategy** is state-based to guarantee that cycling does not stop, even if DE tries non-functioning stimulation patterns. It consists of two states. Directly after initialisation the control strategy is in the motor help state, where a motor at the ergometer crank supports the cycling movement. After 2 s the trial state is entered, the motor help is turned off and the evaluation of the FES induced cycling movement begins. Every time a new cost is calculated, DE assigns this cost to the last tried stimulation pattern and proposes a new one. If one second after entering the trial state the average cadence r_{ave} is smaller than a minimal cadence r_{min} the control strategy switches to the motor help state. Here DE proposes a new stimulation pattern and assigns very high cost to the unsuccessful one. Thus, ensuring that non-functioning stimulation patterns get eliminated by differential evolution over time.
The parameter matrix $\boldsymbol{V}_p$ proposed by DE defines the stimulation pattern and contains start and stop angles of the stimulation for quadriceps (q), hamstring (h) and gluteus (g) muscle group of the right leg:

$$\boldsymbol{V}_p[k] = \begin{bmatrix} q_{start}[k] & q_{stop}[k] \\ h_{start}[k] & h_{stop}[k] \\ g_{start}[k] & g_{stop}[k] \end{bmatrix} \tag{1}$$

In this notation k denotes the sample time instances. Symmetry between both legs is assumed. Hence the stimulation pattern for the left leg is calculated by shifting with 180°. Strict bound constraints at initialisation and during optimization as shown in Figure 1(b) are used. The parameter matrix is quantized by the uniform quantization function $Q()$ to a precision of 2°, because the precision of stimulation is limited by the sample frequency of the crank encoder.

The **stimulator** interprets the parameter vector to generate FES pulses for every stimulated muscle group. In the stimulator block the crank angle is linearly shifted forward in time to compensate the influence of muscle activation delay of approximately 130 ms [1]. The stimulator logic stimulates every muscle group with a pulse width of 300 µs at a frequency of 50 Hz, if the shifted crank angle lies in between the start and stop angles defined by the the parameter vector.

In this study a **FES cycling computer model** is used. The inputs of the model are vectors of pulse widths $\boldsymbol{pw}$ and frequencies $\boldsymbol{f}$, defining the FES stimulation for every muscle group. The electrical stimulation is modelled as applied via surface electrodes. The neuro-muscular model incorporates five muscles per leg, which are the same as depicted in Figure 1(a). The neuromuscular model was taken from Riener and Fuhr [12]. A five bar rigid body network, implemented in the Open Dynamics Engine [14], represents the skeletal system. The fatigue component of the FES cycling computer model is turned off. This makes the interpretation of the optimization easier because the optimum is not time dependent and no warm up routine has to be added to the control strategy.

If the control strategy is in the trial state the **evaluation block** begins to buffer the measurement data for four full revolutions to ensure that the cycling has adapted to the new stimulation pattern. Then the following x full revolutions are used as data input for the objective function[2].

It has to be clarified that the heuristic control strategy presented in this section can not be used in a therapeutic FES application without additional effort. The abrupt engaging motor aid constitutes an injury risk for patients. This is especially true, when DE activates stimulation at non effective ranges and the motor tries to overcome the muscle contraction.

Computational Environment and Computer Code

The control strategy is implemented in a Matlab Simulink model at a sample time of 5 ms. The FES cycling model internally runs with a higher sample rate. The DE algorithm is taken from a C++ Library provided by Michel [8]. To work with the Simulink environment the library was made accessible via a S-function.

2.1 Objective Function

The objective function is key to a reasonable optimization process. In this study an objective function is used, for which the optimum is the global minimum. The evaluation

[1] see arrow in Figure 1(b)

[2] see Section 2.1

of the objective function is conducted over multiple full cycling revolutions. To reflect more than one aspect of FES cycling the objective function is the weighted sum of multiple terms:

$$C = w_{cadence}\, c_{cadence} + w_{StimCost}\, c_{StimCost} + w_{DeadCentre}\, c_{DeadCentre} \tag{2}$$

First of all, the **cadence** r shall be influenceable. Hence a cadence deviation penalty has to be set in such way, that great deviations definitely get eliminated but small deviations do not influence the objective function primarily. Therefore, the cadence deviation penalty divides the squared difference between the desired cadence and the average cadence for all evaluated sample time steps $k \in [0...K]$ by the desired cadence:

$$c_{cadence} = \frac{(r_{desired} - \frac{1}{K}\sum_{k=0}^{K} r[k])^2}{r_{desired}} \tag{3}$$

Furthermore, the **biomechanical efficiency** of FES cycling shall be optimized, which is difficult with limited sensory information. For an able-bodied person many receptors at the joints, the tendons and the skeletal muscles give feedback during cycling. This study only focuses on cadence information and the used stimulation pattern, because these informations can be acquired cost efficient and without additional set-up times.
Research by Hunt et al. suggest that the stimulation rate in FES cycling correlates with the metabolic work measured by the oxygen uptake [4]. Therefore, in this study it is assumed that the **stimulation cost** is a good indicator for the biomechanical effectiveness of the stimulation pattern. For every stimulated muscle group mg and sample time instance $k \in [0...K]$ the product of pulse width $pw_{mg}[k]$ and frequency $f_{mg}[k]$ is summed up over the evaluation time to obtain the raw stimulation cost. Then the average is taken by dividing with the number of evaluated sample time instances K. This average is divided by the maximum pulse width PW, maximum frequency F and the number of stimulated muscles SM, thus scaling the stimulation cost in a range of $[0, 1]$:

$$c_{StimCost} = \frac{\sum_{\forall mg}\sum_{k=0}^{K} pw_{mg}[k] f_{mg}[k]}{K\, SM\, PW\, F} \tag{4}$$

The **dead centre** or dead spot is a state in a mechanical crankshaft system in which an applied force does not produce a torque at the crank. The dead centres of cycling can be defined as the points where extension and flexion at the hip or knee joint alternate or as the points where the resulting force at the pedal is parallel to the crank arm. The position of these dead centres can be influenced by seating position, mechanical set-up and pedalling technique. Either way, every cycling revolution has two dead centres in which it is particularly difficult to produce effective drive torque [7]. To find a stimulation strategy that effectively overcomes the dead centres, the minimum cadence and the average cadence of the evaluated revolutions are taken into account:

$$c_{DeadCentre} = 1 - \frac{\min_{\forall k}(r[k])}{\frac{1}{K}\sum_{k=0}^{K} r[k]} \tag{5}$$

Initial test runs to evaluate the weighting of the cost function have shown, that the cadence penalty was too dominant. Therefore, the following weighting is used:

$$C = \frac{1}{4} c_{cadence} + c_{StimCost} + c_{DeadCentre} \tag{6}$$

2.2 Differential Evolution (DE)

The differential evolution algorithm is an evolutionary algorithm for global function optimization. Introduced by Price and Storn in 1995, DE was intended to be a "simple and efficient adaptive scheme"[10]. The fundamental idea behind evolutionary algorithms is to mimic nature's evolution and survival of the fittest, in order to solve computational problems. DE's general design makes it a direct search method, which enables to optimize non-differentiable and even non-continuous objective functions.
A simple flowchart of DE is displayed in Figure 3. At the start the population has to be initialized. Within each generation a trial population with the same size as the current population is generated by the mutation and crossover processes. Then selection decides based on a cost value which members of the trial or current population survive and become member of the next generation. If a termination criterion is met the algorithm terminates.

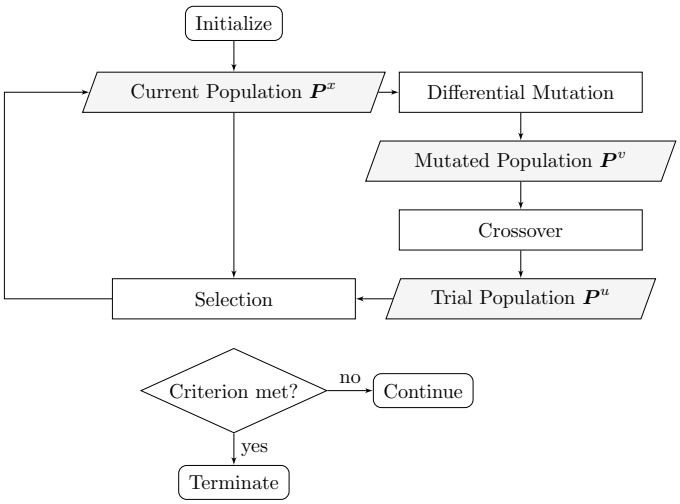


Figure 3: Flowchart of differential evolution. The grey parallelograms represent data input and output. Termination can be invoked by many different criteria and at every state of DE.

Problem Formulation:
It is the goal to find a global optimum x^* of an objective function C:

$$C : D \subset \mathbb{R}^n \to \mathbb{R} \tag{7}$$

The domain D is encoded in floating point representation, regardless of the data type of the parameters it represents. The co-domain of the objective function has to be scaled ordinal with respect to the optimization problem at least.

For many practical applications a approximation of the true global optimum is adequate. Therefore, a termination criteria can be defined e.g. as a value to be met, based on population statistics or a maximum computational time [11, pp. 128-130].

Population Structure and Initialization:

Since DE is a population based algorithm, the currently regarded solutions are stored in a population. The population $\boldsymbol{P}_g^x$ is a vector and consists of Np members which are the parameter vectors $\boldsymbol{x}_{i,g}$. From an evolutionary point of view, the parameter vectors are the individuals of the population. Every parameter vector itself contains D parameter values:

$$\boldsymbol{P}_g^x = (\boldsymbol{x}_{i=0,g}, \boldsymbol{x}_{i=1,g}, ..., \boldsymbol{x}_{i=Np-1,g}), \qquad g = 0...g_{max} \tag{8}$$

$$\boldsymbol{x}_{i,g} = (x_{p=0,i,g}, x_{p=1,i,g}, ..., x_{p=D-1,i,g}) \tag{9}$$

In this syntax the lower index g denotes the generation. The high index x of $\boldsymbol{P}$ indicates that this population is a current population. A population $\boldsymbol{P}$ with a superscript v refers to a mutated population and a superscript u refers to a trial population. The mutant and trial population are identical to the current population in structure and size. The first lower index i of $\boldsymbol{x}$ can be read as individual. This index identifies every individual. Equivalent the first lower index p of x can be read as parameter. This index identifies every parameter of one individual.

At the beginning a start population has to be initialized. Therefore the parameters of Np individuals have to be chosen. These initial points are distributed according to a predefined probability distribution function. If nothing is known about the location of the global optimum a uniform distribution should be used.

The number of the population members Np is one control parameter of the DE Algorithm. Depending on the complexity of the objective function this value has to adapted [11, pp. 53-60].

Differential Mutation:

In analogy to the biological mutation, the differential mutation is part of DE to ensure the diversity of the population.

The differential mutation adds the weighted difference of two parameter vectors to a third, to create a mutant vector $\boldsymbol{v}_{i,g}$. The three mutated vectors have to be chosen randomly in such way, that they differ from each other:

$$\text{classic DE:} \qquad \boldsymbol{v}_{i,g} = \boldsymbol{x}_{r0,g} + F * (\boldsymbol{x}_{r1,g} - \boldsymbol{x}_{r2,g}) \tag{10}$$

$$\text{target-to-best:} \qquad \boldsymbol{v}_{i,g} = \boldsymbol{x}_{i,g} + F * (\boldsymbol{x}_{best,g} - \boldsymbol{x}_{i,g}) + F * (\boldsymbol{x}_{r1,g} - \boldsymbol{x}_{r2,g}) \tag{11}$$

$$\forall i \in Np, \quad r0 \neq r1 \neq r2 \in [0, Np-1]$$

The weighting factor F is a scalar. The first indexes of $\boldsymbol{x}$ indicate which parameter vector, i.e. individual this formula is applied to. In classic DE the base vector index $r0$ and the difference vector indices $r1$ and $r2$ differ from each other and are different from the target vector index i, thus guaranteeing that the DE algorithm does not degenerate. The target-

to-best variant replaces the base vector $\boldsymbol{x}_{r0,g}$ with a vector that lies between the target vector $\boldsymbol{x}_{i,g}$ and the best so far vector $\boldsymbol{x}_{best,g}$, thus shifting the search space towards the best so far individual. Every individual of the current population is mutated. Hence, the mutated population $\boldsymbol{P}_g^v$ is of the same size as the current population.

The weighting factor F is another control parameter of the DE algorithm. It can be interpreted as an indication for the rate at which the population converges. Due to the selection process, population diversity is reduced and premature convergence in a local optimum might occur. To counteract this selection pressure the weighting should be chosen high enough. Dependent on the objective function a value chosen from $[0, 1[$ is advisable [11, pp. 75-91].

Crossover:

As the name suggest the crossover process is inspired by the genetic crossover. The genetic crossover describes which parts of genetic information of two parental chromosomes are passed on to the next generation. In DE the crossover process is applied on two individuals and the genetic information is the value of their parameters.

To derive the trial vector $\boldsymbol{u}_{i,g}$ for the selection process every mutant vector $\boldsymbol{v}_{i,g}$ is crossed over with the parameter vector $\boldsymbol{x}_{i,g}$ it originates from. This means that for each parameter $u_{p,i,g}$ of the newly formed trial vector it is determined with the crossover probability Cr if it originates from the mutant vector or from the current population vector. To avoid duplication of existing vectors at least one of the parameters of the mutant vector, with the random index p, has to be a part of the newly formed trial vector:

$$\forall i \in Np: \quad \boldsymbol{u}_{i,g} = (u_{p,i,g}) = \begin{cases} v_{p,i,g} & \text{if} \quad (\text{rand}_p(0,1) \leq Cr \quad \text{or} \quad p = \text{rand}(0, D-1)) \\ x_{p,i,g} & \text{otherwise} \end{cases} \tag{12}$$

Crossover is applied to the parameters of every individual in the mutated population, thus creating a trial population $\boldsymbol{P}_g^u$ with the same size and structure as the current population. The trial population overwrites the mutant population during crossover, so two vector populations are sufficient when implementing DE.

The discrete crossover strategy explained here is called uniform or binomial crossover, since the genetic information which is derived from one parent follows approximately a binomial probability distribution function with the probability Cr. Hence the crossover probability Cr defines how big the portion of mutated parameters is in the newly formed trial vector and can be interpreted as the mutation rate. Cr is one of the control parameters of the DE algorithm and should be chosen from $[0, 1]$ [11, pp.104-106].

Selection:

After generating a trial population the individuals of the next generation are determined by the selection process. Classic DE directly compares the trial vector $\boldsymbol{u}_{i,g}$ with the

parameter vector $\boldsymbol{x}_{i,g}$ it was crossed over with:

$$\forall i \in Np: \qquad \boldsymbol{x}_{i,g+1} = \begin{cases} \boldsymbol{u}_{i,g} & \text{if} \quad C(\boldsymbol{u}_{i,g}) \leq C(\boldsymbol{x}_{i,g}) \\ \boldsymbol{x}_{i,g} & \text{otherwise} \end{cases} \tag{13}$$

$C()$ refers to the objective function described in Equation (7). The selection is a one-to-one tournament selection. The selection is elitist, which means that under no circumstances the best so far solution can get eliminated [11, pp. 118-123].

3 Results

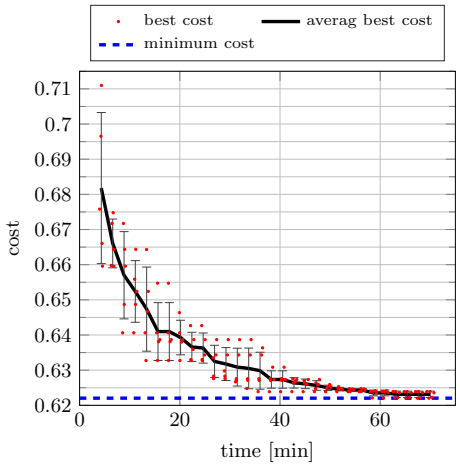
To evaluate DE's ability to effectively optimize the given problem the performance shall be evaluated in two scenarios. Both are optimized five times with the target-to-best DE variant and the following DE control parameters:

population members: $Np = 10$
weight: $F = 0.875$
crossover probability: $Cr = 0.875$

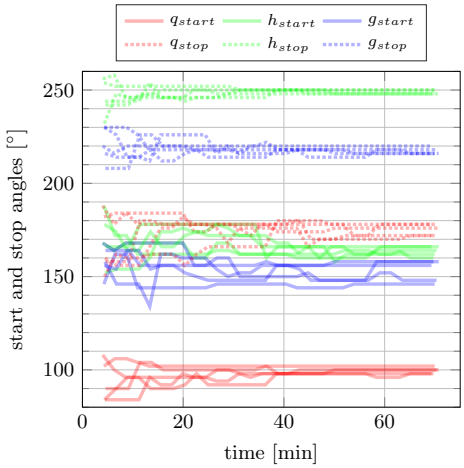
scenario 1: $r_{desired} = 50\,\text{min}^{-1}$
scenario 2: $r_{desired} = 60\,\text{min}^{-1}$

Scenario 1:
Only in one out of the five optimization runs the motor help was needed once in the first generation to support the cycling movement. This results from a sensible definition of the boundary constraints. As can be seen in Figure 4(a) the average best cost converges towards a minimal cost of 0.62. Overall, the average best cost improved by 0.059, with more than 90% of the improvement made within the first 38.3 min. The convergence of the parameter vector shows muscle group specific convergence (see Figure 4(b)). This indicates that multiple optima with comparable costs are present. Figure 5(a) shows the effect of the dead centre cost. Without the dead centre cost active, ceteris paribus, the minimal cadence is $29\,\text{min}^{-1}$. This is $6.9\,\text{min}^{-1}$ lower than with the dead centre criteria. The average cadence of the optimization runs (see Figure 5(c)) settles slightly below the desired $50\,\text{min}^{-1}$, because the stimulation cost rises with increasing cadence.

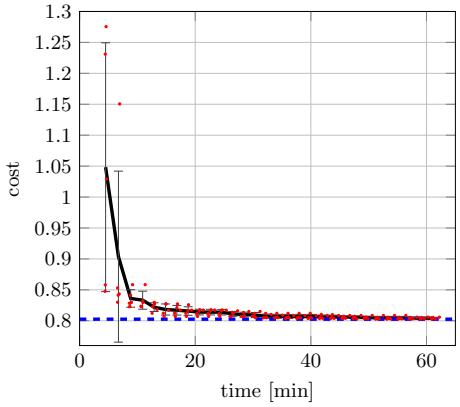
Scenario 2:
In the five optimizations of the second scenario the motor help was only active during initialisation. Compared with scenario 1, the cost converges faster. As can be seen in Figure 4(c) 90% of the improvement in average cost is made within the first 12.9 min. Again the parameter convergence is muscle group specific (see Figure 4(d)). The start angle of the quadriceps stimulation q_{start} is in this case remarkable. In all five optimization runs it converged towards the lower boundary of the constraints, thus indicating that the boundary constraints for this scenario might have to be adapted. The restrictive boundary constraints for quadriceps stimulation might also be the reason, why the average cadence of all successful trials did not rise over about $57\,\text{min}^{-1}$ (see Figure 5(d)). A change in



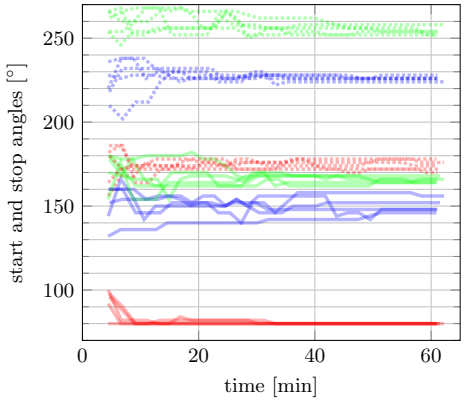
(a) **Scenario 1: cost convergence**



(b) **Scenario 1: parameter convergence**



(c) **Scenario 2: cost convergence**; The best cost is the lowest objective function value at the end of every generation. The error bars indicate the standard derivation of the average best cost.



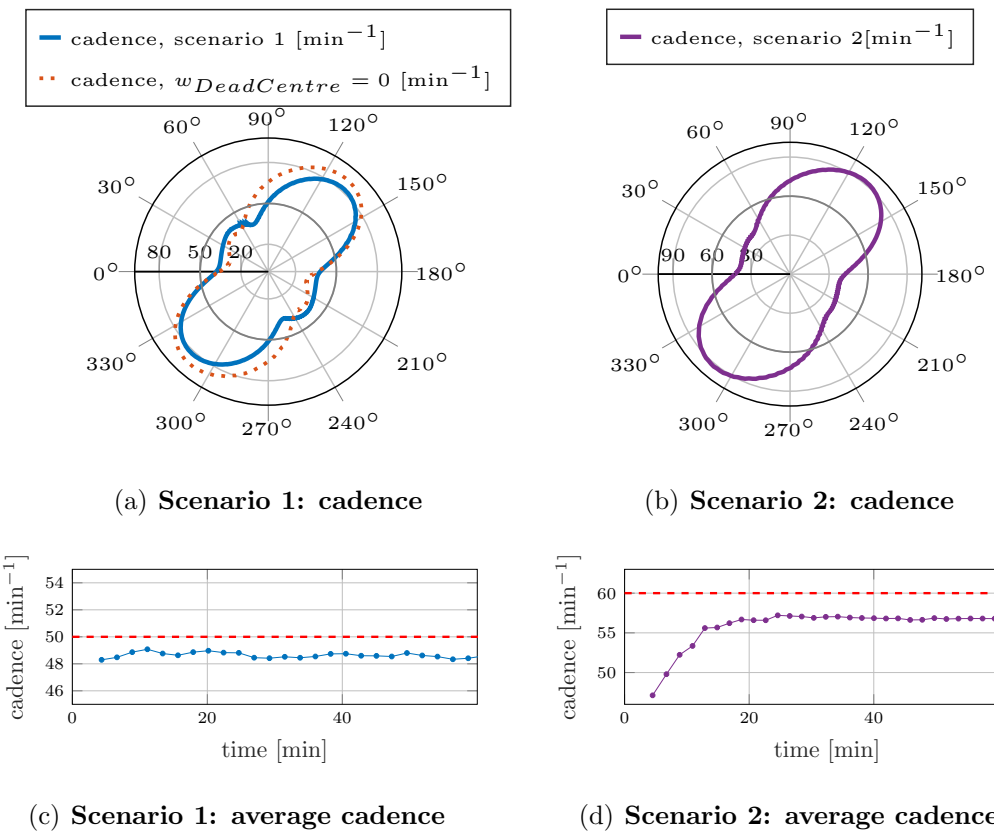
(d) **Scenario 2: parameter convergence**; Here the best start and stop angles of the muscle group stimulation at the end of every generation are displayed.

Figure 4: Cost and parameter convergence for 5 target-to-best optimizations with the boundary constraints from Figure 1(b). (DE/target-to-best/1/bin, weight $F = 0.875$, crossover probability $Cr = 0.875$, population members $Np = 10$, maximum number of generations $g_{max} = 30$; evaluated revolutions $x = 6$)

boundary constraints or weighting of the cost function might bring the average cadence closer to $60\,\mathrm{min}^{-1}$. Nonetheless, it can be seen that DE is able to adapt the stimulation patterns to achieve different cadences.

3.1 Stimulation Cost Savings

As mentioned before, the stimulation cost might indicate how effective a stimulation pattern is. A static classic stimulation strategy with the following start and stop angles



(a) **Scenario 1: cadence**

(b) **Scenario 2: cadence**

(c) **Scenario 1: average cadence**

(d) **Scenario 2: average cadence**

Figure 5: Depicted in (a) and (b) is the cadence resulting from the stimulation pattern with the overall lowest cost. The average cadence shown in (c) and (d) is the average cadence of all five optimizations.

is used as a benchmark:

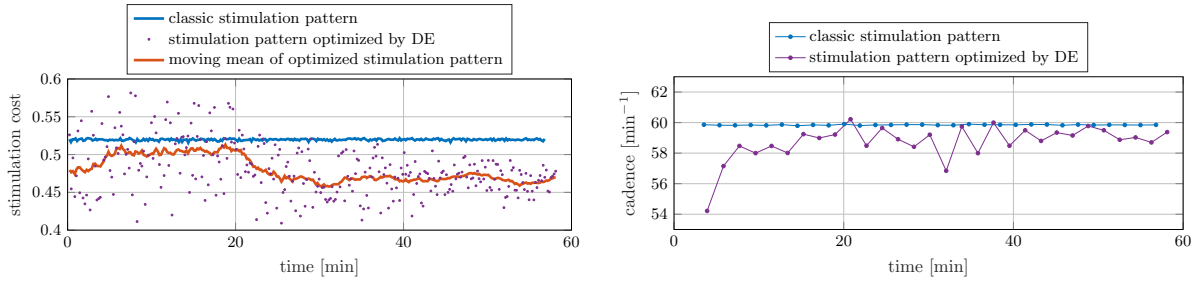
$$\boldsymbol{V}_{p,ClassicStatic}[k] = \begin{bmatrix} q_{start}[k] = 50° & q_{stop}[k] = 160° \\ h_{start}[k] = 190° & h_{stop}[k] = 260° \\ g_{start}[k] = 90° & g_{stop}[k] = 180° \end{bmatrix} \tag{14}$$

To compare the stimulation cost an optimization is needed that also results in the same average cadence of about 60 min^{-1}. This is achieved by setting boundary constraints different from those in the scenarios:

$$\boldsymbol{V}_{p}[k] = \begin{bmatrix} q_{start}[k] \in [\ 30°, 70°] & q_{stop}[k] \in [140°, 200°] \\ h_{start}[k] \in [170°, 210°] & h_{stop}[k] \in [220°, 260°] \\ g_{start}[k] \in [\ 70°, 110°] & g_{stop}[k] \in [180°, 220°] \end{bmatrix} \tag{15}$$

It can be seen in Figure 6(b) that after 10 min the resulting average cadence of the FES cycling optimization fluctuates slightly below of the desired cadence of 60 min^{-1}. Depicted in Figure 6(a) is the corresponding stimulation cost. At the beginning of the optimization DE has to rise the average cadence, therefore the stimulation cost rises within the first 5 min. Not until 20 min DE stops testing stimulation patterns that yield worse stimulation costs than the classic static stimulation pattern. A decline in stimulation cost that does not lower the average cadence significantly is following. After 58 min the moving mean of

the stimulation cost optimized by DE is round about 9.6% percent lower than that of the classic static stimulation pattern.



(a) Comparison of stimulation cost

(b) Comparison of the average cadence

Figure 6: Comparison between classic static stimulation pattern and stimulation pattern optimized by differential evolution.

4 Discussion and Conclusion

The heuristic control strategy relying on differential evolution is able to optimize the FES cycling computer model. It might be that even better stimulation patterns can be found by DE, if more parameters of the stimulation pattern would be changed, but problematic remains the convergence time. Usually, FES cycling therapies last for round about 30 min. Depending on the given scenario the optimization took as long as 15 min or up to 40 min. A further increase in convergence speed can be achieved by setting narrower boundary constraints, reducing the number of population members or reducing the number of evaluated cycling revolutions.

Questionable also remains how much a reduction in average stimulation cost can prolong FES cycling training. Furthermore, it has to be tested if an optimization of the stimulation pattern might lead to stimulation patterns that tend to neglect the weakest muscle groups, thus reducing therapeutic effects.

To evaluate the minimal convergence time under realistic conditions, as well as the resulting optimized stimulations patterns it is indispensable to test this heuristic control strategy in an experiment.

References

[1] G. M. Davis, N. A. Hamzaid, and C. Fornusek. Cardiorespiratory, Metabolic, and Biomechanical Responses During Functional Electrical Stimulation Leg Exercise: Health and Fitness Benefits. *Artificial Organs*, 32(8):625–629, 2008.

[2] R. M. Glaser, S. F. Figoni, S. P. Hooker, M. M. Rodgers, B. N. Ezenwa, A. G. Suryaprasad, S. C. Gupta, and T. Mathews. Efficiency of fns leg cycle ergometry. In *Images of the Twenty-First Century. Proceedings of the Annual International Engineering in Medicine and Biology Society,*, pages 961–963 vol.3, Nov 1989.

[3] L. Griffin, M. Decker, J. Hwang, B. Wang, K. Kitchen, Z. Ding, and J. Ivy. Functional electrical stimulation cycling improves body composition, metabolic and neural factors in persons with spinal cord injury. *Journal of Electromyography and Kinesiology*, 19(4):614 – 622, 2009.

[4] K. Hunt, C. Ferrario, S. Grant, B. Stone, A. McLean, M. Fraser, and D. Allan. Comparison of stimulation patterns for fes-cycling using measures of oxygen cost and stimulation cost. *Medical Engineering & Physics*, 28(7):710 – 718, 2006.

[5] T. W. Janssen, J. M. Beltman, P. Elich, P. A. Koppe, H. Konijnenbelt, A. de Haan, and K. H. Gerrits. Effects of electric stimulation-assisted cycling training in people with chronic stroke. *Archives of Physical Medicine and Rehabilitation*, 89(3):463–469, Mar. 2008.

[6] M. Kraft and C. Disselhorst-Klug (Eds.). *Biomedizinische Technik – Rehabilitationstechnik*. Number Bd. 10. De Gruyter, 2015.

[7] L. Malfait, G. Storme, and M. Derdeyn. Project 003: Considerations about "dead centre" in cycling. `http://www.noncircularchainring.be/pdf/Biomechanical%20study%20-%20Project%20003%20Dead%20Centre.pdf`. Accessed: 2017-06-13.

[8] A. Michel. Differential evolution c++ library. `http://www.amichel.com/de/doc/html/`. Accessed: 2017-07-10.

[9] C.-W. Peng, S.-C. Chen, C.-H. Lai, C.-J. Chen, C.-C. Chen, J. Mizrahi, Y. Handa, et al. Review: Clinical benefits of functional electrical stimulation cycling exercise for subjects with central neurological impairments. *Journal of Medical and Biological Engineering*, 31, Mar. 2011.

[10] K. V. Price and R. M. Storn. Differential evolution - a simple and efficient adaptive scheme for global optimization over continuous spaces. Technical report, International Computer Science Institute, March 1995.

[11] K. V. Price, R. M. Storn, and J. A. Lampinen. *Differential Evolution A Practical Approach to Global Optimization*. Springer-Verlag, 2005.

[12] R. Riener and T. Fuhr. Patient-driven control of fes-supported standing up: a simulation study. *IEEE Transactions on Rehabilitation Engineering*, 6(2):113–124, Jun 1998.

[13] T. Schauer, K. J. Hunt, N. Negard, M. H. Fraser, and W. Stewart. Regelung der trittgeschwindigkeit beim liegedreiradfahren von querschnittgelähmten (cadence control for recumbent cycling of paraplegics). *Automatisierungstechnik Methoden und Anwendungen der Steuerungs-, Regelungs-und Informationstechnik*, 50(6/2002):271, 2002.

[14] R. Smith. Open dynamics engine. `http://www.ode.org/`. Accessed: 2017-06-04.