# A Concept for Optimizing Motor Control Parameters Using Bayesian Optimization

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Abstract: Electrical motors need specific parametrizations to run in highly specialized use cases. However, finding such parametrizations may need a lot of time and expert knowledge. Furthermore, the task gets more complex as multiple optimization goals interplay. Thus, we propose a novel approach using Bayesian Optimization to find optimal configuration parameters for an electric motor. In addition, a multi-objective problem is present as two different and competing objectives must be optimized. At first, the motor must reach a desired revolution per minute as fast as possible. Afterwards, it must be able to continue running without fluctuating currents. For this task, we utilize Bayesian Optimization to optimize parameters. In addition, the evolutionary algorithm NSGA-II is used for the multi-objective setting, as NSGA-II is able to find an optimal pareto front. Our approach is evaluated using three different motors mounted to a test bench. Depending on the motor, we are able to find good parameters in about 60-100%.



## 1 INTRODUCTION

Many new trends, such as e-mobility, highly rely on advanced electrical machines. This is also the case for many everyday devices such as washing machines.

These modern electrical machines rely on complex motor control algorithms and software. Furthermore, motors are usually fine-tuned by an electrical engineer with years of experience in motor development. Such optimization can be important, as choosing wrong parameters may lead to time loss, a failure to run the motor correctly, or even damage it. This, however, is a complex task as many different parameters interplay in a wide range. In addition, finding good parameters require highly specific expert knowledge, which can be very expensive. Furthermore, such expert knowledge might not even be available considering older machines. It is also possible that such expert knowledge does not lead to the best performances. Due to different influences like the environment, load or wear, an optimal configuration of a system might change or must even be reconfigured during runtime.

For that reason, we present a novel approach for optimizing the parametrization of different electrical motors given two competing goals. The first goal is for the motor to achieve a predefined revolutions per minute (RPM) as fast as possible. Afterwards, the second objective is for the motor to maintain the RPM with as little fluctuation in its current ripple as possible. A very fast start may lead to a motor running unstable after reaching its RPM, as its parametrization is only optimized for a fast startup. Hence, the parametrization for maintaining the RPM may not be optimal which could lead to a higher energy consumption.

For our methodology, we utilize *Bayesian Optimization* (Mockus, 2012) to optimize the parametrization. As for multiple, competing objectives, the evolutionary algorithm NSGA-II (Deb et al., 2002) is used.

Following, in Section 2, we give a brief overview of existing related work. We explain our used motor test bed in Section 3 before outlining the overall problem in Section 4. Afterwards, we provide a brief introduction to Bayesian Optimization in Section 5. Finally, we evaluate our approach in Section 6 before concluding with an outlook on possible future work in Section 7.

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## 2 RELATED WORK

Various relevant previous work on using Bayesian Optimization for different kinds of machinery exists. Notable examples focus on optimizing the behaviour of robots, e.g. (Akrour et al., 2017). These approaches, however, vary from our concept such that we focus solely on configuring and optimizing parameters that need to be set in order to able to use the motor, instead of optimizing the behaviour of a complex machinery as whole.

The authors of (Khosravi et al., 2021) tune a motor with the Bayesian optimizer as well. However, they focus on optimizing industrialized brushless motors. We on the other hand utilize DC-motors, a completely different kinds of motor, and consider the whole control scheme as a black box which they do not.

Another work from Neumann-Brosig et al. (Neumann-Brosig et al., 2020) uses Bayesian Optimization in an industrial setting. They optimize parameters for a throttle valve control. While the throttle valve control contains a DC motor, they do not directly optimize motor parameters. Instead, their motor is only indirectly influenced by their parametrization by factors like the voltage input.

König et al. (König et al., 2021) utilizes Bayesian Optimization to find optimal motor parameters, too. However, we differ from their work as they based their work on an AC motor while we utilize a DC motor. Furthermore, they do not aim to optimize speed and voltage fluctuation but to maximize tracking accuracy.

Other noteworthy works focus on automatically improving motors with various other methods. Nature inspired swarm algorithms like the artificial bee colony algorithm or the flower pollination algorithm can be used to tune parameters, as was done in (Tarczewski and Grzesiak, 2018). Alternatively, the particle swarm optimization algorithm can be used, too, as was done by (Sharma et al., 2022) or (Naidu Kommula and Reddy Kota, 2022). Other metaheuristics can be used too, like the grey wolf optimizer (Kaminski, 2020). It is also possible to use specialized optimization algorithms, like an adaptive safe experimentation dynamics method (Ghazali et al., 2022).

## 3 TEST BED

In the following, we introduce our test environment now to better understand the optimization problems we are going to introduce in the next Section 4. Our test bed contains different hardware objects, each performing one or multiple functionalities. An abstracted view of our setup can be seen in Figure 1. The computer is a standard desktop PC on which our software and optimizer runs. It is connected to an oscilloscope, an inverter, a power supply for the inverter and motor as well as a dynamometer and its controller.

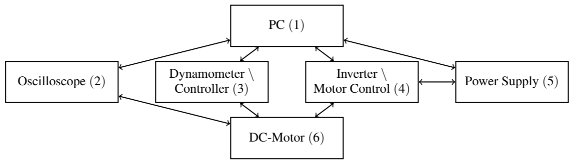



Figure 1: An abstracted overview of the test bed.

The oscilloscope measures the current ripple for a sampling rate $f_s$. This is important as we need this information for the second objective defined in Section 4.

The inverter is build with a motor control unit and controls the DC-motor driven by the direct current (DC) as well as the power supplied to it. Thus, the inverter handles the angular acceleration as well. It receives a set of parameters from the PC to indirectly control the speed up of the motor by changing the frequency of power supplied. Another utility is setting the desired RPM as well as starting and stopping the motor.

The motor control tool is powered by the power supply.

Another hardware object is the dynamometer (Magtrol Inc., 2022b) and its controller (Magtrol Inc., 2022a). They are used to accurately read out the RPM.

At last, we tested our setup on three different motors. We use electric motors which are driven by an *direct current* build for household appliances. Motor 2 and 3 have a smaller or larger axial impeller to simulate a load. Thereby we have a more realistic, real world motor setting. The first motor on the other hand does not utilize an axial impeller. The motors itself are connected to the oscilloscope, inverter and dynanometer to read out useful information for the optimization process.

## 4 PROBLEM DESCRIPTION

In our work, we consider two different problem descriptions. Both problems have in common that we want to optimize 11 parameters in a specific interval. They control the behaviour of motors such as the angular acceleration which defines how fast the motor speeds up, its current ripple, etc.. As we assume no further expert knowledge about these parameters—with the system as a whole being seen as a black-box—we do not discuss the parameters in more detail.

#### 4.0.1 Optimization Problem 1

Our first optimization problem is single objective where we only consider the angular acceleration of the motor. The goal is to reach a fixed *rounds per minute* (RPM) as fast as possible. Let $p = \{p_1, \ldots, p_{11}\}$ and $t_\tau(p)$ be the time it takes for the motor to reach the desired RPM given a set of parameters with $p \in \mathcal{X}$ and $\mathcal{X} \subset \mathbb{R}^n$. Then our fitness value $f_1$ is the defined time:

$$f_1(p) = t_\tau(p) \tag{1}$$

This leads us to the following optimization problem:

$$\min_{p \in \mathcal{X}} f_1(p) \tag{2}$$

#### 4.0.2 Optimization Problem 2

The next use case we consider is a biobjective optimization problem. At first, the motor should accelerate as fast as possible. Furthermore, after it reaches its desired angular speed, the current ripple (CR) should be as consistent as possible. As the motor runs, it requires continuous power due to frictions, resistances, loads, etc. to keep its RPM. With an inconsistent CR, multiple problems might occur such as the motor failing to keep spinning or a decrease of efficiency due to the excessive energy being dissipated in the form of heat. Thus, the lifespan of a motor is shortened, too

Thus, we extend our fitness function from Equation 1. Let $I_t(p)$ be the current ripple of timestep $t$ given parameters $p$ and $I = \{I_1, \ldots, I_t\}$. Furthermore, $Var(X)$ is the variance of a random variable $X$. Then, our second fitness function $f_2$ is defined as follows:

$$f_2(p) = Var(I(p)) \tag{3}$$

Thus, we extend our optimization problem from Equation 2:

$$\min_{p \in X} (f_1(p), f_2(p)) \tag{4}$$

# 5 BAYESIAN OPTIMIZATION

*Bayesian Optimization* (BO) is a global optimization method (Mockus, 2012). As is seen in Section 3, we have a hardware in the loop system consisting of a motor, its controlling mechanism and a RPM measurement system. Furthermore, the system is seen as a black-box. BO is a good choice for our setting, as Jones et al. (Jones et al., 1998) describes BO as a good black-box optimizer, as no prior insight about the fitness landscape is needed. Additionally, BO is even able to find a global optimum in the presence of stochastic noise (Mockus, 2012)—which occurs with our use case. At last, there is still the issue that one evaluation could take several minutes. While BO is not able to fix this problem, the optimization algorithm is able to handle the limitation of a costly evaluation function well (Brochu et al., 2009).

## 5.1 Introduction to Bayesian Optimization

In Bayesian Optimization, we try find a global maximizer (or minimizer) of an unknown objective function $f$. This optimum is found by utilizing every value of previous evaluation points. For this task, BO needs a prior which describes the objective function $f$ for now. In this context of BO, the prior is a function which describes the beliefs about the behaviour of the unknown function. Furthermore, an acquisition function is needed which decides the next sampling point (Jones, 2001; Snoek et al., 2012).

#### 5.1.1 Gaussian Process Prior

To describe our searched-for function $f$, BO creates a *Gaussian process* (GP) from which a distribution over functions is derived. Such a distribution over functions means that we do not calculate a single scalar output for a given input. Instead, we get the mean and variance of a normal distribution describing possible values for a given input (Frazier, 2018). By utilizing a distribution of functions, GP is able to express uncertainties. As a result of this trade off, BO is able to optimize the objective function with fewer evaluations needed (Shahriari et al., 2016).

To utilize a GP, a kernel function is needed as well. The kernel describes the correlation between two points in the input space. In our implementation, we utilize the Matérn covariance function $k_M$ (Rasmussen, 2003) as a kernel function as it shows preferable properties, like being able to model physical processes well (Rasmussen, 2003; Shahriari et al., 2016).

#### 5.1.2 Acquisition Function

The acquisition function $\alpha(\cdot)$ is another important part of BO as it determines which data point to observe next. The main idea is to choose a point based on a high uncertainty of the GP function or where the objective function has a potentially high value.

However, choosing the right acquisition function is no trivial task and requires a lot of evaluation. Thus, we adopt scikit-learns (Buitinck et al., 2013) strategy of utilizing three different acquisition functions: *Probability of Improvement* (Kushner, 1964), *Expected Improvement* (Mockus, 1975) and *Upper Confidence Bound* (Cox and John, 1992). They optimise each acquisition function independently and at each step all three functions propose an candidate point. The next observation point is then chosen probabilistically by choosing the point with the highest gain.

To better visualize the concept of BO, we exemplified this concept in Figure 2. It shows an example of BO on an 1D objective function, calculated over 4 iterations. Each sub-figure is partitioned into two. The top image shows the true objective function $f$ (red line), the Gaussian process model (green area) and its estimation of $f$ (green dashed line). Furthermore, it shows new (magenta points) and old observation points (dark green) if existing. The bottom figure shows the correlating acquisition function $f_a$ (blue line) and the next point to sample (blue 'x'). Figure 2a shows step 0 after its initialization. We sampled 5 random points to create our GP as well as $\alpha(\cdot)$. Now, we choose our next sampling point. The next Figure 2b shows the observed sampling point as well as an updated GP model and acquisition function. We then repeat these steps multiple times to find the global optimum.

For a more indepth view of BO, we refer to the works of Brochu et al. (Brochu et al., 2009), Shahriari et al. (Shahriari et al., 2016) and Mockus (Mockus, 2012).

## 5.2 Multi-Objective Bayesian Optimization

As is described in section 3, another goal is to optimize multiple objectives. New challenges arise with a multi-objective as we have to find the Pareto Set which is a set of solutions where all objectives are optimized as effectively as possible. That means that, for each solution, each objective cannot be improved without worsening another objective (Ngatchou et al., 2005). These goals may be conflicting though which means that both objectives may not be optimal simultaneously given one parameter set (Ehrgott, 2005). In our context, it is possible to have a very fast startup time which, however, leads to an unstable motor. The current may be fluctuating highly which is not desirable. A slower startup time may take a while but it could lead to a higher current ripple. Here, the goal is to find parameters which satisfy both objectives.

Nevertheless, a pure BO is not able to optimize multiple objectives. Because of that, we utilize a multi-objective Bayesian Optimization algorithm introduced by Galuzio et al. (Galuzio et al., 2020). Given two objective functions $f_1(x)$ and $f_2(x)$ and a sampling point $x$. We now try to satisfy both objectives:

$$\mathbf{x}^* = \arg\min_{x \in X} (f_1(\mathbf{x}), f_2(\mathbf{x})) \quad (5)$$

Regarding the multi-objective Bayesian optimizer, the main idea of BO is maintained. The whole functionality and its approach of GP, its kernel function as well as an acquisition function is still the same as is described in Section 5.1. However, each objective is now approximated by an individual GP.

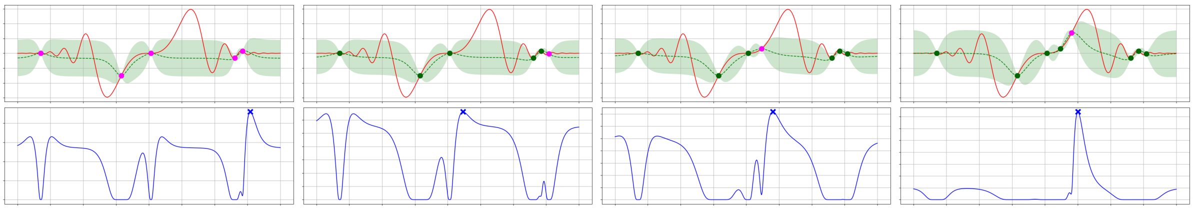
The acquisition function changes for this context, as a new observation point must be sampled from the Pareto front. However, the Pareto front is unknown and must be approximated by estimating all objective functions subject to the input space. This approximation is done by the non-dominated sorting genetic algorithm II (NSGA-II) (Deb et al., 2002). Now, a new observation point can be sampled from the approximated Pareto front. This new data point can now be evaluated by each individual GP and the solution can be used to improve NSGA-IIs approximation of the Pareto front, further increasing the quality of each sampling point.

For a more detailed description of the multi-objective Bayesian optimizer, we refer to (Galuzio et al., 2020).

# 6 EVALUATION

With the fundamental preliminaries done, this section presents our results. The BO always ran for 700 evaluations, given 10 initial sampling points. For each run, the motor sped up to a final RPM of 1500.

Furthermore, we utilize the *Bayesian comparison of classifiers* (BC) introduced by Benavoli et al. (Benavoli et al., 2017) to compare our found parameters with random ones. The advantage here is that we do not need to arbitrarily sample until we succeed at satisfying our significance threshold. We state three different probabilities: $p_r$, $p_e$ and $p_{BO}$. These values indicate different probability values with $p_r$ stating the probability that the random parameters are better. $p_{BO}$ presents the probability that the parameters found by BO are better. At last, $p_e$ expresses the probability that the differences are within the *region of practical equivalence* (rope). This means that, when the difference between two output values are smaller that the rope, both outputs can be seen as equal. Here, we use a rope of 0.5, which means that a difference of 0.5 seconds for the motor speed up time is treated as being equal and not statistically significant. The reason-



(a) Step 0. (b) Step 1. (c) Step 2. (d) Step 3.

Figure 2: An example of BO on an 1D objective function over 4 iterations.

ing here is that real-world motors are seldom perfect systems. Due to friction, capacitor charges, etc. a lot of inconsistency might occur. Thus, we chose a relatively high rope to keep such inconsistencies in mind.

For the second objective, the motor ran for an additional 10 seconds after speed up to measure the current.

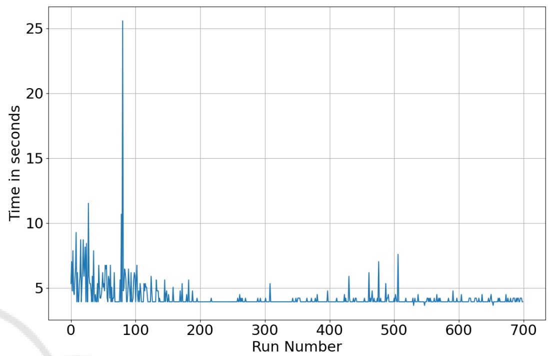
## 6.1 Single Objective

At first, we focus on the angular acceleration. We show the optimization progress as well as an empirical comparison between random parameters and the optimized one. For the last task, we compare 50 runs each for statistical significance.

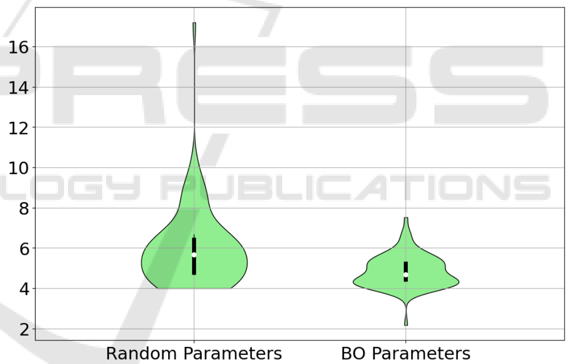
The plain motor should be the simplest one to optimize as it does not include an axial impeller. The other two motors should be more difficult due to their axial impeller.

As we can see in Figure 3a, the plain motor starts with a high variance in time. Nonetheless, as optimization progresses, BO is able to find good parameters. As for motor 2, we see a completely different history in Figure 4. There is a higher variance throughout the optimization progress with some lower peaks. Thus one has to be critical of this optimization progress as there are high peaks throughout the observations. For the last motor 3, the optimization progress looks more promising in Figure 5a compared to the second motor. It is able to periodically find good values and we see a better optimization progress.

An empirical comparison for the motors between the best parameters found and random ones can be seen in violin plots in Figure 3b, 4b and 5b. Here, we compare the startup times between random parameters and the best parameters found by BO. We can see that the random parameters take between 4 and $> 10$ seconds to speed up and most of the runs take about $\sim 6$ seconds for all motors. The optimized parameters take on average between 4 and 5 seconds but show a relatively high variance, too. Nevertheless, the variances of BO parameters are still lower than random ones. Furthermore, it can be said that the



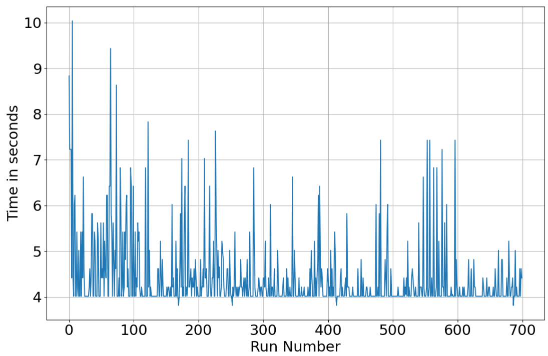

(a) Progression of BO.



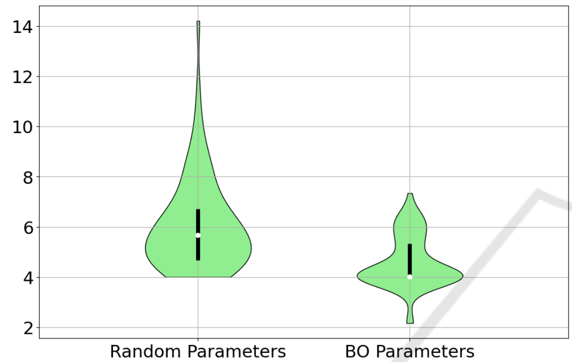

(b) Random vs. best parameter found.

Figure 3: Progression of BO and an empirical comparison given the plain motor.

optimized parameters behave better than the random ones as they show a higher axial acceleration on average. This can be somewhat confirmed by utilizing BC. For the plain motor, the results are $p_r < 0.001$, $p_e = 0.407$ and $p_{BO} = 0.591$. This shows us that our found parameters are statistically better for about 59 percent of runs. However, these parameter sets are statistically equal for about 41 percent. Motor 2 has $p_r < 0.001$, $p_e = 0.002$ and $p_{BO} = 0.998$. On average, the best parameters found should be better than random parameters. At last, motor 3 has a similar behaviour. Here we get $p_r = 0.001$, $p_e = 0.320$ and $p_{BO} = 0.680$. This tells us that both random parameters and our BO parameters are statistically equal for

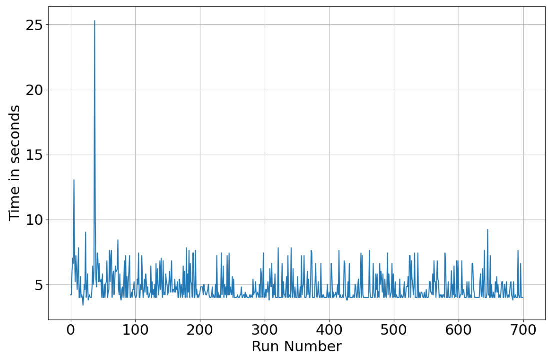



(a) Progression of BO.

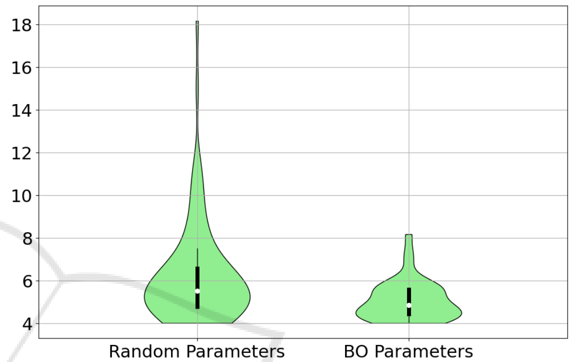



(b) Random vs. best parameter found.

Figure 4: Progression of BO and an empirical comparison given motor 2.




(a) Progression of BO.




(b) Random vs. best parameter found.

Figure 5: Progression of BO and an empirical comparison given motor 3.

32 percent but statistically better for 68 percent.

## 6.2 Multi-Objective

At last, we try to optimize a multi-objective task defined in Section 4. Here, we figuratively compare the best parameter to random ones. For each comparison, we took 80 samples each and show a distribution for *Time in Seconds* and *Var(current)*. Furthermore, we utilize the *Hypervolume indicator* (Zitzler et al., 2008) to quantitatively compare our result.

### 6.2.1 Figurative Comparison

Looking at the plots in Figure 6, 7 and 8 for all three motors, we see distributions of observations. They contain data points from random parameters and the parameters of the best solution found by the multi-objective BO.

The coordinate system shows the variance of the current ripple as well as the time it takes to speed up in seconds. Green dots represent parameters found by BO while red ones represent random ones. A lower distance to the origin indicates a better parameter. We can see that the random parameters are more scattered

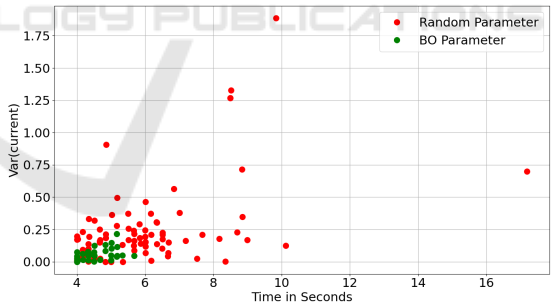



Figure 6: Plain Motor: optimal parameter compared to random ones. Lower distances to the origin are better.

throughout the coordinate system, indicating a high variation. As for the plain motor and motor 2, we see that the parameters found by the BO are more focused at the origin, indicating that those are superior compared to the random parameter. However, Figure 6 still shows a slight variation for the BO parameters which implies inconsistencies to some degree between each run.

As for motor 3, its evaluation results are more of an outlier as is visualized in Figure 8. We see data points of both the random and best parameters found

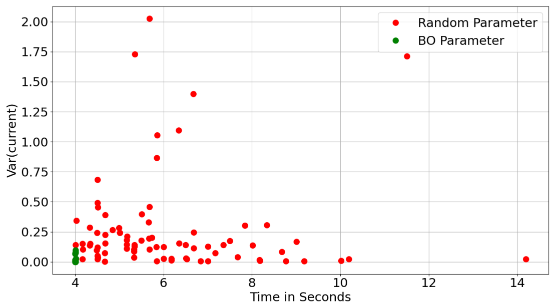



Figure 7: Motor 2: optimal parameter compared to random ones. Lower distances to the origin are better.

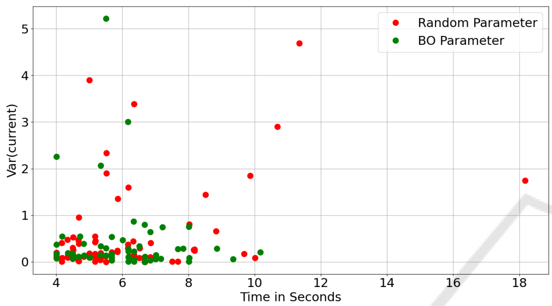



Figure 8: Motor 3: optimal parameter compared to random ones. Lower distances to the origin are better.

scattered throughout the coordinate system. Given the BO parameters, we can see that the runs are highly inconsistent. Thus, it is likely that it is not possible to optimize parameters for this specific setting.

### 6.2.2 Hypervolume Indicator

At last, we compare the found Pareto front with a Pareto front generated from random search (RS). For this comparison, we utilize the Hypervolume indicator. Here, we calculate the volume bound by a reference point and the Pareto set containing all found solutions. For the reference point, we choose a point a little bit larger than the largest value found in both axes as is recommended in (Beume et al., 2007). Here, the greater the volume, the better the Pareto front as a greater volume indicates a Pareto front which is closer to the origin.

Our results can be seen in Table 1. We see that the multi-objective BO finds better results for the plain motor as well as motor 2 compared to a RS. However, motor 3 shows dissimilar results as the RS outperforms the multi-objective BO here. Nevertheless, the difference is only marginal and it can be argued that both Pareto sets are equally good.

Table 1: Hypervolume indicators for each motor and Pareto front.

| Pareto Front | Plain Motor | Motor 2 | Motor 3 |
|---|---|---|---|
| Found by BO | 42.68 | 35.31 | 94.19 |
| Found by RS | 40.93 | 33.84 | 94.27 |

## 7 CONCLUSION

Throughout our work we performed the first steps into automating this process. We provide insight into a possible hardware test bed and how it may be controlled. Our key contribution is development of an optimization routine based on *Bayesian Optimization* (BO) which calibrates up to two motor properties in parallel.

Our evaluation shows mixed results. Generally, there is a trend towards a highly inconsistent setting, as the same parameter can create different evaluation values. Thus, the fluctuating results demonstrate a complex objective for the BO. However, BO is able to find good parameters most of the time and we are able to successfully statistically compare our results to random ones most of the times.

For future work, other acquisition functions as well as kernels for the GP function might result in better products. When adjusted to our problem domain to consider the non-deterministic nature of the motors, Bayesian Optimization might be able to produce better results.

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