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Innovative Approach for the Determination of a DC Motor's and Drive's Parameters Using Evolutionary Methods and Different Measured Current and Angular Speed Responses

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Abstract: The determination is presented of seven parameters of a DC motor's drive. The determination was based on a comparison between the measured and simulated current and speed responses. For the parameters' determination, different evolutionary methods were used and compared to each other. The mathematical model presenting the DC drives model was written using two coupled differential equations, which were solved using the Runge–Kutta first-, second-, third- and fourth-order methods. The approach allows determining the parameters of controlled drives in such a way that the controller is taken into account with the measured voltage. Between the tested evolutionary methods, which were Differential Evolution with three strategies, Teaching-Learning Based Optimization and Artificial Bee Colony, the Differential Evolution (DE/rand/1/exp) can be suggested as the most appropriate for the presented problem. Measurements with different sampling times were used, and it was found out that at least some measuring points should be at the speed-up interval. Different lengths of the measured signal were tested, and it is sufficient to use a signal consisting of the drive's acceleration and a short part of the stationary operation. The analysis showed that the procedure has good repeatability. The biggest deviation of calculated parameters considering 10 repeated measurements was 6% in case of the L_a calculation. The deviations of all the other parameters' calculations were less than 2%.

Keywords: Differential Evolution; Artificial Bee Colony; teaching-learning based optimization; DC motor; electric drive

MSC: 78M25; 78M50; 90C99

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1. Introduction

Direct current motors (DC motors) are still used in many industrial applications. Their good features are a high starting torque and easy control. In many industrial applications, they are connected to power supply units that allow speed or torque control. Correct adjustment of the controllers requires knowledge of the electrical motor parameters. Usually, the electrical motor parameters are specified by the manufacturer. It may happen that these are not accurate enough or have large tolerances, especially in the case of cheaper electrical motors. It also happens that the parameters of older electrical motors are not known, but we need them due to the modernization of the drive in which the electrical motor is preserved, and the older power systems are replaced by more modern ones.

Knowledge of the inertia of the drive, friction, ventilation and load is required in order to determine the transition times and energy balance of the drive correctly. Even if the inertia of the motor is known, the inertia of the load and the friction of the load are often unknown. These data are important for correct dimensioning and optimization of the drive.

We can use a stand-alone program to identify the parameters, or it can be part of the software in the power supply. The stand-alone program offers the possibility of parameters' determination for any drive with or without a power supply and in the case when we do not have access to the software in the power supply unit. The disadvantage of the stand-alone program is that it is necessary to transfer the measured data from the measuring devices, which is not the case if the parameters identification program is integrated into the power supply unit. If it is in the power supply, we want the identification to be as fast and robust as possible, so that it is not necessary to repeat the runs of the optimization method. According to what has been written, the choice of an appropriate optimization method is important. In this paper, we focus on evolutionary optimization methods. We focus on evolutionary methods, mainly because of their good properties. In the case of measured signals, measurement errors may occur, which could lead to a local minimum in the determination of parameters and thus to the determination of incorrect parameters. Evolutionary methods are capable of avoiding local minima, which is not the case for standard optimization methods. They are also robust and easy to use, because it is not necessary to determine the derivatives of the objective function, which can be difficult. or impossible, for many problems.

Other authors also tried to identify the parameters of the DC motor. They used different methods and approaches. In the literature, the following approaches can be found: the use of conjugate gradient and regularization methods [1], the use of curve fitting [2,3], the use of constraint optimization methods [4], the use of the regression method [5], the use of least-squares-based approaches [6–10] and the use of the moment method [11]. Approaches using evolutionary methods can also be found: the use of the Genetic algorithm [12] and the Multiobjective elitist genetic algorithm [13], the use of Differential Evolution [14], the use of the Flower pollination algorithm [15] and the use of the Particle Swarm Optimization [16].

This work presents the determination of seven parameters of a DC motor drive, which are the motor's resistance R_a, the motor's inductance L_a, the motor's constant c_e, the drive's inertia J and the load, expressed with the parameters T_{la}, T_{lb} and T_{lc}. The parameters were determined based on the measured current and speed response of the DC motor. Parameters' determination is an inverse problem. We used the direct approach. The mathematical model of the DC drive was constructed, and simulated current and speed responses were compared to measured values. Described is an optimization problem, where we are searching for the parameters for the mathematical model in such a way that the simulated responses fit with the measured values. The evolutionary optimization method was chosen for the parameter's determination. Different evolutionary methods have different performance for different problems. Different ones have been tested, with the aim of determining a fast and robust method. The first one was Differential Evolution (DE) [14,17–26], and three different strategies were tested. Also tested were the state-of-the-art Artificial Bee Colony (ABC) [27–34] and Teaching Learning Based Optimization (TLBO) [35–43]. All three methods were compared with each other. In the case of the mathematical model, different numerical integrations were tested, and different sampling times and different measuring signals were tested in the case of the measured signals.

Our contributions in the presented work are:

- The supply/control unit was considered in the mathematical model with a measured voltage. Not only the current and speed responses but also the armature supply voltage must be measured in our approach. In this way, no block model is needed of the supply/control unit. Such an approach was not found in the literature to the best of our knowledge.
- Step response [2–5,13–15] or stepped response [1,9] was used in the literature. We made tests for speed-up (SU) and additionally also for speed-up + speed-down (SUD) responses.
- We compared three evolutionary methods, DE (using three strategies), ABC and TLBO, with the aim to find the most suitable one. The methods were compared considering the SU and also SUD responses.

- Different numerical integrations (first, second, third and fourth order) were tested considering precision and calculation time.
- The results for different sampling times of the measured responses were tested to determine the appropriate sampling time according to the speed-up time.
- The calculations were made in such a way that, for each sampling time, all four integration methods are used, and with that the relation was analyzed between the sampling time and the integration method.
- The repeatability of the measurement was analyzed. For each of the 10 repeated measurements, the parameters were determined and compared with each other. In this way, it was determined if the measurement was sufficiently reliable that it was not necessary to repeat it.
- Determination was carried out of the parameters for different length measured signals. These were full signal, signal without a pre-trigger, start only, start + same time operation, and start + operation for twice the start time.

In our work, the supply/control unit voltage was used as the input for the mathematical model; block diagrams of the drive were used in the related works [7,8,11,15,16]. An improved innovative approach is presented in this way. Other authors used a certain evolutionary method to determine the parameters, such as GA [12,13], DE [14] and PSO [16]. We used and compared the three methods with each other.

The paper consists of eight sections. The mathematical model and measurements are described in Section 2. The evolutionary methods and algorithm used are presented in Section 3. The test measurements, together with the parameters' determination results, are presented in Section 4. The convergence of the evolutionary methods is also presented. Section 5 presents an analysis of the interaction between the order of the integration method and the measurements' sampling time. The repeatability of the parameters' determination is shown in Section 6. The parameters' determination results for different lengths of the measured signals are presented in Section 7. Validation based on the simulated input data is shown in Section 8. The conclusions are given in the last section, Section 9.

2. Mathematical Model and Measurements

The parameters' determination was based on the comparison between the measured responses and the simulated responses using evolutionary methods. An appropriate mathematical model of the DC motor's drive was constructed to obtain simulated responses.

2.1. Mathematical Model

The model of the DC motor's drive is presented schematically in Figure 1.

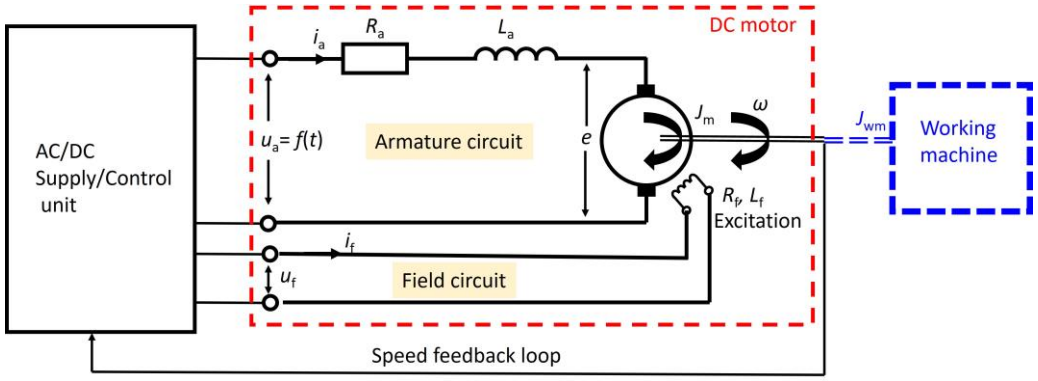

Figure 1. The DC motor's drive.

The DC motor's drive is described using three coupled differential equations. The field circuit of the motor is described using (1), the armature circuit is described using (2) and the mechanical behavior of the drive is described using (3).

$$u_{\mathrm{f}} = i_{\mathrm{f}} \cdot R_{\mathrm{f}} + L_{\mathrm{f}} \cdot \frac{di_{\mathrm{f}}}{dt} \tag{1}$$

$$u_{\mathrm{a}}(t) = i_{\mathrm{a}} \cdot R_{\mathrm{a}} + L_{\mathrm{a}} \cdot \frac{di_{\mathrm{a}}}{dt} + e \tag{2}$$

$$T_{\mathrm{m}} - T_{\mathrm{load}} = J\frac{d\omega}{dt} \tag{3}$$

J is the total inertia of the drive, which is the sum of the inertia of the motor and the inertia of the working machine. The induced voltage e depends on the speed and magnetic field generated in the excitation coil. It is expressed using (4).

$$e = c_{\mathrm{m}} \cdot \omega\ ;\ \ c_{\mathrm{m}} = f(i_{\mathrm{f}}) \tag{4}$$

The torque of the motor is expressed using (5), and load is expressed using (6).

$$T_{\mathrm{m}} = c_{\mathrm{m}} \cdot i_{\mathrm{a}} \tag{5}$$

$$T_{\mathrm{load}} = T_{\mathrm{la}} + T_{\mathrm{lb}} \cdot \omega + T_{\mathrm{lc}} \cdot \omega^2 \tag{6}$$

where T_{la} presents friction and load independent of speed (e.g., Coulomb friction); T_{lb} presents friction and load linearly, depending on the speed (e.g., viscous friction); and T_{lc} presents the friction and load quadratically, depending on the speed. In the case that the excitation is switched on before the armature circuit, the equation of the excitation circuit (1) does not need to be taken into account, because the transient phenomenon at switching on ends before the armature is switched on. Also, a constant magnetic field is established and the motor constant c_{m} no longer changes. The AC/DC Supply/Control unit presented in Figure 1 responds to the speed and current changes. Its response results in a u_{a} voltage. By considering the measured voltage $u_{\mathrm{a}}(t)$ in Equation (2), the AC/DC power supply is covered and its model is not required. In this way, an improved innovative approach is presented.

By entering (4)–(6) into (2) and (3), the system of two coupled deferential equations is obtained, which presents the DC motor's drive model. It is written in (7) and (8).

$$u_{\mathrm{a}}(t) = i_{\mathrm{a}} \cdot R_{\mathrm{a}} + L_{\mathrm{a}} \cdot \frac{di_{\mathrm{a}}}{dt} + c_{\mathrm{m}} \cdot \omega \tag{7}$$

$$c_m \cdot i_a - \left(T_{\mathrm{la}} + T_{\mathrm{lb}} \cdot \omega + T_{\mathrm{lc}} \cdot \omega^2\right) = J\frac{d\omega}{dt} \tag{8}$$

Three different cases can be considered using (7) and (8):

- Only the DC motor is considered. Inertia J is the inertia of the motor and T_{load} is the friction of the motor.
- The DC motor and working machine with no load were considered. Inertia J is the inertia of the motor + inertia of the working machine, and T_{load} is the friction of the motor + friction of the working machine.
- The DC motor and working machine with load were considered. Inertia J is the inertia of the motor + the inertia of the working machine. T_{load} is the friction of the motor + the friction of the working machine + load.

2.2. Numerical Solution of a System of Differential Equations

The system of differential Equations (7) and (8) was solved using the Runge-Kutta method for numerical integration. In order to obtain the relationship between the accuracy

and the calculation time depending on the time step of the measurement, we used the Runge–Kutta method of the first order, second order, third order and fourth order.

The first-order method is presented in (9).

$$\begin{aligned} K_1 &= f\left(x^{(k)}, y^{(k)}\right); \\ y^{(k+1)} &= y^{(k)} + h \cdot K_1 \end{aligned} \tag{9}$$

y is the searched value (in our case, i_a and ω were searched). h is the calculated step, k is a counter, x is an independent variable (in our case, t) and f is the derivative (in our case, di_a/dt and $d\omega/dt$).

The second-order method is presented in (10).

$$\begin{aligned} K_1 &= f\left(x^{(k)}, y^{(k)}\right); \\ K_2 &= f\left(x^{(k)} + h, y^{(k)} + h \cdot K_1\right); \\ y^{(k+1)} &= y^{(k)} + h \cdot \left(\tfrac{1}{2}K_1 + \tfrac{1}{2}K_2\right) \end{aligned} \tag{10}$$

The third-order method is presented in (11).

$$\begin{aligned} K_1 &= f\left(x^{(k)}, y^{(k)}\right); \\ K_2 &= f\left(x^{(k)} + \tfrac{1}{2}h, y^{(k)} + \tfrac{1}{2}hK_1\right); \\ K_3 &= f\left(x^{(k)} + h, y^{(k)} - hK_1 + 2hK_2\right); \\ y^{(k+1)} &= y^{(k)} + h \cdot \left(\tfrac{1}{6}K_1 + \tfrac{2}{3}K_2 + \tfrac{1}{6}K_3\right) \end{aligned} \tag{11}$$

The fourth-order method is presented in (12).

$$\begin{aligned} K_1 &= f\left(x^{(k)}, y^{(k)}\right); \\ K_2 &= f\left(x^{(k)} + \tfrac{1}{2}h, y^{(k)} + \tfrac{1}{2}hK_1\right); \\ K_3 &= f\left(x^{(k)} + \tfrac{1}{2}h, y^{(k)} + \tfrac{1}{2}hK_2\right); \\ K_4 &= f\left(x^{(k)} + h, y^{(k)} + hK_3\right) \\ y^{(k+1)} &= y^{(k)} + h \cdot \left(\tfrac{1}{6}K_1 + \tfrac{1}{3}K_2 + \tfrac{1}{3}K_3 + \tfrac{1}{6}K_4\right) \end{aligned} \tag{12}$$

From (7) and (8) the derivatives of current and speed are expressed, and (13) and (14) are written.

$$\frac{di_\mathrm{a}}{dt} = \frac{1}{L_\mathrm{a}} \cdot (u_\mathrm{a} - i_\mathrm{a} \cdot R_\mathrm{a} - c_\mathrm{m} \cdot \omega) = f(t, i_\mathrm{a}, \omega) \tag{13}$$

$$\frac{d\omega}{dt} = \frac{1}{J} \cdot \left[c_\mathrm{m} \cdot i_\mathrm{a} - \left(T_\mathrm{la} + T_\mathrm{lb} \cdot \omega + T_\mathrm{lc} \cdot \omega^2\right)\right] = g(t, i_\mathrm{a}, \omega) \tag{14}$$

Based on (9) and using (13) and (14), the equations for simulation of current and speed using the first-order method are written in (15) and (16).

$$\begin{aligned} K_1 &= f\left(t^{(k)}, i_\mathrm{a}^{(k)}, \omega^{(k)}\right) = \tfrac{1}{L_\mathrm{a}} \cdot \left(u_\mathrm{a}^{(k-1)} - i_\mathrm{a}^{(k-1)} \cdot R_\mathrm{a} - c_\mathrm{m} \cdot \omega^{(k-1)}\right); \\ i_\mathrm{a}^{(k+1)} &= i_\mathrm{a}^{(k)} + h \cdot K_1 \end{aligned} \tag{15}$$

$$\begin{aligned} L_1 &= g\left(t^{(k)}, i_\mathrm{a}^{(k)}, \omega^{(k)}\right) = \tfrac{1}{J} \cdot \left[c_\mathrm{m} \cdot i_\mathrm{a}^{(k)} - \left(T_\mathrm{la} + T_\mathrm{lb} \cdot \omega^{(k)} + T_\mathrm{lc} \cdot \left(\omega^{(k)}\right)^2\right)\right]; \\ \omega^{(k+1)} &= \omega^{(k)} + h \cdot L_1 \end{aligned} \tag{16}$$

The calculation with the first-order method is presented using (15) and (16). Similar expressions can be written for the second-, third- and fourth-order methods. In the case of the second-order method K_1, L_1, K_2, L_2, i_a and ω were calculated for each time step;

in the case of the third-order method K_1, L_1, K_2, L_2, K_3, L_3, i_a and ω were calculated for each time step; and. K_1, L_1, K_2, L_2, K_3, L_3, K_4, L_4, i_a and ω were calculated in the case of the fourth-order method. Since we were interested in calculation times, we would like to mention that, for the considered problem, in the case of the first-order method we solved 4 equations in each time step; in the case of the second-order method we solved 6 equations in each time step; in the case of the third-order method we solved 8 equations in each time step; and in the case of the fourth-order method we solved 10 equations in each time step.

2.3. Objective Function

We are dealing with an optimization problem. The simulated data obtained by solving differential equations must be as similar as possible to the measured data. The Objective Function (OF) is defined as the sum of squares of differences between the speed and current responses. It is written in (17).

$$\mathrm{OF} = \frac{1}{N}\sum_{i=1}^{N}\left(\left(\frac{i_{a_simulated_i} - i_{a_measured_i}}{i_{a_measured_\max}}\right)^2 + \left(\frac{\omega_{simulated_i} - \omega_{measured_i}}{\omega_{measured_\max}}\right)^2\right) \quad (17)$$

N is the number of measured points. The speed and current are normalized and divided with the maximum measured value to obtain the same influence of speed and current on the OF.

The first part of the OF is the comparison of the simulated current with the measured one. The electrical subsystem that describes the flow of the current is presented by (7) (see Section 2.1). It contains the searched parameters R_a, L_a and c_m, and their selection influences the flow of the current. The second part of the OF is the comparison of the simulated speed with the measured one. The mechanical subsystem that describes the flow of speed is described by (8) (see Section 2.1). It contains the searched parameters J, c_m, T_{la}, T_{lb} and $T_{lc,}$ and their selection influences the flow of the speed. Based on the described inclusion of the searched parameters in (7) and (8), it can be seen that the course of the current and speed is influenced by changing R_a, L_a, c_m, J, T_{la}, T_{lb} and T_{lc}. The objective function is designed in such a way that the simulated courses of current and speed are as close as possible to the measured ones.

2.4. Measurements

Measurements are an important part of the parameters' determination process. Well-executed measurements are a condition for successful parameter determination. For the tests made in the scope of the presented work, a laboratory drive was used, presented in Figure 2.

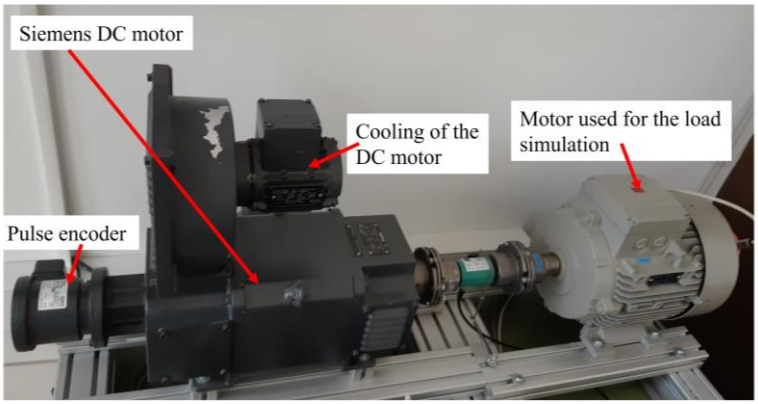

Figure 2. Laboratory drive used for the tests.

The drive shown in Figure 2 consists of the following parts:

- Supply/Control unit: SIEMENS AG, (Munich, Germany), SIMOREG DC-Master 6RA7013-6DV62-0-Z.
- DC motor with separate cooling: SIEMENS AG, (Munich, Germany), 1GG5104-0ED40-6VV1.
- Pulse encoder: HUBNER (Berlin, Germany), P0G 9D 1024.
- Motor used for the load simulation: SIEMENS AG, (Munich, Germany), 1LA7139-4AA10-Z FDB0.
- The "Trace" function was used for the measurements, which is a part of the SIEMENS AG, (Munich, Germany) "Drive Monitor" software, version V05.05.02.00_00.00.02.99, release V05.05.02.00_27.00.00.00.

An example of the measurement is shown in Figure 3.

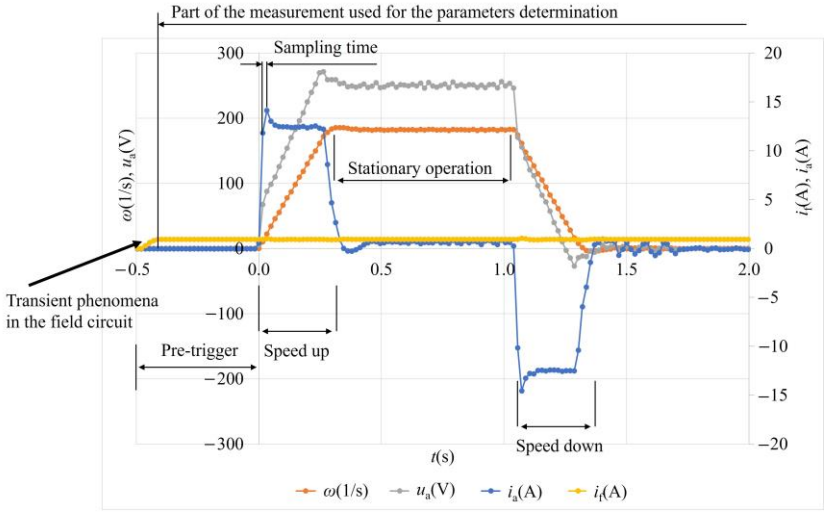

Figure 3. An example of the measurement.

As was mentioned, only a part of the measurement after the transient phenomena in the field circuit can be used, because, with that, (1) can be eliminated for the parameters' determination procedure, c_m becomes a constant and only (2) and (3) are being solved.

In order to determine the most appropriate measurement, we performed various tests:

- Different sampling times were used, which were 3.3 ms, 6.6 ms, 16.5 ms and 33 ms.
- Not only speed up of the drive was considered but also speed down.
- Different parts of the measured signal were used: full signal, signal without a pre-trigger, speed up only, speed up + same time stationary operation, speed up + stationary operation for twice the start time.

Different sampling times were used to make the article useful to a wider readership. The acceleration times are different for different drives, and the sampling times are limited by the measuring devices used. The results for a different number of measured points in the drive acceleration area are shown by changing the sampling time.

3. Used Evolutionary Methods and Algorithm

As described, we were dealing with an inverse problem, which was solved by a direct approach, for which we needed an optimization method. Some authors used standard optimization [1,3–11], and some of them used evolutionary methods, mainly only one of the methods [12–16].

Due to the good properties of evolutionary methods, such as their capacity to avoid local minima, their independence from explicit function derivations and their establishment of stable calculation procedures, we decided to rely solely on these methods. It is well known that different methods are suitable for different problems. Therefore, we tested several different methods on the presented problem, with the aim of determining the most appropriate one for the given and similar problems.

Although we have selected evolutionary methods, it should be noted that their use also has disadvantages. Due to the large number of objective function calculations, especially in the case of a large number of parameters and, thus, a large population, it is a problem if the calculation of the objective function is time-consuming. The quality of the evolutionary method depends on the setting of the parameters of the method, which are not universal but are set according to the problem being solved. The speed of the method depends on the area in which it searches, and only this is defined by the limits of the search parameters. Too large an area is often set, because the exact boundaries of the problem are not known. Finally, the quality of the solution is related directly to a correctly defined objective function, which can be a problem in the case of challenging real-world problems.

The first selected method was DE [14,17–26]. Some of DE's advantages are ease of use, simple structure, speed and robustness. In the case of DE, different strategies can be used, generally written as DE/x/y/z. DE indicates Differential Evolution, x represents a string labeling the vector to be perturbed, y is the number of difference vectors considered for perturbation and z stands for the type of crossover being used. Different strategies perform differently for different problems; therefore, we tested three different strategies, which are DE/best/1/exp, DE/rand/1/exp and DE/best/1/bin. For all calculations we set the differential weight F to 0.6 and the crossover probability CR to 0.8.

The second selected algorithm was the more recent ABC [27–34]. It was proposed by D. Karaboga et al. [27]. The ABC algorithm consists of three steps: sending the employed bees onto the food sources and then measuring their nectar; selection of the food sources by the onlookers after sharing the information of the employed bees and determining the nectar amount of the food; determining the scout bees and then sending them onto possible food sources. Since a scout bee might not be employed for every iteration, the number of fitness evaluations (FEs) cannot be determined statistically. The limit value used as the control parameter for the bee population was set to 100, and only one scout bee was used.

The third selected algorithm was TLBO [35–43], which is a recently proposed population-based algorithm, which simulates the teaching-learning process in a classroom. TLBO is divided into a Teacher Phase and a Learner Phase. In our work the TLBO implementation was used, where the duplicate elimination phase was omitted. The number of FEs consumed can be determined statistically as: FEs = 2 × population size × iterations. TLBO has no additional control parameters beside the population size.

This work presents the determination of seven parameters of the DC motor drive, which are the motor's resistance R_a, the motor's inductance L_a, the motor's constant c_m, the drive's inertia J and load expressed with parameters T_{la} for the constant part of friction and load, T_{lb} for the linear part of friction and load and T_{lc} for the square part of friction and load. The population size was set to 10 times the number of parameters, which was 70. The limits of the parameters were set according to the Laboratory drive used, presented in Section 2.3. The parameters' limits used are presented in Table 1.

Table 1. Parameters' limits.

Parameter	Lower Limit	Upper Limit
Motor's resistance R_a (Ω)	0	100
Motor's inductance L_a (H)	0	100
Motor's constant c_m (Vs)	0	5
Drive's inertia J (kg·m^2)	0	1
Constant part of friction and load T_{la} (Nm)	0	20
Linear part of friction and load T_{lb} (Nm·s)	0	$9.55 \cdot 10^{-2}$ (20 Nm torque at speed 209 s^{-1}; 182 s^{-1} is motor-rated speed)
Square part of friction and load T_{lc} (Nm·s^2)	0	$4.56 \cdot 10^{-4}$ (20 Nm torque at speed 209 s^{-1}; 182 s^{-1} is motor-rated speed)

In the case of a larger or smaller drive, the parameter limits can be increased or decreased accordingly.

To make a fair comparison of the evolutionary methods, the stopping criteria were the same for all methods, which was 140,000 FEs. Because the population size was 70, it means the number of iterations for each of the methods was the following:

- DE: 2000 iterations, determined by (FEs/population size)
- TLBO: 1000 iterations, determined by (FEs/2 × population size) due to the two phases of the TLBO algorithm.
- ABC: ≤2000 iterations, determined by (FEs/population size + scout bees) due to the fact that the scout bee was not employed for every iteration and dynamic counting must be used.

The algorithm for the parameters' determination procedure is presented in Figure 4.

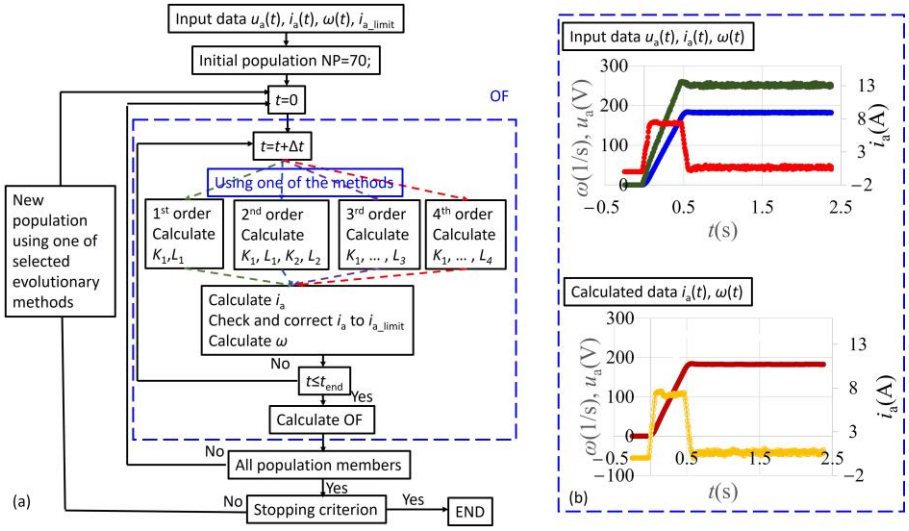

Figure 4. Algorithm of the parameters' determination procedure: (**a**) algorithm; (**b**) presentation of the input and calculated data used for the OF calculation.

The text in Figure 4 "using one of the methods" means that only one of the methods was used in the scope of one calculation procedure.

4. Parameters' Determination

4.1. Test Measurements

We conducted tests and analyses based on four sets of measured data. Two of them were only for speed up, and these are marked as M1U and M2U. In the additional two test cases, we added speed down after the speed, marked with M1UD and M2UD, which was not found in the literature. With this, we wanted to find out if we could achieve better results by adding the speed-down response. The data used for M1U, M2U, M1UD and M2UD are presented in Table 2.

The meaning of t_{speed_up} and t_{speed_down} is presented in Figure 3. The measured signals will be visible when presented together with the results in Figures 5 and 6.

The steady state part of the M1U is also used for the motor constant c_m determination. Considering that, di_a/dt equals 0, the (18) is obtained at steady-state operation.

$$u_a(t) = i_a \cdot R_a + c_m \cdot \omega \quad \Rightarrow \quad c_m = \frac{u_a(t) - i_a \cdot R_a}{\omega} \tag{18}$$

The value c_m = 1.356 Vs is used as a known value in the continuation. The values presented in Table 3 can be seen in Figure 5a.

Table 2. The values used to obtain the measured data.

Value	Measured Input Data			
	M1U	**M2U**	**M1UD**	**M2UD**
t_{speed_up} (s)	0	0.5	0	0.5
t_{speed_down} (s)	/	/	0	0.5
ω_{final} (s^{-1})	182	182	182	182
i_{a_limit} (A)	12.48 (120% of I_{a_rated})	12.48 (120% of I_{a_rated})	12.48 (120% of I_{a_rated})	12.48 (120% of I_{a_rated})
Load (Nm)	no load	no load	no load	no load
Number of measured points	400	400	400	400

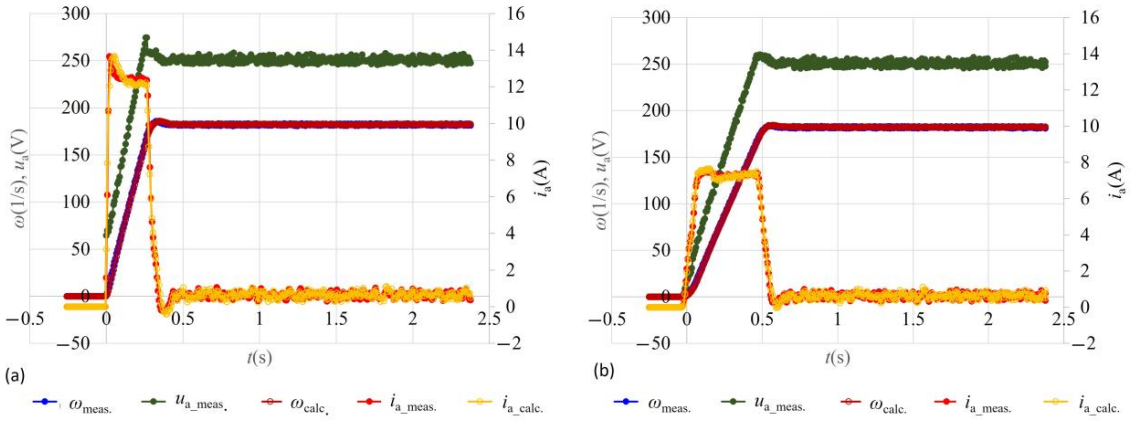

Figure 5. Measured and calculated transient phenomena for (**a**) M1U and (**b**) M2U.

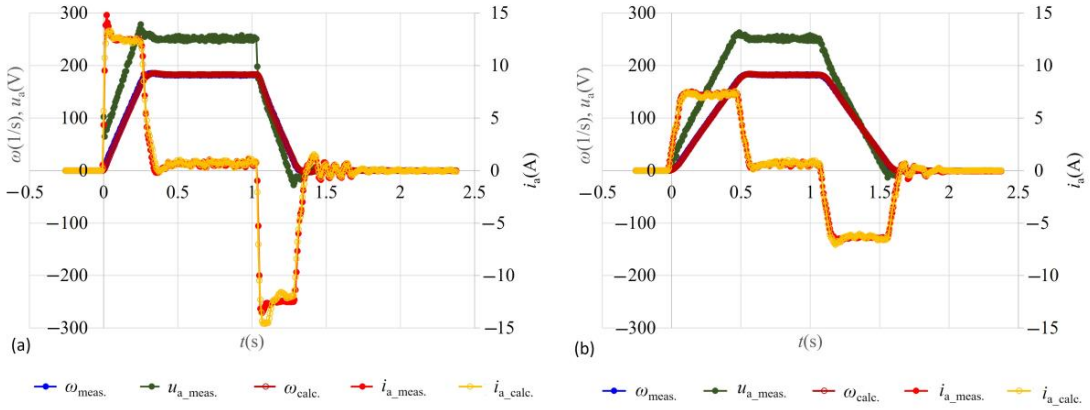

Figure 6. Measured and calculated transient phenomena for (**a**) M1UD and (**b**) M2UD.

Table 3. Determination of the motor constant c_m based on the measured data MU1.

***t* (s)**	**Measured u_a (V)**	**Measured i_a (A)**	**Measured ω (s^{-1})**	**Known R_a (Ω)**	**Calculated c_m (Vs)**
0.5	254.76	0.605	181.66	5.66	1.384
1	255.08	0.780	182.81	5.66	1.371
1.5	251.64	0.636	181.62	5.66	1.366
2	246.26	0.674	181.20	5.66	1.338
Average c_m determined, based on 286 measured points for steady state operation from 0.5 s					1.356

4.2. Results for M1U, M2U, M1UD and M2UD

To determine the parameters, the transient phenomenon of current and speed is necessary, since in (7) (see Section 2.1) L_a is multiplied by di_a/dt, and in Equation (8) (see Section 2.1) J is multiplied by $d\omega/dt$. Acceleration is used by many authors, so we added stopping, in order to determine the possibility of improving the approach.

The sampling time of 6.6 ms was used for all measurements (M1U, M2U, M1UD and M2UD). The Runge–Kutta fourth-order method was used for the simulation used in the scope of the OF determination. For the parameters' determination DE/best/1/exp, DE/rand/1/exp, DE/best/1/bin, TLBO and ABC were used (presented in Section 3). For each evolutionary method, 50 independent runs were conducted. In Tables 4–7 and also in the continuation of the paper, B is used for the best value, W is used for the worst value, M is used for the mean value and SD is used for the Standard Deviation.

Table 4. OF and Mean values of the calculated parameters for 50 independent runs using the Runge–Kutta fourth-order method for M1U with a 6.6 ms sampling time.

OF and Parameters		Method					
		Known Value	**DE/best/1/exp**	**DE/rand/1/exp**	**DE/best/1/bin**	**TLBO**	**ABC**
OF	B	-	$3.8094 \cdot 10^{-4}$	$3.8094 \cdot 10^{-4}$	$3.8094 \cdot 10^{-4}$	$3.8094 \cdot 10^{-4}$	$3.8127 \cdot 10^{-4}$
	W	-	$3.9247 \cdot 10^{-4}$	$3.8094 \cdot 10^{-4}$	$3.9247 \cdot 10^{-4}$	$3.8094 \cdot 10^{-4}$	$3.8094 \cdot 10^{-4}$
	M	-	$3.8164 \cdot 10^{-4}$	$3.8094 \cdot 10^{-4}$	$3.8141 \cdot 10^{-4}$	$3.8094 \cdot 10^{-4}$	$3.8097 \cdot 10^{-4}$
	SD	-	$2.7376 \cdot 10^{-6}$	$5.4210 \cdot 10^{-20}$	$2.2589 \cdot 10^{-6}$	$5.4210 \cdot 10^{-20}$	$6.7087 \cdot 10^{-8}$
R_a (Ω)	M	5.66	4.214	4.213	4.214	4.213	4.213
L_a (H)	M	0.0472	0.0583	0.0583	0.0583	0.0583	0.0583
c_m (Vs)	M	1.356	1.360	1.360	1.360	1.360	1.360
J (kgm^2)	M	$\approx 3.725 \cdot 10^{-2}$	$2.578 \cdot 10^{-2}$	$2.576 \cdot 10^{-2}$	$2.577 \cdot 10^{-2}$	$2.576 \cdot 10^{-2}$	$2.576 \cdot 10^{-2}$
T_{la} (Nm)	M	≈ 0	0.0	$3.764 \cdot 10^{-16}$	0.0	$5.684 \cdot 10^{-16}$	0.0
T_{lb} (Nms)	M	$\approx 4.8 \cdot 10^{-3}$	$4.530 \cdot 10^{-3}$	$4.819 \cdot 10^{-3}$	$4.626 \cdot 10^{-3}$	$4.819 \cdot 10^{-3}$	$4.811 \cdot 10^{-3}$
T_{lc} (Nms^2)	M	≈ 0	$6.244 \cdot 10^{-6}$	$6.871 \cdot 10^{-20}$	$1.052 \cdot 10^{-5}$	$1.984 \cdot 10^{-19}$	$4.0320 \cdot 10^{-8}$

Table 5. OF and Mean values of the calculated parameters for 50 independent runs using the Runge–Kutta fourth-order method for M2U with a 6.6 ms sampling time.

OF and Parameters		Method					
		Known Value	**DE/best/1/exp**	**DE/rand/1/exp**	**DE/best/1/bin**	**TLBO**	**ABC**
OF	B	-	$3.3639 \cdot 10^{-4}$	$3.3639 \cdot 10^{-4}$	$3.3639 \cdot 10^{-4}$	$3.3639 \cdot 10^{-4}$	$3.4054 \cdot 10^{-4}$
	W	-	$3.5599 \cdot 10^{-4}$	$3.3639 \cdot 10^{-4}$	$3.5600 \cdot 10^{-4}$	$3.3639 \cdot 10^{-4}$	$3.3640 \cdot 10^{-4}$
	M	-	$3.3757 \cdot 10^{-4}$	$3.3639 \cdot 10^{-4}$	$3.3757 \cdot 10^{-4}$	$3.3639 \cdot 10^{-4}$	$3.3685 \cdot 10^{-4}$
	SD	-	$4.6540 \cdot 10^{-6}$	$5.4210 \cdot 10^{-20}$	$4.6540 \cdot 10^{-6}$	$5.4210 \cdot 10^{-20}$	$9.0725 \cdot 10^{-7}$
R_a (Ω)	M	5.66	4.530	4.530	4.530	4.530	4.533
L_a (H)	M	0.0472	0.0577	0.0577	0.0577	0.0577	0.0578
c_m (Vs)	M	1.356	1.358	1.358	1.358	1.358	1.358
J (kgm^2)	M	$\approx 3.725 \cdot 10^{-2}$	$2.534 \cdot 10^{-2}$	$2.531 \cdot 10^{-2}$	$2.534 \cdot 10^{-2}$	$2.531 \cdot 10^{-2}$	$2.531 \cdot 10^{-2}$
T_{la} (Nm)	M	≈ 0	$1.466 \cdot 10^{-4}$	$5.309 \cdot 10^{-14}$	$1.466 \cdot 10^{-4}$	$1.385 \cdot 10^{-13}$	$6.868 \cdot 10^{-3}$
T_{lb} (Nms)	M	$\approx 4.8 \cdot 10^{-3}$	$4.432 \cdot 10^{-3}$	$4.715 \cdot 10^{-3}$	$4.432 \cdot 10^{-3}$	$4.715 \cdot 10^{-3}$	$4.6025 \cdot 10^{-3}$
T_{lc} (Nms^2)	M	≈ 0	$1.539 \cdot 10^{-6}$	$6.710 \cdot 10^{-20}$	$1.539 \cdot 10^{-6}$	$1.911 \cdot 10^{-19}$	$3.9619 \cdot 10^{-7}$

Table 6. OF and Mean values of the calculated parameters for 50 independent runs using the Runge–Kutta fourth-order method for M1UD with a 6.6 ms sampling time.

OF and Parameters		Method					
		Known Value	DE/best/1/exp	DE/rand/1/exp	DE/best/1/bin	TLBO	ABC
OF	B	-	$8.0983 \cdot 10^{-4}$	$8.0983 \cdot 10^{-4}$	$8.0983 \cdot 10^{-4}$	$8.0983 \cdot 10^{-4}$	$8.0983 \cdot 10^{-4}$
	W	-	$8.6327 \cdot 10^{-4}$	$8.0983 \cdot 10^{-4}$	$8.6327 \cdot 10^{-4}$	$8.0983 \cdot 10^{-4}$	$8.0983 \cdot 10^{-4}$
	M	-	$8.1090 \cdot 10^{-4}$	$8.0983 \cdot 10^{-4}$	$8.1304 \cdot 10^{-4}$	$8.0983 \cdot 10^{-4}$	$8.0983 \cdot 10^{-4}$
	SD	-	$7.4820 \cdot 10^{-6}$	$3.2526 \cdot 10^{-19}$	$1.2691 \cdot 10^{-5}$	$3.2526 \cdot 10^{-19}$	$3.2526 \cdot 10^{-19}$
R_a (Ω)	M	5.66	4.551	4.551	4.551	4.551	4.551
L_a (H)	M	0.0472	0.0522	0.0522	0.0522	0.0522	0.0522
c_m (Vs)	M	1.356	1.354	1.354	1.354	1.354	1.354
J (kgm^2)	M	$\approx 3.725 \cdot 10^{-2}$	$2.561 \cdot 10^{-2}$	$2.561 \cdot 10^{-2}$	$2.561 \cdot 10^{-2}$	$2.561 \cdot 10^{-2}$	$2.561 \cdot 10^{-2}$
T_{la} (Nm)	M	≈ 0	$2.093 \cdot 10^{-26}$	$2.383 \cdot 10^{-16}$	$2.771 \cdot 10^{-17}$	$3.553 \cdot 10^{-16}$	$1.214 \cdot 10^{-15}$
T_{lb} (Nms)	M	$\approx 4.8 \cdot 10^{-3}$	$9.509 \cdot 10^{-5}$	$3.320 \cdot 10^{-18}$	$2.853 \cdot 10^{-4}$	$2.392 \cdot 10^{-17}$	0.0
T_{lc} (Nms^2)	M	≈ 0	$2.775 \cdot 10^{-5}$	$2.831 \cdot 10^{-5}$	$2.661 \cdot 10^{-5}$	$2.831 \cdot 10^{-5}$	$2.831 \cdot 10^{-5}$

Table 7. OF and Mean values of the calculated parameters for 50 independent runs using the Runge–Kutta fourth-order method for M2UD with a 6.6 ms sampling time.

OF and Parameters		Method					
		Known Value	DE/best/1/exp	DE/rand/1/exp	DE/best/1/bin	TLBO	ABC
OF	B	-	$4.9342 \cdot 10^{-4}$	$4.9432 \cdot 10^{-4}$	$4.9432 \cdot 10^{-4}$	$4.9432 \cdot 10^{-4}$	$4.9432 \cdot 10^{-4}$
	W	-	$6.0877 \cdot 10^{-4}$	$4.9432 \cdot 10^{-4}$	$6.0877 \cdot 10^{-4}$	$4.9432 \cdot 10^{-4}$	$4.9432 \cdot 10^{-4}$
	M	-	$4.9890 \cdot 10^{-4}$	$4.9432 \cdot 10^{-4}$	$5.0119 \cdot 10^{-4}$	$4.9432 \cdot 10^{-4}$	$4.9432 \cdot 10^{-4}$
	SD	-	$2.2426 \cdot 10^{-5}$	$1.0842 \cdot 10^{-19}$	$2.7178 \cdot 10^{-5}$	$1.0842 \cdot 10^{-19}$	$6.8147 \cdot 10^{-13}$
R_a (Ω)	M	5.66	4.536	4.535	4.536	4.535	4.535
L_a (H)	M	0.0472	0.0541	0.0541	0.0541	0.0541	0.0541
c_m (Vs)	M	1.356	1.359	1.359	1.359	1.359	1.359
J (kgm^2)	M	$\approx 3.725 \cdot 10^{-2}$	$2.490 \cdot 10^{-2}$	$2.490 \cdot 10^{-2}$	$2.490 \cdot 10^{-2}$	$2.490 \cdot 10^{-2}$	$2.490 \cdot 10^{-2}$
T_{la} (Nm)	M	≈ 0	$2.856 \cdot 10^{-3}$	$2.911 \cdot 10^{-15}$	$4.284 \cdot 10^{-3}$	$9.344 \cdot 10^{-15}$	0.0
T_{lb} (Nms)	M	$\approx 4.8 \cdot 10^{-3}$	$4.979 \cdot 10^{-3}$	$5.187 \cdot 10^{-3}$	$4.876 \cdot 10^{-3}$	$5.187 \cdot 10^{-3}$	$5.187 \cdot 10^{-3}$
T_{lc} (Nms^2)	M	≈ 0	$1.097 \cdot 10^{-6}$	$5.645 \cdot 10^{-20}$	$1.645 \cdot 10^{-6}$	$1.612 \cdot 10^{-19}$	0.0

The values of OF and parameters for M1U are presented in Table 4, for M2U in Table 5, for M1UD in Table 6 and for M2UD in Table 7.

To see the difference between the measured and simulated i_a and ω, the measured transient phenomena and simulated transient phenomena obtained using the mean values of the calculated parameters using DE/rand/1/exp are presented in Figure 5 for M1U and M2U and in Figure 6 for M1UD and M2UD.

The calculation time was also an important factor, which should be as short as possible. The average calculation times for 50 independent runs are presented in Table 8.

Table 8. Mean values of calculation times for 50 independent runs using the RK fourth-order method for M1U, M2U, M1UD and M2UD input data.

Measured Data		Method				
		DE/best/1/exp	DE/rand/1/exp	DE/best/1/bin	TLBO	ABC
M1U	M t(s)	9.653	9.212	8.739	33.111	36.121
M2U	M t(s)	9.166	9.095	9.301	33.367	35.734
M1UD	M t(s)	9.099	9.036	9.322	33.677	36.738
M2UD	M t(s)	9.035	9.663	8.679	33.917	36.603

4.3. Convergence of the Methods

When comparing evolutionary methods, the convergence of the method is important information. It is known that, due to the use of a random generator, each calculation flow is different. Therefore, we looked for the average convergence speed of each method, which we showed with the average value of FEs needed to achieve a certain value of OF. The results are shown in Figure 7, where the average FEs required to achieve OF < 1, OF < 10^{-1}, OF < 10^{-2} and OF < 10^{-3} values of OF are shown. For better image transparency, the y scale in Figure 7 is a logarithmic scale.

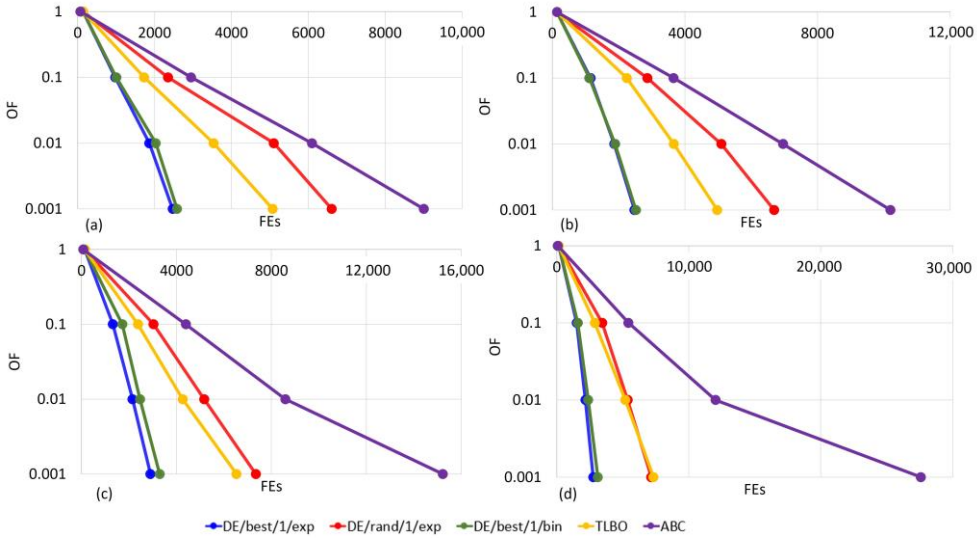

Figure 7. Convergence of the methods in case of (**a**) M1U, (**b**) M2U, (**c**) M1UD and (**d**) M2UD.

Analysis of the results in terms of accuracy and in terms of the evolutionary method used are the following:

- The accuracy of the results was comparable for all test cases and used methods. The deviations in the R_a calculation compared to the known values are as follows: M1U 25%, M2UD 19%, M1UD 19% and M2U 19%. For the L_a calculations, the deviations stood at M1U 23%, M2U 22%, M1UD 10% and M2UD 15%. Slightly smaller deviations were noticeable in the case of M1UD and M2UD, but we could not characterize them as essential.
- When comparing the methods, it is noticeable that DE/rand/1/exp and TLBO were the most robust, as they gave exactly the same result for each of the 50 calculations, which was not the case for DE/best/1/exp, DE/best/1/bin and ABC.
- Comparing the convergence of the methods, it can be observed that DE/best/1/exp and DE/best/1/bin were the fastest. DE/rand/1/exp and TLBO were slower and ABC was the slowest.
- Based on Table 8, it can be seen that the DE methods for all three strategies were three to four times faster than TLBO and ABC.

Since DE/rand/1/exp and TLBO were the most robust methods and DE/rand/1/exp was significantly faster, the DE/rand/1/exp method will be used for further analysis shown in the article. Also, since the results for all the test cases were comparable, we will use only the M1U test case for further analysis (sampling time, order of integration method, repeatability of measurement and length of measurement).

5. Analysis of the Interaction of the Order of Integration Method and Sampling Time

The power supply used enabled measurements with different sampling times. We used sampling times of 3.3 ms, 6.6 ms, 16.5 ms and 33 ms. To simulate the motor response, which

is necessary for the Objective Function's evaluation, we used the first-order, second-order, third-order and fourth-order Runge–Kutta methods.

The results using the shortest sampling time of 3.3 ms for all for the Runge–Kutta (RK) methods for M1U and DE/rand/1/exp are presented in Table 9.

Table 9. OF and Mean value of the calculated parameters for 50 independent runs: data M1U, sampling time 3.3 ms, simulation RK first, second, third and fourth order, solving method DE/rand/1/exp.

OF and Parameters		Method	DE/rand/1/exp			
		Known Value	RK First Order	RK Secons Order	RK Third Order	RK Fourth Order
OF	B	-	$5.7374 \cdot 10^{-4}$	$4.8270 \cdot 10^{-4}$	$4.9176 \cdot 10^{-4}$	$5.0743 \cdot 10^{-3}$
	W	-	$5.7374 \cdot 10^{-4}$	$4.8270 \cdot 10^{-4}$	$4.9176 \cdot 10^{-4}$	$5.0743 \cdot 10^{-4}$
	M	-	$5.7374 \cdot 10^{-4}$	$4.8270 \cdot 10^{-4}$	$4.9176 \cdot 10^{-4}$	$5.0743 \cdot 10^{-4}$
	SD	-	0.0	$5.4210 \cdot 10^{-20}$	$1.0842 \cdot 10^{-19}$	$1.0842 \cdot 10^{-19}$
R_a (Ω)	M	5.66	4.318	4.108	4.144	4.160
L_a (H)	M	0.0472	0.0564	0.0515	0.0536	0.0549
c_m (Vs)	M	1.356	1.362	1.364	1.364	1.364
J (kgm^2)	M	$\approx 3.725 \cdot 10^{-2}$	$2.542 \cdot 10^{-2}$	$2.560 \cdot 10^{-2}$	$2.557 \cdot 10^{-2}$	$2.555 \cdot 10^{-2}$
T_{la} (Nm)	M	≈0	$4.114 \cdot 10^{-16}$	$4.571 \cdot 10^{-16}$	$4.374 \cdot 10^{-16}$	$3.113 \cdot 10^{-16}$
T_{lb} (Nms)	M	$\approx 4.8 \cdot 10^{-3}$	$5.107 \cdot 10^{-3}$	$5.087 \cdot 10^{-3}$	$5.099 \cdot 10^{-3}$	$5.109 \cdot 10^{-3}$
T_{lc} (Nms^2)	M	≈0	$5.226 \cdot 10^{-20}$	$7.082 \cdot 10^{-20}$	$6.399 \cdot 10^{-5}$	$9.638 \cdot 10^{-20}$
t (s)	M	-	6.491	7.176	8.876	8.785

To see the difference between the measured and simulated i_a and ω, the measured and simulated values obtained using the mean values of the calculated parameters using RK first order and fourth order in the case of 3.3 ms sampling time are presented in Figure 8.

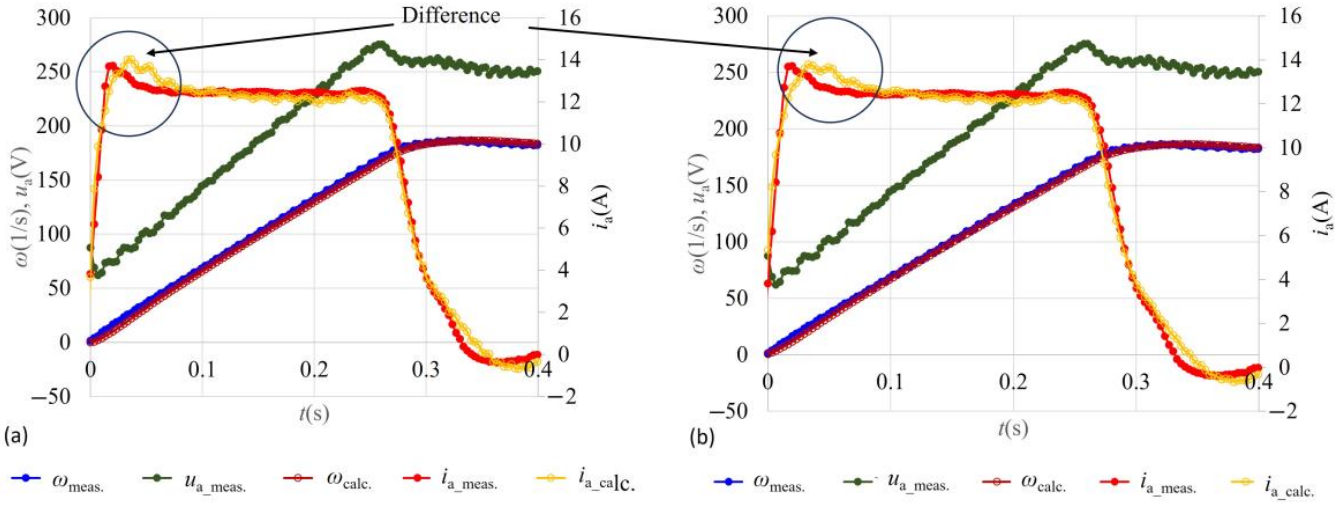

Figure 8. Measured and calculated responses for M1U and sampling time 3.3 ms used for the simulation (**a**) RK first-order and (**b**) RK fourth-order methods.

The results obtained using a sampling time of 6.6 ms for all the Runge–Kutta (RK) methods for M1U and DE/rand/1/exp are presented in Table 10.

Table 10. OF and Mean values of the calculated parameters for 50 independent runs: data M1U, sampling time 6.6 ms, simulation RK first, second, third and fourth order, solving method DE/rand/1/exp.

OF and Parameters		Method	DE/rand/1/exp			
		Known Value	RK First Order	RK Second Order	RK Third Order	RK Fourth Order
OF	B	-	$5.8057 \cdot 10^{-4}$	$3.4525 \cdot 10^{-4}$	$3.5215 \cdot 10^{-4}$	$3.8094 \cdot 10^{-4}$
	W	-	$5.8057 \cdot 10^{-4}$	$3.4525 \cdot 10^{-4}$	$3.5215 \cdot 10^{-4}$	$3.8094 \cdot 10^{-4}$
	M	-	$5.8057 \cdot 10^{-4}$	$3.4525 \cdot 10^{-4}$	$3.5215 \cdot 10^{-4}$	$3.8094 \cdot 10^{-4}$
	SD	-	$1.0842 \cdot 10^{-19}$	$5.4210 \cdot 10^{-20}$	$5.4210 \cdot 10^{-20}$	$5.4210 \cdot 10^{-20}$
R_a (Ω)	M	5.66	4.546	4.067	4.176	4.213
L_a (H)	M	0.0472	0.0643	0.0504	0.0548	0.0583
c_m (Vs)	M	1.356	1.357	1.360	1.360	1.360
J (kgm^2)	M	$\approx 3.725 \cdot 10^{-2}$	$2.548 \cdot 10^{-2}$	$2.604 \cdot 10^{-2}$	$2.583 \cdot 10^{-2}$	$2.576 \cdot 10^{-2}$
T_{la} (Nm)	M	≈0	$6.767 \cdot 10^{-16}$	$3.563 \cdot 10^{-5}$	$3.939 \cdot 10^{-16}$	$3.764 \cdot 10^{-16}$
T_{lb} (Nms)	M	$\approx 4.8 \cdot 10^{-3}$	$4.824 \cdot 10^{-3}$	$4.798 \cdot 10^{-3}$	$4.807 \cdot 10^{-3}$	$4.819 \cdot 10^{-3}$
T_{lc} (Nms^2)	M	≈0	$4.580 \cdot 10^{-20}$	$4.712 \cdot 10^{-20}$	$4.271 \cdot 10^{-19}$	$6.871 \cdot 10^{-20}$
t (s)	M	-	7.453	7.085	8.139	9.212

To see the difference between the measured and simulated i_a and ω, the measured and simulated values obtained using the mean values of the calculated parameters using the RK first order and fourth order in the case of 6.6 ms sampling time are presented in Figure 9.

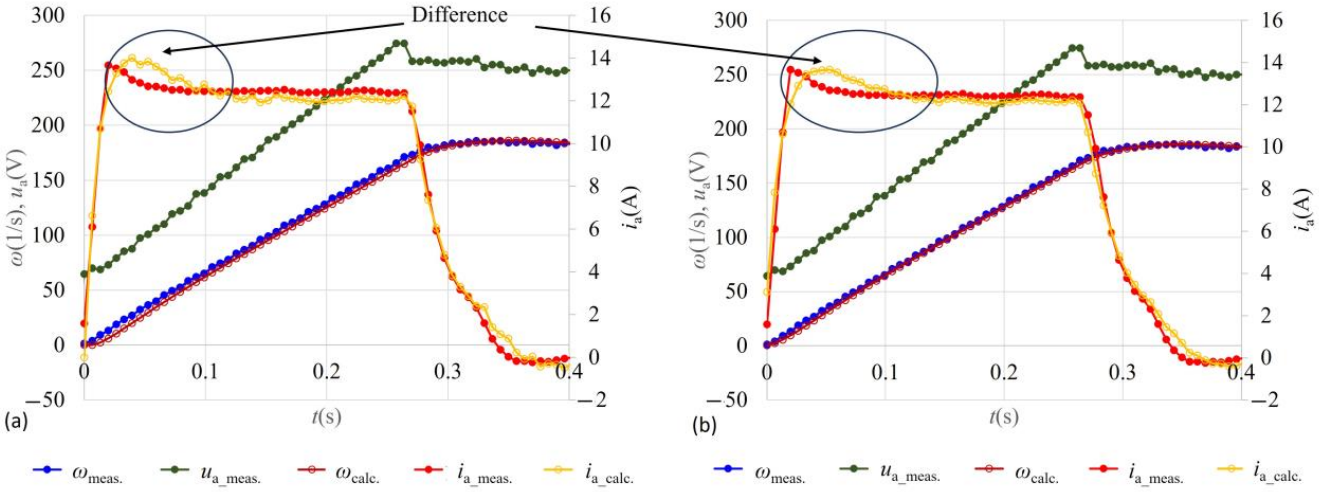

Figure 9. Measured and calculated responses for M1U and sampling time of 6.6 ms using for the simulation (**a**) RK first-order and (**b**) RK fourth-order methods.

The results using the sampling time of 16.5 ms for all four Runge–Kutta (RK) methods for M1U and DE/rand/1/exp are presented in Table 11.

To see the difference between the measured and simulated i_a and ω, the measured and simulated values obtained using the mean values of the calculated parameters using the RK first order and fourth order in the case of a 16.5 ms sampling time are presented in Figure 10.

Table 11. OF and Mean values of the calculated parameters for 50 independent runs: data M1U, sampling time 16.5 ms, simulation RK first, second, third and fourth orders, solving method DE/rand/1/exp.

OF and Parameters		Method	DE/rand/1/exp			
		Known Value	RK First Order	RK Second Order	RK Third Order	RK Fourth Order
OF	B	-	$1.5423 \cdot 10^{-3}$	$5.4764 \cdot 10^{-4}$	$5.4974 \cdot 10^{-4}$	$5.7259 \cdot 10^{-4}$
	W	-	$1.5423 \cdot 10^{-3}$	$5.4764 \cdot 10^{-4}$	$5.4974 \cdot 10^{-4}$	$5.7259 \cdot 10^{-4}$
	M	-	$1.5423 \cdot 10^{-3}$	$5.4764 \cdot 10^{-4}$	$5.4974 \cdot 10^{-4}$	$5.7259 \cdot 10^{-4}$
	SD	-	$1.5423 \cdot 10^{-19}$	0.0	$1.0842 \cdot 10^{-19}$	$1.0842 \cdot 10^{-19}$
R_a (Ω)	M	5.66	5.452	3.760	4.127	4.237
L_a (H)	M	0.0472	0.1293	0.0667	0.0759	0.0883
c_m (Vs)	M	1.356	1.368	1.376	1.375	1.374
J (kgm^2)	M	$\approx 3.725 \cdot 10^{-2}$	$2.239 \cdot 10^{-2}$	$2.697 \cdot 10^{-2}$	$2.551 \cdot 10^{-2}$	$2.522 \cdot 10^{-2}$
T_{la} (Nm)	M	≈0	$1.897 \cdot 10^{-1}$	$1.883 \cdot 10^{-2}$	$2.216 \cdot 10^{-2}$	$5.566 \cdot 10^{-15}$
T_{lb} (Nms)	M	$\approx 4.8 \cdot 10^{-3}$	$7.837 \cdot 10^{-17}$	$4.927 \cdot 10^{-3}$	$4.924 \cdot 10^{-3}$	$5.064 \cdot 10^{-3}$
T_{lc} (Nms^2)	M	≈0	$2.212 \cdot 10^{-5}$	$9.463 \cdot 10^{-19}$	$9.258 \cdot 10^{-19}$	$6.246 \cdot 10^{-18}$
t (s)	M	-	8.703	7.313	7.799	9.196

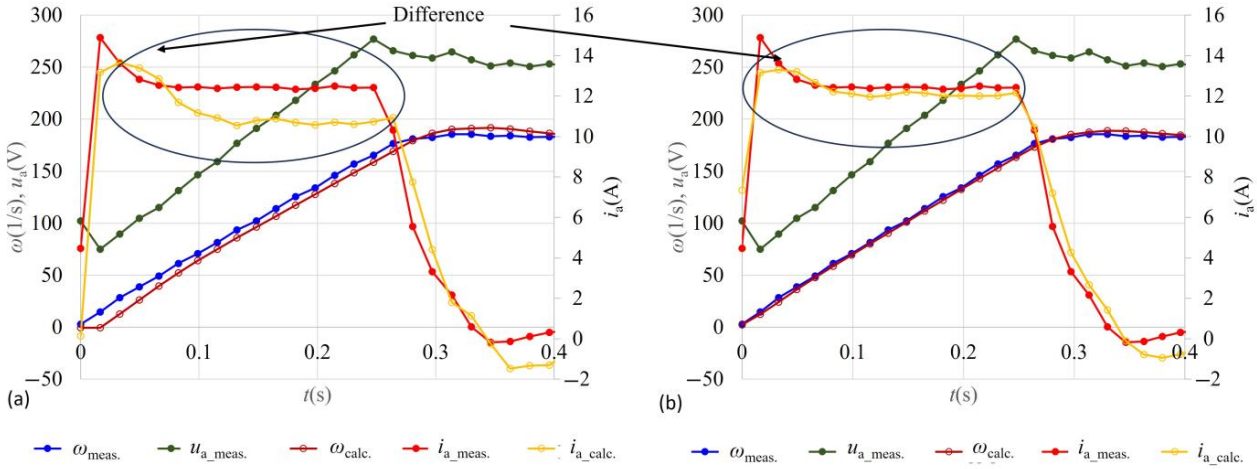

Figure 10. Measured and calculated responses for M1U and sampling time 16.5 ms using for the simulation (**a**) RK first-order and (**b**) RK fourth-order methods.

The results using the sampling time of 33 ms for all four Runge–Kutta (RK) methods for M1U and DE/rand/1/exp are presented in Table 12.

To see the difference between the measured and simulated i_a and ω, the measured and simulated values obtained using the mean values of the calculated parameters using the RK first order and fourth order in the case of a 33 ms sampling time are presented in Figure 11.

The analyses of the results presented in Tables 9–12 and Figures 8–11 are the following:

- For the sampling time 3.3 ms, the OF for the first-order method was $5.7 \cdot 10^{-4}$, and all the other methods were in the range from 4.8 to $5 \cdot 10^{-4}$. A small difference of the simulated values can be seen in Figure 8, where the simulated values for the first- and fourth-order methods are presented. All the calculated parameters were correct.
- For the sampling time 6.6 ms, the OF for the first-order method was $5.8 \cdot 10^{-4}$, and all the other methods were in the range from 3.4 to $3.8 \cdot 10^{-4}$. The parameters calculated with the first-order method showed a larger deviation than with the other methods. A difference of the simulated values can be seen in Figure 9, where the simulated values for the first- and fourth-order methods are presented.

- For the sampling time 16.5 ms, the OF for the first-order method was $1.5 \cdot 10^{-3}$, and all the other methods were in the range from 5.4 to $5.8 \cdot 10^{-4}$. In the case of the first-order method, the calculated parameters were not correct. In the case of the second-order method, R_a and L_a were not accurate. In the case of the third- and fourth-order methods, L_a was not accurate. In Figure 10 it can be seen that only two measuring points were present at the speed up of the motor. Nevertheless, we can use the second-, third- and fourth-order methods to estimate the parameters. A big difference of the simulated values can be seen in Figure 10, where the simulated values are presented for the first-and fourth-order methods.
- For the sampling time 33 ms, the OF for the first-order method was $4.5 \cdot 10^{-3}$, and all the other methods were in the range from 1.1 to $1.9 \cdot 10^{-3}$. The calculated values of the parameters were not calculated well enough with respect to the known values.

Table 12. OF and Mean values of the calculated parameters for 50 independent runs: data M1U, sampling time 33 ms, simulation RK first, second, third and fourth orders, solving method DE/rand/1/exp.

OF and Parameters		Method	DE/rand/1/exp			
		Known Value	RK First Order	RK Second Order	RK Third Order	RK Fourth Order
OF	B	-	$4.5163 \cdot 10^{-3}$	$1.1598 \cdot 10^{-3}$	$1.9605 \cdot 10^{-3}$	$1.1697 \cdot 10^{-3}$
	W	-	$4.5163 \cdot 10^{-3}$	$1.1598 \cdot 10^{-3}$	$1.2945 \cdot 10^{-3}$	$1.1697 \cdot 10^{-3}$
	M	-	$4.5163 \cdot 10^{-3}$	$1.1598 \cdot 10^{-3}$	$1.9160 \cdot 10^{-3}$	$1.1697 \cdot 10^{-3}$
	SD	-	$8.6736 \cdot 10^{-19}$	0.0	$1.2690 \cdot 10^{-4}$	$2.1684 \cdot 10^{-19}$
R_a (Ω)	M	5.66	8.049	3.320	4.076	5.011
L_a (H)	M	0.0472	0.2936	0.0664	0.109	0.0764
c_m (Vs)	M	1.356	1.349	1.367	1.365	1.361
J (kgm^2)	M	$\approx 3.725 \cdot 10^{-2}$	$1.969 \cdot 10^{-2}$	$3.479 \cdot 10^{-2}$	$2.431 \cdot 10^{-2}$	$2.486 \cdot 10^{-2}$
T_{la} (Nm)	M	≈0	$3.625 \cdot 10^{-1}$	$1.269 \cdot 10^{-1}$	$2.486 \cdot 10^{-1}$	$1.115 \cdot 10^{-1}$
T_{lb} (Nms)	M	$\approx 4.8 \cdot 10^{-3}$	$4.443 \cdot 10^{-17}$	$6.333 \cdot 10^{-17}$	$3.339 \cdot 10^{-3}$	$5.411 \cdot 10^{-17}$
T_{lc} (Nms^2)	M	≈0	$1.554 \cdot 10^{-5}$	$2.223 \cdot 10^{-5}$	$8.088 \cdot 10^{-7}$	$2.262 \cdot 10^{-5}$
t (s)	M	-	6.945	7.578	8.038	9.603

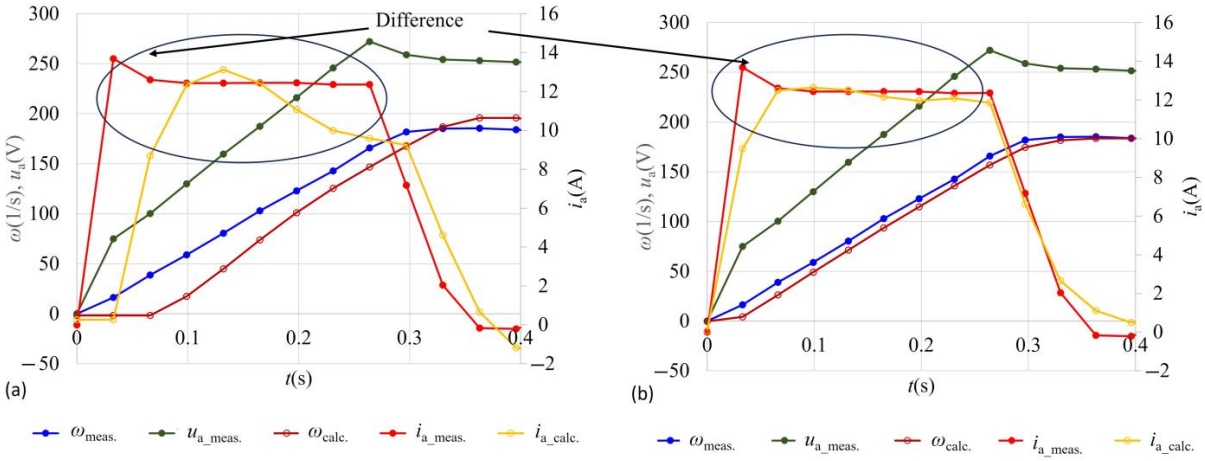

Figure 11. Measured and calculated responses for M1U and sampling time 33 ms used for the simulation (**a**) RK first-order and (**b**) RK fourth-order methods.

Based on the given analysis, we can conclude that the first-order method was not appropriate, except in the case of a small sampling time. The second-, third- and fourth-order methods were comparable. It is advantageous if there are at least a few measurement points during the acceleration, such as in Figures 8 and 9.

6. Repeatability of Parameters' Determination

It is important that the determination of parameters is a stable and repeatable process. In Section 4.2 we defined a robust evolutionary method, which is DE/rand/1/exp. The question was whether we would obtain comparable results if we repeated the measurement under the same conditions. Therefore, we repeated the measurement under the same conditions 10 times and looked at how the calculated parameters were comparable to each other.

The test was made using the M1U data, a sampling time of 6.6 ms, DE/rand/1/exp and the fourth-order method. The results for the 1st to 5th measurements are presented in Table 13 and for the 6th to 10th measurements in Table 14.

Table 13. OF and Mean values of the calculated parameters for 50 independent runs of DE/rand/1/exp using the RK fourth-order method for M1U with a sampling time of 6.6 ms for the first to fifth measurements.

OF and Parameters			**Method**		**DE/rand/1/exp**		
		Known Value	**First Meas.**	**Second Meas.**	**Third Meas.**	**Fourth Meas.**	**Fifth Meas.**
OF	B	-	$3.8094 \cdot 10^{-4}$	$2.9718 \cdot 10^{-4}$	$3.2691 \cdot 10^{-4}$	$3.5838 \cdot 10^{-4}$	$2.9635 \cdot 10^{-4}$
	W	-	$3.8094 \cdot 10^{-4}$	$2.9718 \cdot 10^{-4}$	$3.2691 \cdot 10^{-4}$	$3.5838 \cdot 10^{-4}$	$2.9635 \cdot 10^{-4}$
	M	-	$3.8094 \cdot 10^{-4}$	$2.9718 \cdot 10^{-4}$	$3.2691 \cdot 10^{-4}$	$3.5838 \cdot 10^{-4}$	$2.9635 \cdot 10^{-4}$
	SD	-	$5.4210 \cdot 10^{-20}$	$5.4210 \cdot 10^{-20}$	$5.4210 \cdot 10^{-20}$	0.0	$5.4210 \cdot 10^{-20}$
R_a (Ω)	M	5.66	4.213	4.249	4.189	4.319	4.230
L_a (H)	M	0.0472	0.0583	0.0543	0.0599	0.0533	0.0541
c_m (Vs)	M	1.356	1.360	1.359	1.360	1.359	1.359
J (kgm^2)	M	$\approx 3.725 \cdot 10^{-2}$	$2.576 \cdot 10^{-2}$	$2.582 \cdot 10^{-2}$	$2.585 \cdot 10^{-2}$	$2.580 \cdot 10^{-2}$	$2.588 \cdot 10^{-2}$
T_{la} (Nm)	M	≈ 0	$3.764 \cdot 10^{-16}$	$2.340 \cdot 10^{-16}$	$3.327 \cdot 10^{-16}$	$3.102 \cdot 10^{-16}$	$1.540 \cdot 10^{-16}$
T_{lb} (Nms)	M	$\approx 4.8 \cdot 10^{-3}$	$4.819 \cdot 10^{-3}$	$4.834 \cdot 10^{-3}$	$4.838 \cdot 10^{-3}$	$4.723 \cdot 10^{-3}$	$4.765 \cdot 10^{-3}$
T_{lc} (Nms^2)	M	≈ 0	$6.871 \cdot 10^{-20}$	$8.843 \cdot 10^{-20}$	$3.989 \cdot 10^{-20}$	$5.079 \cdot 10^{-20}$	$4.787 \cdot 10^{-20}$
t (s)	M	-	9.212	8.795	8.668	9.135	8.919

Table 14. OF and Mean values of the calculated parameters for 50 independent runs of DE/rand/1/exp using the RK 4th order for M1U with a sampling time of 6.6 ms for the 6th to 10th measurements.

OF and Parameters			**Method**		**DE/rand/1/exp**		
		Known Value	**6th Meas.**	**7th Meas.**	**8th Meas.**	**9th Meas.**	**10th Meas.**
OF	B	-	$3.1850 \cdot 10^{-4}$	$3.9034 \cdot 10^{-4}$	$3.1248 \cdot 10^{-4}$	$3.2844 \cdot 10^{-4}$	$3.2252 \cdot 10^{-4}$
	W	-	$3.1850 \cdot 10^{-4}$	$3.9034 \cdot 10^{-4}$	$3.1248 \cdot 10^{-4}$	$3.2844 \cdot 10^{-4}$	$3.2252 \cdot 10^{-4}$
	M	-	$3.1850 \cdot 10^{-4}$	$3.9034 \cdot 10^{-4}$	$3.1248 \cdot 10^{-4}$	$3.2844 \cdot 10^{-4}$	$3.2252 \cdot 10^{-4}$
	SD	-	0.0	$1.0842 \cdot 10^{-19}$	$5.4210 \cdot 10^{-20}$	$1.0842 \cdot 10^{-19}$	$5.4210 \cdot 10^{-20}$
R_a (Ω)	M	5.66	4.251	4.267	4.206	4.240	4.258
L_a (H)	M	0.0472	0.0546	0.0574	0.0563	0.0589	0.0596
c_m (Vs)	M	1.356	1.359	1.358	1.359	1.359	1.359
J (kgm^2)	M	$\approx 3.725 \cdot 10^{-2}$	$2.580 \cdot 10^{-2}$	$2.578 \cdot 10^{-2}$	$2.584 \cdot 10^{-2}$	$2.585 \cdot 10^{-2}$	$2.583 \cdot 10^{-2}$
T_{la} (Nm)	M	≈ 0	$2.023 \cdot 10^{-16}$	$2.606 \cdot 10^{-16}$	$2.883 \cdot 10^{-16}$	$2.284 \cdot 10^{-16}$	$3.962 \cdot 10^{-16}$
T_{lb} (Nms)	M	$\approx 4.8 \cdot 10^{-3}$	$4.740 \cdot 10^{-3}$	$4.729 \cdot 10^{-3}$	$4.744 \cdot 10^{-3}$	$4.752 \cdot 10^{-3}$	$4.721 \cdot 10^{-3}$
T_{lc} (Nms^2)	M	≈ 0	$8.943 \cdot 10^{-20}$	$8.483 \cdot 10^{-20}$	$4.873 \cdot 10^{-20}$	$7.036 \cdot 10^{-20}$	$6.796 \cdot 10^{-20}$
t (s)	M	-	8.657	9.233	8.875	9.202	8.919

The overall mean values of the results for all 10 measurements were calculated based on the results presented in Tables 13 and 14.

The deviations of OFs and parameters from the overall mean values for all 10 measurements are presented in Table 15.

Table 15. Deviation of OFs and parameters from the overall mean values for 50 × 10 independent runs using the RK fourth-order method for M1U and sampling 6.6 ms.

OF and Parameters			Method	DE/rand/1/exp		
	Known Value	**Lowest**	**Highest**	**Mean**	**SD**	**% dev. to Mean**
OF	-	$2.9635 \cdot 10^{-4}$	$3.9034 \cdot 10^{-4}$	$3.3320 \cdot 10^{-4}$	$3.1073 \cdot 10^{-5}$	−11.06% to +17.15%
R_a (Ω)	5.66	4.189	4.319	4.242	$3.4588 \cdot 10^{-2}$	−1.25% to +1.82%
L_a (H)	0.0472	0.0533	0.0600	0.0567	$2.3667 \cdot 10^{-3}$	−6.00% to +5.82%
c_m (Vs)	1.356	1.358	1.360	1.359	$4.4725 \cdot 10^{-4}$	−0.07% to +0.07%
J (kgm^2)	$\approx 3.725 \cdot 10^{-2}$	$2.576 \cdot 10^{-2}$	$2.588 \cdot 10^{-2}$	$2.582 \cdot 10^{-2}$	$3.4700 \cdot 10^{-5}$	−0.25% to +0.23%
T_{la} (Nm)	≈0	0.0	$3.569 \cdot 10^{-15}$	$2.783 \cdot 10^{-16}$	$5.3603 \cdot 10^{-16}$	-
T_{lb} (Nms)	$\approx 4.8 \cdot 10^{-3}$	$4.721 \cdot 10^{-3}$	$4.838 \cdot 10^{-3}$	$4.766 \cdot 10^{-3}$	$4.3791 \cdot 10^{-5}$	−0.94% to +1.51%
T_{lc} (Nms^2)	≈0	0.0	$8.511 \cdot 10^{-19}$	$6.570 \cdot 10^{-20}$	$1.1562 \cdot 10^{-19}$	-
t (s)	-	7.563	11.063	8.961	$4.5968 \cdot 10^{-1}$	−15.60% to 23.46%

From Table 15 it can be seen that the biggest deviation was 6% in case of the L_a calculation. The deviations of all the other parameters' calculations were less than 2%. Based on this, we can conclude that the procedure ensures good repeatability of parameter determination.

The statistical distribution of the results is presented in Figure 12, where histograms are presented for OF, R_a, L_a, c_m, J and T_{lb}.

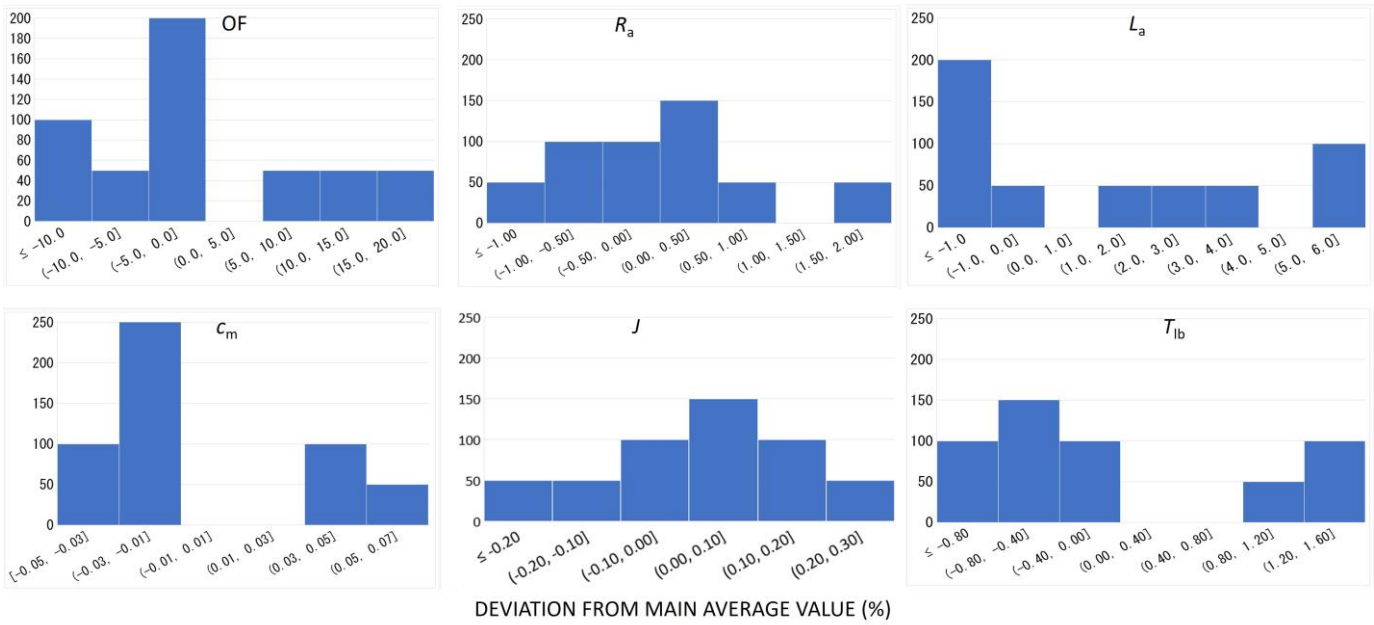

Figure 12. Histograms presenting the statistical distribution of the results.

In the histograms presented in Figure 12, blocks of 50 values can be seen clearly. They appear due to the fact that DE/rand/1/exp is very robust, so for each run with unchanged input data, the results are the same. For each set of measured input data, 50 independent

runs were conducted. In Figure 12, each histogram/chart represents 500 values divided into 10 blocks of 50 values, since 10 sets of measured data were used in the calculation.

7. Analysis of the Influence of Measurement Length

The different lengths of the measurement influenced the calculation time. The tests were made for the following measured signals with a sampling time of 6.6 ms using the M1U data:

- The whole measurement, which contained a pre-trigger, speed up and continuous operation. The whole signal consisted of 400 measurement points.
- A signal with no pre-trigger that contained speed up and continuous operation. The length of the signal with no pre-trigger was 362 measured points.
- Only speed up, which contained 56 measured points with a time duration of 0.35 s. The length of the signal was 56 measured points.
- Speed up with a time duration of 0.35 s and continuous operation with the same time duration of 0.35 s. The length of the signal was 109 measured points.
- Speed up with a time duration of 0.35 s and continuous operation with a time duration of 0.70 s. The length of the signal was 162 measured points.

The results are presented in Table 16.

Table 16. OF and Mean values of the calculated parameters for 50 independent runs using the RK fourth-order method for M1U, sampling time of 6.6 ms and different lengths of the measured values.

OF and Parameters		Method					
		Known Value	Whole Meas.	No Pre-Trigger	Start Only	0.35 s Start + 0.35 s Operation	0.35 s Start + 0.70 s Operation
OF	B	-	$3.8094 \cdot 10^{-4}$	$4.2093 \cdot 10^{-4}$	$1.8684 \cdot 10^{-3}$	$1.0974 \cdot 10^{-3}$	$7.9138 \cdot 10^{-4}$
	W	-	$3.8094 \cdot 10^{-4}$	$4.2093 \cdot 10^{-4}$	$1.8684 \cdot 10^{-3}$	$1.0974 \cdot 10^{-3}$	$7.9138 \cdot 10^{-4}$
	M	-	$3.8094 \cdot 10^{-4}$	$4.2093 \cdot 10^{-4}$	$1.8684 \cdot 10^{-3}$	$1.0974 \cdot 10^{-3}$	$7.9138 \cdot 10^{-4}$
	SD	-	$5.4210 \cdot 10^{-20}$	0.0	$2.1684 \cdot 10^{-19}$	$2.1684 \cdot 10^{-19}$	$2.1584 \cdot 10^{-19}$
R_a (Ω)	M	5.66	4.213	4.213	4.276	4.206	4.208
L_a (H)	M	0.0472	0.0583	0.0583	0.0578	0.0579	0.0580
c_m (Vs)	M	1.356	1.360	1.360	1.340	1.356	1.358
J (kgm^2)	M	$\approx 3.725 \cdot 10^{-2}$	$2.576 \cdot 10^{-2}$	$2.576 \cdot 10^{-2}$	$2.534 \cdot 10^{-2}$	$2.559 \cdot 10^{-2}$	$2.569 \cdot 10^{-2}$
T_{la} (Nm)	M	≈0	$3.764 \cdot 10^{-16}$	$1.544 \cdot 10^{-15}$	$5.264 \cdot 10^{-16}$	$5.692 \cdot 10^{-16}$	$1.083 \cdot 10^{-15}$
T_{lb} (Nms)	M	$\approx 4.8 \cdot 10^{-3}$	$4.819 \cdot 10^{-3}$	$4.819 \cdot 10^{-3}$	$3.087 \cdot 10^{-3}$	$5.060 \cdot 10^{-3}$	$4.927 \cdot 10^{-3}$
T_{lc} (Nms^2)	M	≈0	$6.871 \cdot 10^{-20}$	$7.404 \cdot 10^{-20}$	$3.234 \cdot 10^{-20}$	$5.122 \cdot 10^{-20}$	$7.601 \cdot 10^{-20}$
t (s)	M	-	9.212	9.557	6.309	6.894	7.043
Data			400	362	56	109	162

If we compare the results for all five measured signals by calculating the overall mean values in the same way as presented in Figure 12, we obtain the results presented in Table 17.

Based on Table 17 it can be seen that the deviations of R_a, L_a, c_m and J were less than 2%. A bigger deviation can be observed in the case of T_{lb}, which appeared for the START ONLY measured signal, and it was up to 32%. Based on this, it is suggested to use speed up and at least the same time of the continuous operation. Using signal 0.35 start + 0.35 continuous operation, the calculation times decreased from approximately 9 s to approximately 7 s. The measurements and simulations for the whole signal, signal with no pre-trigger, start only signal and signal containing start + 0.35 s of continuous operation are shown in Figure 13.

Table 17. Differences of OFs and parameters from the overall mean values of the calculated parameters for 50 × 5 independent runs using the RK fourth-order method for M1U with a sampling time of 6.6 ms.

OF and Parameters			Method	DE/rand/1/exp		
	Known Value	Lowest	Highest	Mean	SD	% dev. to Mean
OF	-	$3.8094 \cdot 10^{-4}$	$1.8684 \cdot 10^{-3}$	$9.1182 \cdot 10^{-4}$	$5.4532 \cdot 10^{-4}$	−58.22% to +104.91%
R_a (Ω)	5.66	4.206	4.276	4.223	$2.6351 \cdot 10^{-2}$	−0.40 to +1.24%
L_a (H)	0.0472	0.0578	0.0583	0.0581	$2.1877 \cdot 10^{-4}$	−0.52% to +0.34%
c_m (Vs)	1.356	1.340	1.360	1.355	$7.4982 \cdot 10^{-3}$	−1.11% to +0.37%
J (kgm^2)	$\approx 3.725 \cdot 10^{-2}$	$2.534 \cdot 10^{-2}$	$2.576 \cdot 10^{-2}$	$2.563 \cdot 10^{-2}$	$1.5774 \cdot 10^{-4}$	−1.13% to +0.51%
T_{la} (Nm)	≈0	0.0	$1.323 \cdot 10^{-14}$	$8.197 \cdot 10^{-16}$	$1.6478 \cdot 10^{-15}$	-
T_{lb} (Nms)	$\approx 4.8 \cdot 10^{-3}$	$3.087 \cdot 10^{-3}$	$5.060 \cdot 10^{-3}$	$4.542 \cdot 10^{-3}$	$7.3313 \cdot 10^{-4}$	−32.03% to +11.40%
T_{lc} (Nms^2)	≈0	0.0	$6.757 \cdot 10^{-19}$	$6.046 \cdot 10^{-20}$	$1.0705 \cdot 10^{-19}$	-
t (s)	-	5.719	11.563	7.803	1.4173	−26.71% to +48.19

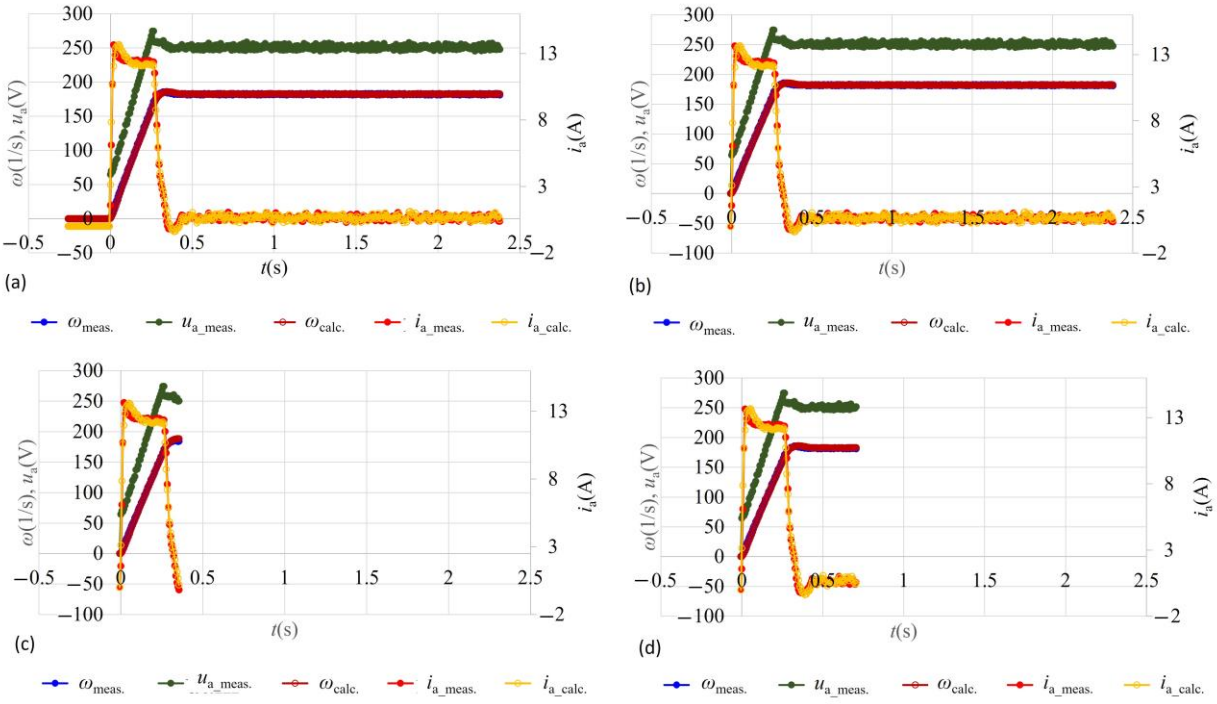

Figure 13. Measured and simulated values for (**a**) the whole signal, (**b**) a signal with no pre-trigger, (**c**) a start only signal, (**d**) a start + 0.35 s of continuous operation signal.

8. Validation Based on the Simulated Input Data

To validate the presented approach, the DC motor model was used to generate $u_a(t)$, $i_a(t)$ and ω. Generation was made using the RK fourth-order method and a time step of 6.6 ms. The parameters used for the generation of the simulated input data were the known data from the presented drive, shown in Table 18 in the column "Parameters used for the generation of the responses." For the input voltage, a linear increase up to 255 V was used, which can be seen in Figure 14.

Table 18. Parameters used for the generated responses and OF and Mean values of the calculated parameters for 50 independent runs using the RK fourth-order method for simulated responses, with a sampling time of 6.6 ms.

OF and Parameters		DE/rand/1/exp	
		Parameters Used for Generation of the Responses	Calculated Parameters
OF	B	-	$2.9207 \cdot 10^{-18}$
	W	-	$2.9207 \cdot 10^{-18}$
	M	-	$2.9207 \cdot 10^{-18}$
	SD	-	$5.4553 \cdot 10^{-27}$
R_a (Ω)	M	5.66	5.66
L_a (H)	M	0.0472	0.0472
c_m (Vs)	M	1.356	1.356
J (kgm^2)	M	$3.725 \cdot 10^{-2}$	$3.725 \cdot 10^{-2}$
T_{la} (Nm)	M	0	$4.03 \cdot 10^{-13}$
T_{lb} (Nms)	M	$4.8 \cdot 10^{-3}$	$4.80 \cdot 10^{-3}$
T_{lc} (Nms^2)	M	0	$1.22 \cdot 10^{-12}$

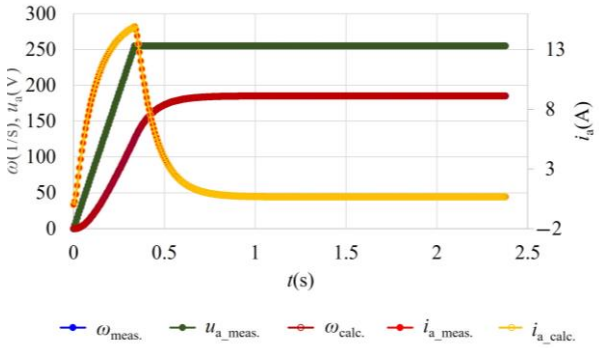

Figure 14. Input and simulated signals (input and simulated data of i_a being covered and also input and simulated data of ω being covered).

The generated responses were then used as input data for the parameters' determination. For the parameters' determination the RK fourth-order method was used (the same as was used for the simulated data generation). The results of the 50 independent runs are presented in Table 18 in the column "Calculated parameters".

From Table 18 it can be seen that the calculated parameters are the same as the parameters used for simulated data determination. In this way, the used model was validated against the used data set.

The input data and simulated data obtained as a result of parameters' determination are presented in Figure 14.

9. Conclusions

This paper introduced an approach that incorporates the measurement of voltage and not only current and speed response, as is common in the literature. It was proven that such an approach is appropriate to be used. Not only the parameters of drives with small DC motors but also drives with big DC motors powered by control/supply units can be determined with such an approach. The good side of this approach is simplicity, because the control/supply unit does not need to be modeled; it is considered with measured voltage.

The presented use of measured values are not only for speed up but also for speed down. It was found that the use of speed down did not improve the parameter determination process significantly.

An important part of the presented work is the determination of the appropriate evolutionary optimization method. The algorithms DE/best/1/exp, DE/rand/1/exp, DE/best/1/bin, TLBO and ABC were used and analyzed. The most robust were DE/rand/1/exp and TLBO, which led to the same calculated parameters for each of the 50 calculations in the case of all 4 test data (M1U, M2U, M1UD, M2UD). The convergence of TLBO was slightly better (Figure 7), but its calculation times were 3–6 times longer that the calculation times of DE/rand/1/exp (Table 8). DE/rand/1/exp can be presented as the most appropriate method for the presented problem. The selected method is the best only between those tested. We did not test other methods, since DE/rand/1/exp satisfied our expectations considering robustness and speed. Due to the NFL theorem, there are a plethora of different evolutionary algorithms and their derivatives, making it impossible to test all of them. Also, most of the algorithms were tested on benchmark problems, but their performance is usually very different on real-world problems.

The comparison of results using four sampling times (3.3 ms, 6.6 ms, 16.5 ms and 33 ms) and four different methods used for solving of coupled differential equations were analyzed (first-order, second-order, third-order and fourth-order methods). It can be concluded that at least some measured points should be at the speed-up interval, such as in the case of 3.3 ms (Figure 8) and 6.6 ms (Figure 9). The sampling times of 16.5 ms and 33 ms were not appropriate in the case of the used drive (Figures 10 and 11). The results obtained using the first-order method were the worst. The results obtained using the second-, third- and fourth-order methods were better and comparable.

The parameters' determination procedure showed very good repeatability, although three measured signals (speed, current and voltage) were used as the input data. In Section 6 it can be seen that, for 10 repeated measurements, the results were almost identical.

If we want to speed up the parameter determination process, we can use only part of the signal. The analysis in Section 7 showed that it is sufficient to use a signal consisting of a part of the signal when the motor/drive is accelerating and a part of the signal when the motor/drive is in constant operation, which is approximately the same length as the acceleration time.

Future research will involve exploring evolutionary methods and utilizing parameter determination techniques, not only for this specific motor type but also for various other types of motors. As a future work, also the findings of this research could be analyzed using artificial intelligence.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to the use of the laboratory equipment.

Conflicts of Interest: The authors declare no conflicts.

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