Parameter Identification of Induction Motors Using Differential Evolution

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Abstract- Parameter identification of system models is a fundamental step in the process of designing a controller for a system. In control engineering, a wide selection of analytic identification techniques exists for linear systems, but not for non-linear systems. Instead, the model parameters may be determined by an optimization algorithm by minimizing the error between model output and measured data.

In this paper, we apply the differential evolution algorithm to parameter identification of two induction motors. The motors are used in the house circulation pumps produced by the Danish pump manufacturer Grundfos A/S. The experiments presented in this paper use differential evolution, and is a followup study of an comparison of eight stochastic search algorithms on the two motor identification problems. In conclusion, the differential evolution algorithm outperformed the previously best known algorithms on both problems.

1 Introduction

A fundamental step in controller design is the identification of the system subject to control. In system identification, considerable effort have been invested in developing methods for identification of system models and their parameters. Currently, a wide range of analytical techniques exists for linear systems. For a survey, see [6]. For non-linear systems, limited progress have been made with analytical methods. Instead, some success have been achieved with various traditional optimization algorithms. However, a fundamental problem with traditional techniques is their dependence on unrealistic assumptions such as unimodal landscapes and differentiability and continuity of the objective function. Consequently, non-linear problems are often oversimplified to fulfill such assumptions. In contrast, evolutionary algorithms (EAs) and other stochastic search techniques seem to be a promising alternative to traditional approaches. First, EAs do not rely on any assumptions such as unimodality, differentiability, or continuity. Second, they are capable of handling problems with non-linear constraints, multiple objectives, and time-varying components. Third, they have shown superior performance in numerous real-world applications. A particular promising EA for numeric search spaces is the so-called differential evolution algorithm (DE), which has gained increasing attention since Storn and Price introduced the algorithm in 1995 [8].

In this paper, we investigate DE for parameter identification of two induction motors used in the pumps produced by Grundfos A/S (see figure 1 for an example). Induction motors have been investigated and described extensively in the engineering literature for several decades. In this context, a number of non-linear models of the induction motor incorporating magnetic saturation effects have been suggested, e.g., [12]. The first identification task studied in this paper is a 1.1 kW motor and is modeled without taking magnetic saturation into account. The second task is a 5.5 kW motor, in which the saturation is modeled by a function of two parameters. These two parameters are also to be discovered by the algorithm. The experiments presented in this paper extends an earlier investigation of eight stochastic search algorithms [11].

Figure 1: The Alpha circulation pump, which is one of the pumps produced by Grundfos A/S.

In spite of the considerable theoretical foundation of induction motors, few studies have used EAs and other stochastic search techniques to identify the model parameters. However, some investigations have been presented relying on models not accounting for non-linear effects. These methods are primarily used for control purposes and they recursively estimate the parameters by use of various methods – mainly Extended Kalman Filters. See [7], [13], and [3] for further information on these methods. Regarding EA-investigations, Alonge et al. recently studied a 1.0 kW motor and showed that the evolutionary algorithm GENESIS was better than least squares fitting [2]. Alonge et al. determined stator resistance (R_s), stator inductance (L_s), leakage inductance (L_e), motor load (τ_r), and mass of inertia (J_m) using a state space model with scaled rotor flux. In a study from 1994, Haque et al. used a simple evolutionary algorithm to determine stator resistance (R_s), rotor resistance (R_r), and combination of stator and rotor reactance (X_{lr}) from motor data provided by the motor's manufacturer [4]. Other more distantly related work includes an investigation on determining the loads of the motor [5].

2 Differential Evolution

As other evolutionary algorithms, DE maintains a population (a set) of solutions to the optimization problem at hand. The main idea in DE is to use vector differences in the generation of new candidate solutions. Until now, several schemes have been suggested for creating the new candidate solutions (for variants, see [8] and [9]). In this paper, we use the scheme described by the pseudocode in figure 2. Figure 3 illustrates the three possible candidate solutions $C_1[i]$, $C_2[i]$, and $C_3[i]$ for a two-dimensional search space. The solution $C_1[i]$ is created when the if-sentence in figure 2 enters the true-branch twice, whereas $C_2[i]$ and $C_3[i]$ occur when the algorithm enters the true-branch once. A fourth solution may appear when zero entries of the true-branch occurs, but this solution is equal to $P[i]$. In the general case of N-dimensional problems, the candidate will be a corner in the hypercube spanned by $P[i]$ and the solution created by $P[i_1] + f \cdot (P[i_2] - P[i_3])$, i.e., $C_1[i]$ in figure 2.

Create candidate $C[i]$
  Randomly select population members $P[i_1]$, $P[i_2]$, and $P[i_3]$ where i, i_1, i_2, and i_3 are different.
  for ($j = 0$; $j < N$; j++) {
    if ($U(0,1) < p_c$)
      $C[i][j] = P[i_1][j] + f \cdot (P[i_2][j] - P[i_3][j])$
    else
      $C[i][j] = P[i][j]$
  }

Figure 2: Pseudocode for the creation procedure in DE. $C[i]$ is candidate solution with population index i, $C[i][j]$ is the j'th entry in the solution vector of $C[i]$, N is the problem dimensionality, $U(0,1)$ is a uniformly distributed number between 0 and 1, p_c is the probability of crossover, and f is the scaling factor.

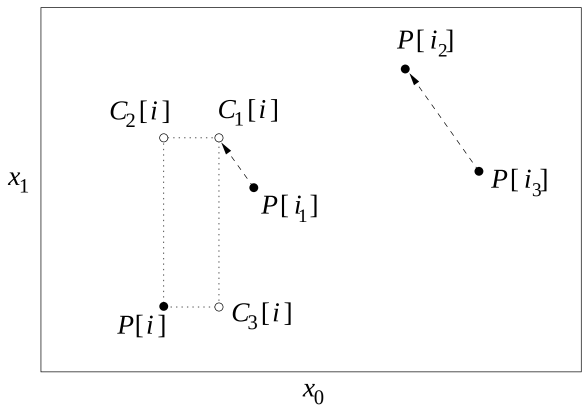

Figure 3: Example of alternative candidate solutions for a two-dimensional problem.

The selection process in DE is straightforward; the candidate solution $C[i]$ replaces $P[i]$ if it is better. Figure 4 illustrates the entire DE algorithm.

Differential Evolution
  Initialize and evaluate population P
  while (not done) {
    for ($i = 0$; $i < ps$; i++) {
      Create candidate $C[i]$
      Evaluate $C[i]$
      if ($C[i]$ is better than $P[i]$)
        $P'[i] = C[i]$
      else
        $P'[i] = P[i]$
    }
    $P = P'$
  }

Figure 4: Pseudocode for DE. ps is the population size, P is the population of the current generation, and P' is the population to be formed for the next generation. The routine **Create candidate** $C[i]$ is listed in figure 2.

3 Problem Formulation

The basic idea in parameter identification is to compare the time dependent response of the system and a parameterized model by a norm or some performance criterion giving a measure to how well the model response fits the system response. Hence, the objective is to find a set of parameters that minimize the prediction error between system output $y(t)$, i.e., the measured data, and model output $\hat{y}(t, \hat{\theta})$ at each time-step t (see figure 5).

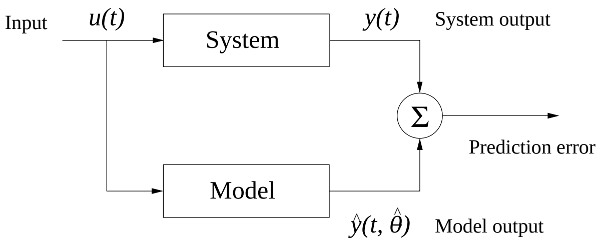

Figure 5: Components of parameter identification.

Normally, the dynamic response of the system is given by the solution to a vector differential equation of the form:

$$\begin{aligned}\dot{x} &= f(\theta, x, u) \\ y &= g(\theta, x)\end{aligned}$$

with the initial condition $x(0) = x_o$. In this system, u is the input signal vector, x is the state vector, y is the measurable output vector and θ is the parameter vector. Normally, the system is affected by noise in both states and measurement, which may be real noise or noise caused by unmodeled dynamics. The parameter vector θ is unknown for real systems. Hence, the objective in system identification is to determine this vector as accurately as possible. To do this, a model of the system is introduced with the same structure as the real system. The model is described by:

$$\begin{aligned}\dot{\hat{x}} &= f\left(\hat{\theta}, \hat{x}, u\right) \\ \hat{y} &= g\left(\hat{\theta}, \hat{x}\right)\end{aligned}$$

with assumed known initial condition $\hat{x}(0) = x_o$. From the system an output signal y for a given input signal u can be measured, and for a given guess of the parameter $\hat{\theta}$ the output response $\hat{y}$ of the model can be calculated, supported by the same input signal as the real system. The system response and the model response can then be compared by a performance criterion, which in the simple case can be quadratic.

$$I\left(\hat{\theta}\right) = \int_0^T (y - \hat{y})^T \cdot W \cdot (y - \hat{y}) \cdot dt$$

where W is a positive definite weight matrix. The criterion is a function of $\hat{\theta}$ and will obtain its minimum vale zero when $\hat{\theta} = \theta$. The system identification problem can now be formulated as an optimization problem, namely

$$\arg\min_{\hat{\theta}} I\left(\hat{\theta}\right)$$

Obviously, the fitness landscape of this problem type may have many local optima and a highly complex topology.

In the next two subsections, the differential equations for the induction motor will be derived together with an application specific performance criterion.

3.1 Model of the 1.1 kW motor without saturation

The dynamics of the 1.1 kW induction motor can be described by a set of differential equations, derived from fundamental laws of physics. Here, only the final equations and not the assumptions will be discussed. A comprehensive derivation of the model was performed by Vas [12]. The motor is supplied by three voltages supported from mains[1] or from an electronic unit that can convert the mains voltages to user specified voltages u_1, u_2, and u_3. In order to simplify the notation, we introduce complex voltages and currents. The transformation of the voltages from a three phase system to a complex system is:

$$\begin{aligned}u_s &= u_{sd} + j \cdot u_{sq} \\ &= \frac{2}{3} \cdot (u_1 + a \cdot u_2 + a^* \cdot u_3)\end{aligned}$$

where $a = e^{j\frac{2\pi}{3}}$. The real and imaginary voltages are then:

$$\begin{aligned}u_{sd} &= \frac{1}{3} \cdot (2 \cdot u_1 - u_2 - u_3) \\ u_{sq} &= \frac{1}{\sqrt{3}} \cdot (u_2 - u_3)\end{aligned}$$

The inverse transformation from the complex notation to the three phase system is for the currents given by the following set of equations.

$$\begin{aligned}i_1 &= i_{sd} \\ i_2 &= -\frac{1}{2} \cdot i_{sd} + \frac{\sqrt{3}}{2} \cdot i_{sq} \\ i_3 &= -\frac{1}{2} \cdot i_{sd} - \frac{\sqrt{3}}{2} \cdot i_{sq}\end{aligned} \tag{1}$$

where i_{sd} and i_{sq} are the complex currents.

From now on we treat the motor as a two phase motor and derive the differential equations in complex notation. The motor consists of a stator where the voltages are applied to two sets of windings perpendicular to each other. In a similar manner, the rotor is composed by two windings, but they can be revolved with respect to the stator. The voltages in the rotor are induced by the movement of the rotor with respect to the stator, the voltage equations for the stator and the rotor are given by the following equations, respectively.

$$\begin{aligned}\dot{\psi}_s &= -R_s \cdot i_s + u_s \\ \dot{\psi}_r - j \cdot \omega_r \cdot \psi_r &= -R_r \cdot i_r\end{aligned} \tag{2}$$

The left hand sides are the induced voltages and the right hand sides are the supplied voltages reduced by the resistive voltage drop of the windings. The rotor windings do not have any external supply at all, only the stator windings are

[1]The national power grid.

supplied. ψ_s and ψ_r are the fluxes through the stator and the rotor windings. In the induced rotor voltage equation, ω_r is the speed of the rotor that enters the induced voltage together with the normal induction part due to the flux changes with respect to time. This extra speed dependent term evolves because the rotor terms are calculated in a stator frame of reference. To eliminate the currents in the voltage equations, the flux linkage between the stator and rotor and visa versa have to be calculated. The resulting linkages are given by the following set of equations.

$$\begin{aligned}\psi_s &= L_{sl} \cdot i_s + L_m \cdot (i_s + i_r) = L_{sl} \cdot i_s + \psi_m \\ \psi_r &= L_{rl} \cdot i_r + L_m \cdot (i_s + i_r) = L_{rl} \cdot i_r + \psi_m\end{aligned} \tag{3}$$

The first expression shows how the flux through the stator windings is composed of the current in the stator itself and by the currents in the rotor windings. The term ψ_m expresses the main flux shared by the stator and the rotor and the rest expresses the leakage flux in the stator and the rotor. The currents in these expressions can be isolated and applied in the differential equations in expression (2). Consequently, the differential equations can be solved by applying the voltage u_s, if the speed ω_r of the motor is known. However, the speed is not an input, but is governed by the following equation of motion for the rotor.

$$\dot{\omega}_r = \frac{1}{J} \cdot (M - M_L) \tag{4}$$

in this expression M is the developed torque of the motor and M_L is the torque load and friction. Furthermore, J is the moment of inertia of the rotor and the load. The developed torque of the motor can be calculated from the electromechanical states by the expression:

$$M = \frac{3}{2} \cdot Im\left(\psi_s^* \cdot i_s\right) \tag{5}$$

In our experiments, we assume that the load torque M_L is zero, which eliminates the load torque as an additional input. The model can be described by a set of explicit differential equations if in the above expressions the parameters are constant. In summary, we have:

$$\begin{aligned}\dot{x} &= f(\theta, x, u) \\ y &= g(\theta, x)\end{aligned}$$

where for the actual system the input, state and output are given by the following vectors.

$$\begin{aligned}u &= [u_1, u_2, u_3]^T \\ x &= [\psi_{sd}, \psi_{sq}, \psi_{rd}, \psi_{rq}, \omega_r]^T \\ y &= [i_1, i_2, i_3, \omega_r]^T\end{aligned}$$

and the parameter vector given by:

$$\theta = [R_s, R_{r,} L_{sl}, L_{rl}, L_m, J]^T$$

3.2 Model of the 5.5 kW motor with saturation

Unfortunately, the real world is more complex, because not all the parameters are constant. In real motors, the iron in the motor saturates, which means that the main flux ψ_m is a function of the scalar magnetization current $i_m = |i_s + i_r|$. To account for saturation, some rewriting of the above equations is necessary. In equation (3), the currents can be calculated as a function of the stator, the rotor, and the main flux.

$$\begin{aligned}i_s &= \frac{1}{L_{sl}} \cdot (\psi_s - \psi_m) \\ i_r &= \frac{1}{L_{rl}} \cdot (\psi_r - \psi_m)\end{aligned} \tag{6}$$

These currents can be inserted into the voltage equations (2), and thereby eliminate the currents.

$$\begin{aligned}\dot{\psi}_s &= -\frac{R_s}{L_{sl}} \cdot (\psi_s - \psi_m) + u_s \\ \dot{\psi}_r &= -\frac{R_r}{L_{rl}} \cdot (\psi_r - \psi_m) + j \cdot \omega_r \cdot \psi_r\end{aligned} \tag{7}$$

However, this set of differential equations does not express the main flux ψ_m by the states ψ_s and ψ_r. The main flux ψ_m can be expressed by ψ_s and ψ_r by inserting equation (6) into either of following expressions.

$$\begin{aligned}\psi_s &= L_{sl} \cdot i_s + L_m \cdot (i_s + i_r) \\ \psi_r &= L_{rl} \cdot i_r + L_m \cdot (i_s + i_r)\end{aligned} \tag{8}$$

Isolating ψ_m, gives the explicit expression of the main flux:

$$\psi_m = \frac{\left(\frac{1}{L_{sl}} \cdot \psi_s + \frac{1}{L_{rl}} \cdot \psi_r\right)}{\left(\frac{1}{L_m(i_m)} + \frac{1}{L_{sl}} + \frac{1}{L_{rl}}\right)} \tag{9}$$

In this expression, the inductance L_m is a function of the magnetization current i_m, which can be calculated from the actual motor currents.

$$i_m = \sqrt{(i_{sd} + i_{rd})^2 + (i_{sq} + i_{rq})^2} \tag{10}$$

The varying inductance is determined by the magnetization current according to equation (11), which has shown to be a good approximation in practice. L_{mo} is the inductance when the iron in the motor is not saturated and i_{mo} is the current at which saturation begins. Finally, α is a factor giving the decaying curve shape of L_m at high currents.

$$L_m = \begin{cases} L_{mo} & i_m \le i_{mo} \\ \frac{L_{mo}}{1 + \alpha \cdot L_{mo} \cdot i_m \cdot \left(\frac{1}{i_{mo}} - \frac{1}{i_m}\right)^2} & i_m > i_{mo} \end{cases} \tag{11}$$

The differential equation governing the dynamic behavior of the motor is given by equation (7), in which ψ_m is given in an implicit manner given by the expressions (9), (10), (6), and (11). The value of ψ_m cannot be explicitly calculated for given values of ψ_s and ψ_r, but has to be approximated iteratively by a fixpoint calculation. The steps are first to assume a certain value for L_m and insert this into (9) to calculate ψ_m. Then calculate (6) to determine i_s and i_r. Next, calculate the scalar magnetization current i_m. Finally, a new value of L_m can be calculated from the lower branch of equation (11). The exact value of ψ_m has been reached if this value is equal to the value at the beginning of the iteration cycle.

In summary, the differential equations consist of (7) together with (4), and the currents for the output vector is given by (6). By comparison with the model without saturation, the input vector and the output vector are the same, but the structure of the differential equation is different. Thus, the parameter vector is now given by:

$$\theta = [R_s, R_r, L_{sl}, L_{rl}, L_{mo}, i_{mo}, \alpha, J]^T$$

Hence, two extra parameters have been introduced compared with the model of the 1.1 kW motor.

3.3 Fitness function

The result of the solution of the differential equations is the states $x = [\psi_{sd}, \psi_{sq}, \psi_{rd}, \psi_{rq}, \omega_r]^T$. From these states, the stator current can be calculated using equation (3). This complex stator current can now be converted to three phase currents comparable with real life currents. The performance criterion then becomes.

$$I\left(\hat{\theta}\right) = \int_0^T \left((i_1 - \hat{i}_1)^2 + (i_2 - \hat{i}_2)^2 + (i_3 - \hat{i}_3)^2\right) dt$$

Notice that the criterion does not include the squared deviation in the rotor's motion $(\omega_r - \hat{\omega}_r)^2$. This is excluded because motion measurements on the real motor is more noisy than the measurements of the currents.

In our experiments, the non-linear differential equations are approximated using the Fourth-order Runge-Kutta method [1]. One second of the motor's startup-phase was simulated using a step-size of 0.1 millisecond, i.e., 10000 steps. Hence, we used the sum-of-squared-errors as the fitness function.

$$I'\left(\hat{\theta}\right) = \sum_{t=1}^{10000} \left((i_1(t) - \hat{i}_1(t))^2 + (i_2(t) - \hat{i}_2(t))^2 + (i_3(t) - \hat{i}_3(t))^2\right) \quad (12)$$

4 Experiments and Results

As mentioned in the introduction, the experiments presented here is a continuation of an earlier study on eight stochastic search algorithms. The previously tested algorithms are: steepest decent local search, simulated annealing, simple EA, diversity-guided EA [10], evolution strategies with adaptation of one σ, evolution strategies with adaptation of both standard deviations σ_i and rotation angles α_{ij}, standard particle swarm optimization, and diversity-guided particle swarm optimization. For more information on these algorithms, see [10] and chapter 7 in [11]. In summary, the best previous algorithms were the two evolution strategies and the diversity-guided EA. The results achieved by these algorithms are used as comparison with the DE algorithm.

4.1 Experimental Setup

The population size was set to $ps = 100$ for all algorithms. The DE parameters were $p_c = 0.5$ and $f = 0.5$, which were found by trail-and-error tuning. However, compared with the other algorithms significantly fewer runs were necessary to obtain reasonable settings. Each algorithm was tested 20 times on the two motor identification problems. The experiments were carried out using a simulated reference signal generated by the real motor's parameters, which have been experimentally determined by Grundfos (see below). The advantage of this setup is that the exact optimum is known, which allows us to compare the algorithms based on how close the found solutions are to the true optimum. Parameter estimation at Grundfos is considered satisfactory if the percentwise deviation is less than 5% from the true value, which is about the best precision obtainable on the real motor using traditional system identification techniques. In practice, this is done by conducting a series of experiments and calculating the motor's parameters directly. However, there is a 5-10% error in these parameters, because of the experimental setup. Hence, conducting an investigation on a simulated signal will allow us to compare the methods and decide if time and money should be invested in obtaining real data and performing the identification of the physical motors.

4.2 Identification of the 1.1 kW motor

Each algorithm was given 200000 evaluations of the fitness (equation 12) to find the parameters of the 1.1 kW motor. The two parameters L_{sl} and L_{rl} are linearly dependent and were therefore combined into one parameter $L_{sl} + L_{rl}$. Table 1 lists the reference values, the search intervals, and the step-sizes for the five parameters of the 1.1 kW motor.

Table 2 lists the optimization results from the four algorithms. The previously best results obtained by the diversity-guided EA (DGEA), evolution strategies with adaptation of one σ (ES1), evolution strategies with adaptation of both standard deviations σ_i and rotation angles α_{ij} (ES2) are shown for comparison. As seen in the table, DE and DGEA were capable of locating the exact solution in 20

	Ref. value	Min	Max	Step
R_s	9.203	6	10	0.0001
R_r	6.61	6	10	0.0001
$L_{sl} + L_{rl}$	0.09718	0.029	0.5	0.00001
L_m	1.6816	1.5	2.0	0.0001
J	0.00077	0.0001	0.01	0.00001

Table 1: Intervals and step-sizes for the five parameters of the 1.1 kW motor.

of 20 runs. To further analyze this, the two algorithms were ran an additional 80 times each. The DE algorithm managed to locate the exact optimum in all 100 runs whereas the DGEA found the solution in 99 of 100 runs. However, the convergence of the DE algorithm was significantly faster than the DGEA's. Figure 6 illustrates the convergence for the four algorithms. As seen, the DE algorithm converged in about 30000 evaluations, which is 3-4 times faster than the DGEA and also the ES2.

Algorithm	# Exact	Avg. fitness	± std. err.
DE	20	0.00	± 0.00
ES1	16	3.91	± 2.13
ES2	17	1.80E-5	± 9.82E-6
DGEA	20	0.00	± 0.00

Table 2: Results for parameter identification of the 1.1 kW motor. Average of 20 runs. The column denoted “# Exact” displays the number of runs where the algorithm discovered the exact optimum.

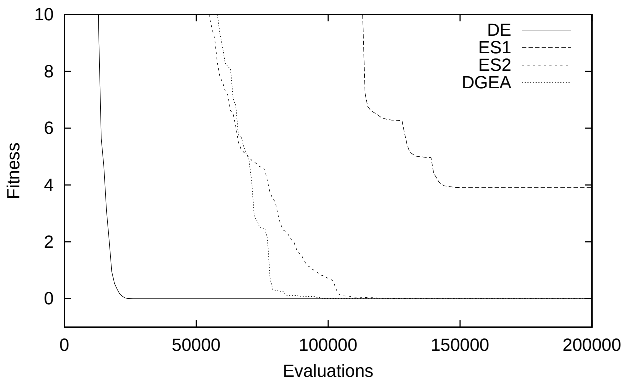

Figure 6: Number of evaluations versus average fitness for the 1.1 kW motor.

4.3 Identification of the 5.5 kW motor

In preliminary runs, the identification of the 5.5 kW motor with saturation turned out to be considerably more challenging than the simpler 1.1 kW motor. Therefore, each algorithm was given 300000 evaluations. In this problem, the two parameters L_{sl} and L_{rl} are independent and cannot be combined. Hence, eight parameters were identified. The 8-dimensional search space was discretized again. Table 3 displays the reference values, the search intervals, and the step-sizes for the eight parameters of the 5.5 kW motor.

	Ref. value	Min	Max	Step
R_s	3.914	3.52	4.30	0.0001
R_r	2.71	1.35	4.06	0.0001
L_{sl}	0.0358	0.03	0.1	0.0001
L_{rl}	0.0586	0.05	0.1	0.0001
L_{mo}	1.09	0.5	2.0	0.0001
i_{mo}	1.096	0.5	2.0	0.0001
α	0.55	0.2	1.0	0.0001
J	0.0084	0.008	0.009	0.0001

Table 3: Intervals and step-sizes for the eight parameters of the 5.5 kW motor.

The optimization results are displayed in table 4. As mentioned, the problem is significantly more challenging than the 1.1 kW motor's. In the previous investigation, neither of the algorithms found the exact solution for the 5.5 kW motor problem. However, the DE approach was capable of locating the global optimum in all 20 runs, which was very surprising in comparison with the results achieved by the previous algorithms. To further test DE, we ran an additional 80 runs. Again, the algorithm discovered the exact optimum in all runs.

Algorithm	# Exact	Avg. fitness	± std. err.
DE	20	0.00	± 0.00
ES1	0	82.03	± 13.37
ES2	0	191.88	± 56.31
DGEA	0	12.34	± 3.39

Table 4: Results for parameter identification of the 5.5 kW motor. Average of 20 runs. The column denoted “# Exact” displays the number of runs where the algorithm discovered the exact optimum.

To analyze the convergence rate, we plotted the average fitness versus number of evaluations. Figure 7 illustrates the convergence for the four algorithms. DE converged most rapidly using about 100000 evaluations to find the global optimum, whereas the other algorithms slowed significantly after about 50000 evaluations. Interestingly, the advanced evolution strategies with adaptation on both standard deviations and rotation angles (ES2) performed worse than the simpler variant with only self-adaptation of one standard deviation (ES1). The most likely explanation is the search overhead caused by the additional self-adapting parameters in ES2.

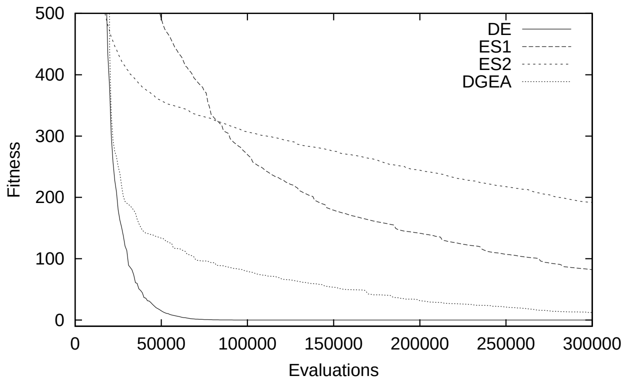

Figure 7: Number of evaluations versus average fitness for the 5.5 kW motor.

5 Conclusions

In this paper, we have compared differential evolution (DE) with three other evolutionary algorithms for parameter identification of two induction motors produced by the Danish pump manufacturer Grundfos A/S.

In summary, DE outperformed the other three algorithms by several magnitudes. Furthermore, DE showed both more robust results and faster convergence – especially on the 5.5 kW motor problem, which was the most challenging of the two tested problems. Additionally, DE is a lot simpler to implement than the other algorithms and it appears to require less parameter tuning.

As mentioned in section 4, we used simulated data to be able to compare the obtained parameters with a reference setting. The main purpose of this study and the previous was to determine if evolutionary computation (EC) is a feasible approach to parameter identification of the induction motors and other related problems at Grundfos. The success of DE on these two problems certainly underlines that EC is a promising direction and parameter identification using real motor data is now being planned.

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