We are IntechOpen,
the world's leading publisher of
Open Access books
Built by scientists, for scientists

6,900
Open access books available

185,000
International authors and editors

200M
Downloads

154
Countries delivered to

Our authors are among the

TOP 1%
most cited scientists

12.2%
Contributors from top 500 universities

BOOK CITATION INDEX
CLARIVATE ANALYTICS
INDEXED

WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index
in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?
Contact book.department@intechopen.com

Numbers displayed above are based on latest data collected.
For more information visit www.intechopen.com

Optimization of Induction Motors Using Design of Experiments and Particle Swarm Optimization

Houssem Rafik El-Hana Bouchekara, Mohammed Simsim and Makbul Anwari

Additional information is available at the end of the chapter

http://dx.doi.org/10.5772/38665

1. Introduction

The level of prosperity of a community is related to its ability to produce goods and services. But producing goods and services is strongly related to the use of energy in an intelligent way. Energy can be exploited in several forms such as thermal, mechanical and electrical (Boldea & Nasar, 2002). Electrical energy, measured in kWh, represents more than 30% of all used energy and it is on the rise (Boldea & Nasar, 2002). The larger part of electrical energy is converted into mechanical energy in electric motors. Among electric motors, the induction motor is without doubt the most frequently used electrical motor and is a great energy consumer. About 70% of all industrial loads on a specific utility are represented by induction motors (Maljkovic, 2001). The vast majority of induction motor drives are used for heating, ventilation and air conditioning (Blanusa, 2010; Cunkas & Akkaya 2006).

The design of an induction motor aims to determine the induction motor geometry and all data required for manufacturing to satisfy a vector of performance variables together with a set of constraints (Boldea & Nasar, 2002). Because induction motors are now a well developed technology, there is a wealth of practical knowledge, validated in industry, on the relationship between their performance constraints and their physical aspects. Moreover, mathematical modeling of induction motors using circuit, field or hybrid models provides formulas of performance and constraint variables as functions of design variables (Boldea & Nasar, 2002).

The journey from given design variables to performance and constraints is called analysis, while the reverse path is called synthesis. Optimization design refers to ways of doing efficient synthesis by repeated analysis such that some single (or multiple) objective (performance) function is maximized and/or minimized while all constraints (or part of them) are fulfilled (Boldea & Nasar, 2002). The aim of this chapter is to present an optimal

design method for induction motors using design of experiments (DOE) and particle swarm optimization (PSO) methods.

The outline of this paper is as follows. The current section is the introduction. Section 2 introduces and explains the DOE method. Section 3 gives an overview of the PSO method. In Section 4 the application of the DOE and PSO to optimize induction motors is explained and its results are also presented and discussed in detail. Finally, the conclusions are drawn in Section 5.

2. Design of Experiments (DOE)

With modern technological advances, the design and optimization of induction motors or any other electromechanical devices are becoming exceedingly complicated. As the cost of experimentation rises rapidly it is becoming impossible for the analyst, who is already constrained by resources and time, to investigate the numerous factors that affect these complex processes using trial and error methods (ReliaSoft Corporation, 2008). Computer simulations can solve partially this issue. Rather than building actual prototypes engineers and analysts can build computer simulation prototypes. However, the process of building, verifying, and validating induction motor simulation model can be arduous, but once completed, it can be utilized to explore different aspects of the modeled machine. Moreover, many simulation practitioners could obtain more information from their analysis if they use statistical theories, especially with the use of DOE.

In this section the DOE method is explained in order to make its use in this chapter understandable. The aim here is not to explain the whole method in detail (with all the mathematical developments behind), but to present the basics to demonstrate its interesting capabilities.

2.1. Why DOE?

Compared to one-factor-at-a-time experiments, i.e. only one factor is changed at a time while all the other factors remain constant, the DOE technique is much more efficient and reliable. Though, the one-factor-at-a-time experiments are easy to understand, they do not tell how a factor affects a product or process in the presence of other factors (ReliaSoft Corporation, 2008). If the effect of a factor is altered, due to the presence of one or more other factors, we say that there is an interaction between these factors. Usually the interactions' effects are more influential than the effect of individual factors (ReliaSoft Corporation, 2008). This is because the actual environment of the product or process comprises the presence of many factors together instead of isolated occurrences of each factor at different times.

The DOE methodology ensures that all factors and their interactions are systematically investigated. Therefore, information obtained from a DOE analysis is much more reliable and comprehensive than results from the one-factor-at-a-time experiments that ignore

interactions between factors and, therefore, may lead to wrong conclusions (ReliaSoft Corporation, 2008).

Let's assume, for instance, that we want to optimize an induction motor taking into account, for simplicity, only two factors: the length and the external radius. Hence, the length is the first factor and is denoted by x_1 while the external radius is the second factor and it is denoted by x_2. Each factor can take several values between two limits, i.e. $\{x_{1_{min}}, x_{1_{max}}\}$ and $\{x_{2_{min}}, x_{2_{max}}\}$. We desire to study the influence of each of these factors on the system response or output for example the torque called Y. The classical or traditional approach consists of studying the two factors x_1 and x_2, separately. First we put x_2 at the average level $x_{2_{average}}$ and study the response of the system when x_1 varies between $x_{1_{min}}$ and $x_{1_{max}}$ using for example 4 steps (experiments) as shown in Fig. 1. Similarly, we repeat the same procedure to study the effect of x_2. Accordingly, the total number of tests is 8. However, we should ask a paramount question here, are these 8 experiments sufficient to have a good knowledge about the system? The simple and direct answer to this question is no. To get a better knowledge about the system, we have to mesh the validity domain of the two factors and test each node of this mesh as shown in Fig. 2. Thus, 16 experiments are needed for this investigation. In this example only two factors are taken into account. Therefore, if for example 7 factors are taken into account, the number of tests to be performed rises to $4^7 = 16384$ experiments, which is a highly time and cost consuming process.

Knowing that it is impossible to reduce the number of values for each factor to less than 2, the designer often reduces the number of factors, which leads to incertitude of results. To reduce both cost and time, the DOE is used to establish a design experiment with less number of tests. The DOE, for example, allows identifying the influence of 7 factors with 2 points per variable with only 8 or 12 tests rather than 128 tests used by the traditional method (Bouchekara, 2011; Uy & Telford, 2009).

Recently, the DOE technique has been adopted in the design and testing of various applications including automotive assembly (Altayib, 2011), computational intelligence (Garcia, 2010), bioassay robustness studies (Kutlea, 2010) and many others.
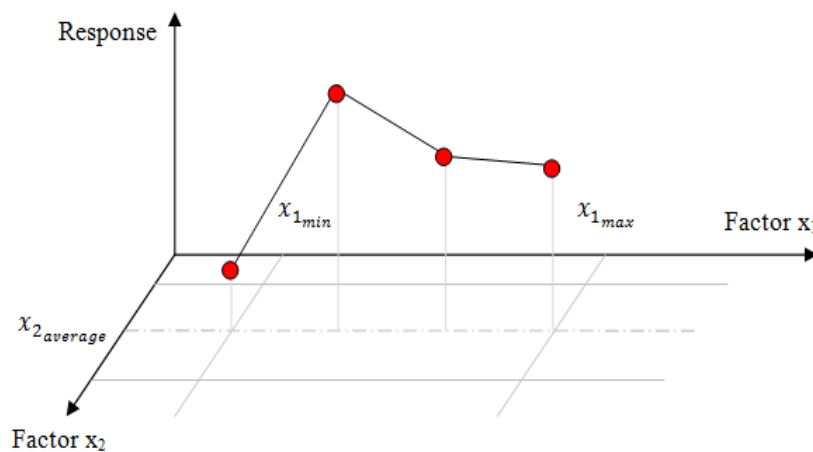

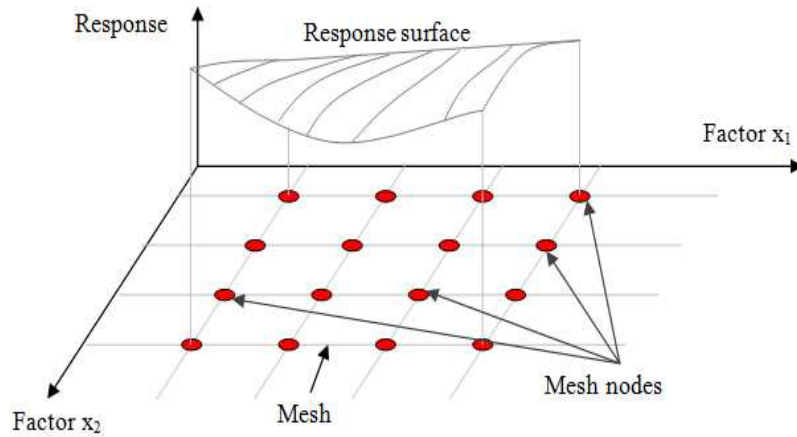**Figure 1.** Traditional method of experiments.

Figure 2. One experiment at each node of the mesh.

2.2. Methodology

The design and analysis of experiments revolves around the understanding of the effects of different variables on other variable(s). The dependent variable, in the context of DOE, is called the response, and the independent variables are called factors. Experiments are run at different values of the factors, called levels. Each run of an experiment involves a combination of levels of the investigated factors. The number of runs of an experiment is determined by the number of levels being investigated in the experiment (ReliaSoft Corporation, 2008).

For example, if an experiment involving two factors is to be performed, with the first factor having n_1 levels and the second having n_2 levels, then $n_1 \times n_2$ combinations can possibly be run, and the experiment is an $n_1 \times n_2$ factorial design. If all $n_1 \times n_2$ combinations are run, then the experiment is a full factorial. If only some of the $n_1 \times n_2$ combinations are run, then the experiment is a fractional factorial. Therefore, in full factorial experiments, all factors and their interactions are investigated, whereas in fractional factorial experiments, certain interactions are not considered.

2.3. Mathematical concept

Assume that y is the response of an experiment and $\{x_1, x_2, x_3, \ldots, x_k\}$ are k factors acting on this experiment where each factor has two levels of variation x_{i-} and x_{i+}. The value of y, is approximated by an algebraic model given in the following equation:

$$y = a_0 + a_1 x_1 + a_2 x_2 + \cdots + a_k x_k + \cdots + a_1 x_1 x_2 + \cdots a_1 x_1 x_k + a_{1\ldots k} x_{1\ldots k} \qquad (1)$$

where a_j are coefficients which represent the effect of factors and their interactions on the response of the experiment.

2.4. Full factorial design

As mentioned above, the study of full factorial design consists of exploring all possible combinations of the factors considered in the experiment (Kleijnen et al., 2005). Note that the design X^k means that this experiment concerns a system with k factors with x levels. Usually, two levels of the x's are used. The use of only two levels implies that the effects are monotonic on the response variable, but not necessarily linear (Uy & Telford, 2009). For each factor, the two levels are denoted using the "rating Yates" notation by -1 and +1 respectively to represent the low and the high levels of each factor. Hence, the number of experiments carried out by a full factorial design for k factors with 2 levels is $n = 2^k$. For example, Table 1 shows the design matrix of a full factorial design for 2 factors while, Fig. 3 shows the mesh of the experimental field where points correspond to nodes.

Run	Factor x_1	Factor x_2	Response Y
1	-1	-1	Y_1
2	-1	+1	Y_2
3	+1	-1	Y_3
4	+1	+1	Y_4

Table 1. Design Matrix for a full factorial design for 2 factors with 2 levels.
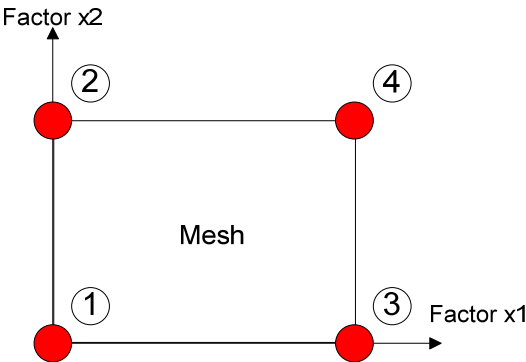

Figure 3. Strategy of experimentation; points corresponding to nodes in the mesh of the experimental field for a full factorial design for 2 factors with 2 levels.

2.5. Fractional factorial design

The advantage of full factorial designs, is their ability to estimate not only the main effects of factors, but also all their interactions, i.e. two by two, three by three, up to the interaction involving all k factors. However, when the number of factors increases, the use of such design leads to a prohibitive number of experiments. The question to be asked here is: is it necessary to perform all experiments of the full factorial design to estimate the system's response? In other words, is it necessary to conduct a test at each node of the mesh?

It is not necessary to identify the effect of all interactions because the interactions of order ≥ 2 (like $x_1 x_2 x_3$) are usually negligible. Therefore, certain runs specified by the full

factorial design can be used instead of using all runs. To illustrate this phenomenon, an analogy can be made with a Taylor series approximation where the information given by each term decreases when its order increases. So, fractional factorial designs can be used to estimate factors effect and interactions that influence the experiments more with a reduced number of runs (Bouchekara, 2011). Taguchi Tables (Pillet, 1997), or Box generators (Demonsant, 1996), can be used to generate the fractional factorial design matrix of experiments.

To illustrate fractional factorial designs let's take an example. If $k = 3$, the design matrix of these three factors is given by Box generators in a way that the third factor is the product of the two other factors. The factor x_3 and interaction x_1x_2 are either confused or aliased, and there is a confusion of these aliases because only their sums are reachable (Pillet, 1997; Costa, 2001).

Table 2 shows a full factorial design for 3 factors with 2 levels. The number of runs is $2^3 = 8$. This number is reduced to 4 using a fractional factorial design as shown in Table 3 where the third factor is generated using Box generator for 3 factors given in Table 4. The comparison of the 2 designs is shown in Fig. 4.

Run	Factor x_1	Factor x_2	Factor x_3	Response Y
1	-1	-1	-1	Y_1
2	-1	-1	+1	Y_2
3	-1	+1	-1	Y_3
4	-1	+1	+1	Y_4
5	+1	-1	-1	Y_5
6	+1	-1	+1	Y_6
7	+1	+1	-1	Y_7
8	+1	+1	+1	Y_8

Table 2. Design Matrix for a full factorial design for 3 factors with 2 levels.

Run	Factor x_1	Factor x_2	Factor x_3	Response Y
1	-1	-1	+1	Y_1
2	-1	+1	-1	Y_2
3	+1	-1	-1	Y_3
4	+1	+1	+1	Y_4

Table 3. Design Matrix for a fractional factorial design for 3 factors with 2 levels.

Resolution	Design name	Number of Runs	Generators
3	2^{3-1}	4	$x_3 = x_1 \times x_2$

Table 4. G. Box generator of fractional factorial design for 3 factors.
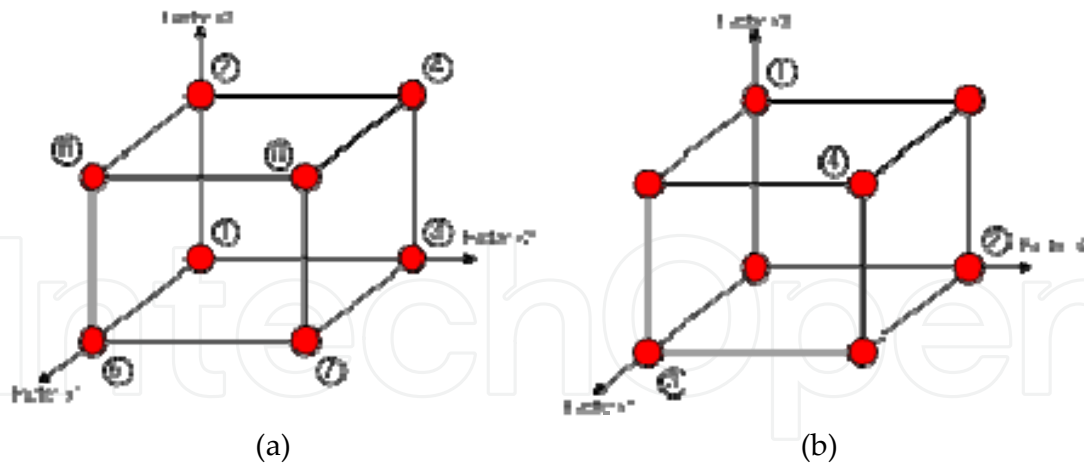
Figure 4. Comparison between the design experimental field of full and fractional factorial designs with 3 factors. (a) full factorial design; (b) fractional factorial design

2.6. Estimation of model coefficients

The coefficient a_0 of (1) is estimated from the arithmetic average of all observed responses and it is given by:

$$a_0 = \bar{y} = \frac{1}{n} \sum_{i=1}^{n} y_i \tag{2}$$

where y_i is the response observed for the experiment i and n is the total number of experiments.

The effect of a factor x_j at the level x_{j+} can be calculated thus, the coefficient associated with this effect can be identified using the following equations:

$$a_j = e_{a_j} = y^+_{x_j} - a_0 \tag{3}$$

and

$$y^+_{x_j} = \frac{1}{n^+} \sum_{i=1}^{n} y^+_i \tag{4}$$

where $y^+_{x_j}$ is the response observed for experiment i when x_j is at level x_{j+}, n^+ is the number of experiments when x_j is at level x_{j+} and e_{a_j} is the effect of coefficient a_j.

Once the method of how to calculate the coefficients of the model and how to identify the existing confusion between these factors has been presented, we can evaluate the contributions of contrasts (the sum of confusions) and therefore the most significant factors (affecting the response).

In (Demonsant, 1996) the identification of the significant factors has been proposed by evaluating the coefficients contribution (or contrasts, for fractional designs) on the model response from the normalization of their values compared to the sum of squared responses, such as given in the following equations:

$$C_{a_j} = \frac{SCE(a_j)}{SCE(y)} \ [\%]$$

(5)

with

$$SCE(y) = \sum_{i=1}^{n} (y_i - \bar{y})^2$$

(6)

$$SCE(a_j) = \frac{n}{s} \sum_{j=1}^{s} \left(e_{a_j}\right)^2$$

(7)

where s is the number of levels (equals to 2 in this case), e_{a_j} is the effect of coefficient a_j, and C_{aj} is the contribution of the contrast associated with the coefficient a_j.

According to (Demonsant, 1996):

- The contribution given by (5) is significant if it is higher than 5%.
- The interactions of order higher than two are negligible.
- If a contrast is negligible, all effects composing this contrast are negligible also.
- Two significant factors can generate a significant interaction. On the other side, two insignificant factors do not generate a significant interaction.

3. Particle Swarm Optimization

3.1. Introduction

PSO (Kennedy & Eberhart, 1995; Kennedy et al., 2001; Clerc, 2006) is an evolutionary algorithm for the solution of optimization problems. It belongs to the field of Swarm Intelligence and Collective Intelligence and is a sub-field of Computational Intelligence. PSO is related to other Swarm Intelligence algorithms such as Ant Colony Optimization and it is a baseline algorithm for many variations, too numerous to list (Brownlee, 2011). PSO was developed by James Kennedy and Russell Eberhart in 1995 (Kennedy & Eberhart, 1995).

PSO has similar techniques to traditional stochastic search algorithms, but the difference is that PSO is not totally stochastic. PSO can avoid trapping on suboptimal and provide a highly adaptive optimal method. Because of fast convergence, PSO has gradually been applied in identification of graphics, optimization of clustering, scheduling assignment, network optimization and multi-objective optimization. For an analysis of the publications on the applications of particle swarm optimization see (Poli, 2008).

3.2. Strategy

The goal of the algorithm is to have all the particles locate the optima in a multi-dimensional hyper-volume. This is achieved by assigning initially random positions to all particles in the space and small initial random velocities. The algorithm is executed like a simulation, advancing the position of each particle in turn based on its velocity, the best known global position in the problem space and the best position known to a particle. The objective function is sampled after each position update. Over time, through a combination of exploration and exploitation of known good positions in the search space, the particles cluster or converge together around an optimum, or several optima (Brownlee, 2011).

3.3. Procedure

The Particle Swarm Optimization algorithm is comprised of a collection of particles that move around the search space influenced by their own best past location and the best past location of the whole swarm or a close neighbor (Brownlee, 2011). In each iteration a particle's velocity is updated using:

$$v_i(t+1) = v_i(t) + \ c_1 \times rand() \times \left(p_i^{best} - p_i(t) \right) + c_2 \times rand() \times (\mathrm{p_{gbest}} - p_i(t)) \qquad (8)$$

where $v_i(t+1)$ is the new velocity for the ith particle, c_1 and c_2 are the weighting coefficients for the personal best and global best positions respectively, $p_i(t)$ is the ith particle's position at time t, p_i^{best} is the ith particle's best known position, and $\mathrm{p_{gbest}}$ is the best position known to the swarm. The $rand()$ function generates a uniformly random variable $\in [0, 1]$.

Variants on this update equation consider best positions within a particles local neighborhood at time t. A particle's position is updated using:

$$p_i(t+1) = \ p_i(t) + v_i(t) \qquad (9)$$

3.4. PSO algorithm

It is important to mention here that PSO has undergone many changes since its introduction in 1995. As researchers have learned about the technique, they have derived new versions, developed new applications, and published theoretical studies of the effects of the various parameters and aspects of the algorithm. (Poli, 2007) gives a snapshot of particle swarming from the authors' perspective, including variations in the algorithm, current and ongoing research, applications and open problems. Algorithm 1 provides a pseudocode listing of the Particle Swarm Optimization algorithm for minimizing a cost function used in this chapter.

Algorithm 1: Pseudocode for PSO (Brownlee, 2011).

Input: ProblemSize, $Population_{size}$
Output: P_{g_best}

```
1    Population ← ∅;
2    P_g_best ← ∅;
3    for       i = 1 to Population_size do
4                  P_velocity ← RandomVelocity();
5                  P_position ← RandomPosition(Population_size);
6                  P_cost ← Cost(P_position);
7                  P_p_best ← P_position ;
8                  if      P_cost ≤ P_g_best  then
9                             P_g_best ← P_p_best;
10                 end
11   End
12   while    StopCondition() do
13                  foreach   P ∈ Population do
14                             P_velocity ← UpdateVelocity(P_velocity, P_g_best , P_p_best);
15                             P_position ← UpdatePosition(P_position, P_velocity);
16                             P_cost ← Cost(P_position);
17                             if      P_cost ≤ P_p_best then
18                                        P_p_best ← P_position ;
19                                        if      P_cost ≤ P_g_best then
20                                                   P_g_best ← P_p_best ;
21                                        end
22                             end
23                  end
24   end
25   return P_p_best;
```

According to (Brownlee, 2011):

- The number of particles should be low, around 20-40
- The speed a particle should be bounded.
- The learning factors (biases towards global and personal best positions) should be between 0 and 4, typically 2.
- A local bias (local neighborhood) factor can be introduced where neighbors are determined based on Euclidean distance between particle positions.
- Particles may leave the boundary of the problem space and may be penalized, be reflected back into the domain or biased to return back toward a position in the

problem domain. Alternatively, a wrapping strategy may be used at the edge of the domain creating a loop, torrid or related geometrical structures at the chosen dimensionality.

• An inertia coefficient can be introduced to limit the change in velocity.

4. Induction motor design: An optimization problem

Induction motors with power below 100 kW (Fig. 5) constitute a sizable portion of the global electric motor markets (Boldea & Nasar, 2002). The induction motor design optimization is a nature mixture of art and science. Detailed theory of design is not given in this chapter. Here we present what may constitute the main steps of the design methodology. For further information, see (Vogt, 1988; Boldea & Nasar, 2002; Murthy, 2008). The suitability of the DOE and the PSO techniques in induction motor design optimization will be demonstrated in this section.
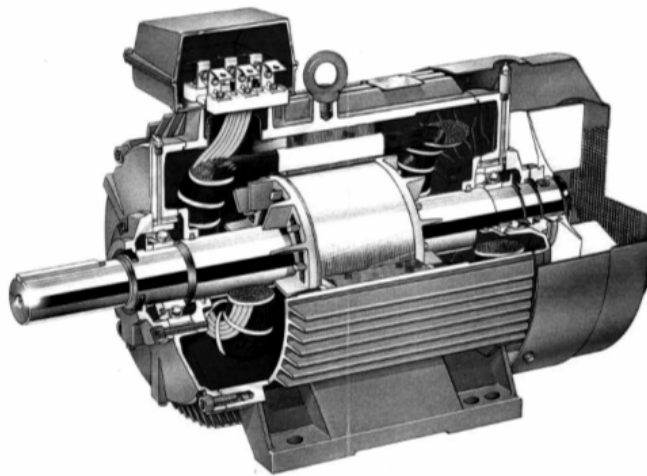

Figure 5. Low power 3 phase induction motor with cage rotor (Boldea & Nasar, 2002).

4.1. The algorithm

The main steps in induction motor design optimization are shown in Fig. 6.

Step (1): Initialization

The design process may start with design specifications and assigned values of: rated power, nominal voltage, frequency, power factor, type (squirrel Cage or slip-ring), connection (star or delta), ventilation, ducts, iron factor, insulation, curves like B/H, losses, Carter coefficient, tables like specific magnetic loading, specific electric loading, density etc. Then, design constraints for flux densities, current densities are specified. After that, the computer program is formulated with imposing max & min limits for rotor peripheral speed, length/pole pitch, stator slot-pitch, number of rotor slots. Finally, suitable values for certain parameters are assumed and objective functions are defined.
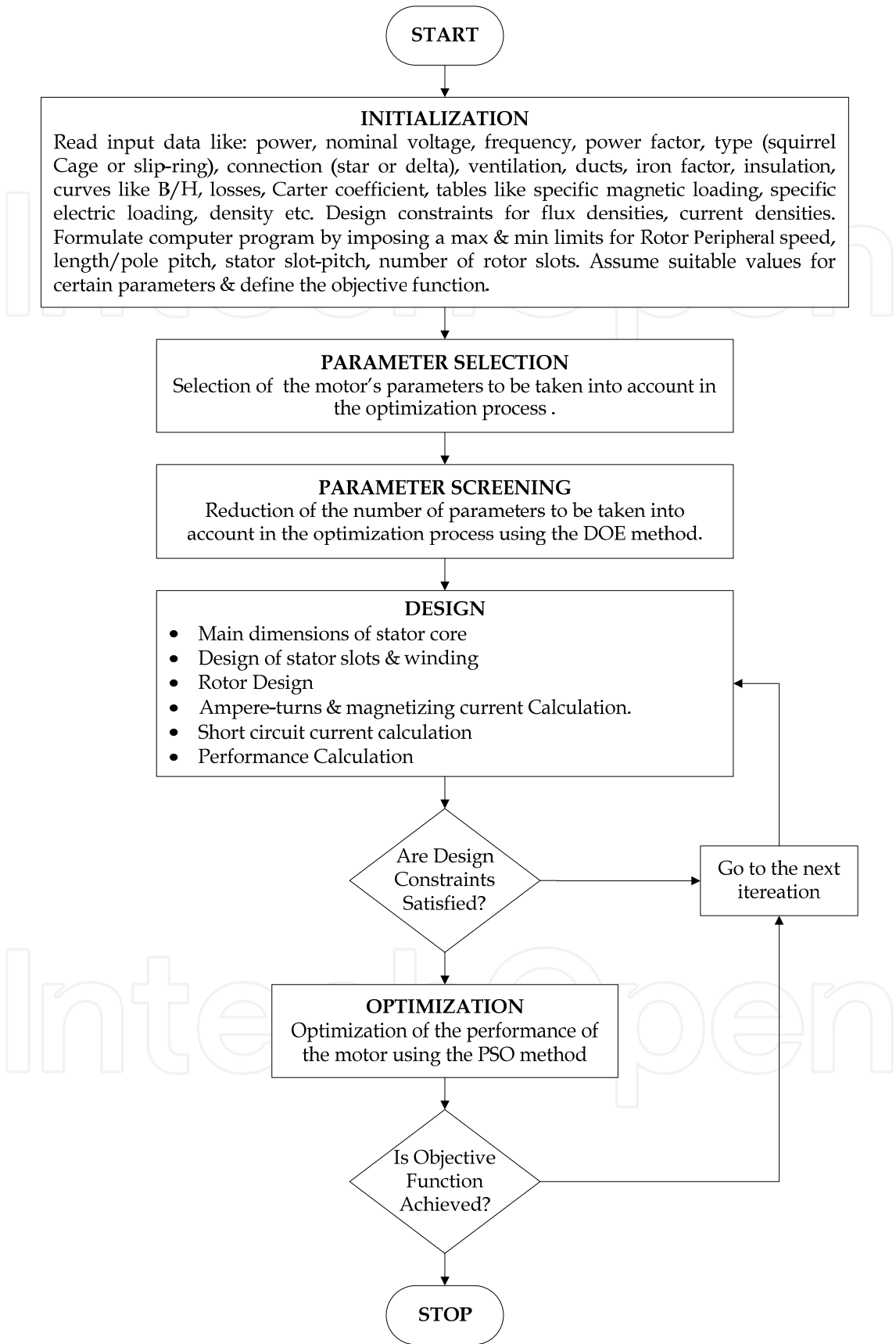
Figure 6. Flowchart for computer-aided optimal design of 3-ph induction motor.

Step (2): Parameter selection

In this step the parameters to be taken into account in the optimization process are selected. The selection of parameters may be chosen by the designer or imposed by the user (for specific application for instance).

Step (3): Parameter screening

While there are potentially many parameters (factors) that affect the performance (objective functions) of the induction motor, some parameters are more important, *viz*, have a greater impact on the performance. The DOE provides a systematic & efficient plan of experimentation to compute the effect of factors on the performance of the motor, so that several factors can be studied simultaneously (Bouchekara, 2011). As said earlier, the DOE technique is an effective tool for maximizing the amount of information obtained from a study while minimizing the amount of data to be collected (Bouchekara, 2011). The DOE technique is used here to reduce the number of parameters (screening) to be taken into account in the optimization process. This goal is achieved by identifying the effect of each parameter on the objective function to be optimized. Only significant parameters (with contribution higher than 5%) are considered in the optimization step.

Step (4): Design

Total design is split into six parts in a proper sequence as shown in Fig. 6. The sequential steps for design of each part are briefly describes in the following sub sections. For more details see (Murthy, 2008).

Part I: Design of magnetic frame

In this part the output coefficient (C0) is calculated by:

$$C0 = 11 \times kW \times Bav \times q \times EFF \times pf \times 10^{-3} \tag{10}$$

where: kW is the rating power, Bav is the specific magnetic loading, q is the specific electric loading, EFF is the efficiency and pf is the power factor.

Then the rotor volume that is (rotor diameter D)^2 × (rotor length L) is computed using the following formula:

$$D^2L = \frac{kW}{C0 \times ns} \tag{11}$$

where: ns is the synchronous speed measured in rps.

Finally, the flux per pole ϕ is calculated by:

$$\phi = \frac{\tau_p \times L \times Bav}{10^6} \tag{12}$$

where: τ_p is the pole pitch and its is given by:

$$\tau_p = \frac{\pi \times D}{P} \tag{13}$$

Part II: Design of stator winding

The first step of this part consists of calculating the size of slots using the following equations:

$$\text{Slot Width(Ws)} = [\text{Zsw} \times (\text{Tstrip} + \text{insS}) + \text{insW}] \tag{14}$$

$$\text{Slot Height (Hs)} = [\text{Zsh} \times (\text{Hstrip} + \text{insS}) + \text{Hw} + \text{HL} + \text{insH}] \tag{15}$$

where: Zsw is the width-wise number of conductors, Tstrip is the assuming thickness of strip/conductor, insS is the strip insulation thickness, insW is the width-wise insulation, Zsh is the number of strips/conductors height-wise in a slot, Hstrip is the height of the strip, HL is height of lip, Hw is the height of wedge and insH is the height-wise insulation.

Then, the copper losses and the weight of copper are calculated by:

$$\text{Copper Losses (Pcus)} = 3 \times \text{Iph}^2 \times \text{Rph} \tag{16}$$

$$\text{Weight of Copper (Wcus)} = \text{Lmt} \times \text{Tph} \times 3 \times \text{As} \times 8.9 \times 10^{-3} \tag{17}$$

where: Iph is the current per phase, Rph is the resistance at 20°C, Lmt is the mean length of turn, Tph represents the turns per phase and As is the area of strip/conductor.

Finally, the iron losses are calculated by multiplying the coefficient deduced from the curve giving the losses in (W/kg) in function of the flux density in (T) by the core weight.

Part III: Design of Squirrel Cage Rotor

First, the air gap length is calculated by:

$$\text{Air} - \text{Gap Length (Lg)} = 0.2 + 2 \times \sqrt{D \times L \times 10^6} \tag{18}$$

Then, the rotor diameter is calculated using the following formula:

$$\text{Rotor Diameter (Dr)} = D - 2 \times \text{Lg} \tag{19}$$

Finally, the copper losses and the rotor weight are calculated using equations (20), (21) and (22).

$$\begin{aligned}\text{Total Rotor Copper Loss (Pcur)}\\ = \text{Copper Loss in the Bars } + \text{ Copper Losses in the 2 End Rings}\end{aligned} \tag{20}$$

$$\text{Weight of Rotor Copper (Wcur)} = \text{Lb} \times \text{Sr} \times \text{Ab} \times 8.9 \times 10^{-6} \qquad (21)$$

$$\text{Weight of Rotor End} - \text{Rings (Weue)} = \pi \times \text{Dme} \times 2 \times \text{Ae} \times 8.9 \times 10^{-6} \qquad (22)$$

where: Lb is the length of bar, Sr is the number of Rotor Slots, Ab is the rotor bar area, Ae the area of cross sectional of end ring and Dme is mean diameter of end-ring.

Part IV: Total ampere turns and magnetizing current

First, the total ampere turns (ATT) for the motor are calculated using (23). Then, the magnetizing current (Im) is calculated using (24). Finally, the no load phase current (I0) and the no load power factor (pf0) are calculated using respectively (25) and (26).

$$\text{ATT} = \text{ATS} + \text{ATR} + \text{ATg} \qquad (23)$$

$$\text{Im} = \frac{\text{P} \times \text{ATT}}{2 \times 1.17 \times \text{kW} \times \text{Tph}} \qquad (24)$$

$$\text{I0} = \sqrt{\text{Iw}^2 + \text{Im}^2} \qquad (25)$$

$$\text{pf0} = \frac{\text{Iw}}{\text{I0}} \qquad (26)$$

where: ATS, ATR and ATg are the total ampere turns for the stator, the rotor and the air gap and Iw is the Wattful current.

Part V: Short-circuit current calculation

In this part the total reactance per phase, short-circuit current, and short-circuit power factor are calculated using the following formulas:

$$\text{Total Reactance/ph} = \text{Xs} + \text{X0} + \text{Xz} \qquad (27)$$

$$\text{Short Circuit Current (Isc)} = \frac{\text{Vph}}{\text{Z}} \qquad (28)$$

$$\text{Short Circuit pf} = \frac{\text{R}}{\text{Z}} \qquad (29)$$

where: Xs is the slot reactance, X0 is the overhang reactance , Xz is the zig-zag reactance, R is the resistance and Z is the impedance.

Part VI: Performance calculation

In this last part of the design the performance of the induction motor are evaluated. The efficiency, the slip, the starting torque, the temperature rise and the total weight per kilo watt are calculated using the following formulas:

$$\text{Efficiency (EFF)} = \frac{\text{kW}}{\text{KW} + \text{Total Losses}} \tag{30}$$

$$\text{Slip at Full Load (SFL)} = \text{Total Rotor copper loss} \times \text{Rotor Input} \times 100 \tag{31}$$

$$\text{Starting Torque (Tst)} = \left(\frac{\text{Isc}}{\text{Ir}}\right)^2 \times \text{Slip at Full Load} \tag{32}$$

$$\text{Temperature Rise (Tr)} = 0.03 \times \frac{\text{Total Stator Losses}}{\text{Total Cooling Area}} \tag{33}$$

$$\text{kg/kW} = \frac{\text{Total Weight}}{\text{kW}} \tag{34}$$

where: Isc is the short circuit current and Ir is the equivalent rotor current.

At the end of step (4) an automatic check is performed. If the design constraints are satisfied we move to step (5) otherwise step (4) is restarted with new values of parameters.

Step (5): Optimization

In this step the motor's performances are checked and if found unsatisfactory, the process is restarted in step (4) with new values of parameters. The decision is made based on the PSO optimization method.

4.2. Design specifications

Design calculations are done for a given rating of an induction motor. Standard design specifications are:

- Rated power: P [kW] = 30.
- Line supply voltage: V [V] = 440.
- Supply frequency: f [Hz] = 50.
- Number of phases: 3.
- Phase connections: delta.
- Rotor type (squirrel cage or sling-ring): squirrel cage.
- Insulation class: F;
- Temperature rise: class B.
- Protection degree: IP55 – IC411.
- Environment conditions: standard (no derating).
- Configuration (vertical or horizontal shaft etc.): horizontal shaft.
- NEMA class: B.

4.3. Problem formulation

A very important problem in the induction motor design is to select the independent variables otherwise the problem would have been very much complicated using too many

variables (Thanga, 2008). Therefore variables selection is important in the motor design optimization. A general nonlinear programming problem can be stated in mathematical terms as follows.

Find X $= (x_1, x_2 \ldots \ldots x_n)$ such that
$F_i(x)$ is a minimum or maximum
$g_i(x) \leq 0, i = 1, 2, \ldots m$

F_i is known as objective function which is to be minimized or maximized; g_i's are constants and x_i's are the variables. The following variables and constraints (Thanga, 2008) are considered to get optimal values of objective functions.

4.3.1. Variables

The variables considered are given in Table 5.

Name	Description	Minimum Value	Maximum Value	Type
P	Number of poles	4	6	Discrete
CDSW	Stator winding current density	3 [A/mm²]	5 [A/mm²]	Continuous
cdb	Current density in rotor bar	4 [A/mm²]	6 [A/mm²]	Continuous
Spp	Slots/pole/phase	3	4	Discrete
Tstrip	Stator conductor thickness	1 [mm]	2 [mm]	Continuous
Zsw	Number of conductors width-wise	1	2	Discrete

Table 5. Design optimization parameters with their domains.

4.3.2. Objective functions

Five different objective functions are considered while designing the machine using optimization algorithm. The objective functions are,

1. Maximization of efficiency; $F_1(x) = \max(EFF)$.
2. Minimization of kg/kW; $F_2(x) = \min(kg/kW)$.
3. Minimization of temperature rise in the stator; $F_3(x) = \min(Tr)$.
4. Minimization of I0/I ratio; $F_4(x) = \min(I0/I)$.
5. Maximization of starting torque; $F_5(x) = \max(Tst)$.

4.4. Fractional 2 levels factorial design

Here, the DOE is applied to analyze the objective functions. The proposed approach uses tools of the experimental design method: fractional designs, notably of Box generators to estimate the performance of the induction motor. The interest is to save calculation time and to find a near global optimum. The saving of time can be substantial because the number of simulations needed is significantly reduced.

Since six parameters define the shape of the motor, it is advisable to determine the effect of each parameter on the objective functions. Thus, it is very important to provide proper parameter ranges. The considered parameters are listed in Table 5. There are two types of parameters; continuous parameters and discrete parameters.

4.4.1. Results

Using two-level full factorial design needs $2^6=64$ runs (simulations) to evaluate objective functions. However, using a 2^{6-2} fractional factorial design will significantly reduce the number of runs from 64 to 16. The 2^{6-2} design matrix and the simulation results obtained for this design are given in Table 6. This design has been generated using Box generators given in Table 7. The choice of a 2^{6-2} means that we have a 2 levels design with 6 factors where 2 of these factors are generated using the other 4 factors as shown in Table 7. Thus:

- The factor (5) will be generated using the product of factors (1), (2) & (3).
- The factor (6) will be generated using the product of factors (2), (3) & (4).

The contributions of obtained contrasts are given in Table 8. It shows in its first column contrasts and in the other columns their contribution or influences on objective functions. Keep in mind that a contribution is significant if it is higher than 5% and high order interactions (higher than 2) are considered negligible while only interactions of significant parameters are also significant.

N°	P	CDSW [A/mm²]	Cdb [A/mm²]	Spp	Tstrip [mm]	Zsw	EFF	Kg/kW	Tr [°]	I0/I	Tst [pu]
1	4	3	4	3	1	1	86.09	16.94	69.25	0.30	0.07
2	4	3	4	4	1	2	88.98	8.07	55.06	0.29	0.42
3	4	3	6	3	2	2	89.40	7.02	50.15	0.27	0.37
4	4	3	6	4	2	1	88.46	8.20	55.30	0.29	0.52
5	4	5	4	3	2	2	89.30	5.94	54.81	0.26	0.30
6	4	5	4	4	2	1	88.69	6.55	58.44	0.28	0.48
7	4	5	6	3	1	1	86.34	10.95	69.06	0.28	0.15
8	4	5	6	4	1	2	88.33	6.17	57.99	0.28	0.70
9	6	3	4	3	2	1	87.73	9.58	60.22	0.30	0.22
10	6	3	4	4	2	2	89.35	6.26	51.54	0.39	0.94
11	6	3	6	3	1	2	87.29	9.04	59.93	0.30	0.32
12	6	3	6	4	1	1	85.96	11.06	69.10	0.35	0.36
13	6	5	4	3	1	2	87.38	7.15	64.56	0.29	0.31
14	6	5	4	4	1	1	86.49	8.19	70.80	0.35	0.42
15	6	5	6	3	2	1	86.78	7.18	65.09	0.29	0.38
16	6	5	6	4	2	2	87.99	5.18	58.95	0.40	1.30

Table 6. Design matrix generated by the 2^{6-2} Box-Wilson fractional factorial design and the simulation results.

Resolution	Design name	Number of Runs	Generators
4	2^{6-2}	16	$x_5 = x_1 \times x_2 \times x_3$
			$x_6 = x_2 \times x_3 \times x_4$

Table 7. Box generator of the fractional factorial design 2^{6-2}.

Contrasts	EFF	kg/kW	Tr	I0/I	Tst
P	13	2	9	45	7
CDSW	1	18	8	0	3
Cdb	3	1	0	0	5
Spp	4	10	2	25	41
Tstrip	34	24	36	0	14
Zsw	38	29	39	0	19
P × CDSW + Cdb × Tstrip	1	0	1	0	0
P × cdb + CDSW × Tstrip	2	2	1	0	0
P × Spp + Tstrip × Zsw	2	5	3	18	1
P × Tstrip + CDSW × Cdb + Spp × Zsw	1	3	0	4	5
P × Zsw + Spp × Tstrip	1	3	0	4	5
CDSW × Spp + Cdb × Zsw	0	1	0	0	1
Cdb × Spp + CDSW × Zsw	1	2	1	0	0

Table 8. Contrasts and contribution obtained.

The application of DOE identifies the effect of each parameter on each objective function. We can notice that for the efficiency Zsw, Tsrip, and P are the most significant factors with respectively 38% 34% and 13% of contribution on the objective function. Moreover, Fig. 7 gives more details. When P is low the efficiency is high and vice versa when P is high.
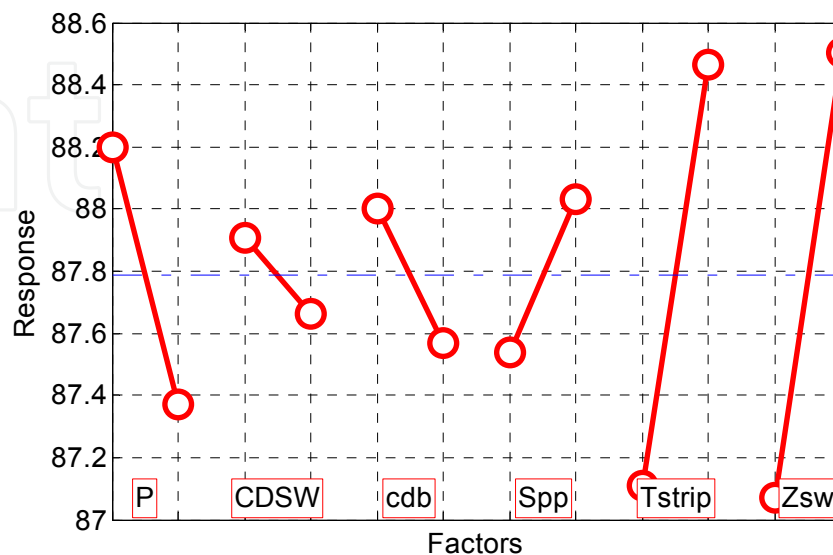

Figure 7. Plot of effects for the efficiency.

Contrariwise, when Tstrip and Zsw are low the efficiency is low, while it is high when Tstrip and Zsw are high.

For the objective function kg/kW the most important parameters are respectively Zsw (29%), Tstrip (24%), CDSW (18%) and Spp (10%). Fig. 8 shows that when each one of these parameters is low the kg/kW is high and inversely when they are high. Furthermore, for this objective function there is a significant interaction between some factors 'P × Spp + Tstrip × Zsw' (5%). Note that we have isolated all of the main effects from every 2-factors interaction. The two largest effects are Zsw and Tstrip, hence it seems reasonable to attribute this to the Tstrip × Zsw interaction.
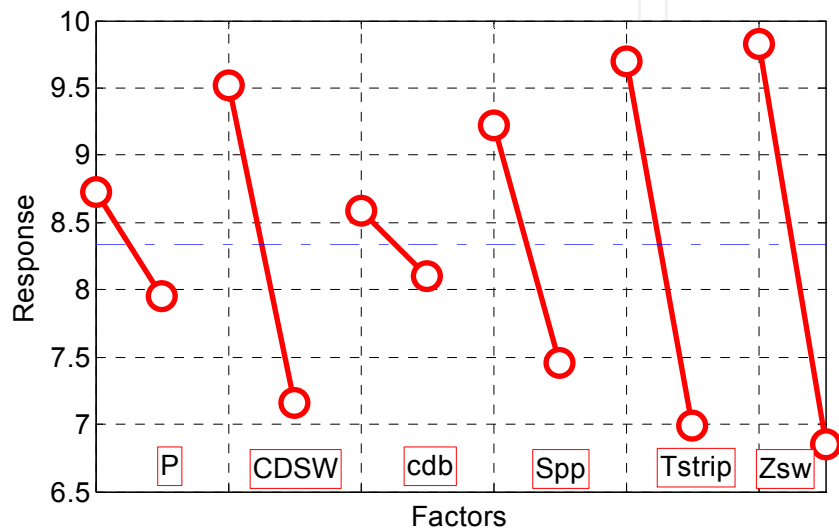
Figure 8. Plot of effects for kg/kW.

Concerning the temperature rise we can observe that, Zsw (39%), Tstrip (36%), P(9%) and CDSW (8%) are the most significant parameters. On the contrary, no significant interaction is discerned. Fig. 9 shows that the temperature rise is low when P and CDSW are low and it
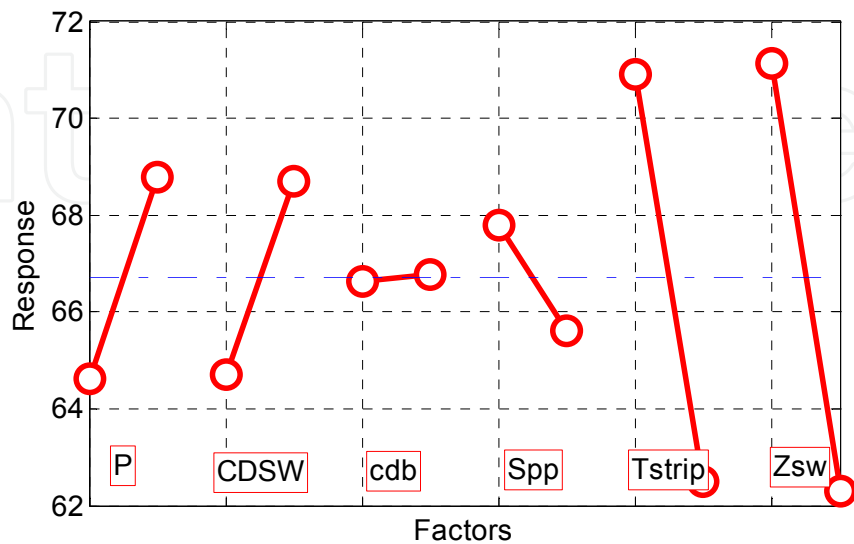

Figure 9. Plot of effects for temperature rise.

is high when they are high. Inversely, for Tstrip and Zsw the temperature rise is low when they are high.

For the objective function I0/I the significant parameters are P (45%) and Spp (25)%. Furthermore, there is a significant interaction between P and Spp included in the contrast 'P × Spp + Tstrip × Zsw'. Fig. 10 shows that I0/I is low when each parameter is low and vise versa.
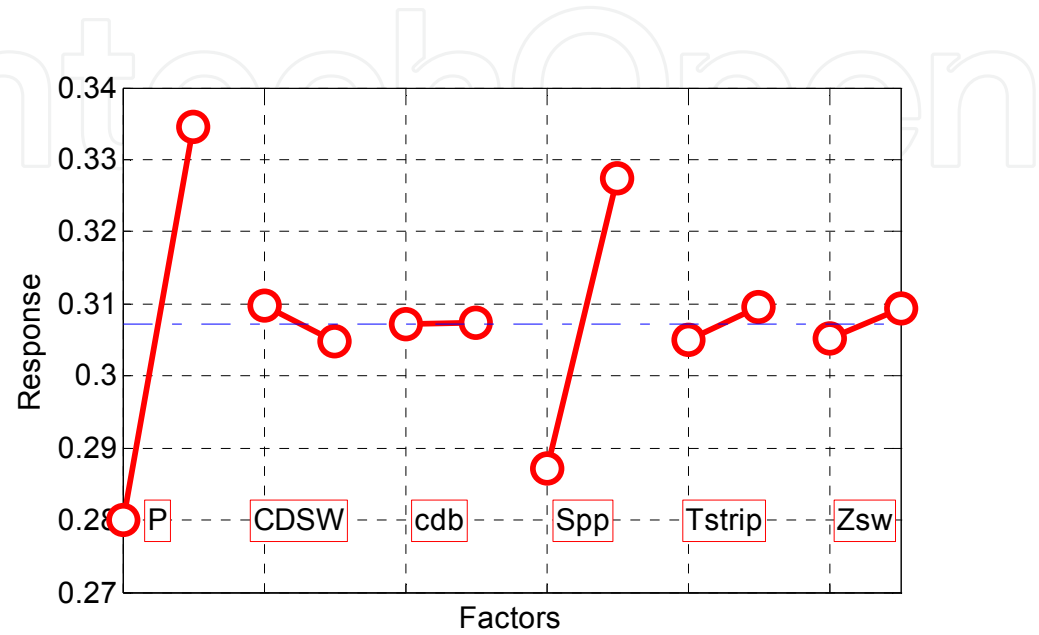

Figure 10. Plot of effects for I0/I.

Finally, for the starting torque the most significant parameters are given in this order: Spp (4%), Zsw (19%), Tstrip (14%), P (7%) and Cdb (5%). From Fig. 11 we can notice that when
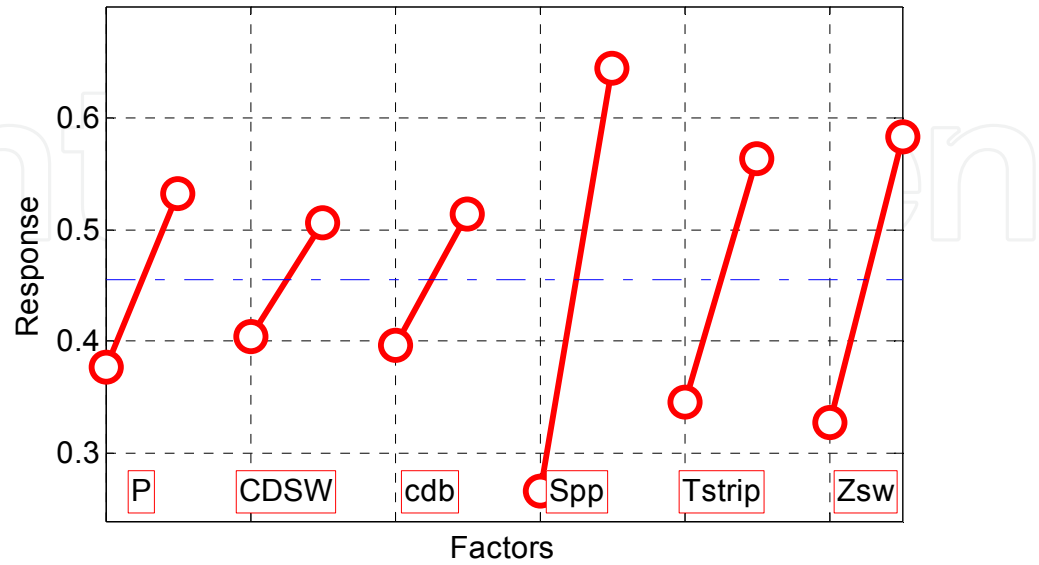

Figure 11. Plot of effects for starting torque.

each one of these parameters is low the starting torque is low. Likewise, when these parameters are high, the starting torque is high. Furthermore, for this objective function there is two significant interaction between some factors 'P × Tstrip + CDSW × Cdb + Spp × Zsw' (5%) and 'P × Zsw + Spp × Tstrip' (5%). Note that we have isolated all of the main effects from every 2-factor interaction. For the first contrast the two largest effects are Spp and Zsw. Thus, it seems reasonable to attribute this to the Spp × Zsw interaction. While, for the second contrast the two largest effects are Spp and Tstrip. Hence, it is appropriate to attribute this to the Spp × Tstrip interaction.

4.5. Optimization

Two optimization approaches can be achieved. The first one is to treat 1 of the 5 objective functions (defined in the Objective Function section) at a time. Thus, every time a single objective function is taken into account regardless of the 4 others. The second approach is to consider a multi objective function where the 5 objective functions are taken into account at the same time. The resulted complicated multiple-objective function can be converted into a simple and practical single-objective function scalarization. Among scalarization methods we can find the weighting method. In this method, the problem is posed as follows:

$$F_{objective} = \sum_{i=1}^{5} w_i f_i \tag{35}$$

where: $f_1 = EFF$, $f_2 = -kg / kW$, $f_3 = -Tr$, $f_4 = -I0 / I$, $f_5 = Tst$ and w_i is a constant indicating the weight (and hence importance) assigned to f_i. By giving a relatively large value to w_i it is possible to favor f_i over other objective functions. Note that the condition $\sum_{i=1}^{k} w_i = 1$ can be posed in Eq.(35).

Nevertheless, since the 5 functions of the multi-objective function have different ranges, for instance f_1 varies from 85 to 91 and f_5 varies from 0.07 to 1.3. Thus, the values of these functions must be normalized between 0 and 1. The minimum of a given function is equal to 0 and the maximum is equal to 1. The normalization operation is given by:

$$Normalized_{Value} = \frac{\left(Actual_{Value} - min(f_i)\right)}{max(f_i) - min(f_i)} \tag{36}$$

and (35) becomes:

$$F_{objective} = \sum_{i=1}^{5} w_i f_{i\,Normalized} \tag{37}$$

For this chapter we have chosen the first approach i.e. the single objective one.

The PSO algorithm is implemented to optimize the design of induction motor whose specifications are given above. The results of PSO algorithm for the optimized motor are given in the Table 9. The algorithm has returned an acceptable solution every time, which is indicated by a good value for objective with no constraint violations.

Parameters	EFF	Kg/KW	Tr	I0/I	Tst
P	4	4	4	4	6
CDSW	3	5	3	5	5
Cdb	4	6	4	6	6
Spp	4	4	4	3	4
Tstrip	2	2	2	2	2
Zsw	2	2	2	2	2
Existing Motor	89.7	5.36	53.8	0.27	0.5
Optimized Motor	90.1	5.15	48.5	0.26	1.3

Table 9. Optimum design results for efficiency maximization, minimization of kg/kW, minimization of temperature rise, minimization of the ratio I0/I and starting torque maximization.

According to the results presented in Table 9, when the efficiency of the motor is considered as the objective function, we can see that it increased from 89.7 to 90.1 compared to the existing motor. We can notice also that the when Kg/KW is minimized, it reduced from 5.36 to 5.15. Moreover, the optimization process allowed to the temperature rise to decrease form 53.8 to 48.5 which is a important reduction. Likewise, the I0/I is slightly reduced from 0.27 to 0.26 when it is the objective function. Finally, Table 9, shows that the starting torque is higher for the optimized motor (1.3) compared to the existing one (0.5).

According to these results, we can say that PSO is suitable for motor design and can reach successful designs with better performances than the existing motor while satisfying almost every constraint.

5. Conclusion

This chapter investigated the optimal design of induction motor using DOE and PSO techniques with five objective functions namely, maximization of efficiency, minimization of kg/kW, minimization of temperature rise in the stator, minimization of I0/I ratio, maximization of starting torque. It has been shown that DOE and PSO based algorithms constitute a viable and powerful tool for the optimal design of induction motor. The main objective of the DEO here is to identify the effect of each parameter on the objective functions. This is of a paramount importance mainly because of two reasons. The first one and also the obvious one is the reduction of the number of parameters to be taken into

consideration in the optimization stage called screening. This can be achieved by neglecting the parameters with less effect. This will reduce the computing time burden and simplify the analysis of the designed motor. The second reason is that among the influent parameters themselves we can classify the parameters in function of their calculated effect. This will help the designer to have a clear picture of the importance of each parameter. For instance, if two parameters having respectively 45% and 5% of influence on a given objective function are compared; it is obvious that even if both parameters have an effect on the given objective function, the first one is greatly more important than the second one.

The approach developed here is universal and, although demonstrated here for induction motor design optimization, it may be applied to the design optimization of other types of electromagnetic device. It can be used also to investigate new types of motors or more generally electromagnetic devices. MATLAB code was used for implementing the entire algorithm. Thus, another valuable feature is that the developed approach is implementable on a desktop computer.

Author details

Houssem Rafik El-Hana Bouchekara
Department of Electrical Engineering, College of Engineering and Islamic Architecture,
Umm Al-Qura University, Makkah, Saudi Arabia
Electrical Laboratory of Constantine "LEC", Department of Electrical Engineering,
Mentouri University – Constantine, Constantine, Algeria

Mohammed Simsim and Makbul Anwari
Department of Electrical Engineering, College of Engineering and Islamic Architecture,
Umm Al-Qura University, Makkah, Saudi Arabia

6. References

Altayib K., Ali, A. (2011). Improvement for alignment process of automotive assembly plant using simulation and design of experiments. International Journal of Experimental Design and Process Optimization, vol.2, no.2, pp.145-160.

Blanusa, B. (2010). New Trends in Efficiency Optimization of Induction Motor Drives, New Trends in Technologies: Devices, Computer, Communication and Industrial Systems, Meng Joo Er (Ed.), ISBN: 978-953-307-212-8, InTech.

Boldea, I. Nasar, S.A. (2002). The Induction Machine Handbook. CRC Press LLC, ISBN 0-8493-0004-5.

Bouchekara, H., Dahman, G., Nahas, M. (2011). Smart Electromagnetic Simulations: Guide Lines for Design of Experiments Technique. Progress in Electromagnetics Research B, Vol. 31, 357-379.

Brownlee, J. (2011). Clever Algorithms: Nature-Inspired Programming Recipes, lulu.com; 1ST edition, ISBN-10: 1446785068.

Clerc, M. (2006). Particle Swarm Optimization, Hermes Science Publishing Ltd., ISBN 1905209045, London.

Costa, M. C. (2001). Optimisation De Dispositifs Electromagnétiques Dans Un Contexte D'analyse Par La Méthode Des Eléments Finis. PhD thesis, National polytechnic institute of Grenoble.

Cunkas, M. Akkaya, R. (2006). Design Optimization of Induction Motor by Genetic Algorithm and Comparison with Existing Motor. Mathematical and Computational Applications, Vol. 11, No. 3., pp. 193-203.

Demonsant, J. (1996). Comprendre et Mener des Plans d'Expériences. Afnor, ISBN 2-124-75032-1.

Kennedy, J. Eberhart, R. C. (1995). Particle swarm optimization. Proceedings IEEE international conference on neural networks, Vol. IV, pp. 1942– 1948.

Kennedy, J., Eberhart, R. C., Shi, Y. (2001). Swarm Intelligence, San Francisco: Morgan Kaufmann Publishers.

Kleijnen, J. P. C., Sanchez S. M, T.W. Lucas, Cioppa, T. M. (2005). State-of-the-Art Review: A User's Guide to the Brave New World of Designing Simulation Experiments. Journal on Computing 17(3): 263–289.

Kutlea, L., Pavlovića, N., Dorotića, M., Zadroa, I., Kapustića, M., Halassy, B. (2010). Robustness testing of live attenuated rubella vaccine potency assay using fractional factorial design of experiments. Vaccine, vol.28, no.33, 2010, pp.5497-5502.

Maljkovic, Z., Cettolo, M. (2001). The Impact of the Induction Motor on Short-Circuit Current", IEEE Ind. Application Magazine, pp. 11-17.

Murthy, K.M.V. (2008). Computer-Aided Design of Electrical Machines', ISBN: 978-81-7800-146-3, Bs Publications/bsp Books.

Pillet, M. (1997). Les Plans d'Expériences par la Méthode TAGUCHI. Les Editions d'Organisation, ISBN 2-70-812031-X.

Poli, R. (2008). Analysis of the publications on the applications of particle swarm optimisation. Journal of Artificial Evolution and Applications, 1:1–10.

Poli, R., Kennedy, J., Blackwell, T. (2007). Particle swarm optimization an overview. Swarm Intelligence, 1:33–57.

ReliaSoft Corporation, 2008, Chapter 2: Overview. Available from: http://www.weibull.com/DOEWeb/experiment_design_and_analysis_reference.htm#introduction.htm>.

Thanga Raj, C., Srivastava, S. P., Agarwal, P. (2008). Realization on Particle Swarm Optimized Induction Motor Via SPEED/PC-IMD", IAENG Int. J. of Computer Science, Vol. 16, No. 4, pp. 486-492.

Uy, M., Telford, J.K. (2009). Optimization by Design of Experiment techniques. Aerospace conference, IEEE, pp.1-10, 7-14.

Vogt. V. (1988). Electrical Machines. Design of Rotary Electric Machines, Fourth edition (in German), VEB Verlag Technik Berlin.