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# Energy Optimal Consumption in Squirrel Cage Induction Motor Using Firefly Algorithm Optimization

Department of Electrical Engineering, University 20 Août 1955 Skikda, Algeria

H.Ladaycia[#1], A.Boukadoum[*2]

[1] hania_ladaycia@live.fr

[2] boukadoum2003@yahoo.fr

***Abstract* — Motors are by far the most important type of electric charges, and so constitute the main targets to achieve energy saving. Every effort to save energy in motor application can be made by always attempting to use energy only as much as what needed during its operation. It can be achieved by optimizing the induction motor design. This paper presents a firefly algorithm for optimizing the IM design considering different formulations in order to show how we can handle the design process for certain characteristics. The proposed method has been applied to optimize the design of squirrel cage induction motor having specifications 37kW, 380V, 60Hz. The validity of the design results is clarified by comparison between calculated results and existing ones.**

**Keywords:** Energy saving, Squirrel cage induction motor, Formulation, Optimization, Firefly algorithm

## 1. Introduction :

Squirrel cage induction motors (SCIM) are the most energy consuming electric machines in the world, intelligent use of energy means higher productivity with lower active energy and lower losses at moderate costs. The induction motor (IM) has been, intensively, studied and described in the literature during several decades. They are employed in great quantity in different applications and have a significant impact on the consumption of electricity. Consequently, their design takes a great importance [1], [2], [3]-[13]. As induction machines are now a mature technology, there is a wealth of practical knowledge, validated in industry, on the relationship between performance constraints and the physical aspects of the induction machine itself.

In the literature numerous stochastic searching algorithms have been used to solve the IM design problems. Such as GA (Genetic Algorithm) [5], [10], [12], PSO (Particle Swarm Optimization) [2], [4]-[5], EA (Evolutionary Algorithm) [7] and Hooke Jeeves Method [1]. Such optimization approaches tend to find the global optimum but for a larger computation time (slower convergence). They do not need the computation of the gradients of the fitness function and constraints. Nor do they require an already good initial design variable set as most nongradient deterministic methods do.

Though heuristic algorithms such as GA have been employed to solve IM design problems, recent research has identified some deficiencies in GA performance and also for PSO often suffers from the problem of being trapped in local optima [4].

In this paper, the optimum design method is introduced to minimize the total losses of the high efficiency induction motor by using firefly algorithm optimization.

## 2. Conventional method and model validation:

Results simulation of the model are calculated by equivalent circuit method [14] and the characteristics of SCIM are compared with simulation and experimental results obtained in [10]. Table 2 shows the results of equivalent parameters and efficiency, power factor and rated phase current results. Their values are closer to analysis and optimum model test results presented in [10].

Note that the leakage reactance of stator and rotor ($X_s$ and $X_r$) is calculated considering leakage flux lines which cross the stator and, respectively, the rotor slots, end-turn flux, zig-zag flux, and air-gap flux. The rotor resistance ($R_r$) is equivalent value using bar and end-ring resistance.

**Table 1.** Specification of 37 kW three phase SCIM

| Item | Value |
|---|---|
| Phase number | 3 |
| Input voltage [V] | 380 |
| Frequency [Hz] | 60 |
| Output power [kW] | 37 |
| Pole number | 4 |
| Stator Out Diameter [mm] | 343 |
| Shaft Diameter [mm] | 70 |

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**Table 2.** Model validation

| Items | Unit | Conventional method | Ref model [10] |
|---|---|---|---|
| Efficiency | % | 93.23 | 93.6 |
| Power factor | % | 86.44 | 86.1 |
| Rated phase current | A | 69.7555 | 69.9 |
| Stator resistance ($R_s$) at 25℃ | Ω | 0.0594 | 0.0483 |
| Rotor resistance (Rr) at 25℃ | Ω | 0.0333 | 0.0266 |
| Stator leakage reactance (Xs) | Ω | 0.3125 | 0.232 |
| Rotor leakage reactance (Xr) | Ω | 0.2812 | 0.278 |
| Magnetizing reactance (Xm) | Ω | 7.9196 | 7.68 |

## 3. Definition of the optimization problem

The goal of the optimization is to minimize losses in SCIM in order to reduce energy consumption. The optimal design parameters of the motor can be obtained by solving a constrained nonlinear optimization problem. The problem consists of an objective function which is optimized (minimized) subject to a set of constraints. A typical form for the addressed optimization problem can be expressed in the form:

$$\begin{cases} \min F(x) & \\ \quad g_j(x) = 0; \quad j = 1........m_e & \\ s.t. \quad g_j(x) \geq 0; \quad j = m_e + 1,..........,m & \\ \quad X_{low} \leq X \leq X_{high} & \\ where \quad X = \{X_1, X_2, ..., X_n\} & \end{cases} \tag{1}$$

A good solution of an optimization problem is obtained by means of both an appropriate model (also called formulation) and an efficient algorithm to solve it. The aim of this paper is to investigate the efficiency and reliability of stochastic optimization solvers when handling different mathematical formulations. We present the impact of such different formulations on solver performance with the aim of providing guidelines for designers in practical engineering applications.

## 4- Formulation of the optimization problem

The problem consists of an objective function which is optimized (minimized) with a set of constraints. Choosing the objective function is very intricate in real applications which have to observe many contradictory requirements such as: improving the motor efficiency and power factor, reducing the motor size and weight, improving the locked torque, reducing the locked current and limit the components temperature to a feasible level. It is known that the same optimization problem can be often formulated in different ways, using different objective function, different constraints and variables. Furthermore, the formal description of optimization problems has an impact on the applicability and efficiency of the corresponding solution methods. Indeed, the study of reformulations is an active research area in the optimization community [13], [15]-[16]. The optimization problem of SCIM can be formulated as follow:

$$\begin{cases} \min \sum losses(D_{is}, d_1, d_2, h_r, b_{tr}, b_{ts}, b_{s1}, b_{s2}, h_r) \\ s.t. \quad \cos\varphi \geq 0.861 \\ \quad \eta \geq 0.936 \\ \quad T_{c0} \leq 101 \\ \quad i_{LR} \leq 6 \\ \quad t_{LR} \geq 1.75 \\ \quad t_{bk} \leq 2.5 \\ \quad D_{out} = 343 \\ \quad D_{shaft} = 70 \end{cases} \tag{2}$$

Where ∑ losses (W) is the total losses of the induction motor including stator ($P_{c0}$) and rotor loss ($P_{Al}$), iron loss ($P_{iron}$), friction and windage loss ($P_{mv}$) and stray load loss ($P_{stray}$). $D_{is}$ (m) the stator bore diameter, $d_1$ (m) the rotor higher slot diameter, $d_2$ the rotor lower slot diameter (m), $h_r$ the rotor slot useful height, $b_{ts}$ the rotor tooth width (m) the stator tooth width, $h_s$ (m) the stator slot useful height, $b_{s1}$ (m) the slot lower width, $b_{s2}$ (m) the slot higher width, η the efficiency, $T_{c0}$ the winding temperature, $i_{LR}$ the per unit locked current, $t_{LR}$ the per unit locked torque.

In this work we discuss four different formulations but mathematically equivalent because the only difference is the choice of number of variables and constraint, also the quality of used constraints. We discuss about the four following formulations:

**i. Formulation 1:**

- $D_{is}$, $h_s$, $h_r$, $b_{s1}$, $b_{s2}$, $b_{ts}$, $b_{tr}$, $d_1$, $d_2$ 9 variables
- Losses is a function depending on $D_{is}$, $h_s$, $h_r$ ...
- Equations in (2) yield 6 inequalities constraints and 2 equality ones: $D_{out}$, $D_{shaft}$
- Add constraints to the bounds of the variables

**ii. Formulation 2**

- $D_{is}$, $h_s$, $h_r$, $b_{s1}$, $b_{s2}$, $b_{ts}$, $b_{tr}$, $d_1$, $d_2$ 9 variables
- Losses is a function depending on $D_{is}$, $h_s$, $h_r$ ...
- Equations in (2) yield 2 inequalities constraints and 2 equality ones: $D_{out}$, $D_{shaft}$

$$\begin{cases} \min \sum losses\left(D_{is}, d_1, d_2, h_r, b_{tr}, b_{s1}, b_{s2}, h_r\right) \\ s.t. \quad \cos\varphi \geq 0.861 \\ \qquad T_{c0} \leq 101 \\ \qquad D_{out} = 343 \\ \qquad D_{shaft} = 70 \end{cases} \tag{3}$$

- Add constraints to the bounds of the variables

### iii. Formulation 3

- $D_{is}$, $h_s$, $h_r$, $b_{ts}$, $b_{tr}$, $d_1$, $d_2$ 7 variables
- Losses is a function depending on $D_{is}$, $h_s$, $h_r$ ...
- Equations in (2) yield 6 inequalities constraints and 2 equality ones: $D_{out}$, $D_{shaft}$

$$\begin{cases} \min \sum losses\left(D_{is}, d_1, d_2, h_r, b_{tr}, b_{ts}, h_r\right) \\ s.t. \quad \cos\varphi \geq 0.861 \\ \qquad \eta \geq 0.936 \\ \qquad T_{c0} \leq 101 \\ \qquad i_{LR} \leq 6 \\ \qquad t_{LR} \geq 1.75 \\ \qquad t_{bk} \leq 2.5 \\ \qquad D_{out} = 343 \\ \qquad D_{shaft} = 70 \end{cases} \tag{4}$$

- Add constraints to the bounds of the variables

### iv. Formulation 4

- $D_{is}$, $h_s$, $h_r$, $b_{ts}$, $b_{tr}$, $d_1$, $d_2$ 7 variables
- Losses is a function depending on $D_{is}$, $h_s$, $h_r$ ...
- Equations in (2) yield 2 inequalities constraints and 2 equality ones: $D_{out}$, $D_{shaft}$

$$\begin{cases} \min \sum losses\left(D_{is}, d_1, d_2, h_r, b_{tr}, b_{ts}, h_r\right) \\ s.t. \quad \cos\varphi \geq 0.861 \\ \qquad T_{c0} \leq 101 \\ \qquad D_{out} = 343 \\ \qquad D_{shaft} = 70 \end{cases} \tag{5}$$

- Add constraints to the bounds of the variables

## 4. Firefly algorithm:

The firefly algorithm (FA) is a novel metaheuristic algorithm. It was first developed by Xin-She Yang in late 2007 and 2008. Its idea is based on the behavior of fireflies. The algorithm uses the difference in light intensity that is proportional to the value of the objective function. Each individual has a certain attractiveness which determines the direction of movement. All fireflies are characterized by light intensity associated with the objective function [17], [19]. Yang was used three rules for the FA [18], [20]:

- All fireflies are unisexual and every firefly attracts/gets attracted to every other firefly.
- The attractiveness of a firefly is directly proportional to the brightness of the firefly. (The brightness decreases as the distance increases.)
- They move randomly if they do not find a more attractive firefly in adjacent regions

The movement of a firefly i is attracted to another more attractive (brighter) firefly j is determined by

$$x_i^{t+1} = x_i^t + \beta_0 e^{-\gamma r_{ij}^2}\left(x_j^t - x_i^t\right) + \alpha_t \in_i^t$$

Where $\beta = \beta_0 e^{-\gamma r_{ij}^2}$ attractiveness between the i-th and j-th firefly $r_{ij}$ is Cartesian distance between *i*-th and *j*-th firefly The FA implementation steps are listed below [19]:

**Table. 3** Pseudo code of the firefly algorithm (FA)

| Firefly algorithm |
| --- |
| *Objective function f(x),* $x=(x_1,\ldots,x_d)^T$ |
| *Generate initial population of fireflies* $x_i=(i=1,2,\ldots,n)$ |
| *Light intensity* $I_i$ *at* $x_i$ *is determined by* $f(x_i)$ |
| *Define light absorption coefficient γ* |
| ***While*** *(t<MaxGenerqation)* |
| ***for*** *i=1:n all n fireflies* |
| ***for*** *j=1:n all n fireflies (inner loop)* |
| ***if*** *(*$I_i<I_j$*), Move firefly I towards j:* ***end if*** |
| *Vary attractiveness with distance r via exp (-γr)* |
| *Evaluate new solutions and update light intensity* |
| ***end for i*** |
| ***end for j*** |
| *rank the fireflies and find the current global best* |
| ***end while*** |
| *Postprocess results and visualization* |

## 5. Simulation and results

In order to compare FA performance and compare it between optimum model and optimization approach used in [14], numerical simulation have been conducted in which formulation 1, formulation 2, formulation 3 and formulation 4 shown in section 4 are better. Each formulations were executed with the same population size $m$ = 10, iteration number N = 50. The algorithm stop after 500 function evolution. The obtained results are presented in Tab. 4, Tab. 5 and Tab. 6.

**Table. 4** Comparison between optimized design for formulation 1 and 2.

| Items | Formulation 1 | Formulation 2 | Conventional design |
|---|---|---|---|
| $D_{is}$ [mm] | 115 | 188.8083 | 221 |
| $d_1$ [mm] | 6.1333 | 6.6190 | 7.3477 |
| $d_2$ [mm] | 2.0039 | 2.2284 | 2.8419 |
| $h_r$ [mm] | 29.6675 | 29.5218 | 28.6257 |
| $b_{tr}$ [mm] | 8.3090 | 8.4635 | 9.2754 |
| $b_{ts}$ [mm] | 7.7836 | 7.6326 | 8.2721 |
| $h_s$ [mm] | 28.2564 | 28.7046 | 29.4923 |
| $b_{s1}$ [mm] | 6.2258 | 5.8526 | 6.5195 |
| $b_{s2}$ [mm] | 10.0353 | 10.1813 | 10.3856 |
| Power factor [%] | 85.49 | 86.1 | 86.44 |
| Efficiency [%] | 94.27 | 93.6 | 93.23 |
| Temperature of winding [°C] | 102.4672 | 109.3804 | 112.2971 |

As is observed in table 4 the optimization with more constraints has high efficiency and the power factor constraint is not satisfied, we can note that formulation 2 gives the best solution. From results in table 5, we remark that formulation 4 with fewer variables and fewer constraints gives the best result in terms of the best found solution.

The performance of the FA algorithm is emphasized by comparing its results with those of the conventional design method and the optimum model test [10] in table 6.

**Table. 5** Comparison between optimized design for formulation 3 and 4.

| Items | Formulation 3 | Formulation 4 | Conventional design |
|---|---|---|---|
| $D_{is}$ [mm] | 115 | 178.5319 | 221 |
| $d_1$ [mm] | 6.2028 | 6.5318 | 7.3477 |
| $d_2$ [mm] | 2.0958 | 2.3480 | 2.8419 |
| $h_r$ [mm] | 29.0283 | 29.4876 | 28.6257 |
| $b_{tr}$ [mm] | 9.0523 | 8.7098 | 9.2754 |
| $b_{ts}$ [mm] | 7.8289 | 7.9924 | 8.2721 |
| $h_s$ [mm] | 28.5358 | 28.8196 | 29.4923 |
| Power factor [%] | 85.51 | 86.02 | 86.44 |
| Efficiency [%] | 94.25 | 93.68 | 93.23 |
| Temperature of winding [°C] | 103.3586 | 109.3715 | 112.2971 |

From these tables, it is most clear that, using the formulation with fewer variables and fewer constraints allows to obtain the best solution.

The plot in fig. 1 represents the variation of the objective function during optimization process for four different formulations. It can be seen from the function evolution that using more constraints lead to important decreasing of function value. We found that formulation 1 and 3 provide a solution which is far from the best one. However we remark that formulation 2 and 4 give the best results. The efficiency is little higher for formulation 4 (93.68%) than for formulation 2 (93.6%).

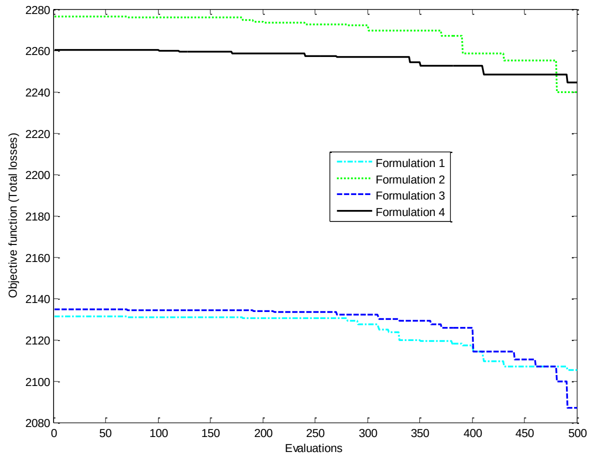


Fig.1 Evaluation of objective function during optimization process for different formulations

In an optimization program there should be the flexibility to declare any of the problem functions an objective function or others of them as constraints. The reason for such an option is that we may not always be interested in maximizing efficiency or reducing cost. Depending on the need, the choice must be left to the designer.

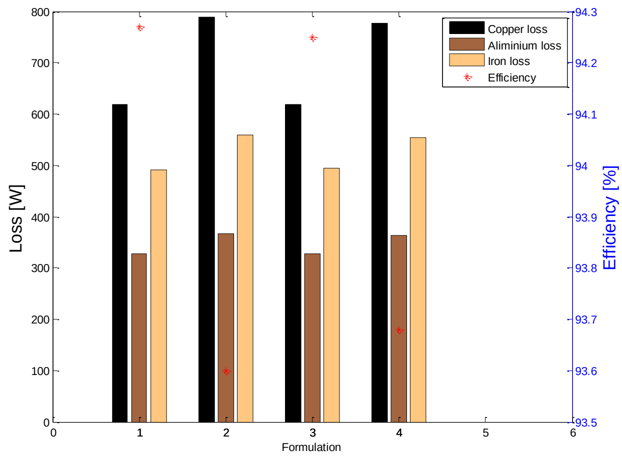


Fig.2 Loss and efficiency .vs. formulation

In figure 2 we compare four formulations in terms of the best solution found, considering different choices of design variables and constraints. It is seen that efficiency for each formulation satisfies high efficiency level (> 93.0%). However

**Table 6.** Change of performance parameters with formulations

| Items | Formulation 1 | Formulation 2 | Formulation 3 | Formulation 4 | Optimum model [10] | Conventional design |
|---|---|---|---|---|---|---|
| Stator copper loss [W] | 617.9047 | 788.1237 | 617.9047 | 777.0595 | 906 | 867.5804 |
| Rotor Alimunium loss [W] | 327.1347 | 365.9811 | 327.3180 | 363.1499 | 488 | 383.8568 |
| Iron loss [W] | 491.5146 | 559.5209 | 493.7658 | 554.0259 | 497 | 622.7908 |
| Power factor [%] | 85.49 | 86.1 | 85.51 | 86.02 | 87.1 | 86.44 |
| Efficiency [%] | 94.27 | 93.6 | 94.25 | 93.68 | 93.6 | 93.23 |

other performances are not achieved to the goal such as power factor as discussed above for formulation 1 and 3. This proves the non-equivalence of the four formulations in a numerical sense. Moreover we note that formulation 2 and 4 give closer results. We remark that formulation 4 is more efficient providing satisfactory constraints. Therefore, this seems to show that it is beneficial to reduce the zone of research in order to improve the chances to find the global minimum.

## 5. Conclusions

The proposed paper has presented a bird's eye view of the research work under progress. We have discussed the solutions found using four reformulations of SCIM design problem showing that the formulation of optimization design has significant impact on final optimal structure and performances. If properly utilized, the optimization will lead to the design that satisfies all imposed requirements. The results of the FA algorithm are compared those of the Analysis, test and conventional design method, which show the effectiveness of the proposed method in terms of solution quality, convergence and computational efficiency.

The design process proposed in this paper will be useful for minimizing total losses in SCIM design with fewer design variables and fewer constraints. It seems to be more efficient to use this formulation.

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