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ELMA based Design of SCMFIM to Improve the Efficiency and Power Factor

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ABSTRACT
The squirrel-cage Induction motors (SCIMs) are approximately 80% of the overall electricity use in industrialized countries. In the agricultural and commercial sectors also, power consumption by high power SCIMs are quite substantial. On an average, the energy consumed by a motor during its life cycle is 40-80 times the initial cost of the motors. Therefore efficiency and power factor (PF) of the motor is very essential for both during design and operation. Even small increase in efficiency and power factor, improvement can make a big difference in energy savings in variable load applications. In this paper mainly focusing on optimal design of multiple stator-winding to improve efficiency and power factor of high power SCIMs during variable loads, the different flux level of stator winding are designed [4] (star-delta) according to variable loads and its performance is discussed. The Extreme Learning Machine Algorithm (ELMA) is used for the multiple stator winding design and optimization process and the obtained simulation results are compared. The importance of this work is to improve the efficiency and power factor of the high power three phase SCIMs during variable load applications, and to reduce power losses [15, 23] energy consumption in the industry and in the territory sectors.

Keywords: ELMA, Energy efficiency, Efficiency, Induction Motor, Multi-Flux, P ower factor.

1. INTRODUCTION
Three phase SCIMs are widely used for various industrial and domestic applications such as pump drives, variable speed drives and etc., More than 80% of the electrical motors are three-phase squirrel-cage induction motors because of low production costs, more reliability and other features Induction motors are the main energy consuming devices in industries contributing to more than 80% of electromechanical energy conservation. Most physically high power three-phase SCIMs operate with low efficiency [3, 22] with large amount of power [23], which are the most important causes of poor power factor in industrial installations [16]. In the design, optimization of energy efficient induction motor is therefore the need of the day [17, 20].

ELMA was proposed by Huang, et al.,[9, 10] all the parameters of multi-layer neural networks based on gradient descent-based learning methods need to be learned [6] and usually many iterative learning steps are required to obtain better learning performance [6,24]. So, gradient descent based learning methods are suitable to be slow due to improper learning steps or may easily converge to local minimums. Finally, the ELMA based design values and it was compared with conventional design methods [1]. However, the ELMA optimization can be tailored to exploit the structure of the optimization model [7, 18]. Robustness and ill-conditioning are not big issues since the algorithm need only be effective for a narrow class of functions and constraints and high accuracy solutions [8, 13, 14]. To summarize, desirable properties of an extreme machine learning algorithm are follows:

1. Good generalization,
2. Scalability to large problems,
3. Good performance in practice in terms of execution times and memory requirements,
4. Simple and easy implementation of algorithm,
5. Exploitation of problem structure
6. Fast convergence to an approximate solution of model,
7. Robustness and numerical stability for class of machine learning models attempted,
8. Theoretically known convergence and complexity.

In this paper, a multiple stator winding induction motor is proposed with different possible winding connections, which allow the magnetizing flux to be regulated up to ten different levels. Alternatively, for the same magnetizing flux of induction motor can operate at up to ten different voltage levels, in which both the efficiency and power factor can be maximized as a function of load. The application of the proposed design in such motors can lead to significant energy savings, efficiency [20] and power factor improvement. This novel method for multi objective design and optimization can be of great value in industry due to its flexibility, particularly, for variable load applications in which significant energy savings can be obtained by ElMA based design. ELMA using multi-flux level [4] (multiple stator winding) problem as proposed for induction motor and the obtained optimal parameters are compared with conventionally designed induction motor.

2. PROBLEM FORMULATION
The problem in the induction motor design is to select an appropriate combination of the design variables [12] which will minimize the losses and improved the efficiency, power factor of the three phase squirrel-cage induction motor during light loading periods. The design ultimate process is much complicated while using too many variables [5]. Therefore the number of design variables selection is important in the motor design optimization. The design has some constraints, to guarantee the same motor performance indices. The design optimization problem can be formulated as a general nonlinear programming problem of the standard form: Find$X(X_1, X_2, \ldots, X_n)$, such that J(X) is a maximum subject to $g_j(X) \geq 0$, $j = 1, 2, \ldots m$ and $xL_i \leq xL_i \leq xU_{ii} = 1, 2, \ldots n$, where is the set of independent design variables with their lower and upper limits as xL_i and xU_i, for all n variables. J(X) is the objective function to be optimized and $g_i(X)$ is the constraint imposed on the design.

If J is the objective function to maximize the efficiency [11,21], it depends on the design variables $X = (X_1, X_2, X_3 \ldots Xn)$, the corresponding optimization problem can be written as:

$$\begin{cases} \text{MAX } J(X) \\ \text{Subject to } G(X) \geq 0 \end{cases}$$

A set *X* of seven independent variables which affect constraints and objective function is listed below:

(a).Ampere conductors (m) - X_1
(b). Ratio of stack length to pole pitch- X_2
(c).Stator slot depth to width ratio - X_3

(d).Stator core depth (mm) - X_4
(e) Average air gap flux densities (T) - X_5
(f) Stator current densities (A/mm^2) - X_6
(g) Rotor current densities (A/mm^2)- X_7.
The remaining parameters can be expressed in terms of these variables or may be treated as fixed for a particular design.

The following factors are considered as SCIM design constraints:
a).Stator Copper Loss,
b).Rotor Copper Loss,
c).Stator Iron Loss,
d). Friction Loss,
e).Full Load Efficiency,
f).Stator Temperature Rise,
g).Maximum Rotor Temperature Rise,
h). Full Load Slip,
i). Starting to Full-Load Torque Ratio,
j). Maximum to Full-Load Torque ratio,
k). Starting to Full-Load Current Ratio,
l). Full Load Power Factor.

The design and optimization of SCIM requires a particular attention in the choice of the objective function that usually concerns economic or performance features [2,16]. In this proposed design, our main objective to improve the efficiency during light loads. The expression of objective function, in terms of the design variables are summarized in the form of different constraints as follows.
The Stator Copper Loss are given by:

$$W_{SCL} = 3 \cdot I_{ph}^2 \cdot R_s \quad , \qquad (1)$$

where I_{ph} is the phase current (A) and R_S is the equivalent per-phase stator resistance (Ω).
The Rotor Copper Loss are given by:

$$W_{RCL} = \frac{\rho_r S_2 I_b^2}{a_b}(L, + \frac{2D_e}{P}) \quad , \qquad (2)$$

where ρ_r is a constant (0.021), S_2 is the number of rotor slots, I_b is the rotor bar current (A), D_e is the mean end-ring diameter (mm), L_r is the length of the core (m), and P is the number of poles.
The Stator Iron Loss are given by:

$$W_{SIL} = W_t \cdot W_{tk} + W_c \cdot W_{ck} \qquad (3)$$

where W_t is the weight of the stator teeth, W_c is the weight of the stator core, W_{tk} is the losses in stator tooth portion (W/kg), and W_{ck} is the losses in stator core (W/kg).
The Full Load Efficiency is given in percentage by:

$$\eta = \frac{1000\ P_o}{1000\ P_o + W_{SCL} + W_{RCL} + W_{SIL} + W_F} \times 100 \qquad (4)$$

where P_o is the output power (kW) and W_F are the friction losses (W). The stray load losses are neglected in the analysis.

For continuously rated machines, the final stator temperature rise θ_{ms} is a determining factor and with the assumption that cooling by convection, conduction and radiation is proportional to the temperature rise [19].

The temperature rise is directly proportional to the heat developed due to losses and indirectly proportional to cooling surface area, according to (5):

$$\theta_{ms} = \frac{\tau_c (W_{SCL} + W_{SIL})}{S_S} \qquad (5)$$

where the cooling coefficient is:

$$\text{Cooling coefficicent}\,\tau_c = \frac{0.03 - 0.05}{1 + 0.1u}\,u = \frac{2\pi f D}{P} \qquad (6)$$

and the total effective cooling surface area is:

$$S_s = S_i(1 + 0.1u) + S_0 \quad , \qquad (7)$$

where S_i and S_o are the inside and outside cylindrical surface area of the motor respectively.

This stator temperature optimization is an important design aspect due to the demand for reduced weights and costs and increased efficiency. To obtain an accurate analytical thermal model, all the important heat transfer paths must be included in the network and suitable algorithms should be used to calculate thermal resistances for such paths. This usually requires the experience of a heat transfer specialist, to use his skills and experience to construct an accurate thermal network. However, motor optimal design mathematical model have developed genetic algorithm, which automatically constructs an electric motor thermal network from the users inputs for motor geometry and their selection of materials and cooling coefficient.

The calculations of rotor temperature rise are based on similar considerations as that of stator temperature rise. The cooling surface is calculated from the rotor dimension. Thus the full load rotor temperature rise is calculated as

$$\theta_{mr} = \frac{\tau_c W_{RCL}}{S_r} \qquad (8)$$

Where, S_r is total rotor cooling surface area

The full load slip is given by:

$$s = \frac{W_{RCL}}{1000 P_o + W_{RCL} + W_F} \qquad (9)$$

The summation of friction and windage losses is assumed to be 1%

Starting torque to full load torque ratio is given by:

$$\text{Ratio,} = \frac{T_{st}}{T_{fl}} \quad , \qquad (10)$$

Where T_{st} is starting torque, T_{fl} is full load torque

Maximum torque to full load torque ratio is given by:

$$\text{Ratio,} = \frac{T_{max}}{T_{fl}} \quad , \qquad (11)$$

Where T_{max} is maximum Torque

Starting to Full Load Current Ratio is given by:

$$\text{Ratio,} = \frac{I_0}{I_{ph}} \quad , \qquad (12)$$

Whereas I_0 is total no-load current in amps, I_{ph} is phase current in amps

Full Load Power Factor is given by:

$$PF = \frac{R_s + G_4}{\sqrt{\{(R_s + G_4)^2 + (X_5 + G_5)^2\}}} \qquad (13)$$

Whereas R_S is stator resistance in ohms, X_5 is average air gap flux density (wb / m^2), G_4, G_5 is magnetizing constants.

3. DESIGN AND OPTIMIZATION

3.1 Optimization of Multiple Flux Stator Winding Using EMLA

In the ELMA, the output weights are analytically computed [2, 24] by using the MP generalized inverse instead of iterative learning scheme. Fig.2 shows the learning procedure and structure in ELMA. As shown in Fig.1, the ELM consists of single-hidden layer feed forward networks (SLFNs). The significant features of ELM can be summarized as follows:

1. The learning speed of ELM is extremely fast. It can train SLFNs much faster than classical learning methods.
2. The ELMA tends to reach not only the smallest training error but also the smallest norm of weights. Thus, the ELMA tends to have good performance for neural networks.
3. The ELMA learning algorithm can be used to train SLFNs with non-differentiable activation functions.
4. The ELM tends to reach the solutions straightforward without such trivial issues.

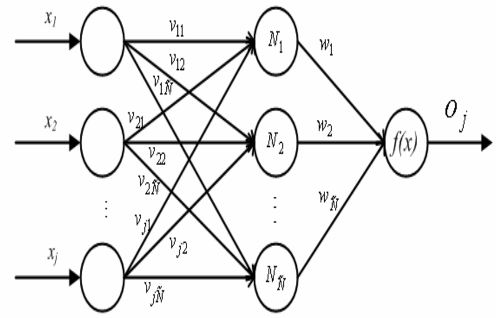

Fig.1-The structure of ELMA

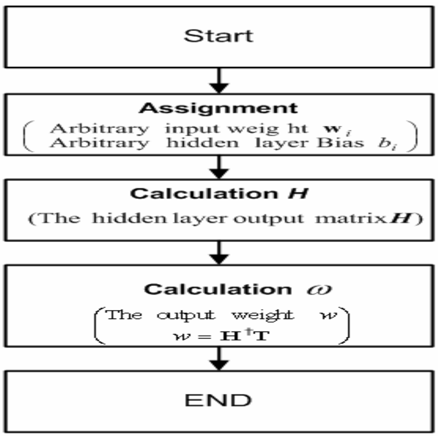

Fig. 2-The Learning Process of ELM

3.2. Different Types of Stator Winding Connections

Three phase SCIM has six numbers of input terminals. So, it is possible to connect either star or delta connection mode with each phase energized two sets of turns in the stator winding. These two sets of turns can be connected either in series or parallel with the input supply, to cause variation of either star to delta or delta to star connection mode. These are the following different possibilities of stator winding connections are presented below as shown in figures 3 to 12.

4. SIMULATION RESULTS AND DISCUSSION

4.1 Conventional Design

In Fig. 13. shows a conventional design of Efficiency as a function of percentage of load for various types of stator winding and Fig.14 represent a Power factor as a function of output power for various types of stator winding. The motor efficiency and power factor are considered stator winding connection modes. The intersection points are identified. The YS2 is connection was not considered in those zones because it does not contribute to the improvement of the resultant motor efficiency curve.

4.2. Optimal Design

Fig. 15 exhibits optimal design results for efficiency as a function of percentage of load for various types of stator winding and Fig.16 shows power factor as a function of output power for various types of stator winding. In Table–1 a comparison for Normal Design and Optimal Design in made. The two different cases are considered in the three phase IM design:Case 1. The power loss effect is not included in the objective function, Case 2. The power loss effect is included in the objective function.

5. CONCLUSION

A three-phase stator winding with two sets of turns is proposed. The described idea can be used in motors with wide load variations and with long low load in service periods. ELMA-based design approach has been successufully applied to a 7.5-kW, 4-pole, multiflux SCIM, in order to improve the efficiency-load curves resulting from each possible connection mode. A software package that analyzes and optimizes the steady-sate performance of multiflux SCIMs has been developed. The presented simulated results demonstrate that the proposed method can lead to signiifcant improvements in the efficiency curves of multiflux SCIM, contributing to increase their benefits in terms of energy savings. Nevertheless, further studies are necessary to prove the accuracy and effectiveness of the presented approach, including the construnction and experimental test of an optimized multiflux SCIM prototype.

6. ACKNOWLEDGMENT

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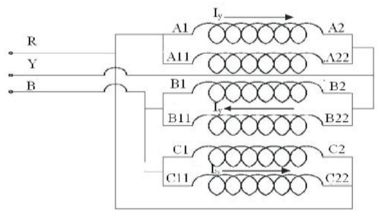


Fig. 3: Delta Parallel (DP) Connection.

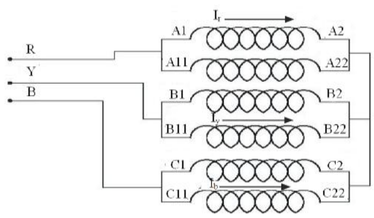


Fig. 4: Star-Parallel (YP) Connection.

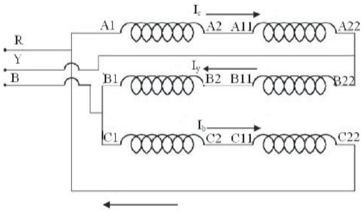


Fig. 5: Delta-series type I (DS1) Connection.

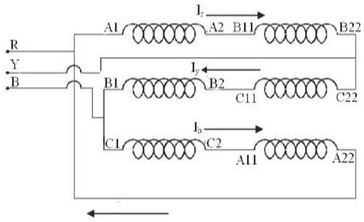


Fig. 6: Delta-series type II (DS2) Connection.

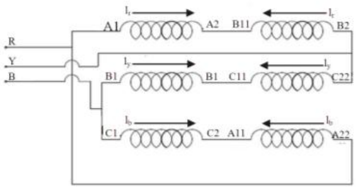


Fig. 7: Delta-series type III (DS3) Connection.

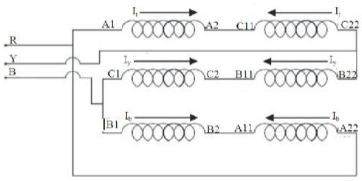


Fig. 8: Delta-series type IV (DS4) Connection.

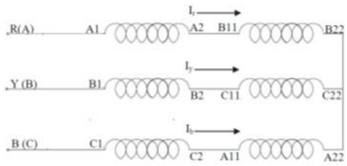


Fig. 9: Star Delta (YD) Connection.

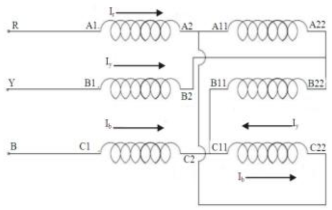


Fig. 10: Star-series type I (YS1) Connection.

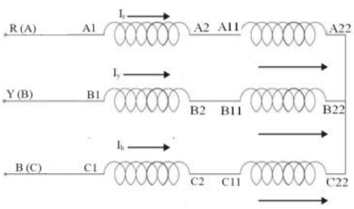


Fig. 11: Star-series type II (YS2) Connection.

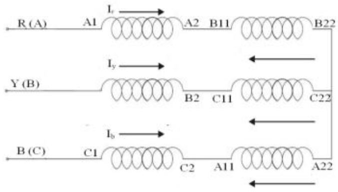
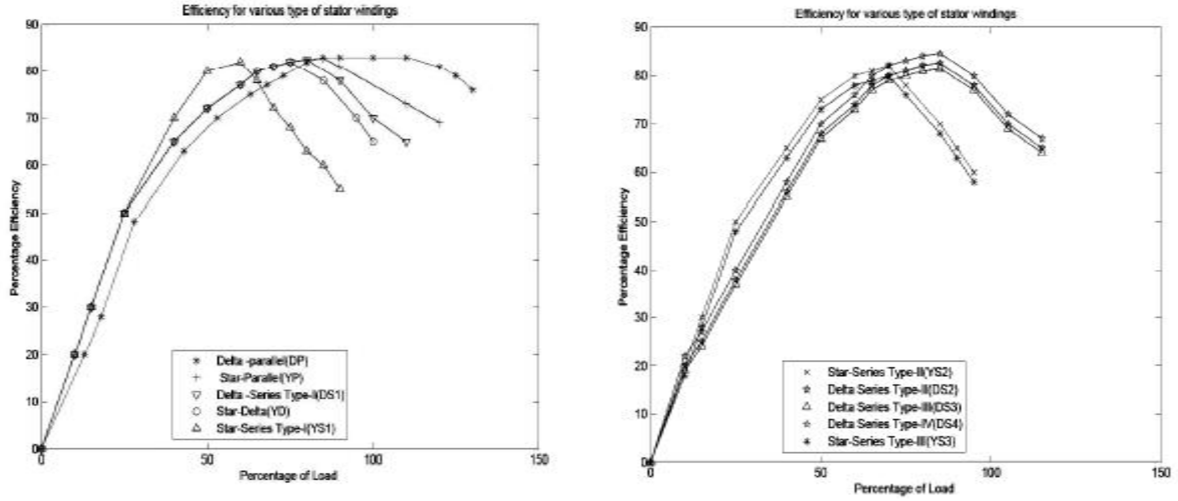


Fig. 12: Star-series type III (YS3) Connection

TABLE.1

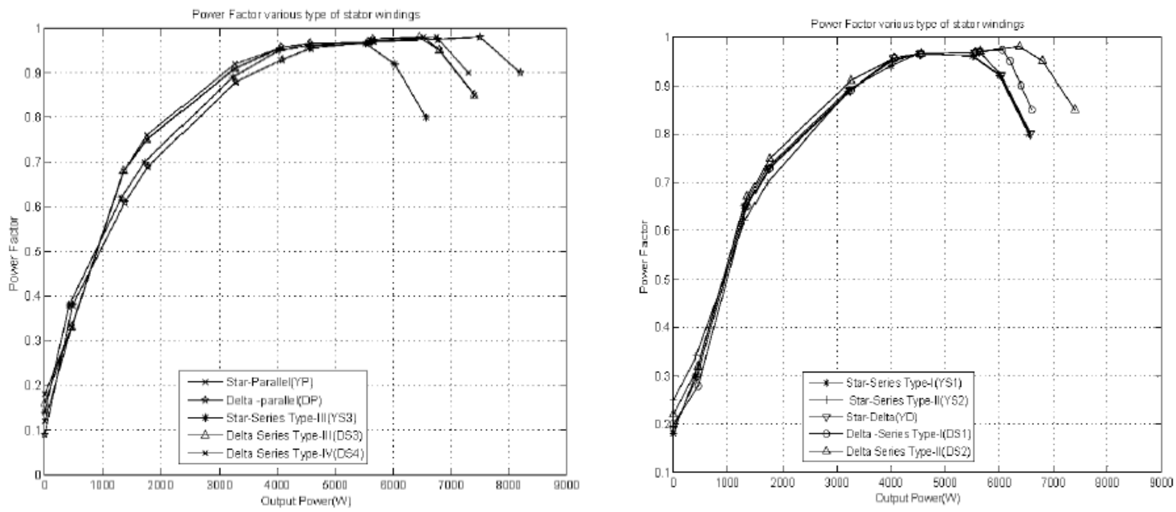
Comparison for normal design and optimal design.

Description	Normal design	Optimal design	
		Case-1	Case-2
Full-Load Efficiency (%)	84.176	**96.02**	**93.743**
Full-Load Power Factor	0.8432	**0.984**	**0.962**
Maximum Stator Temperature Rise in C°	76.437	57.431	57.320
Maximum Rotor Temperature Rise in C°	76.437	57.297.	57.341
Maximum to Full-Load Torque ratio	2.735	3.023	2.952
Starting to Full-Load Torque Ratio	1.52	1.83	1.73
Starting to Full-Load Current Ratio	4.425	5.3	5.195
Length of Stator in m	0.563	0.5175	0.5262
Diameter of Stator in m	0.387	0.3583	0.3596
Outer Diameter of Stator in m	0.448	0.5387	0.5398
Ratio L/τ	1.342	1.682	1.5932
Stack Length to Pole Pitch Ratio	1.325	-	1.7394
Stator Depth to Width ratio	4.055	-	34.923
Stator Core Depth in mm	4.239	-	119.987
Average Air gap Flux Density in wb / mm^2	0.468	18200	18300
Stator Winding Current Density in A/ mm^2	4.57	3.243	3.193
Rotor Winding Current Density in A/ mm^2	7.76	4.362	4.273
Stator Iron Loss in watts	273.450	4.7327	4.6893
Rotor Copper Loss in watts	126.720	3.284	3.19984
Stator Copper Loss in watts	287.930	7.621	7.743
Ampere Conductors per meter	18500	7.6	7.743



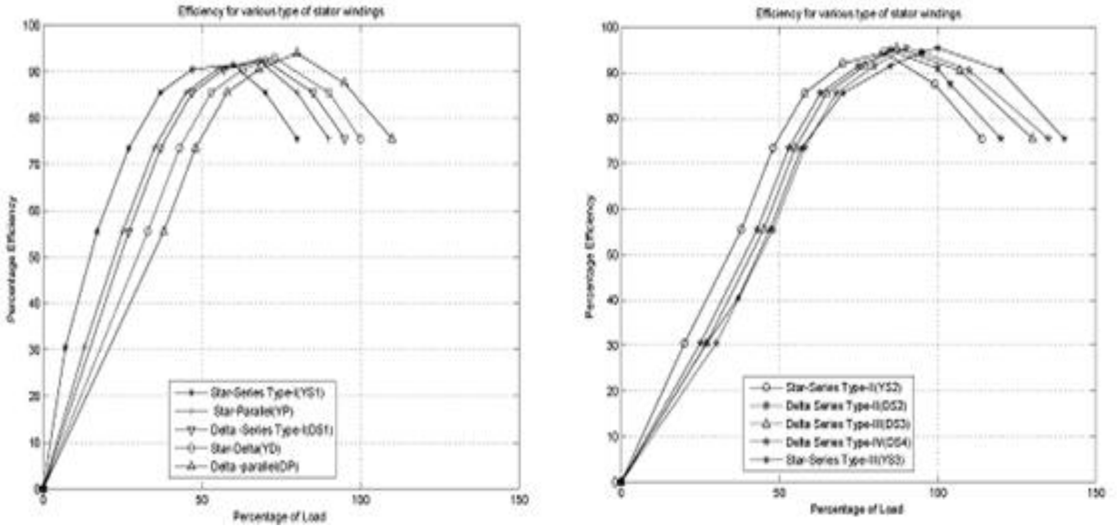
(a) (b)

Fig. 13. Efficiency as a function of load for: (a) DP, YP, DS1, YD and YS1connections;(b) YS2, DS2, DS3, DS4 and YS3 connections.



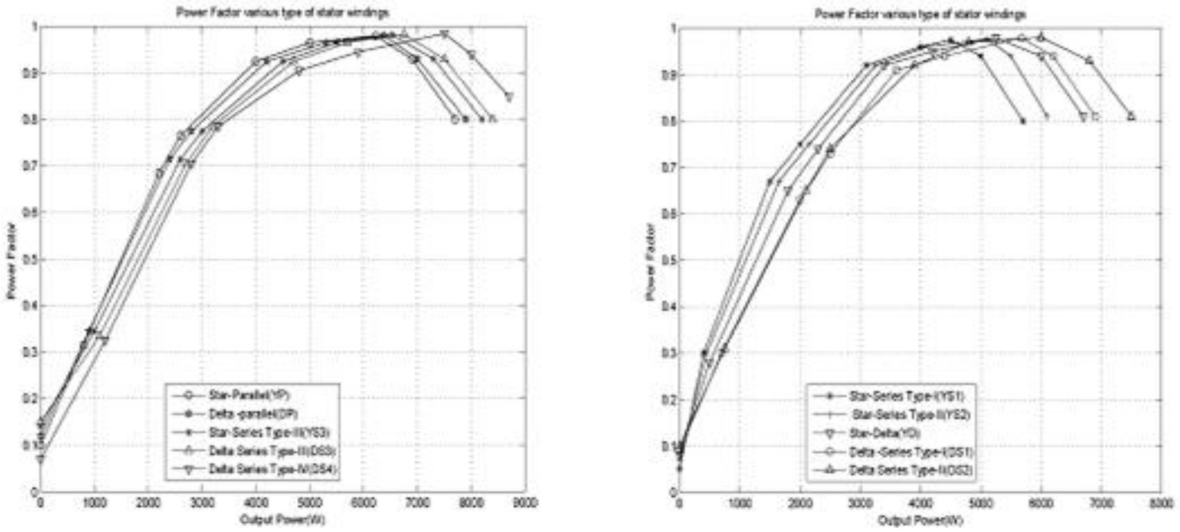
(a) (b)

Fig. 14. Power factor as a function of load for: (a) YP,DP,YS3,DS3 and DS4 connections;(b) YS1,YS2,YD,DS1and DS2 connections.



(a) (b)

Fig. 15. Efficiency as a function of load for: (a) DP, YP, DS1, YD and YS1connections; (b)YS2, DS2, DS3, DS4 and YS3 connections.



(a) **(b)**

Fig. 16. Power factor as a function of load for:(a)YS1,YS2,YD,DS1 and DS2 connections; (b)YP,DP,YS3,DS3 and DS4 connections.

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