Chapter 2

Thermal Model of Induction Motor and Parameters' Identification using PSO algorithm

2.1 Introduction

"Induction motors are the workhorses of industry"—this well-known statement reflects the overall trend to electrify an increasing number of industrial processes in the past two centuries. According to [115], despite reliability and successful operation of inductionmotors, their annual failure rate is estimated to be 3–5% up to even 12% in harsh applications. Statistics show [116] that motor bearing and stator winding insulation are the two components, which fail the most frequently. The major reason of stator damage is insulation failure, which is related to excessive heat and insufficient cooling. It is estimated that particularly in offshore applications, overheating and insulation breakdowns cause more than 30% of all stator winding failures [117]. Since downtime in operation is often more expensive than motor drive replacement (especially in the offshore industry), proper protection is required to prevent drivetrain failures, and to ensure both personnel safety and production objectives. Motor thermal protection has been an important aspect of condition monitoring of electric actuation systems—see, for instance, [118-120] and the references therein. Currently, there are numerous examples of estimation of motors' lifetime expectancies based on their thermal performance [121], application of motor thermal protection strategies [122–124], thermal modeling of electric drivetrains [125–127] and stator winding [128], thermal analysis in fault operating conditions [129], or design optimization driven by the need to reduce thermal overloads [130]. However, to the knowledge of the authors, there is limited work done in the area of thermal modeling of motor drives based on allowable loadability data provided by equipment manufacturers. Although loadability curves are among fundamental design constraints of electric drivetrains, typically, there is not enough catalog information regarding permissible duration of overloads. Since one of the main design criteria is to prevent motor drives from reaching thermal protection limits [131], this has a critical impact on designing tailor-made electric actuation systems. Therefore, the current chapter presents a method to estimate motor temperature rise under various operating conditions and ambient temperatures to verify if a given drivetrain design does not violate thermal protection limits specified by the IEC standard [132].

2.2. Thermal Protection Theory

According to [115], degradation of insulation of stator and/or rotor conductors are the two main thermal risks for an overheated machine. It is found [122] and references therein) that thermal aging of insulation can be represented as the chemical rate equation (Arrhenius equation), which has the following relationship for the life of insulation aged at elevated temperatures:

$$\mathrm{L} = \mathrm{F}e^{\frac{\vartheta}{k\varphi}} \tag{2.1}$$

Where L is life in time, F is constant which is determined by experiment, ϑ is energy of actvation in Ev, φ is absolute temperature in Kelvin and k = 0.8617×10^{-7} eV/K the Boltzman constant. The IEC standard [132] defines the permissible operating temperatures and maximum allowable temperature rises above the ambient for induction motors. Table 2.1 shows safety margins for different thermal classes. Typically, manufacturers use class F insulation with a class B rise to gain additional 25^0C safety margin [133]. The recommended maximum continuous temperature for class F is 155^0 C, which in this example consists of a maximum ambient temperature of

40^0C, permissible temperature rise of 105^0C, and a hot spot temperature margin of 10^0C. Obviously, lowering the value of ambient temperature allows for higher temperature rise, as long as the maximum limit of 155^0 C is not violated. Exceeding the thermal limit causes gradual degradation of the insulation expected lifetime. Figure 2.1 illustrates the relationship Eq. (2.1) for different classes of insulation and based on the accepted rule that thermal life is halved for each increase of 10^0C above the maximum thermal limit, according to [115] and [121]. Therefore, apart from checking if a given motor will satisfy mechanical specifications (in short— if it provides sufficient torque values at certain speeds), design engineers have to investigate if overloads do not violate thermal margins of the drivetrains they design. Motor and drive manufacturers provide guidelines and recommendations for maximum permissible thermal overload magnitudes and durations, but these suggestions are typically so general that they could only be applied in a few very specific scenarios [134–138]. To address this issue, the current chapter focuses on formulating a more general framework to examine drivetrains' thermal performance, which allows us to estimate motor temperature under various operating conditions using the available limited catalog data.

TABLE 2.1: Composition of Insulation Classes [128]

Thermal level	Class A	Class B	Class F	Class H
Max ambient temp. [℃]	40	40	40	40
Permissible temp. rise [℃]	60	80	105	125
Hot spot temp. margin [℃]	105	130	155	180

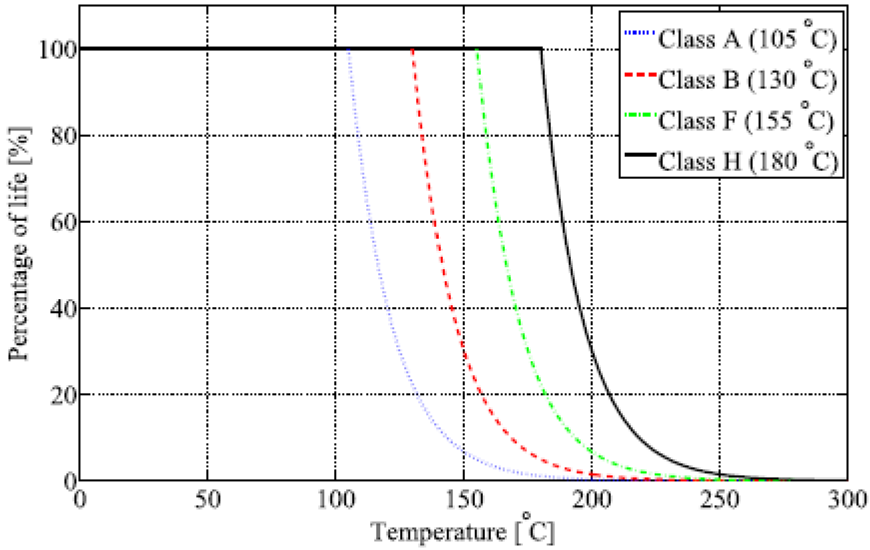

Figure 2.1: Effect of thermal aging on insulation life of motor [111].

2.3 Motor Thermal Loadability

According to manufacturers' guidelines [139] the continuous maximum load of a converter driven motor is mainly influenced by the modulation pattern and switching frequency of the converter and by the motor design. The practical solution that suppliers use is to display these guidelines in the form of loadability curves as Figure 2.2. where $\frac{T}{T_n}$ represents the torque with respect to nominal torque and $\frac{n}{n_n}$ represents the rotor speed with respect to nominal speed.

Manufacturer guidelines present the maximum continuous load torque of a motor as a function of frequency (speed) to give the same temperature rise as with rated sinusoidal voltage supply at nominal frequency and full rated load [139]. They define the maximum load of a motor above its continuous rating as well as determine a safe level of loads that a motor can withstand during steady-state operation [140]. A standard induction motor is self-ventilated [141]; therefore, at low speeds where cooling is reduced, its thermal loadability is lowered. As a consequence, the continuous output torque of the drive is derated for lower speeds, unless an external fan or other cooling method is used.

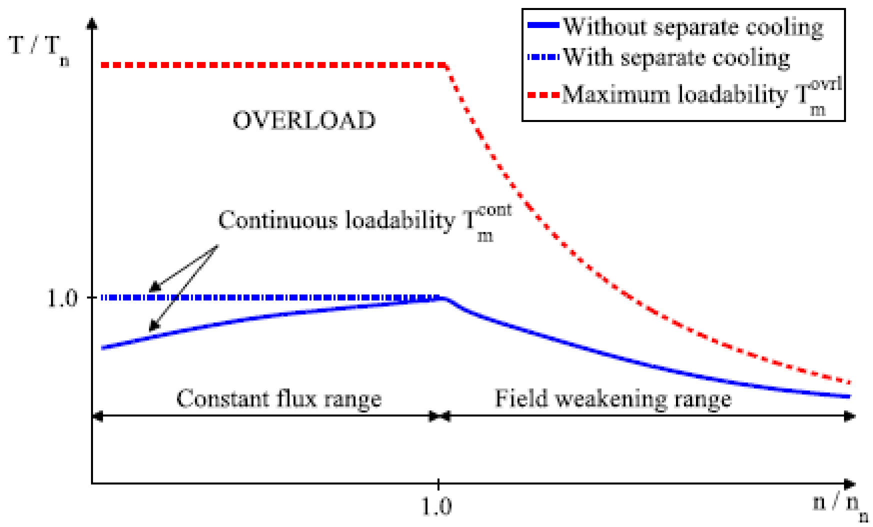

Figure 2.2: Induction motor's loadability curve in a frequency controlled drive.

The loadability curves do not specify thermal limits of a motor alone, but are applicable only to frequency controlled motors. Hence, they provide basic information about the thermal loadability of an inverter as well, which makes them a convenient tool to monitor the combined heating effect on both motor and drive. A significant drawback of loadability curves is the fact that they do not specify exactly for how long a motor drive can operate above its continuous rating. Suppliers give just rough estimates and rules of thumb, which define permissible loads only for a discrete set of operating conditions, e.g., an overload of 150% is allowed for 1min every 5 min at a given ambient temperature. Hence, investigation of drivetrain thermal performance in different operating points becomes impossible when using only the catalog data. We propose to overcome this limitation by formulating a motor thermal model, which is still based on loadability curves but which combines them with the temperature margins summarized in Table 2.1 and allows us to freely specify overload conditions and capture the phenomenon of reduced torque availability at low motor speeds.

2.4 First-Order Thermal Model

There is evidence that relatively simple models can represent major phenomena associated with thermal behavior of electric motors and drives [127]. In addition, thermal limit curves of induction motors, which are widely adopted in industry and which define safe operating times for various levels of input currents, are fundamentally equivalent to thermal protection based on the first-order thermal model [142]. Therefore, we analyze a single time constant model to represent temperature changes of a motor drive over a duty cycle. According to [115], a single time constant thermal equation describes the thermodynamic behavior of homogeneous body at rest heated by electric current

$$C\frac{d\Delta\theta(t)}{dt} = R(I_m(t))^2 - H\,\Delta\theta(t) \qquad (2.2)$$

Where,

$\Delta\theta(t) = \theta(t) - \theta_{amb}$ is machine temperature rise above the ambient temperature in Kelvin.

θ_{amb} is temperature of ambient in Kelvin.

$I_m(t)$ is current of motor in Ampere

C is heat capacity J/K

H is heat dissipation factor in running condition in W/K

R is resistance in Ohm

Eq. (2.2) considers only Joule losses; however, there exist other types of losses that contribute to the increased waste heat emission of induction motors, e.g., core losses, friction, and windage or no-load Joule stator losses. Stator winding is identified to be the most critical component, which affects thermal life of motor's insulation. Therefore, its average temperature rise is modeled by Eq. (2.2) to monitor thermal performance of the drivetrain. However, parameters of Eq. (2.2) are not those of the stator alone. Instead, they combine the effect of total losses to capture the overall heating of the induction motor drive. The overall heating capacity, on the other hand, is represented by loadability curves available in manufacturers' catalogs.

Normally, detailed parameters of motors (such as copper winding length or mass) are not available to customers, which makes it burdensome to determine fundamental thermal model parameters (R,C,H). Therefore, we further simplify the model so that it contains two unknown parameters: factor $B = \frac{R}{C}$ $[K/(s.A^2)]$, thermal time constant $\tau = \frac{C}{H}$ seconds.

According to [111] and [122]

$$\frac{d\Delta\theta(t)}{dt} = \frac{R}{C}(I_m(t))^2 - \frac{H}{C}\,\Delta\theta(t) \tag{2.3}$$

$$\frac{d\Delta\theta(t)}{dt} = B(I_m(t))^2 - \frac{1}{\tau}\,\Delta\theta(t) \tag{2.4}$$

The parameter *B* includes the combined effect of electrical and thermal resistances as well as the heat capacity of the motor.

Such a representation facilitates model identification, since what influences its response is not the individual values of parameters (R, C, H) but the ratio of electric resistance and heat capacity R/C and the thermal time constant τ . Motor current could easily be obtained given motor torque and speed values, according to [143]. Below the field weakening point, the reactive and active current components of the induction motor can be approximated as, respectively.

$$I_{sd}^{cf} = I_n(\sin(\varphi_n) + \cos(\varphi_n)\left(\sqrt{\left(\frac{T_{\max}}{T_n}\right)^2 - 1} \; - \sqrt{\left(\left(\frac{T_{\max}}{T_n}\right)^2 - \left(\frac{T_{\text{load}}}{T_n}\right)^2\right)}\right) \quad (2.5)$$

$$I_{sq}^{cf} = I_n\left(\frac{T_{\text{load}}}{T_n}\right)\cos(\varphi_n) \quad (2.6)$$

Where,

$T_{\max}$, T_{n} , and I_{n} are the motor's maximum and rated torques and current, respectively, T_{load} is the load torque, and $\cos(\varphi_n)$ is the motor's power factor. In the field weakening region, the motor's currents also depend on the motor speed n and can be approximated as (n_n is the rated motor speed)

$$I_{sd}^{fw} = I_n\left[\frac{n_n}{n}\left(\sin(\varphi_n) + \cos(\varphi_n)\left(\sqrt{\left(\frac{T_{\max}}{T_n}\right)^2 - 1}\right)\right) - cos(\varphi_n)\sqrt{\left(\frac{T_{\max}}{T_n}\cdot\frac{n_n}{n}\right)^2 - \left(\frac{T_{\text{load}}}{T_n}\cdot\frac{n}{n_n}\right)^2}\right] \quad (2.7)$$

$$I_{sq}^{fw} = I_n\left(\frac{T_{\text{load}}}{T_n}\cdot\frac{n}{n_n}\right)\cos(\varphi_n) \quad (2.8)$$

Hence, the total motor current in each respective region is

$$I_m = \sqrt{({I_{sd}}^2 + {I_{sq}}^2)} \quad (2.9)$$

Reference values of thermal time constants τ_{ref} are provided in [136] and reproduced in Table 2.2. They are treated as general guidelines when generating reference temperature rise profiles for model identification purpose.

TABLE 2.2: TypicalThermal Time Constant τ_{ref} for IMs [26]

Rated Power P_n [kW]	2 Pole [min]	4 Pole [min]	6 Pole [min]	8 Pole [min]
0.09…101	7…10	11…10	12	-
1.5…3.0	5…8	9…12	12	12…16
4.0	14	11	13	12
5.5…18.5	11…15	10…19	13…20	10…14
22…45	25…35	30…40	40…50	45…55
55…90	40	45…50	50…55	55…65
110…132	45…50	55	60	75

However, at this stage, it is sufficient to assume their values as listed in Table 2.2 to illustrate the practicality of the proposed thermal modeling and estimation method. Even though the single time constant model is not always adequate to represent detailed temperature changes in a motor [118] (e.g., in reality, there might be multiple time constants that describe temperature rise in the stator), it is still an effective method to quickly assess thermal protection levels of motor drives in industrial applications [115]. Therefore, the values presented in Table 2.2 are suitable to only roughly approximate thermal response of the stator. Although this is not an ideal approach and it requires further experimental validation, it is already by all means more practical (and equally accurate) than relying on a discretized set of allowable overload durations provided in catalogs. In addition, there are the following limitations of the proposed method.

1) It is not applicable for checking the intermittent temperature rise caused by the motor starting current (i.e., a short-term overload with approximately 6 I_n).

2) In general, parameters of the thermal model depend on speed, load (torque/current), and temperature. In this study, however, the parameter B depends only on the motor speed.

3) Similarly, the thermal time constant τ_{ref} is constant for a given motor, whereas in reality, it depends on the operating speed as well.

2.5 Parameters' Identification as an Optimization Problem

Identification of unknown model parameters can be analyzed in the same way as an optimization problem where the cost function to be minimized is the error between the original and estimated signals with optimization variables being the model parameters [144]. In general, an optimization problem has the form [145].

$$\text{minimize } f_o(x)$$
$$\text{subject to } f_i(x) \le b_i, \qquad i=1,\ldots\ldots,k \tag{2.10}$$

The vector $x = (x_1, \ldots\ldots.. x_n)$ is the optimization variable of the problem, the function $f_o\colon R^n \to R$ is the objective function, the functions $f_i\colon R^n \to R$, i=1,……,k are the (inequality) constraint functions, and the constants $b_1, \ldots\ldots.. b_k$ are the limits for the constraints. A vector x^* is called optimal, or a solution of the Eq. (2.10), if it has the smallest objective value among all vectors that satisfy the constraints. An optimization problem of such a general form is called a nonlinear program [146]. Identification of parameters of the thermal model Eq. (2.4) is, therefore, represented as the following nonlinear optimization problem:

$$\begin{bmatrix} x_{1,1} \\ x_{2,1} \end{bmatrix} = \begin{bmatrix} x_{1,inti} \\ x_{2,inti} \end{bmatrix}$$

$$\text{For } j = 1 \text{ to } m$$

$$\min J$$

where

$$J = \sum_{i=1}^{r} \left(\Delta\theta_{i,j}^{ref} - \Delta\hat{\theta}_{i,j}^{ref}\right)^2$$

$$\text{subject to} \quad \begin{bmatrix} b_{min}^{B} \\ b_{min}^{\tau} \end{bmatrix} \le \begin{bmatrix} x_{1,j} \\ x_{2,j} \end{bmatrix} \le \begin{bmatrix} b_{max}^{B} \\ b_{max}^{\tau} \end{bmatrix} \tag{2.11}$$

where,

x is the vector of parameters (x_1 = B and x_2 = τ), J is the cost function to be minimized, (b_{min}, b_{max}) are the constraint vectors, and x_{init} is the vector of initial values of parameters. The estimated temperature $\Delta\hat{\theta}_{i,j}$ is obtained by solving Eq. (2.4) at each evaluation point *j* and time instant *i*. The length of the time vector *r* should be long enough for the motor temperature to settle at a steady-state value, whereas the final number of evaluation points m depends on how frequently we update the model with a new set of parameters. The reference temperature rise $\Delta\theta^{ref}(t)$ corresponds to an increase in motor temperature at each point of motor continuous loadability curve illustrated in Figure 2.2 It follows the first-order model:

$$\Delta\theta^{ref}(t) = \Delta\theta_{max}(1 - \exp\,(\frac{-t}{\tau_{ref}})) \tag{2.12}$$

where the maximum operating temperature $\Delta\theta_{max}$ is taken from Table 2.1 for a given motor insulation class, whereas the reference thermal time constant τ_{ref} reflects the size of the motor, as presented in Table 2.2.

2.6 Particle Swarm Optimization (PSO) Algorithm

Particle Swarm Optimization (PSO) algorithm is a stochastic optimization method which is based swarm and suggested by Eberhart and Kennedy [147]. It simulates social behavior of animals including fishes and birds. These swarms conform a collective way for finding food, and every member in the swarms keeps changing the pattern of search according to the learning experiences of its own and other members. In order to demonstrate invention background and improvement algorithm of the PSO, we first introduce the simple early model, Boid (Bird-oid) model [148]. This model is intended to simulate the birds' behavior, and it is a direct source of the PSO technique.

The simplest model of PSO can be described as follows. Each entity of the birds is represented by a point in system of cartesian coordinate, and arbitrarily assigned with the initial position and velocity. Then run the program in agreement with "the nearest proximity velocity match rule," so that one entity has the identical speed as its adjacent neighbor. With the same way the iteration going on, all the points will achieve the same velocity rapidly. Since this model is very simple and not fit for the real cases, in speed item a random variable is added. That is to say, at each iteration, aside from meeting "the nearest proximity velocity match," every speed will be added with a random variablemsuch that the simulation approaches to the real case. Heppner proposed a "cornfield model" for simulating the behavior of foraging of a group of birds [149]. Let us assume that there was a "cornfield model" on the plane, i.e., food's location, and at the beginning birds sre randomly dispersed on the plane. For finding the location of the food, birds moved inaccordance with the subsequent rules. First, we suppose that cornfield position in the coordinate of the is (a_0,b_o), and position and velocity coordinates of individual bird are (a,b) and (v_a , v_b), respectively. For measuring the the performance of the recent position and speed the distance between the recent position and cornfield has been used. The extra the distance to the "cornfield", the superior the performance, on the converse, the performance is inferior. Assuming that every bird has the memory skill and can memorize the best position it ever reached, denoted as *pbest*, *m* is velocity adjusting constant, *rand* denotes a random number in [0,1], change in the velocity item can be set according to the following rules:

$$\text{if } a > pbest\ a,\ v_a = v_a - rand \times \text{m, otherwise, } v_a = v_a + rand \times \text{m} \tag{2.13}$$

$$\text{if } b > pbestb,\ v_b = v_b - rand \times \text{m, otherwise, } v_b = v_b + rand \times \text{m} \tag{2.14}$$

Now assume that the swarm can communicate in some way, and each entity has its ability to know and remember the best location (i.e. *gbest*) of the total swarm so far.

And n is the velocity adjusting constant; then, after the velocity item was adjusted according to above rules, it must also update according to the following rules:

$$\text{if } a > gbesta,\ v_a = v_a - rand \times \text{n} \text{ , otherwise, } v_a = v_a + rand \times \text{n} \tag{2.15}$$

$$\text{if } b > gbestb,\ v_b = v_b - rand \times \text{n}\text{, otherwise, } v_b = v_b + rand \times \text{n} \tag{2.16}$$

Results shows by the computer simulation that if *m/n* is relatively large, all individuals will group to the "cornfield" quickly; on the other way, if *m/n* is small, the particles will group around the "cornfield" unsteadily and slowly. Through this simple simulation, it can be found that the swarm can find the optimal point rapidly. Inspired by this model, Kennedy and Eberhart [150] derived an evolutionary optimization algorithm, after a sea of trials and errors, they lastly fixed the basic algorithm as follows:

$$v_a = v_a + 2 * rand * (pbesta\text{-}a) + 2 * rand * (gbesta\text{-a}) \tag{2.17}$$

$$a = a + v_a \tag{2.18}$$

Since they abstracted each individual to be a particle (without mass and volume) , with only position and velocity, so they called this algorithm as "particle swarm optimization algorithm.

On the basis of this, PSO algorithm can be summarized as follows: PSO algorithm is a type of searching method which is based on swarm, in which each individual is called a particle defined as a potential solution of the optimized problem in *D*-dimensional search space, and it can memorize the swarm optimal position and that of its own, in addition to the velocity. In each generation, the particles information is collective together for adjusting the velocity of each dimension, which is used to calculate the particle's new position. Particles change their states continuously in the search space which is multi-dimensional, until they reach balance or optimal state, or beyond the calculating limits. Unique connection among different dimensions of the problem space is introduced via the objective functions. Many empirical evidences have showed that this algorithm is an effective optimization tool. Flowchart of the PSO algorithm is shown in Figure 2.3.

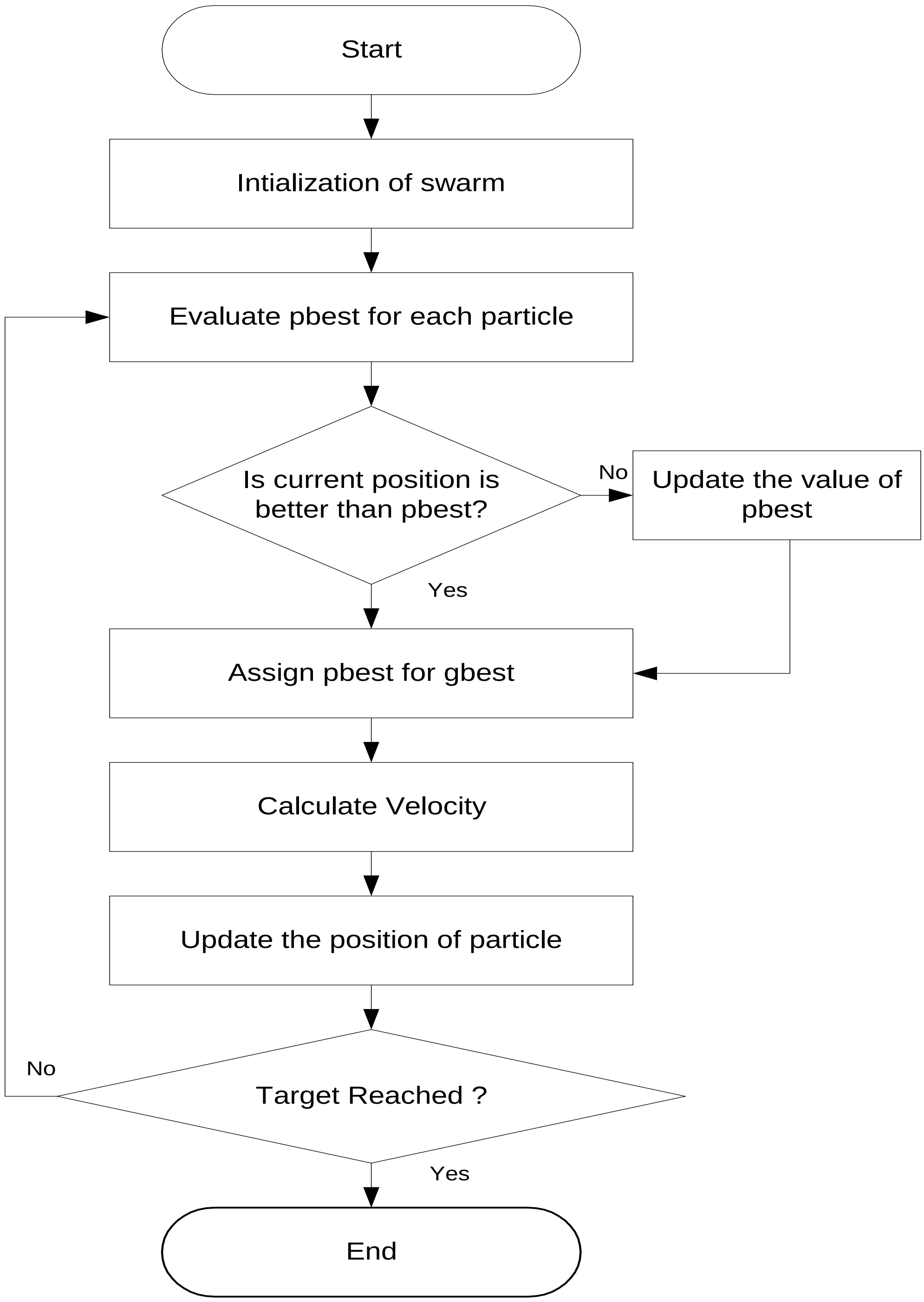

Figure 2.3: Flowchart of the PSO algorithm

PSO algorithm has two versions, called global version and local version, respectively. In the global version, two extremes that the particles track are the optimal position *pbest* of its own and the optimal position *gbest* of the swarm. Accordingly, in local version, aside from tracking its own optimal position *pbest,* the particle does not track the swarm optimal position *gbest*, instead it tracks all particles' optimal position *nbest* in its topology neighborhood.

2.7 Parameters' identification using PSO Algorithm

The underlying assumption for constructing a loadability curve is that at each value of speed and the corresponding torque, the temperature rise is the same, as in section 2.3. Therefore, the loadability curve for a self-ventilated motor from Figure 2.2 is discretized into m points, such that the identified parameters of the thermal model Eq. (2.4) depend on the motor speed n. At each evaluation point, the thermal model is simulated, and its parameters (B,τ) are adjusted until its response is as close to the reference temperature rise Eq, (2.12) as possible. Then, the optimization routine Eq. (2.11) saves those identified parameters, which yield the minimum error signal and moves on to the next evaluation point. In the current chapter, we use the PSO algorithm to achieve the best convergence of the model's response so that the sum of squared errors between the reference and estimated temperatures is negligible. The motor which have used in parameter identification is 45 kW; specifications are given in Table 2.3.

Table 2.3: Specifications of IM for parameter identification

Parameters	Rated power P_n	Rated torque T_n	Max.Torque T_{max}	Rated speed n_n	Rated current I_n	Power factor φ_n	Time constant τ_{ref}
Value	45 kW	290 N-m	3.2 T_n	1480 rpm	81.3	0.85	40 min

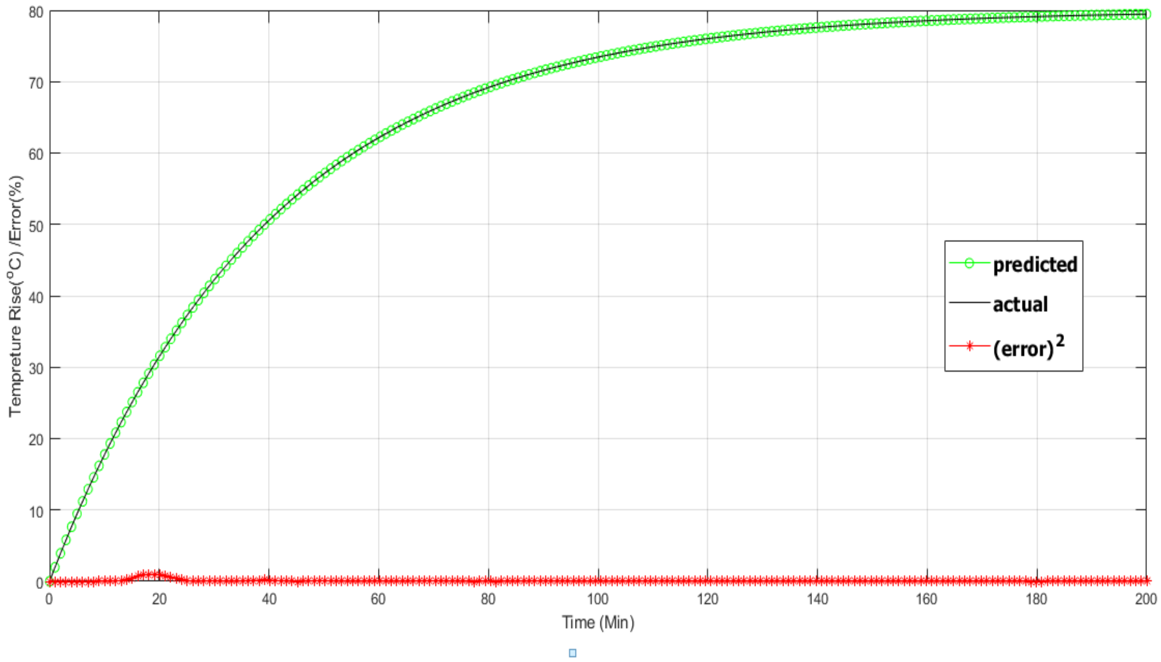

Figure 2.4: Temperature tracking using PSO

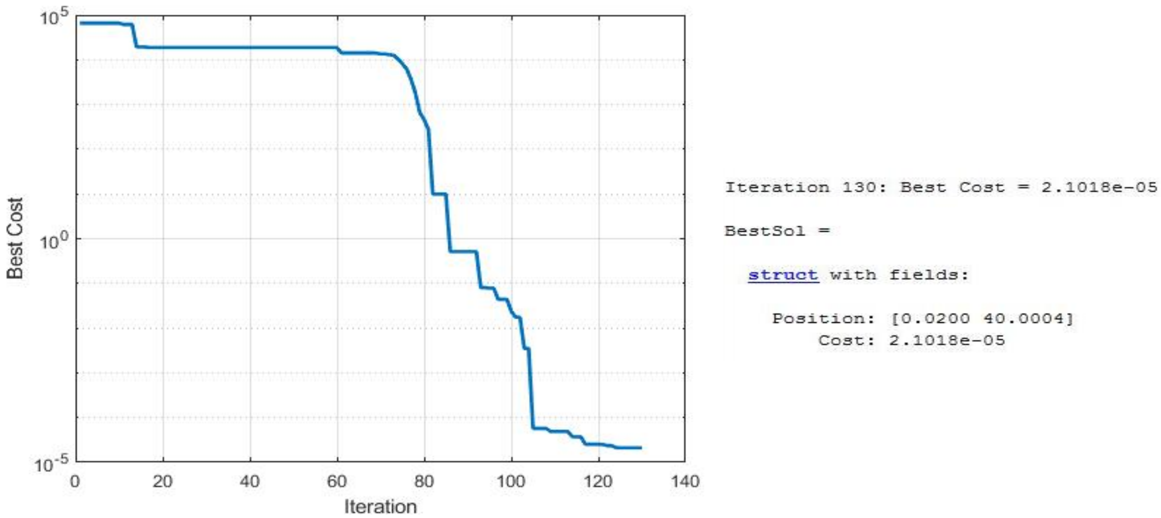

Figure 2.5: Best cost Vs iteration using PSO

2.8 Result and Discussion

PSO algorithm is implemented in the processor, Intel® Core™ i5-6200U CPU @2.30GHz with memory (RAM) of 8 GB and the value of the cognitive parameters c_1 and c_2 were 0.2 and 0.3 respectively. The formulation of the objective function as mentioned in equation number Eq. (2.10) and Eq. (2.11) subjected to the constraints was considered and final value of the optimized parameters B = 0.02 and $\tau = 40.00$ as obtained by PSO after 130 iterations with convergence error of 2.1018×10^{-5}.Thus PSO is proved to be a suitable optimization technique in order to design the thermal relay for protection objective of induction motor.

The Figure 2.4 reflects the tracking performance of the rise in temperature with that of estimated value of the rise in temperature. The above two curves concides with efficacy of PSO algorithm, in context of convergence which can be subsequently adapted for the design of thermal relay.

2.9 Conclusion

The PSO being a strong candidate for the optimization scheme is explored in the above work in order to obtain the relevant parameter B and τ respectively. The obtained result exhibits the satisfactory performance for the parameter identification scheme. The detailed protection scheme for proper discrimination of voltage unbalance with that of overload is discussed in next chapter.