A Novel Analytical Approach Using Rough Set and Genetic Algorithm of a Stable Sensorless Induction Motor Drives in the Regenerating Mode

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ABSTRACT A novel approach for optimized observer feedback gains of a stable sensorless induction motor (IM) drives at very low speeds in the regenerating mode is presented. The proposed approach depends on the rough set (RS) and genetic algorithm (GA) in a cascading construction. The RS is used to obtain the most dominant machine parameters that affect the stability of the sensorless IM drive at very low speeds in the regenerating mode. The parameter’s values are randomly selected to investigate their influence on the stability. Then, a reduction is obtained for the most dominant machine parameters affecting the stability. GA is applied to search for the optimal design of the observer feedback gains under the dominant parameter deviation. The proposed RS theory and GA guarantees a stable speed estimate and efficient sensorless IM drive at very low speeds in the regenerating mode. Theoretical analysis, design procedure, and simulation work of the proposed approach are presented. A sensorless IM drive is executed in the laboratory using the digital signal processor (DSP)-DS1104 control board. Extensive results in the different operating conditions to verify the efficacy of the proposed approach are presented and compared with previous works.

INDEX TERMS Rough set theory, genetic algorithm, sensorless drive, observers, parameters deviation.

NOMENCLATURE

\( v_{ds}, v_{qs} \) dq stator voltages
\( i_{ds}, i_{qs} \) dq stator currents
\( i_{dr}, i_{qr} \) dq rotor currents
\( \lambda_{ds}, \lambda_{qs} \) dq stator flux linkages
\( \lambda_{dr}, \lambda_{qr} \) dq rotor flux linkages
\( R_s, R_r \) stator and rotor resistances
\( L_m \) magnetizing inductance
\( L_s, L_r \) stator and rotor inductances
\( \omega_r \) rotor speed
\( \hat{\omega}_r \) estimated rotor speed
\( K_1, K_2 \) observer feedback gains
\( e_{id}, e_{iq} \) errors of dq stator currents
\( e_{idr}, e_{idr} \) errors of dq rotor flux linkages

\( \hat{\omega}_r, \hat{\omega}_q \) speed estimation error
\( \Delta \omega_r \) estimated dq stator currents
\( K_{P\omega}, K_{I\omega} \) proportional and integral gains of speed adaptive law
\( \hat{R}_s, \hat{R}_r \) estimated rotor resistance
\( K_{PR}, K_{IR} \) proportional and integral gains of stator resistance adaptive law
\( \hat{e}_{id}, \hat{e}_{iq} \) vector of stator current error
\( \hat{e}_{idr}, \hat{e}_{idr} \) vector of rotor flux linkages
\( \hat{\lambda}_{dr}, \hat{\lambda}_{qr} \) estimated dq rotor flux linkages

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A = 
\[
\begin{bmatrix}
A_{11} & A_{12} \\
A_{21} & A_{22}
\end{bmatrix}
\]
coefficient matrix of IM model with actual values

\hat{A}

coefficient matrix with estimated parameters

\Delta A = \hat{A} - A
estimated error of coefficient matrix

\omega_b
frequency of rotor flux.

I. INTRODUCTION

Sensorless control of an induction motor (IM) has become very important in the field of electric drive applications. Thus, knowledge of speed and flux is crucial for attaining a speed-sensorless control of IM. Nevertheless, Hall sensors and encoders reduce system reliability and robustness. Also, they increase the size, installation costs, add extra wiring of IM drives; and restrict their applications in a relatively harsh environment [1]. Therefore, many sensorless methods have been developed in recent years. They minimize installation costs and attain a reliable and robust drive system. Also, they are considered a good alternative in hostile environments; and in case of sensor failure [2].

Several kinds of approaches that use state observer theory have been developed for sensorless IM drives. They include full-order observers [3]–[5], reduced-order observers [6], [7], extended Kalman filters [8], nonlinear observers [9], [10], and sliding mode observer [11], [12].

Adaptive flux observer (AFO) as one of the state observers-based methods of sensorless IM drives guarantees robust and precise estimation at high and medium speeds [13]. But, its robustness and precision depend primarily on the accuracy of the motor parameters [14]. This issue is highly raised during the operation in the regenerating mode at very low and zero speeds [15]. Observer feedback gains are the main reason for this obstacle. Their design should be precisely guaranteed to remedy speed divergence and instability during the operation in the regenerating mode at very low and zero speeds. Also, the deviation of parameters should be taken into account in selecting the observer feedback gains of AFO [15].

Recently, significant research works have been presented to design a stable AFO [13]–[25]. Routh–Hurwitz based-stability analysis determined the unstable issue of AFO in the regenerative region due to unstable zeros [13]. The Lyapunov criterion was used to design AFO gains for good tracking performance [14]. The coupling between estimation loops of speed and stator resistance, which may be the main cause for instability of AFO, was treated in [15]–[17]. Stability analysis using the Routh-Hurwitz criterion and root-locus was used to illustrate the stable and unstable regions of AFO. In [18], the coupling among three estimators of speed, rotor resistance, and stator resistance was neglected for simplified purposes. However, the coupling among the three estimators was introduced in [19]. Complete stability conditions for fast convergence of current and speed estimations of reduced-order and full-order observers were derived from the Routh–Hurwitz criterion and the linearized error dynamics [20]. A linearized model of AFO was derived for stability analysis using the Routh-Hurwitz criterion or root-locus plot [21]–[24]. In [25], adaptive law and parameter adaptation were proposed to enhance the AFO robustness to parameters deviation. The convergence rate of AFO was enhanced using tuned feedback gains in [26]. Speed estimators using model reference adaptive system and AFO methods were compared during the operation in the regenerating mode [27]. The effect of the gross error on AFO stability was alleviated by selecting the feedback gains using a scaling factor [3]. To remedy the observability issue of AFO around zero speed without signal injection, a stator voltage error was added to the speed estimator in [28]. AFO with an auxiliary adaptive variable in the observer state matrix was proposed in [29] and compared with previous AFO methods in the regenerating mode. The unobservable issue of low speed was treated using a virtual voltage injection method; and the stability was proved by Lyapunov’s stability theorem [30]. An estimated speed error due to the virtual voltage injection was compensated in [31]. The stability method was analyzed using the input-state-stability concept. The observability of rotor speed and stability of the transfer function of the sensorless IM drive were analyzed in [32].

In a sensorless IM, it is well-known that the speed sensor is omitted. Thus, the estimated speed is used instead of the actual speed for closed-loop control. The machine model-based sensorless methods use the mathematical model of IM for speed estimation. This depends on the machine parameters and variables. Machine parameters affect the speed estimation accuracy, particularly at low speeds. The literature review stated that the effect of machine parameters is a big challenge of the stability and performance of the sensorless IM drive in the low-speed region, particularly in the regenerating mode [33]. Usually, some of these parameters are predefined and kept constant during the operation of the IM drive. Previous works were presented to estimate these parameters to increase the accuracy of the estimation algorithms, particularly at very low speeds [7], [34], [35]. These works assume that the estimated parameters are variable parameters and the other parameters are kept constant. Actually, all parameters may be simultaneously changed under the operating conditions. Estimation of all the machine parameters may lead to accurate speed estimation. However, both the complexity and computation time are highly increased. A high fast microprocessor is required, and accordingly, the cost is increased.

This article proposes a new approach using the rough set (RS) theory to deal with the issue of simultaneous changes of machine parameters. This is the main difference between the proposed algorithm compared with other works. The RS theory is applied to obtain the most dominant machine parameters affecting the stability of the sensorless IM drive at very low speeds in the regenerating mode. The parameter’s values are randomly selected to investigate their influence on the stability. Then, a reduction is obtained for the most dominant parameter affecting the stability and performance of a sensorless IM drive. Accordingly, optimal observer...
feedback gains under the dominant parameter variation using the genetic algorithm (GA) are designed. Stable and unstable regions of AFO are analyzed under the parameter’s deviation, particularly in the regenerating mode of operation. Dominant zero location is studied under the parameter’s deviation using both zero observer feedback gains and optimized observer feedback gains. The proposed design achieves a stable AFO for the sensorless IM drive at low speeds in the regenerating mode. Experimental results at low speeds in the regenerating mode are presented to prove the effectiveness of the proposed approach and compared with previous works.

The article is organized as follows: Section II introduces the mathematical models of IM and AFO. RS theory is presented in Section III. Section IV discusses the optimization of the observer feedback gains using GA. In Section V, the experimental system setup of sensorless IM drive and the experimental results are presented in detail. A comparison with previous works is introduced in Section VI. Finally, Section VII presents the conclusion.

II. MATHEMATICAL MODELS

A. MODEL OF AN IM

The d-q model of the IM is defined in a stationary reference frame as (1).

\[
\begin{align*}
\dot{p}i_{ds} &= bv_{ds} + ai_{ds} + c\lambda_{dr} + d\omega_r\lambda_{qr} + K_1e_{id} \\
\dot{p}i_{qs} &= bv_{qs} + ai_{qs} + c\lambda_{qr} - d\omega_r\lambda_{dr} \\
\dot{p}\lambda_{dr} &= g_{ds} - \omega_r\lambda_{qr} - f\lambda_{dr} \\
\dot{p}\lambda_{qr} &= g_{qs} + \omega_r\lambda_{dr} - f\lambda_{qr}
\end{align*}
\]

where,

\[
\begin{align*}
a &= \left( \frac{R_s}{L_s} + \frac{L_m^2}{\sigma L_s T_r L_r} \right), \quad c = \frac{1}{\sigma T_r}, \quad d = \frac{1}{\varepsilon}, \quad \varepsilon = \frac{\sigma L_o L_r}{L_m} \\
b &= \frac{1}{\sigma L_s}, \quad \sigma = 1 - L_m L_s L_r, \quad T_r = \frac{L_r}{R_r}, \quad f = \frac{1}{T_r}
\end{align*}
\]

B. MODEL OF AN AFO

The AFO is derived using (1) as given in (2):

\[
\begin{align*}
\dot{p}i_{ds} &= bv_{ds} + ai_{ds} + c\lambda_{dr} + d\omega_r\lambda_{qr} + K_1e_{id} \\
\dot{p}i_{qs} &= bv_{qs} + ai_{qs} + c\lambda_{qr} - d\omega_r\lambda_{dr} + K_2e_{iq} \\
\dot{p}\lambda_{dr} &= g_{ds} - \omega_r\lambda_{qr} - f\lambda_{dr} \\
\dot{p}\lambda_{qr} &= g_{qs} + \omega_r\lambda_{dr} - f\lambda_{qr}
\end{align*}
\]

where, \(K_1\) and \(K_2\) are the current observer feedback gains, \(e_{id} = \hat{i}_{ds} - i_{ds}\), and \(e_{iq} = \hat{i}_{qs} - i_{qs}\).

The errors of dq stator currents and dq rotor fluxes are derived using (1) and (2):

\[
\begin{align*}
pe_{id} &= ae_{id} + ce_{id} + d\omega_r e_{iq} + d\lambda_{qr} \Delta \omega_r + K_1e_{id} \\
pe_{iq} &= ae_{iq} + ce_{iq} - d\omega_r e_{id} - d\lambda_{dr} \Delta \omega_r + K_2e_{iq} \\
pe_{e_{id}} &= ge_{id} - \omega_r e_{id} - \lambda_{dr} \Delta \omega_r - fe_{id} \\
pe_{e_{iq}} &= ge_{iq} + \omega_r e_{iq} + \lambda_{dr} \Delta \omega_r - fe_{iq}
\end{align*}
\]

where, \(\Delta \omega_r = \omega_r - \omega_r, e_{id} = \hat{i}_{dr} - \lambda_{dr}, e_{iq} = \hat{i}_{qr} - \lambda_{qr}\).

The speed and stator resistance are estimated by (4) and (5).

\[
\dot{\omega}_s = \left( K_{P_o} + K_{I_o} \int dt \right) \frac{e}{T_s} J_{\omega}^2 \\
\hat{R}_s = \left( K_{P_r} + K_{I_r} \int dt \right) \frac{e}{T_r} \frac{\hat{J}_{\omega}}{J_{\omega}}
\]

Fig. 1 presents a block diagram of the proposed sensorless IM with indirect field oriented control (IFOC) technique.

C. ANALYSIS OF SPEED OBSERVER

Stability of AFO in the regenerating mode at low speeds is analyzed to examine the conditions of stable and unstable operation under parameters deviation. The transfer function of the speed observer can be derived for this purpose.
The speed is considered as a variable parameter. Using (3), stator current and flux errors can be derived as given in (6).

\[ p\epsilon_i = (A_{11} - K)\hat{\epsilon}_i + A_{12}\hat{\epsilon}_r + \Delta A_{12}\lambda^s_r + \Delta A_{11}\lambda^p_r \]  

(6a)

\[ p\epsilon\lambda = A_{21}\hat{\epsilon}_i + A_{22}\hat{\epsilon}_r + \Delta A_{22}\lambda^s_r \]  

(6b)

where,

\[ A_{11} = aI, A_{12} = cl + \omega_d J, A_{21} = gl, \]

\[ A_{22} = -eA_{12}\hat{\epsilon}_\lambda = \lambda^s - \lambda^p, \]

\[ \Delta A = \hat{A} - A = \begin{bmatrix} \Delta A_{11} & \Delta A_{12} \\ \Delta A_{21} & \Delta A_{22} \end{bmatrix} \]

The matrix \( \Delta A \) can be calculated with taking into account that the speed is a variable parameter. This yields:

\[ \Delta A_{11} = 0, \Delta A_{12} = \frac{\Delta \omega J}{\epsilon}, \Delta A_{21} = 0, \Delta A_{22} = -\Delta \omega J \]

Equation (6) can be transformed to s-domain using Laplace transform as follows:

\[ [sI - (A_{11} - K)]\hat{\epsilon}_i = A_{12}\hat{\epsilon}_r + \Delta A_{12}\lambda^s_r + \Delta A_{11}\lambda^p_r \]  

(7a)

\[ [sI - A_{22}]\hat{\epsilon}_\lambda = A_{21}\hat{\epsilon}_i + \Delta A_{22}\lambda^s_r \]  

(7b)

Using (7a) and (7b), the relation between the stator current error and the speed error is derived using (8):

\[ \tilde{\epsilon}_\omega = G_{\omega}(s) \cdot J\lambda^s_r \Delta \omega_r \]  

(8)

where,

\[ G_{\omega}(s) = \frac{s^2I + s(a_1I + a_2J) + (a_3I + a_4J)^{-1}}{\epsilon} \]

\[ a_1 = \left( \frac{R_s}{\sigma L_s} + \frac{L^2_m}{\sigma L_s T_m \epsilon T_r} + \frac{1}{T_r} + K_1 \right) \]

\[ a_2 = (K_2 - \omega_r) \]

\[ a_3 = \frac{1}{T_r} \left( \frac{R_s}{\sigma L_s} + \frac{L^2_m}{\sigma L_s T_m \epsilon T_r} + \frac{L_m}{\epsilon T_r} + K_1 \right) + K_2 \omega_r \]

\[ a_4 = \frac{K_2}{T_r} - \omega_r \left( \frac{R_s}{\sigma L_s} + \frac{L^2_m}{\sigma L_s T_m \epsilon T_r} + \frac{L_m}{\epsilon T_r} + K_1 \right) \]

Then, equation (8) gives

\[ \epsilon_{1q} = \lambda^s_r \left( G'_{\omega_{22}}(s) \Delta \omega_r \right) \]

(10)

It should be noted that \( G'_{\omega_{22}}(s) \) onto the rotor reference frame is derived using (11), as shown at the bottom of the next page. Derivation of stability conditions of AFO proved that the main stability problem of AFO is the design of the feedback gains \( (K_1 \) and \( K_2) \) in the regenerating mode of operation [15], [21], [24], [25], [27].

### III. ROUGH SET THEORY

At the starting of 1980, an approach called RS is first advanced by mathematician Pawlak [36]. It is considered a mathematical tool to treat vague and imprecise. RS theory is defined as one of the first non-statistical approaches in data analysis. It is in a state of continuous progress. Today, the extent of RS applications is much wider than in the past. These applications are mainly in the fields of medicine, analysis of database attributes, and process control.

There is a similarity between the RS theory and fuzzy set theory. However, the description of uncertainty and imprecision is the main difference between the two methodologies. RS theory expresses the uncertainty and imprecision using a boundary region of a set. But, the fuzzy set theory expresses the uncertainty and imprecision by a partial membership [36], [37].

RS methodology focuses on the analysis and classification of uncertain, imprecise, or incomplete information and knowledge. The basic concept of RS theory is to approximate the lower and upper spaces of a set. The approximation of spaces is being the formal classification of knowledge regarding the interest domain. Lower approximations generate a subset characterized by objects that will definitely form part of an interesting subset. The upper approximation is characterized by objects that will possibly form part of an interesting subset. Every subset introduced through upper and lower approximation is recognized as RS [38], [39].

A detailed explanation of the basic concepts of RS theory with the mathematical modelling is presented in Appendix A. An illustrative example using a step by step procedure to explain the theoretical analysis of RS theory is also introduced.

### A. INFORMATION SYSTEM (DECISION TABLE)

An information system is a table that composed of objects (rows) and attributes (columns). This table represents the data that will be used by RS. In which, each object has a given amount of attributes. Table 1 shows the information system. Finite cases of machine parameters are introduced in rows as the objects. The columns are defined as attributes which represents the variables value of the machine parameters. The decision attribute is the result of each case due to the variables attributes. The first step of the proposed rough set-based is to construct the decision table as shown in Table 1. It is mainly consisting of number objects \( n \) (\( x_1 \) to \( x_n \)) in the universe \( U \). The number of IM parameters \( (R_s, R_t, L_s, L_t, L_m) \) is defined as condition attributes. The decision attribute \( (D) \) represents the AFO stability using the transfer function of speed estimator as given in (11).

#### TABLE 1. Decision table of rough set.

| \( U \) | Condition Attribute (Parameters of IM) | Decision Attribute |
|---|---|---|
| \( R_s \) | \( R_t \) | \( L_s \) | \( L_t \) | \( L_m \) | \( D \) |
| \( x_1 \) | 8.067 | 4.163 | 0.018 | 0.021 | 0.371 | 1.391 |
| \( x_2 \) | 8.596 | 4.467 | 0.019 | 0.022 | 0.445 | 1.495 |
| \( x_3 \) | 8.830 | 4.521 | 0.021 | 0.025 | 0.450 | 1.500 |
| \( x_4 \) | 9.368 | 4.813 | 0.025 | 0.022 | 0.362 | 1.230 |
| \( x_5 \) | \( \cdot \) | \( \cdot \) | \( \cdot \) | \( \cdot \) | \( \cdot \) |
| \( x_{10} \) | 9.395 | 4.360 | 0.024 | 0.022 | 0.462 | 1.568 |
TABLE 2. Definition of attribute coding.

| Attributes | Code |
|------------|------|
|            | 0    | 1    | 2    |
| C1 R_s     | 8.726 ≤ C1 ≤ 9.964 | 9.964 ≤ C1 |
| C2 R_s     | 4.296 ≤ C2 ≤ 4.907 | 4.907 ≤ C2 |
| C3 L_s     | 0.0205 ≤ C3 ≤ 0.0236 | 0.0236 ≤ C3 |
| C4 L_r     | 0.0206 ≤ C4 ≤ 0.0235 | 0.0235 ≤ C4 |
| C5 L_m     | 0.3843 ≤ C5 ≤ 0.4389 | 0.4389 ≤ C5 |
| D d        | 1.3136 ≤ D ≤ 1.564 | 1.564 ≤ D |

B. DISCRETIZATION AND CODING OF INFORMATION SYSTEM

The decision table is discretized by transforming the continuous values of the quantitative attributes (C1 – C5), and the decision attribute (D) into qualitative terms. The condition attributes of IM parameters are coded into three qualitative terms; (0, 1 and 2). Furthermore, the decision attribute (D) is coded into three qualitative terms; (0, 1 and 2). The definition of attribute coding is shown in Table 2. This coding method is applied as presented in the coded information system of Table 3.

TABLE 3. Coded decision table.

| Condition Attribute | Decision Attribute |
|---------------------|--------------------|
| C1 R_s | C2 R_r | C3 L_s | C4 L_r | C5 L_m | D | System Stability |
| x_1  | 2  | 1  | 1  | 1  | 0  | 0  |
| x_2  | 1  | 1  | 1  | 1  | 0  | 2  |
| x_3  | 0  | 0  | 1  | 1  | 0  | 1  |
| x_4  | 2  | 2  | 2  | 1  | 0  | 0  |
|      | :  | :  | :  | :  | :  | :  |
|      | :  | :  | :  | :  | :  | :  |
| x_5  | 2  | 1  | 2  | 1  | 1  | 2  |

C. INDISCERNIBILITY RELATION

Indiscernibility relation has a dominant concept in RS theory. It can be defined as a relation between more than one object that has identical values in relation to a subset of considered attributes. Therefore, indiscernibility relation can be introduced as an equivalence relation. In which, all identical objects of a set are considered as elementary.

For example, in the condition attribute C1 (R_s), the object cases (x_1, x_4, x_5) are in the same class because they have the same attribute value (2). The union of these classes is described by indiscernibility relation of attribute C1 (R_s).

D. REDUCTION AND CORE

The reduction obtained as the output of the RS indicates that there is a core reduction that involves R_s only. However, the reduction of the decision table is R_s and L_m.

\[
G'_{ω22}(s) = \frac{s^3 + a_1s^2 + (ω_o^2 + a_1)s + ω_o^2a_1 + ω_oa_4}{ε \left( s^2 + a_1s - ω_o^2 - ω_oa_2 + a_3 \right)^2 + (2ω_o + a_2)s - ω_oa_1 + a_4^2} \tag{11}
\]

Analytical results of dominant zero locations under deviations of stator resistance and mutual inductance in motoring and regenerating modes of operations are shown in Fig. 2. These results are taken under zero observer feedback gains (K_1 = K_2 = 0). It is obvious that the deviations of stator resistance and mutual inductance do not affect the speed estimator stability at low speeds in the motoring mode. However, the situation is changed at low speeds in the regenerating mode. The deviations of stator resistance and mutual inductance cause unstable zero of the speed estimator.

The observer feedback gains should be properly designed to move the dominant unstable zero of the speed estimator from an unstable region to a stable one. This article presents...
an offline analysis to remedy this issue using a GA to optimize the observer feedback gains under parameter deviations to guarantee a stable speed estimator. A detailed explanation is presented in the next section.

IV. OPTIMIZATION OF THE OBSERVER FEEDBACK GAINS USING GA

The machine parameters have a major effect on the speed estimation, particularly in the very low speeds regenerating mode. The RS theory proved that the stator resistance and the magnetizing inductance are the two main core parameters that highly affect the speed estimation transfer function in the very low speeds regenerating mode. From this analysis, the observer feedback gains need to be properly designed and optimized to improve the speed estimation accuracy and the stability of the system. The GA is applied to obtain the optimal values of the observer feedback gains that guarantee the stability by moving the unstable zero in the right s-plane to the stable region.

A. GENETIC ALGORITHM

The spread use of modern heuristic algorithms makes them valuable tools to solve many practical problems in the field of electrical power industry. These algorithms are effective tools for non-linear optimization problems. The algorithms do not require that the objective function have to be differentiable and continuous and it can solve the model-based problems. GA is considered a powerful modern heuristic technique used for finding the global optimal solution.

GA is a numerical optimization algorithm inspired by both natural selection and natural genetics. Rather than starting from a single point within the search space, GA is initialized with a population of random guesses and that will be spread throughout the search space. A typical algorithm might consist of the following:

1) INITIALIZATION

GA is initialized with a population of guesses or chromosomes. With a population size equal to number of chromosomes (pop), each chromosome has length of (m) bits, the initial population is set in a matrix of dimensions (pop x m). The elements of the matrix are random binary 1 or 0.

2) SELECTION

The poor performing chromosomes are weeded out. However, better performing chromosomes are promoted to the next generation. The roulette wheel is applied as a selection operator. The wheel is divided into a number of sectors equal to the population size; the sector width is proportional to the fitness of the corresponding chromosome.

Roulette Wheel Selection Algorithm:

1. Calculate the fitness of each chromosome (\( f_i \)), \( i = 1 \text{ to } \text{pop} \)
2. Calculate the total fitness \( F_{sum} = \sum_{i=1}^{\text{pop}} f_i \)
3. Determine the probability of a selection \( P_i \) for each chromosome. \( P_i = f_i / F_{sum} \)
4. Calculate a cumulative probability \( q_i \) for each chromosome. \( q_i = \sum_{j=1}^{i} P_j \)
5. Generate a random number \( r \) where, \( 0 \leq r \leq 1 \)
6. If \( r < q_i \) select the first chromosome, otherwise, select the \( i^{th} \) chromosome such that: \( q_{i-1} \leq r \leq q_i \)
7. Repeat 5 and 6 for pop-times.

3) CROSSOVER

Fragments of the fittest chromosomes are mixed to form a new generation. The crossover occurs when two parents exchange parts of their corresponding chromosomes. The number of chromosomes that undergoes the crossover operation is determined by the crossover probability \( P_c \). Two-point crossover is applied as shown in Fig. 3:

4) MUTATION

Mutation operator is used to avoid permanent loss of diversity within the chromosomes. It is used to flip the value of single bits within chromosome strings by switching it from 0 to 1 or vice versa. The number of mutated bits is determined according to the probability of mutation \( P_m \).

5) CONVERGENCE

The process of selection, crossover and mutation is continued until a fixed number of populations have elapsed or some form of convergence criterion has been met.

Analytical results of adaptation of observer feedback gains \((K_1 \& K_2)\) are shown in Fig. 4 and Fig. 5. The gains are optimized using GA under deviations of stator resistance and mutual inductance to guarantee a stable dominant zero in the regenerating mode of IM.

The optimized observer feedback gains \((K_1 \& K_2)\) can be calculated as a function of the stator resistance deviations based on the previous analysis. It is observed that the value of \( K_2 \) has a very small change under stator resistance deviations. However, the value of \( K_1 \) is changed to enforce the dominant zero to stay in the stable region. A curve fitting for Fig. 4 is used to calculate the value of \( K_1 \) and \( K_2 \) as follows:

\[
\begin{bmatrix}
K_1 = 0.1172 (\Delta R_s \%) + 12.329 \\
K_2 = -1.04e^{-0.05} (\Delta R_s \%) - 0.55345
\end{bmatrix}
\] (12)

Fig. 6 shows a flow chart of the proposed new RS and GA for observer feedback gains optimization. The first
stage of the proposed RS is to construct the decision table (the information system) as shown in Table 1. The number of IM parameters \( (R_s, R_r, L_s, L_r, L_m) \) is defined as condition attributes. The decision attribute \( (D) \) represents the AFO stability condition based on (11).

In the second stage of Fig. 6, the decision table is discretized by transforming the continuous values of the quantitative attributes \( (C1 – C5) \), and the decision attribute \( (D) \) into qualitative terms as described in Table 2 and Table 3.

The Indiscernibility relation is the third stage of RS theory. It is an equivalence relation. In which, all identical objects of sets are considered as elementary.

In the fourth stage, the reduction is obtained as the output of the RS. It is observed that the reduction of the decision table is \( R_s \) and \( L_m \). However, there is a core reduction that involves \( R_s \) only.

This indicates that the stator resistance is the dominant parameter affecting the stability of AFO at low speeds in the regenerating mode.

In the last step, GA begins with a random population of chromosomes which spread through the search space. Three operators; selection, crossover and mutation are applied to enforce the population to converge to the optimum solution of the problem. Here, the observer feedback gains are optimized to move the dominant zero into the stable region under deviations of \( R_s \) and \( L_m \). The process of selection, crossover and mutation is continued until a fixed number of populations have elapsed or some convergence criterion has been obtained.

V. SENSORLESS DRIVE

A. EXPERIMENTAL SYSTEM IMPLEMENTATION

The sensorless IM drive is implemented in the laboratory to examine the proposed design of the observer feedback gains using GA optimization technique. A DSP-DS11104 control board is used to execute the sensorless IM drive. The structure of the experimental drive is presented in Fig. 7. Two current transducers are utilized to measure the stator currents. They are transmitted to the DSP-DS1104 control board using analog to digital converters for current control and generation of PWM pulses. The pulses excite the gates of the inverter switches through interface circuit. A position incremental encoder with 1024 pulses is used to compare the measured speed with the estimated one. This is for validation and verification of the speed estimator accuracy.
A. OPERATION UNDER STATOR RESISTANCE DEVIATIONS

From the abovementioned analysis using RS theory, it is noticed that the stator resistance is considered the most important parameter that has a major effect on the stability of AFO at low speeds in the regenerating mode. So, the observer feedback gains are optimized using a GA to be robust under deviations of the stator resistance.

Experimental results under stator resistance deviations are presented during the regenerating mode at 2.1 rad/sec and a load torque of $-7$ Nm. The results to validate the proposed design of the observer feedback gains are compared with the corresponding results with zero feedback gains.

Figs. 9(a) and 9(b) illustrate a 50% and 30% step change in $R_s$ applied to AFO model, respectively. Divergence and instability of the measured speed with zero observer feedback gains are confirmed during the operation in the regenerating mode at very low and zero speeds. However, the measured and estimated speeds are stable and in a good convergence using the proposed observer feedback gains as shown in Fig. 9(c). This validates the theoretical analysis of Fig. 2.

C. OPERATION AT LOW SPEEDS

The sensorless IM drive operates at $\omega_r = 14$ rad/s and $T_L = 0$ N.m using $K_1 = K_2 = 0$ as presented in Fig. 10. The first subplot shows the measured and estimated speeds in rad/s. The second subplot presents the $i_{qs}$ of stator current in the synchronously reference frame, So, it is a DC component. The third subplot shows $dq$-rotor fluxes in a rotating reference frame. Therefore, they are sine wave components. A load torque of $T_L = -7$ N·m is applied at $t = 2$ s. It is

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**FIGURE 6.** Flow chart of proposed new rough set and GA for observer feedback gains optimization.

**FIGURE 7.** Structure of the experimental system with IFOC sensorless IM drive using DSP-DS1104 control board.
observed that the AFO with $K_1 = K_2 = 0$ is unstable in the regenerating mode of operation. The same variables are captured using the proposed design of the observer feedback gains as presented in Fig. 11. It is obvious that the proposed design of the observer feedback gains achieves a stable AFO in the regenerating mode of operation.

D. SLOW SPEED REVERSAL

Slow speed reversal at $\omega_r = 10 \text{ rad/s}$ is presented in Fig. 12 with the optimized observer feedback gains. These experimental results show a slow speed reversal at 10 rad/s using the optimized observer feedback gains. The ramped reference speed changes gradually from 10 rad/s at $3 \text{ s}$
TABLE 4. The rated values and parameters of the IM.

| Rated output power | 1.1 kW | L_s | 0.0221 H |
|--------------------|--------|-----|----------|
| Rated voltage      | 380 V  | L_m | 0.0221 H |
| Rated current      | 2.545 A| L_m | 0.4114 H |
| Rated frequency    | 50 Hz  | R_s | 7.48262 Ω|
| No. of pole pairs  | 2      | R_s | 3.6840 Ω |
| J                  | 0.02 kg.m² |

FIGURE 10. Results of sensorless IM drive with load torque change (TL = 0 → −7 N.m) at ω_r = 14 rad/s in the regenerating mode using zero feedback gains (K_1 = K_2 = 0). First subplot: Actual and estimated speeds. Second subplot: iqs of stator current. Third subplot: Rotor fluxes in dq frame. (Experimental).

FIGURE 11. Results of sensorless IM drive with load torque change (TL = 0 → −7 N.m) at ω_r = 14 rad/s in the regenerating mode using optimized observer feedback gains. (Experimental).

E. ZERO SPEED

Fig. 13 presents experimental results at zero speed operation. The sensorless IM drive guarantees a good estimation and a stable operation at ω_r = 0 rad/s under loading and no-load conditions.

VI. COMPARISON WITH PREVIOUS WORKS

To confirm the effectiveness of the optimized observer feedback gains, a comparison with previous works are presented. The performance of the sensorless IM drive with nominal load at low speed; high speed; and very low speed (zero frequency) is presented in Fig. 14. It is a controlled benchmark to assess the performances of the sensorless drive, as given in [11], [40]–[43]. The first subplot shows the measured and estimated speeds, and the second subplot gives stator currents.
in the d-q frame. The estimated and measured speeds are in a good convergence as shown in Fig. 14 (1st graph). The results of $i_{qs}$ and $i_{ds}$ are shown in Fig. 14 (2nd graph). This figure is presented in comparison to previous works [11], [43].

Experimental results showing the performance at zero speed are presented in Fig. 13. This figure is presented in comparison to the designed AFO as in [23, Fig. 9] and [25, Fig. 12]. It is observed that the performance with the proposed observer feedback gains is comparable with [23], [25]. This proves the effectiveness of the proposed design.

The proposed RS theory and GA is an offline analytical method. This is considered a limitation of the proposed method. Therefore, the designed observer feedback gains by offline method may not working properly in online operations. This is the motivation for proposing a curve fitting equation between the observer feedback gains and the deviations of stator resistance to guarantee the dominant zero location in the stable region.
In the future work, a RS controller will be designed and programmed as an online adaptive mechanism that can be used instead of PI adaptive mechanism.

VII. CONCLUSION
The RS theory is applied in this article to obtain the most dominant machine parameters that affect the stability and performance of the sensorless IM drive at very low speeds in the regenerating mode. It is developed to deal with the issue of simultaneous changes of machine parameters. This is the main difference of the proposed algorithm compared with other works that assumed the estimated parameters are variable parameters and the other parameters are kept constant. Actually, all parameters may be simultaneously changed under the operating conditions. The genetic algorithm is applied to find the optimal observer feedback gains to move the unstable dominant zero location to the stable region under deviations of the stator resistance at low speeds in the regenerating mode. The performance of the AFO of sensorless IM drives using the proposed analysis is verified using the experimental results under the parameter’s deviation at low speeds in the regenerating mode. It can be observed from the results that the performance of the AFO of sensorless IM drives using the proposed analysis achieves the stability of a sensorless IM drives and gives a good speed estimation accuracy at very low speeds, particularly in the regenerating mode of operation.

APPENDIX A
BASIC CONCEPTS OF ROUGH SET THEORY
In this section, the basic concepts of RS theory is explained with an illustrative example.

A. DECISION TABLE
A data set is represented as a table in the RS theory and each row is a case, a process, or simply an object. For an object, each column represents a measurable property (a variable, an observation, etc.) [36], [37]. This table is called decision table (DT). More formally, the DT is represented by 4-tuple as \( DT = (U, A, V_a, F_a) \). Where, \( U \) is a finite set of cases (experiments reading) called universe, \( A \) is a set of primitive features; \( A = C \cup D \), in which \( C \) is called condition attribute (input variable) and \( D \) is called decision attribute (output variable), for each \( a \in A \), the set \( V_a \) contains all possible values of attribute \( a \), \( F_a : U \rightarrow V_a \) is called the decision function.

B. INDISCERNIBILITY RELATION
Let \( DT = (U, A, V_a, F_a) \) be a decision table, then, \( (B \subseteq A) \). The binary relation \( IND(B) \) called indiscernibility relation is defined by:

\[
IND(B) = \{(x, y) \in U^2 | a(x) = a(y), \forall a \in B\}.
\]  

(B1)

So, \( IND(B) \) is an equivalence relation and

\[
IND(B) = \bigcap_{a \in B} IND(a)
\]  

(B2)

C. LOWER APPROXIMATION AND UPPER APPROXIMATION
Let \( DT = (U, A, V_a, F_a) \) be a decision table, for any subset \( (X \subseteq U) \) and indiscernibility relation \( IND(B) \), the B lower-approximation and upper-approximation of \( X \) is defined as:

\[
BX = \bigcup \{[x]_B | [x]_B \subseteq X\} \quad \text{(B3)}
\]

\[
BX = \bigcup \{[x]_B | [x]_B \cap X \neq \phi\} \quad \text{(B4)}
\]

D. POSITIVE REGION
Let \( DT = (U, A, V_a, F_a) \) be a decision table, \( P \subseteq A \) and \( Q \subseteq A \), the positive region of \( Q \) is defined as

\[
Pos_P(Q) = \bigcup_{x \in IND(Q) \cap P} X
\]  

(B5)

E. ATTRIBUTES REDUCT AND CORE ATTRIBUTES
Let \( DT = (U, A, V_a, F_a) \) be a \( DT \), any minimal subset \( R \subseteq C \) such that \( Pos_R(D) = Pos_C(D) \) is called a reduct in the \( DT \). Core attribute is certain condition attributes that cannot be reduced during the RS theory reduction. The intersection of these reduct subsets is called core and symbolized as \( CORE = \cap RED(C) \)

F. ILLUSTRATIVE EXAMPLE
This example shows basic concepts of RS theory using a step by step procedure to explain the previous theoretical analysis:

For the example shown in the Table 5, the universe is \( U = \{x_1, x_2, x_3, x_4, x_5, x_6\} \), the set of conditional attributes is \( C = \{T, M, H\} \) and the decision attribute is \( D = \{\} \). Possible values for the conditionals attributes values are: \( V_T = \{0, 1, 2\} \) and \( V_M = V_H = \{0, 1\} \). For the decision attribute \( V_D = \{0, 1\} \).

**TABLE 5. Sample data set.**

| U | T | M | H | D |
|---|---|---|---|---|
| x_1 | 0 | 1 | 1 | 0 |
| x_2 | 1 | 1 | 1 | 1 |
| x_3 | 2 | 1 | 1 | 1 |
| x_4 | 0 | 1 | 0 | 0 |
| x_5 | 0 | 0 | 0 | 0 |
| x_6 | 2 | 1 | 0 | 1 |

The indiscernibility relation for the given set of conditional and decision attributes are obtained as follows,

\[
IND(T) = \{\{x_1, x_4\}, \{x_2, x_5\}, \{x_3, x_6\}\}
\]

It is noted that for the condition attribute \( T \), objects \( x_1 \) and \( x_4 \) belong to the same equivalence class. This means that they have the value for attribute \( T \{x_1, x_4\} \). Then, they are indiscernible. The same situation is identical for \( x_2 \) and \( x_3 \). They have the same value for attribute \( T \) and belong to another indiscernibility class \( T \{x_2, x_5\} \). Also, the objects \( x_3 \) and \( x_6 \) belong to another indiscernibility class that mean both of them have the same value for attribute \( T \{x_3, x_6\} \). Then, the other relations are constructed in the same way for
\[ \text{IND}(\{ M \}) = \{ \{ x_1, x_2, x_3, x_4, x_6 \}, \{ x_5 \} \} \]
\[ \text{IND}(\{ H \}) = \{ \{ x_1, x_2, x_3 \}, \{ x_4, x_5, x_6 \} \} \]
\[ \text{IND}(\{ C \} = \{ T, M, H \}) = \{ \{ x_1, x_2, x_3, x_4, x_5, x_6 \} \} \]
\[ \text{IND}(\{ D \}) = \{ \{ x_1, x_2, x_3, x_4, x_5, x_6 \} \} \]

Here, the \( \text{POS}_C(D) \) are the objects that belong to the \( \text{IND}(\{ C = \{ T, M, H \} \}) \), which are all included in the \( \text{IND}(\{ D \}) \). In the same way, \( \text{POS}_{(M,H)}(D), \text{POS}_{(T,M)}(D) \) and \( \text{POS}_{(T,H)}(D) \).

\[ \text{IND}(\{ M \}) = \{ \{ x_1, x_2, x_3 \}, \{ x_4, x_6, x_5 \} \} \]
\[ \text{IND}(\{ H \}) = \{ \{ x_1, x_3, x_4 \}, \{ x_2, x_5, x_6 \} \} \]
\[ \text{IND}(\{ C \} = \{ T, M, H \}) = \{ \{ x_1, x_2, x_3, x_4, x_5, x_6 \} \} \]
\[ \text{IND}(\{ D \}) = \{ \{ x_1, x_2, x_3, x_4, x_5, x_6 \} \} \]

Since \( \text{POS}_{(M,H)}(D) \neq \text{POS}_C(D) \):
\[ \text{IND}(\{ T, M \}) = \{ \{ x_1, x_4 \}, \{ x_2, x_3, x_6 \}, \{ x_5 \} \} \]
\[ \text{IND}(\{ T, H \}) = \{ \{ x_1, x_4, x_5 \}, \{ x_2, x_3, x_6 \} \} \]
\[ \text{IND}(\{ T, M \}) = \{ \{ x_1, x_2, x_3, x_4, x_5, x_6 \} \} \]

Since \( \text{POS}_{(T,M)}(D) = \text{POS}_C(D) \):
\[ \text{IND}(\{ T, H \}) = \{ \{ x_1, x_2, x_3, x_4, x_5, x_6 \} \} \]
\[ \text{IND}(\{ T, H \}) = \{ \{ x_1, x_2, x_3, x_4, x_5, x_6 \} \} \]

Since \( \text{POS}_{(T,H)}(D) = \text{POS}_C(D) \):
\[ \text{IND}(\{ T, H \}) = \{ \{ x_1, x_2, x_3, x_4, x_5, x_6 \} \} \]
\[ \text{IND}(\{ T, H \}) = \{ \{ x_1, x_2, x_3, x_4, x_5, x_6 \} \} \]

It is found that, the sets \( \{ T, M \} \) and \( \{ T, H \} \) are reducible.

The intersection of the two reducts defined as the core (the main parameter in the DT):
\[ \text{Core} = \{ T, M \} \cap \{ T, H \} = \{ T \} \]

REFERENCES

[1] M. Pacas, “Sensorless drives in industrial applications,” IEEE Ind. Electron. Mag., vol. 5, no. 2, pp. 16–23, Jun. 2011.
[2] J. Holtz, “Sensorless control of induction machines—With or without signal injection?” IEEE Trans. Ind. Electron., vol. 53, no. 1, pp. 7–30, Feb. 2006.
[3] Z. Yin, Y. Zhang, C. Du, J. Liu, X. Sun, and Y. Zhong, “Research on anti-error performance of speed and flux estimation for induction motors based on robust adaptive state observer,” IEEE Trans. Ind. Electron., vol. 63, no. 6, pp. 3499–3510, Jun. 2016.
[24] E. Etien, C. Chaigne, and N. Bensiali, “On the stability of full adaptive observer for induction motor in regenerating mode,” IEEE Trans. Ind. Electron., vol. 57, no. 5, pp. 1599–1608, May 2010.

[25] M. Hinkkanen and J. Luomi, “Stabilization of regenerating-mode operation in sensorless induction motor drives by full-order flux observer design,” IEEE Trans. Ind. Electron., vol. 51, no. 6, pp. 1318–1328, Dec. 2004.

[26] B. Chen, T. Wang, Z. Lu, W. Yao, and K. Lee, “Speed convergence rate-based feedback gains design of adaptive full-order observer in sensorless induction motor drives,” IET Elect. Power Appl., vol. 8, no. 1, pp. 13–22, Jan. 2014.

[27] T. Orlowska-Kowalska, M. Korzonek, and G. Tarchala, “Stability analysis of selected speed estimators for induction motor drive in regenerating Mode—A comparative study,” IEEE Trans. Ind. Electron., vol. 64, no. 10, pp. 7721–7730, Oct. 2017.

[28] W. Sun, X. Liu, J. Gao, Y. Yu, G. Wang, and D. Xu, “Zero stator current frequency operation of speed-sensorless induction motor drives using stator input voltage error for speed estimation,” IEEE Trans. Ind. Electron., vol. 63, no. 3, pp. 1490–1498, Mar. 2016.

[29] T. Orlowska-Kowalska, M. Korzonek, and G. Tarchala, “Stability improvement methods of the adaptive full-order observer for sensorless induction motor Drive—Comparative study,” IEEE Trans. Ind. Informat., vol. 15, no. 11, pp. 6114–6126, Nov. 2019.

[30] W. Sun, D. Xu, and D. Jiang, “Observability analysis for speed sensorless induction motor drives with and without virtual voltage injection,” IEEE Trans. Power Electron., vol. 34, no. 9, pp. 9356–9364, Sep. 2019.

[31] W. Sun, Z. Wang, D. Xu, X. Yu, and D. Jiang, “Stable operation method for speed sensorless induction motor drives at zero synchronous speed with estimated speed error compensation,” IEEE Trans. Power Electron., vol. 34, no. 11, pp. 11454–11466, Nov. 2019.

[32] W. Sun, Z. Wang, D. Xu, and B. Wang, “Robust stability improvement for speed sensorless induction motor drive at low speed range by virtual voltage injection,” IEEE Trans. Ind. Electron., vol. 67, no. 4, pp. 2642–2654, Apr. 2020.

[33] J. Chen, J. Huang, and Y. Sun, “Resistances and speed estimation in sensorless induction motor drives using a model with known regressors,” IEEE Trans. Ind. Electron., vol. 66, no. 4, pp. 2659–2667, Apr. 2019.

[34] B. Chen, W. Yao, F. Chen, and Z. Lu, “Parameter sensitivity in sensorless induction motor drives with the adaptive full-order observer,” IEEE Trans. Ind. Electron., vol. 62, no. 7, pp. 4307–4318, Jul. 2015.

[35] M. Hinkkanen and J. Luomi, “Parameter sensitivity of full-order flux observers for induction motors,” IEEE Trans. Ind. Appl., vol. 39, no. 4, pp. 1127–1135, Jul. 2003.

[36] Z. Pawlak, “Rough set,” Int. J. Inf. Comput. Sci., vol. 11, no. 5, pp. 341–356, Sep. 1982.

[37] A. Skowron and S. Dutta, “Rough sets: Past, present, and future,” Natural Comput., vol. 17, no. 4, pp. 855–876, Jul. 2018.

[38] R. Ghimire, C. Zhang, and K. R. Pattipati, “A rough set-theory-based fault-diagnosis method for an electric power-steering system,” IEEE/ASME Trans. Mechatronics, vol. 23, no. 5, pp. 2042–2053, Oct. 2018.

[39] T. Fetouh and M. S. Zaky, “New approach to design SVC-based stabilizer using genetic algorithm and rough set theory,” IET Gener. Transmiss. Distrib., vol. 11, no. 2, pp. 372–382, Jan. 2017.

[40] L. Zhao, J. Huang, H. Liu, B. Li, and W. Kong, “Second-order sliding mode observer with online parameter identification for sensorless induction motor drives,” IEEE Trans. Ind. Electron., vol. 61, no. 10, pp. 5280–5289, Oct. 2014.

[41] M. Ghanes and Z. Zheng, “On sensorless induction motor drives: Sliding-mode observer and output feedback controller,” IEEE Trans. Ind. Electron., vol. 56, no. 9, pp. 3404–3413, Sep. 2009.

[42] D. Traore, F. Plestan, A. Glumineau, and J. de Leon, “Sensorless induction motor: High-order sliding-mode controller and adaptive interconnected observer,” IEEE Trans. Ind. Electron., vol. 55, no. 11, pp. 3818–3827, Nov. 2008.

[43] S. Di Gennaro, J. R. Domínguez, and M. A. Meza, “Sensorless high order sliding mode control of induction motors with core loss,” IEEE Trans. Ind. Electron., vol. 61, no. 6, pp. 2678–2689, Jun. 2014.

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