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Prescriptive Modelling System Design for an Armature Multi-coil Rewinding Cobot Machine

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Abstract

Digital transformation has ushered in the digital economy, powered by digital intelligence and quantum computing. The various winding topologies in rotary machines result from multi-variant design specifications and connection types. Rewinding of rotary machines is a behaviour-based decision-making process conducted within the shop floor, as the procedure is dependent on multi-input multi-output variables. Due to high data variability in service remanufacturing of armature windings in rotary machines, data abstraction for intelligent automation and analytics leads to increased operational productivity and new insights into market dynamics. In this light, the aim of the paper is to illustrate the design of a prescriptive modelling system of a symmetrical multi-coil winding machine for armature winding. The proposed system is a hybrid least squares support vector machine and adaptive neuro-fuzzy inference system for optimizing and maintaining a copper fill factor at 90.7%. A mixed method research was utilized for qualitative and quantitative for the multivariate parameters. The results show that the system through in-slot repetitive orthocyclic winding process, with multi-spindle concentric layering improves the energy efficiency of the induction motors, which in turn lowers winding faults during the remanufacturing process. Streamlining operations through fog computing further enhances system latency and process reliability towards sustainable industrialization.

Keywords: orthocyclic winding; deep learning, support vector machine; collaborative design; energy efficiency

Introduction

In recent years, digital transformation has ushered in the digital economy, powered by digital intelligence and quantum computing. Fog-based cyber-manufacturing systems provide the foundation to next-generation smart manufacturing networks in which manufacturers have access to on-demand computing infrastructures, mobile applications for cyber-manufacturing and parallel machine learning tools [1].However, in the emerging cyber-physical systems domain, data is the new fuel that powers decision making across the whole product lifecycle [2]. Statistics show that 82% of the companies using smart manufacturing technologies have experienced increased efficiency and 45% of the companies of the companies experienced increased customer satisfaction [3]. Induction motor stators are robust equipment, which has a long lifespan of 20-25 years [4]. They are continuously repaired during their operational life. According to [4], the cost of operating an induction motor is the most considerable cost during its lifecycle, which is directly proportional to the winding layout, and hence heat dissipation. The autonomous remanufacturing of induction motors has been developed in [5] using an ANFIS for classification and motion control. In contrast, a continuous function approximation using a two-stage neural network model involving Support Vector Machines (SVM) and a Neural Network has been applied to real functions of many variables [6]. There exist multiple and varying underlying fuzzy rules for classification and rewinding process. Generally, navigation methods based on deep learning (DL) are included in two genres, i.e., data-driven control methods and model-predictive control (MPC) methods [7]. As such, the proposed system is a hybrid least squares support vector machines LS-SVM and ANFIS system for robotic motion planning, where the system is optimized through LR-SVM to attain a high stator fill factor. Hence, through statistical learning using LS-SVM, an optimization model was developed. The model is utilized during remanufacturing of induction motors, to maintain a high stator fill factor of 0.907, improving the energy efficiency of the upcycled induction motor.

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Nomenclature

Main Abbreviations

MIM0	Multiple input multiple output	N_T	Number of turns
AI	Artificial intelligence	A_u	Air gap area
CPS	Cyber physical system	k_{co}	Copper packing factor
ANFIS	Adaptive neuro-fuzzy inference system	f_{cu}	Copper stator fill factor
SVM	Support vector machine	A_{cu}	Area of copper wire
DL	Deep learning	A_{slot}	Area of slot
OEM	Original equipment manufacturer	A_{eff}	Effective air gap area
MPC	Model predictive control	A_{coil}	Total area of coil
LS-SVM	Least squares- support vector machine	R_i	Trapezoidal base
IT/OT	Information/ operation technology	H_i	Trapezoidal height
MOP	Multi-variate optimization problem	γ	Regularization parameter
PSO	Particle swarm optimization	ε_i	Error between predicted output
Parameters		w_j	Shift winding for concentrated layer
z_{cond}	Number of conductors	n	nth layer in shift winding
r	Radius of wire	b	Decision bias of the

1. Literature Review

1.1. Stator rewinding

The energy efficiency of induction motor systems typically can be improved by 20-30 %, representing a huge, untapped potential for cost-effective energy savings and greenhouse gas emission reduction [8] Short-circuit faults form 21% of the faults occurring in electrical machines [9], [10]. Thermal overloading induces mechanical stress in windings of electrical machines, due to heat dissipation challenges in air cooled electrical machines. The realisation of windings with an ordered structure was very difficult and burdensome, until the end of the last century, were the realization of commercial solutions that allow a sustainable realization of distributed windings with ordered structures is possible [11]. Existing winding methods are linear winding, flyer winding and needle winding process [12], illustrated in Fig.1 below. Polyphase windings are widely applied in rotary machines using random wires, as random wound coils are more amenable for factory automation compared with the copper bars used for higher power rating machines [13]. The general expression based on the winding ampere-turns for the air gap distribution is the conventional means for distinguishing the harmonics due to winding layout from those due to saturation and by slot permeance variations [14].

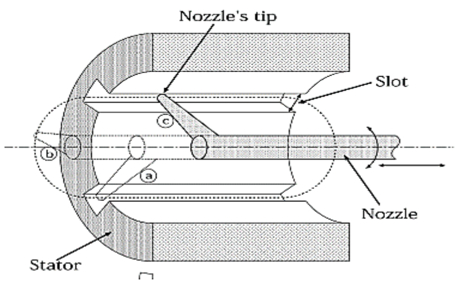

Fig. 1 Needle/nozzle winding [15]

1.2. Deep learning and SVM

Collaborative design through data sharing and learning reduces the burden of collecting massive training data for each robot in training deep models, while the models are personalized for each robot at the edge of the network within a trusted infrastructure [16]. DL is, in essence, a collection of models for non-linear function estimates through conceptualising the features concealed in inputs by deep neural networks and currently used in robotic applications, such as robot manipulation, indoor navigation [7]. The influence of deep learning mostly originates from architectural flexibility, which permits the design of neural nets to fit nearly any complex software structures [17]. SVMs have been proven to be very effective methods for inference [18]. They are constructed based on statistical learning and structural risk minimisation, which can give attention to both the expected risk and generalisation performance [19]. In high dimensional data sets, SVMs can consider complex non-linear relations between covariates and outcome by using kernel functions [20]. This approach can optimise complex non-linear problems by using an exclusive objective function that minimises the structural risk of the model [21]. Although normal SVMs have been fundamentally used only on static glitches like classification and function estimation, LS-SVM models have stretched to the recurrent models and use in optimal control problems [22]. Trained SVMs are firmly data-dependent: the data with generally unknown statistics are passed through a non-linear kernel function, and the use of standard optimisation methods to find the best classifier [23].

1.3. Prescriptive analytics

Information technology (IT) has been integrated with operational technology (OT), this has led to collaborative computing. Operations require a rapid change from a highly organised and uneven system that strongly relies on tactical decision making and with few strategic planning functions based on uncertain information, to an integrated one based on collaborative strategic management of trajectories and information sharing [24]. Real-time data analytics methods are key elements to overcome the currently rigid planning and improve manufacturing processes by analysing historical data, detecting patterns and deriving measures to counteract the issues [25]. A model analytical control method, machine learning techniques, self-optimising and control mechanisms are useful tools in the construction, adaptation and application of real-time optimisation methods [26]. Prescriptive analytics automates the decision–making of any physical system concerning its design, planning, scheduling, control and

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operations using any combination of optimisation, heuristics, machine-learning and cyber-physical systems [27]. It predicts strategies to improve the current process or system using simulation and optimisation algorithms [28]. In machine learning, instance-based learning or memory-based learning is a family of learning algorithms that, instead of performing explicit generalisation, compare new problem instances with instances seen in training, which have been stored in memory [29]. Prescriptive analytics is named instance-based because it constructs hypotheses directly from the training instances themselves, which entails that the hypothesis complexity can grow with the data [29].

2. System conceptualization

2.1. Neural networks

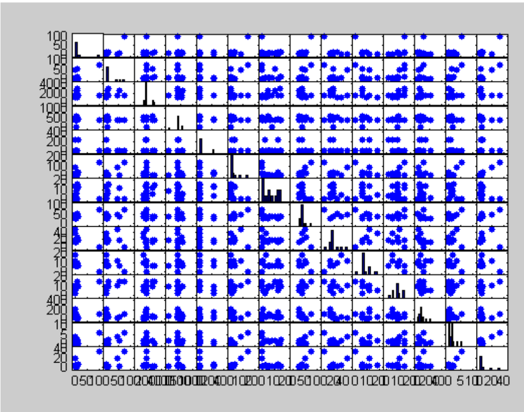

Fig. 2: Plot matrix various classes of induction motors

Fully automating the process inhibits the possibility of abstracting the machines operating conditions and life cycle data from the client. Therefore, a semi-autonomous system is adopted. Upcycling of electrical machines is dependent on both performance parameters and free parameters; whereby functional analysis is performed through descriptive analytics. The combination of fuzzy logic with architectural design of neural network led to creation of neuro-fuzzy systems which benefit from feed forward calculation of output and back-propagation learning capability of neural networks, while keeping interpretability of a fuzzy system [30]. Both of them encode the information in a parallel and distribute architecture in a numerical framework. As highlighted in Fig. 2 above, there exist multiple and various classes of induction motors based on design, energy efficiency vs. standard, horsepower, geometrical size, winding pattern, number of poles, coil thickness etc., hence ANFIS was used for multi-layered hierarchical neural network classification [5]. During the rewinding process, various changes are effected onto the core which usually negatively impact the efficiency of the rewound motor, such as changing wire thickness or winding pattern of the induction motor. Induction motor cores are usually wound with random wires, hence an orthocyclic winding pattern was selected as it gives the best packing factor. LS-SVMs were chosen as they perform pattern recognition and vector regression, towards attaining a goal target of a high stator fill factor through optimization. Through instance-based learning, the recursive neural system undergoes incremental learning and optimization.

2.2. Shift and orthocyclic winding analysis

The multi-physics nature of induction motors e.g. electromagnetics, heat transfer and mechanics, requires minute consideration before undertaking any changes in the design. Numerous requirements, corresponding to different objective functions have to be fulfilled at a time such as winding type, tension control, trajectory path mapping. Winding technology plays a decisive role, because the product attributes can be influenced substantially through enhancement of the copper fill factor k_{co}. The thermal conductivity is largely dependent on packing factor and thermal conductivity of insulating material [31], and the packing factor (γ), depends on the method of winding, wire diameter and thickness of insulation [31], as illustrated in Fig.3 below.

Fig. 3: Traditional rewinding of an induction motor stator with distributed windings [32].

Compared to other winding schemes the orthocyclic-winding scheme is able to reach a theoretical mechanical fill factor of 90.7% due to the special layer structure in which the windings of the upper layer are in the grooves provided by the lower layers [33]. Since thermal conductivity directly impacts heat energy dissipated in windings, and insulation breakdown leads to short circuitry, it becomes essential to devise the best packing factor that allows high flux density in a small air gap ideal for heat dissemination.

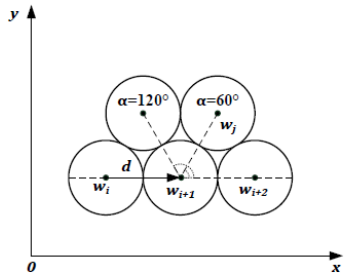

Fig. 4: Orthocyclic and concentrated windings [15].

Orientation arrangement and placement of the coils into stator slots is dependent on nodal and radial analysis, as shown in Fig 4 above. Spiral winding uses cylindrical wires, therefore recycled and/or new wires of uniform cross-section are intrinsically oriented, allowing continuous flexural movement through continuous rotation. Group winding is a prevalent winding technique in induction motors wherein the total winding is divided into separate parts composed of adjacent coils, parallel and symmetrically arranged with respect to each other, however, to faults all windings are equal. A multi-spindle approach is adopted for wire supply, to attain direct rewinds for a high stator fill factor and uniformity in xy plane. Shift winding is performed in the z Cartesian co-ordinate; hence the needle base is shifted upwards by the shift angle. Since path generation is an optimal control challenge for tooling, model predictive

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control is adapted for motion control.

3. Methodology

In this paper, mixed-method research, which includes both qualitative and quantitative, were utilised due to MIMO variables, of both performance and configuration data. Parameterisation of operation data in shift winding, merging it with configuration data allowed for deep neural learning and optimisation through vector mapping, for behaviour-based control of robotic remanufacturing. In particular, a deep convolutional net is first trained using supervised or unsupervised objectives. This helps in learning good invariant hidden, latent representations [34]. The system was modelled using static data found on induction motor nameplates of all models, and 60% of energy-efficient motor details were used as testing data. ANFIS has two parameters that need training, i.e., antecedent and conclusion part parameters, whereby LS-SVM and antecedent will optimise the conclusion parameters by particle swarm optimisation (PSO). Since new designs with improved variables such as energy efficiency, torque, power factor is continuously being manufactured, a PSO type 3 algorithm is used [30]. It is used for optimisation and prescriptive analytics for the upcycling process, enhanced by data sharing amongst rewinders, OEMs and plant designers.

In-slot winding eliminates the extra production step of inserting the coils into the stator [26], as highlighted in Fig. 5 below. A needle winding approach was adopted for the rewinding process and a detachable end effector for holding wire conductors whilst rewinding, and also to prevent ribbon winding. Rewinding in an agile environment requires effective resource utilization, especially time, therefore adaptation of multi-coil winding decreases throughput time by a factor of $(z_{cond}N_T)^{-1}$.

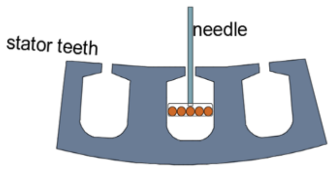

Fig. 5: Stator In-slot needle winding

4. Adaptive-Neural system

Once all input attributes are captured, the number of coils and ampere turns becomes the rate determining factors towards shift winding and trajectory path mapping, whereas motor efficiency is affected by the effective copper area, as highlighted by equation 1.

$$A_{coil} = A_{cu}z_{cond}N_T \quad (1)$$

In shift winding, wires are layered in-between each other, hence multiple-spindle winding was used for concentrated windings, by in-slot winding. Since variable input combinations affect the slot-fill factor, heuristic algorithms are adopted for MOP. Inputs are classified and mapped to produce desired outputs by scalar transformation in each ANFIS layer. The output layer of the ANFIS is optimized through multi-dimensional LS-SVM, as illustrated in the Fig.6 below. Due to the existing recursive neural network, supervised learning and instance-based memory occur instantly while the adaptive system is continuously learning and updating itself based on set weights, namely the winding pattern and air gap fill factor.

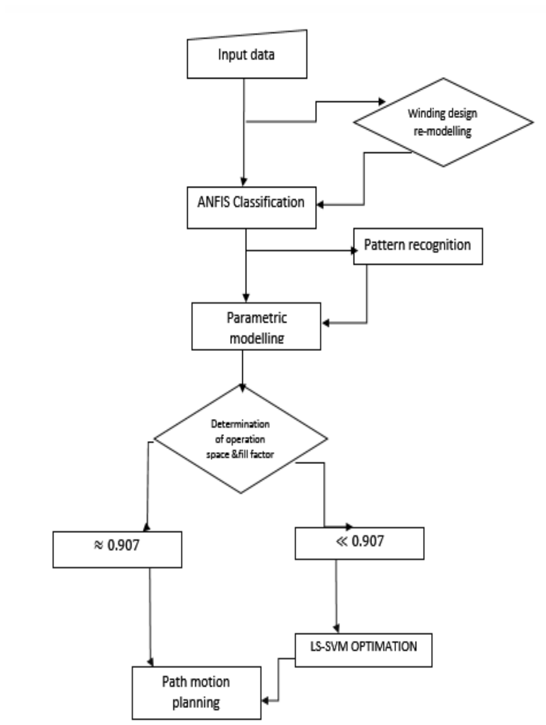

Fig. 6: Self-learning hybrid ANFIS and LS-SVM for rewinding cores.

4.1. Operational space for needle rewinding

Autonomous manipulation requires identification and localizing relevant workspace i.e. the operation space. Since stator frame core laminations are equidistant from the centroid with respect to the radii and core length. Loci of points are mapped with respect of the initial vectors and co-ordinates. Wire distribution conditions are applied to all conductors within group winding. The air gap profile is trapezoidal i.e.

$$A_u = (R_{1s} + R_{2s})(H_{1s} - R_{2s}) + \frac{\pi R_{2s}^2}{2} \quad (2)$$

The copper stator-fill is calculated as

$$f_{cu} = \frac{N_W A_{cu}}{A_{slot}} \quad (3)$$

Since distributed spiral windings are used, an elliptical path is defined for each conductor through shift winding, as coils are wound layer above layer for N_T turns. Periodicity, polarity and symmetry of phases/poles of slots is conducted through reverse winding, and for consecutive phase slots in phase and poles an arithmetic progression (AP) formulation is mapped for direct trajectory positioning. The first conductor gives the reference;

$$w_i = \begin{bmatrix} x_i \\ y_i \end{bmatrix} \quad (4)$$

The distance between two conductors is equivalent to the diameter of each wire. Through shift winding, co-ordinates of the following layer w_j are;

$$w_j = \begin{pmatrix} \cos\alpha & -\sin\alpha \\ \sin\alpha & \cos\alpha \end{pmatrix}.2r + w_i \quad (5)$$

To allow for effective orthocyclic arrangement of wires, each shift layer is displaced by $(-1^n.r)$, with reference to the winding direction for a maximum stator fill, Were$^{\boldsymbol{B}}_{\boldsymbol{A}}\boldsymbol{R}$; initial position of flat base is determined by $(-1^n.r)$.

$$w_j = \left[\begin{pmatrix} \cos\alpha & -\sin\alpha \\ \sin\alpha & \cos\alpha \end{pmatrix}.2r + w_i\right] + (-1^n.r) \quad (6)$$

Due to various stator and winding designs, ANFIS system through self-learning, pattern recognition and back propagation is able to integrate the multiple rewinding variants towards self-organization into classes.

4.2. Inverse kinematics Model vector regression using LS-

SVM

The training set of the data points of the regression set M; $\{(x_i, y_i)\}_{i=1}^{M}$ are abstracted from nameplates of failed induction motors that come for repair. ANFIS were used for multi-layered and hierarchical training in [5] to determine path motion of the robotic manipulator. The output is calculated as

$$y(x) = \sum_{i=0}^{m} f_i w_i \quad where\ f_{i=} w_j \tag{7}$$

Where f_i is the function of input values and w_i the weight of the matrix. A radial basis function LS-SVM was used for robotic manipulator dynamics. In high dimensional space, the model becomes

$$y(x) = w^T(x) + b \tag{8}$$

$$w \in Z, \qquad b \in R$$

$$\min \boldsymbol{J}(w,e) = \frac{1}{2} w^T w + \frac{\gamma}{2} \sum_{i=1}^{m} \varepsilon^{2,}, \gamma > 0 \tag{9}$$

Subject to the following constraints

$$y_i = w^T \varphi(x) + b + \varepsilon_i \tag{10}$$

The Lagrange function becomes

$$L = \frac{1}{2} w^T w + \frac{\gamma}{2} \sum_{i=1}^{m} \varepsilon^2 - \sum_{i=1}^{m} \alpha_i [w^T \varphi(x_i)] + b + \sum_{i} -y_i \tag{10}$$

$$\alpha_i = \frac{y_i - b}{x^T x + (2\mu)}^{-1} \tag{11}$$

The Kernel function becomes

$$k(x,x) = g(x_i) g(x)^T \tag{12}$$

And the radial basis function is

$$k(x,x) = e^{\left(\frac{x_i - x^2}{\sigma^2}\right)} \tag{13}$$

5. Results and discussion

A CPS is a high-dimensional hierarchical system whereby control computation minimises the difference between predicted process response and desired trajectory. The system itself develops a model of the system to be controlled. The multi-coil winding of the armature is a complex process resulting in event-triggered task parallelisation of the control and monitoring process in a heterogeneous environment. A stator in-slot continuous system was adopted in preference to segmented rewinding, as discontinuity makes the system complex. A multi-spindle approach was adopted for effective tension control, maintain uniformity and therefore prevent ribbon winding during the rewinding process, which lowers the stator fill factor. A CPS is a high-dimensional hierarchical system whereby control computation minimises the difference between predicted process response and desired trajectory. The system itself develops a model of the system to be controlled.

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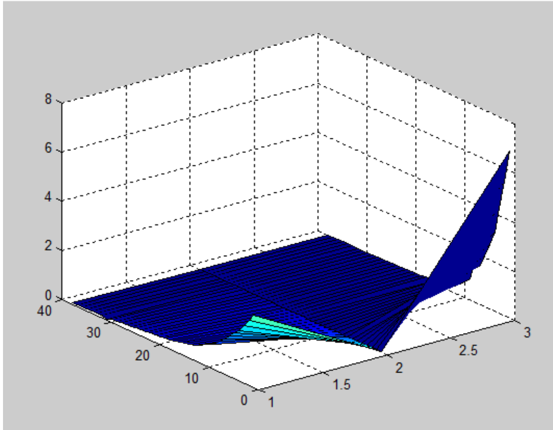

Fig. 7: Performance analysis of rewound induction motor

Due to various underlying fuzzy rules, weight-based hierarchical multi-layer perceptrons were used for classification and pattern recognition through ANFIS and SVM. For induction motors that work in corrosive environments with missing input data entities, *k-nearest-neighbour* and clustering determine the winding parameters. Hence, the hyperplane was designed to separate energy-efficient motors from standard motors. As the wire area and winding layout affect the energy efficiency of a motor, a radial basis function was used to differentiate between energy-efficient and standard motors. LS-SVM regression was used for the optimisation of the outputs of neural network and through incremental, iterative learning, the system can adapt to future design trends, as data is prioritised accordingly. Supervised learning allows testing for data integrity, as SVM are robust on outliers via anomaly detection.

EEG statistical analysis of the hybrid system showed that the system was able to undergo continuous online learning. Through experimentation of electric motors that came for rewinding and were used as test subjects for the proposed system, they were shown to have improved their energy efficiency by 25% at the motor test bench. However, due to the various designs and classes of induction motors, it is a challenge. Use of an adaptive online robotic manipulator allows for collaborative learning and data sharing. Hence the system is data intensive. The online system was trained within various distributed rewinding shops of the country, in various location. Through collaboration, multi-layer clusters were used for anomaly detection. Prescriptive analytics is a goal-oriented data-driven framework to prescribe an optimal condition for parameters, in this case, enhancing the energy efficiency of the induction. Through experimentation, the system was able to detect prior rewinding errors and rectify them, through upcycling the induction motors to be energy efficient. As the autonomous operation is dependent on the event scheduled driven object objectives and conducted in a shop floor, fog computing allows for improved agility and data security through parallel control and communication in a distributed system, with the cloud being used for data storage. Through self-organisation and learning of given motor details, prescriptive analysis enhances adaptive control, especially in the face of uncertainty, downsizing and upcycling. As such, this proposed system is highly applicable as companies are losing revenues as poorly rewound motor energy costs are a hidden cost. It has been illustrated that improving 10% of electric motor rewinding results in savings worth 650GWh energy savings and USD 45 million in India [8] [35], results in a

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significant impact in energy efficiency and reduces the carbon footprint.

6. Conclusion

A semi-autonomous robotic manipulator system was designed to rewind orthocyclic windings on stator cores to enhance the packing factor of copper wires. Through in-slot continuous multi-spindle concentric windings, flexural and intrinsic orientation occurs, thereby preventing ribbon winding. The dense orthocyclic winding gives the highest packing density for random wires of 90.7%. The hybrid ANFIS and LS-SVM system were designed for optimisation of multi-variate inputs to get the optimal output variable. Hence, the robotic manipulator path motion was predetermined according to its induction motor nameplate. Through online statistical learning, the hybrid system was able to collaborate with another machine, for data sharing, management and analytics. Since the system consists of various underlying weights and rules, the system can devise and recommend the best winding parameters to improve the stator core winding parameters through prescriptive analytics. Iterative and incremental learning allows for the continual system adaptation to new and future designs, towards upcycling stator cores by improving energy efficiency. Future work is based on utilising blockchain to improve data sharing between OEMs and rewinders, to improve the quality of remanufacturing induction motors. Furthermore, the use of machine vision in conceptualisation is with the nameplate data.

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