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Analysis of Optimal Orthocyclic Winding Strategy for Electric Motor Performance Improvement

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ABSTRACT

Electrical machines are referred to as electromechanically energy conversion devices. The electromechanical energy conversion device is the link between electrical system and mechanical system. It should be noted that most studies on rated load have used the motor efficiency values that were achieved. One-third of the motors operate at less than 50% of rated load, while the majority of motors are at least 25% under-loaded. The purpose of rewinding should thus be focused on reaching the highest efficiency at the working point of the particular electric motor. The method used to study the behavior of winding characteristics of othocyclic winding using crow search algorithm (CRA) with different simulations on the influence of flux sizes at different iterations and Matlab codes A1.1 CSA OW program. Optimization of the equal-number-of-turns-per-layer orthocyclic winding (ENOTPL-OW) scheme is presented in this study and considerations were given to the influence of the CSA parameters - the flock size, and the maximal iterations for different scenarios. The potentials of a well-documented linear winding scheme called orthocyclic winding (OW) which is currently gaining grounds in automotive applications are also analyzed.

Keywords: Crow Search Algorithm, Electromechanical, Iterations, Matlab Codes, Orthocyclic Winding

INTRODUCTION

Electrical machines are referred to as electromechanically energy conversion devices. That is they convert electrical energy to mechanical energy (motor) or convert mechanical energy to electrical energy (generator). The electromechanical energy conversion device is the link between electrical system and mechanical system. In this research, the optimal operation of a typical direct winding strategy is proposed for the rewound of electric motors in the field of mobile traction such as Electric Hybrid Vehicles (EHVs).

In many circumstances, it might be more affordable to repair electric motors when they malfunction. If the price and efficiency of the two solutions are known, it is possible to compare the economics of fixing a broken electric motor with buying a new one. It is simple to determine the costs of the two solutions and the new motor efficiency [1].

The efficiency of the motor after repair is not easily accessible, and Nigerian motor repair facilities are not outfitted to measure it with a high level of precision, claims [2]. To address this gap, there are very few verified efficiency data available in the public domain.

In a report on motor rewinding and efficiency [1], the economic analyses of repair vs replacement decisions often depend on an estimated value for restored motor efficiency. These assumptions can include using the manufacturer's original efficiency value that was stamped on the motor nameplate, occasionally removing an assumed efficiency value from a table based on the motor rating and measuring the parameters on no load after rewinding.

Since the electric motor rewind operation is a typical re-production operation, standard practices during a winding operation also apply. One popular winding strategy is the linear winding which allows for faster delivery of electric motors from the production shop to the service field and lower full automation costs [3]. Such winding also promises better efficiencies at a more cost-effective rate.

A machine is a device that does useful work in a predictable way according to some physical laws. It acts as a transducer, or convertors, accepting an input of energy in one physical from and transforming it, more or less effectively, into another. Electric motor employs principle of interaction. An electric current flowing in a direction making an angle (preferably a right-angle) with a magnetic field produced by another current (or a magnet) experience a force fe, the relative direction. The force, fe, arises from the interaction of the flux (created by the current l' flowing in the conductor with the flux produced by a second current or magnet. Since lines of flux do not cross, the two fluxes will realign. Resulting in a stronger field one side. The conductor and weaker filed on t6he other side. The conductor then tends to move from the region of stronger field to the region of weaker filed [4].

An electric motor is a device that converts electrical energy into mechanical energy [5]. The majority of motors operate on the premise that the magnetic field and electric current within a wire winding interact. Shaft rotation can result in the generation of force. DC or AC sources can be used to power these motors. Batteries are considered DC sources, whereas inverters, power grids, and generators are considered AC sources.

LITERATURE REVIEW

[6] described major types of electric motors as DC and AC Electric motors. The major difference between them is that DC motors are constructed with brushes and a commutator which add to the maintenance, limit the speed and normally reduce the life expectancy of the brushes while induction AC motors do not use brushes, they are very rugged and have a long life span.

[7] explain that induction motor's temperature distribution is not uniform, and there is a possibility of localized overheating. Reducing the winding temperature rise will increase the motor's dependability because the winding is a major source of heat and its insulation is thermally sensitive. High electrical loads and a high torque density are needed for large-end winding. The losses in the machine are mostly caused by those from the winding because of the low speed and high torque application.

[8] suggested that motor rewinding procedures may be broken down into; Coil removal, winding fresh coils, and varnishing the stator as the three processes. These methods may be divided into two categories: traditional and alternative, depending on the methodologies used. Traditional methods typically endure for a long time. One must wait until the preceding step is complete, which might take a few hours, before beginning the subsequent phase. The insulation class rating is greater for traditional methods because they demand higher operating temperatures. Additionally, higher operating temperatures put more strain on mechanical parts (such as bearings), reducing their lifespan. The other techniques take less time, but they also have specific requirements, such better slot filling and fewer turns at the ends of the 1^2R stator, which require extra, more expensive equipment.

[9] discussed that industrial motor uses a major fraction of total industrial energy, it is therefore of utmost importance to always find a way to maximize the efficiency of electric motor in order to reduce the industrial energy consumed.

For instance, the load point of 63% is where efficiency is at its highest. The goal of the rewinding process would be to shift the maximum efficiency point in the direction of the motor operating point, which is, let's say, at 90% load. If the fixed losses are raised while the variable losses are lowered, it is possible to move the point of maximum efficiency to greater loads using relation (1), however this is typically not advised.

Thus, 1^2R stator losses may be decreased by optimizing the stator winding design [5]. According to connection (1), the goal would be feasible because the rewinding procedure will surely result in a minor increase in core losses. The objective might also be accomplished by minimizing the number of stator rotations. As a result, the stator losses would be reduced while core losses would increase [10].

[11] conducted an experimental investigations to determine the frequency-dependent behavior of the equivalent inductance of three-phase IMs and to validate the analytical advancements based on the condensed equivalent circuit shown in the following figure. There are four IMs in the set of motors under examination, each with a different rated power. The skin effect in aluminium rotor bars must be taken into consideration since three out of the four tested IMs had squirrel-cage rotors. The fourth one has wound-rotor windings that are primarily employed in experimental settings to highlight the much-diminished skin effect in such rotor windings.

MATERIALS AND METHOD

Materials

The required data to carry out a comprehensive analysis and investigation of the study is collected by considering the following winding parameters for different winding scenarios

(1) Winding diameter d
(2) Winding width w
(3) Maximum diameter d_{max}
(4) Geometric winding shape A, c, e and f

Orthocyclic Winding Design

The process of winding or re-winding an E-motor requires certain structural process design requirements to be met and/or specified to maintain the required fill factor and hence optimum results in terms of motor speed performance and power efficiency. For the case of Orthocyclic Winding (OW), the structural outlay depicted in Figure 1 forms the basis of the method that facilitates an optimization plan.

Method

A study was conducted to ascertain the behavior of winding characteristics of Othocyclic winding using Crow Search Algorithm (CRA) with different simulations on the influence of flux sizes at different iterations. Consideration were given to the influence of the flock size, f_z, and iteration maxima, $iter_{max}$, while fixating the two core parameters of the Crow Search Algorithm (CSA) optimizer – length-of-flight (lof) and probability-of-awarenes (poa) at their default values.

Crow Search Algorithm

The Crow Search Algorithm (CSA) follows a greedy and vicious approach of optimally sourcing for food (solutions). The best solutions are sorted using thieving and hiding policy and based on two key parameters - length-of-flight (lof) and probability-of-awarenes (poa). Depending on the lof value state from its reference state (1 in this case), the crows' families (corvids) may encounter a local (<1) or global optima (> 1) search experience.

MATLAB Codes

A1.1 CSA OW Program

```
% -------------------------------------------------
% Citation details:
% Alireza Askarzadeh, Anovel metaheuristic method for solving constrained
% engineering optimization problems: Crow search algorithm, Computers &
% Structures, Vol. 169, 1-12, 2016.

% Programmed by Alireza Askarzadeh at Kerman Graduate %
% University of Advanced Technology (KGUT) %
% Date of programming: September 2015 %
% -------------------------------------------------
%Re-programmed by EN Osegi
%Orthocyclic Winding Optimization Using Equalized Turn-Layered Structure:
%Rev. Date: 11th-Dec-2022
% -------------------------------------------------
% Note:
% Due to the stochastic nature of meta-heuristc algorithms, different runs
% may lead to slightly different results.
% -------------------------------------------------
%%
format long; close all; clear all; clc
%%
%% Problem Size:
pd=3; % Problem dimension (number of decision variables)
%% CSA Parameters:
tmax=50; % Maximum number of iterations (itermax) Default: 5000
N=[5,10,15,20,25,30]; % Flock (population) size Default: 20
AP=0.1; % Awareness probability Default: 0.1
fl=2; % Flight length (fl) Default: 2
%[x l u]=init(N,pd); % Function for initialization
%%
%%
%%
%% Load initial data for CSA:
%d W A
x_up = [1.5 50 1.5];
x_down = [0.5 10 1.5];
%% Boundary Concatenation:
u = [x_up];
l = [x_down];
x = 1-(l-u)*rand;
for nn = 1:length(N)
  %% Initialization:
  for i=1:N(nn) % Generation of initial solutions (position of crows)
     x(i,:) = 1-(l-u)*rand; % Position of the crows in the space
  end
  CostFunction=@(x) fitness(x);
```

```
    xn=x;
    ft=CostFunction(x); % Function for fitness evaluation
    mem=x; % Memory initialization
    fit_mem=(ft); % Fitness of memory positions
    for t=1:tmax
        num=ceil(N(nn)*rand(1,N(nn))); % Generation of random candidate crows for following (chasing)
        for i=1:N(nn)
            if rand>AP
                xnew(i,:)= x(i,:)+fl*rand*(mem(num(i),:)-x(i,:)); % Generation of a new position for crow i (state 1)
            else
                for j=1:pd
                    xnew(i,:)=l-(l-u)*rand; % Generation of a new position for crow i (state 2)
                end
            end
        end
        xn=xnew;
        ft=CostFunction(xn); % Function for fitness evaluation of new solutions
        for i=1:N(nn) % Update position and memory
            if xnew(i,:)>=l & xnew(i,:)<=u
                x(i,:)=xnew(i,:); % Update position
                if ft(i)<fit_mem(i)
                    mem(i,:)=(xnew(i,:)); % Update memory
                    fit_mem(i)=(ft(i));
                end
            end
        end
        ffit(t,nn)=min(fit_mem); % Best found value until iteration t
        min(fit_mem)
    end
    ngbest=find(fit_mem== min(fit_mem));
    g_best =mem(ngbest(1),:); % Solutin of the problem
    %% Computed Winding Parameters:
    A = g_best(3); %in mm^2
    c = 0.3*A; %
    e = A/2;
    f = 0.75*A;
    %% Optimized Winding Parameters:
    d = g_best(1); %in mm
    W = g_best(2); %in mm
    R = d/2; %in mm
    Htheoretical = ((1+(W-1)*sin(60/57.3))*d) + 0.1; %in mm (hagedorn et al (2018)
    %% Caster angle computation:
    alpha_max = 11.89 + 3.41*log(d); %Bonig et al (2015)
    alpha_max_S = alpha_max * 0.4; %With safety factor
    A_c_e_f_d_W_R_Htheo(:,nn) = roundn([A;c;e;f;d;W;R;Htheoretical],-2)
end
figure;
%plot(BestCost_bbo,'LineWidth',2);
semilogy(ffit,'LineWidth',2);
xlabel('Iteration');
ylabel('Best Cost');
legend('Best Cost Estimate at flock size 5',...
    'Best Cost Estimate at flock size 10',...
    'Best Cost Estimate at flock size 15',...
    'Best Cost Estimate at flock size 20',...
    'Best Cost Estimate at flock size 25',...
    'Best Cost Estimate at flock size 30');
grid on”;3 cvrvf
```

RESULTS AND DISCUSSION

Simulation Details

The simulation was performed on an i-core 5 PC with the MATLAB® software installed. The key parameters for the ENOTPL-OW process optimization including bordering constraints are as provided in Table 1. The CSA system parameter values are also as specified in Table 2.

Simulations Using Default Settings

Simulations were performed considering the default CSA parameters (Table 2) and for the specified **ENOTPL-OW** boundary constraints (Table 1). The optimized numerical results are as presented in Table 3. These values were obtained at a perfect fitness error level of 0. Thus, these results serve as baseline for comparative evaluations.

Simulations Considering the influence of flock size, f_z at reduced t_{max}

To study the influence of CSA flock size on the dynamic optimization of the ENOTPL-OW process and at reduced maximum iterations, t_{max}, set to 100iters, several intervals of flock size were set at a width of 5units and incrementally re-run from a base value of 5 to 30units. In Figure 1 is shown the fitness cost responses at the aforementioned settings. The optimized numerical optimization value (OV) results are equally presented in Table 4.

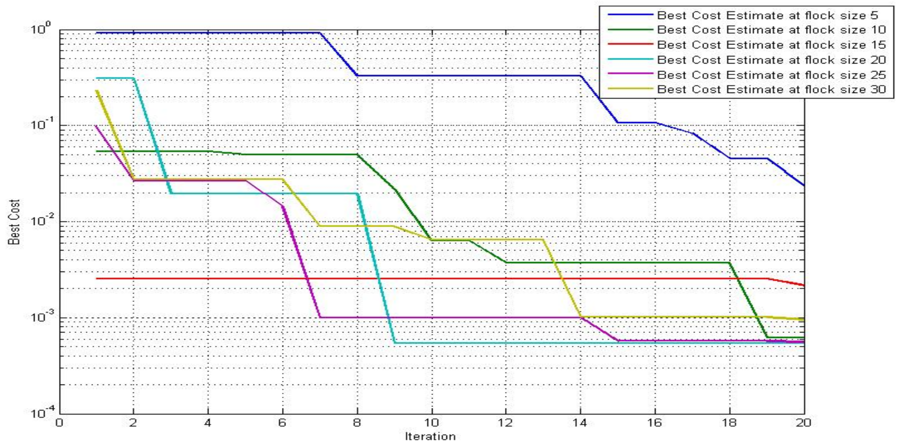

Figure 1: Fitness cost responses at the various flock size settings at t_{max} = 20iters

As can be seen from the Figure 1, the best cost estimate is not clearly distinguishable as flock size f_z = 10, 20, 25 show competitive net error tolerance at around 10^{-3}, for a t_{max} = 20iters. This may be attributed to the low number of iterations for the crows to conduct a search operation. Also, it is observed the constancy of error at the t_{max} = 9iters for f_z = 20, t_{max} = 15iters for f_z = 25 and the t_{max} = 19iters for f_z = 10. Further increase in iterations from these points gave no appreciable reduction in error margins.

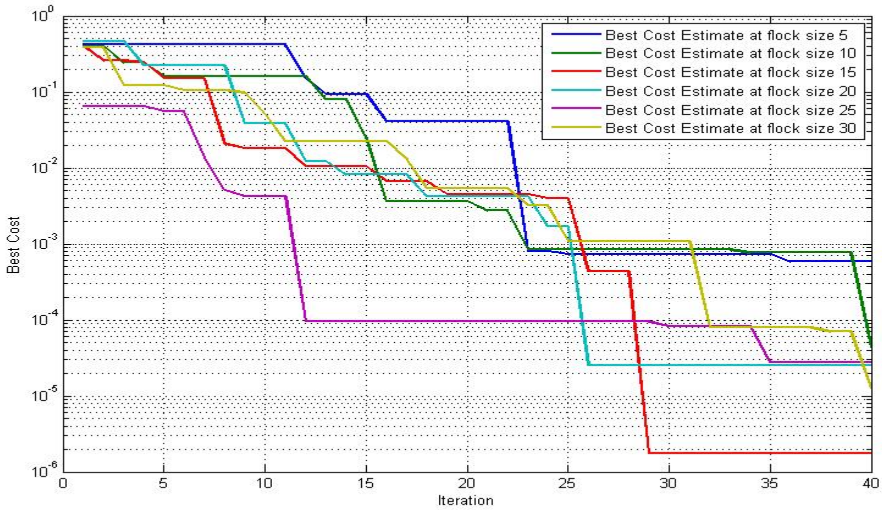

Figure 2: Fitness cost responses at the various flock size settings at t_{max} = 40iters

As can be seen from the Figure 4.5, the best cost estimate at a net error tolerance of about 10^{-6} is obtained at a f_z = 15, for a t_{max} = 40iters. In particular, it is observed the constancy of error at the t_{max} = 28iters further which no appreciable reduction in error is possible.

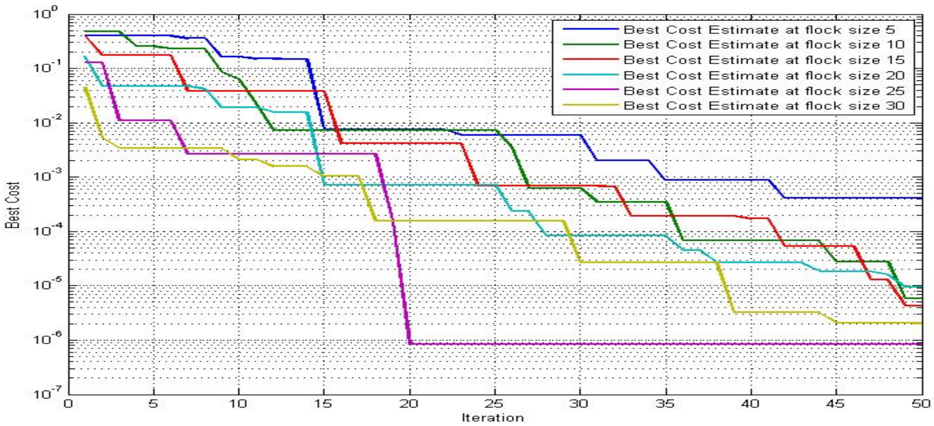

Figure 3: Fitness cost responses at the various flock size settings at t_{max} = 50iters

As can be seen from the Figure 3, the best cost estimate at a net error tolerance of about 10^{-6} is obtained at a f_z = 25, for a t_{max} = 50iters. In particular, it is observed the constancy of error at the t_{max} = 20iters further which no appreciable reduction in error is possible. Also, it is important to note that the optimal flock size is same as that obtained for maximal iterations of 100iters.

To investigate the effect of further reducing maximum iteration count on the fitness result at the varying numerical optimization values (OV). It is observed from table 4.5 that the operating winding design parameters from A,C and F, the numerical optimization values remains the same for t_{max}=10_{iters} between flux sizes fx 5 and 30, the corresponding OV_s are the same while for D,W and R, there is significant increase in numerical optimization values. It was noted that at OV, fx = 15, the value drops to maximum point before it continue to increase again.

Table 1: Numerical OV results for different flock populations, t_{max} = 10iters

OW Design Parameter	OV, fz = 5	OV, fz = 10	OV, fz = 15	OV, fz = 20	OV, fz = 25	OV, fz = 30
A	1.50	1.50	1.50	1.50	1.50	1.50
C	0.45	0.45	0.45	0.45	0.45	0.45
E	0.75	0.75	0.75	0.75	0.75	0.75
F	1.13	1.13	1.13	1.13	1.13	1.13
D	1.28	1.29	1.24	1.26	1.25	1.24
W	41.17	41.52	39.51	40.24	40.13	39.55
R	0.64	0.64	0.62	0.63	0.63	0.62
Htheo	45.87	46.57	42.62	44.04	43.82	42.70

It was also noted from table 4.6 that there is similarities in the behavior of flock population t_{max} = 10_{iters} and t_{max} = 20_{ites}. The only notable difference is that instead of the previous increase for D, W and R in table 4.5 at tx = 15, there is a notable numerical constant figure in the values obtained after the first iteration on R in table 1.

Table 2: Numerical OV results for different flock populations, t_{max} = 20iters

OW Design Parameter	OV, fz = 5	OV, fz = 10	OV, fz = 15	OV, fz = 20	OV, fz = 25	OV, fz = 30
A	1.50	1.50	1.50	1.50	1.50	1.50
C	0.45	0.45	0.45	0.45	0.45	0.45
E	0.75	0.75	0.75	0.75	0.75	0.75
F	1.13	1.13	1.13	1.13	1.13	1.13
D	1.26	1.24	1.24	1.24	1.24	1.24
W	40.37	39.60	39.51	39.56	39.60	39.61
R	0.63	0.62	0.62	0.62	0.62	0.62
Htheo	44.30	42.80	42.62	42.72	42.79	42.82

Similarly, careful observation shows that table 3, table 4 and table 5 has the same behavior for t_{max} = 30_{iters}, 40_{iters} and 50_{iters}. These tables shows immediate fluctuations after OV, Fx=15.

As can be seen from the table 4.5 through 4.9 the primary changes in OVs occur for the parameters D,W,R and Htheo. In conclusion, it is possible to attain an equivalent OV set to the baseline at a t_{max} = 50_{iters} at fx = 15 as clearly shown in table 5 below.

Table 3: Numerical OV results for different flock populations, t_{max} = 30iters

OW Design Parameter	OV, fz = 5	OV, fz = 10	OV, fz = 15	OV, fz = 20	OV, fz = 25	OV, fz = 30
A	1.50	1.50	1.50	1.50	1.50	1.50
C	0.45	0.45	0.45	0.45	0.45	0.45
E	0.75	0.75	0.75	0.75	0.75	0.75
F	1.13	1.13	1.13	1.13	1.13	1.13
D	1.24	1.24	1.24	1.24	1.24	1.24
W	39.62	39.58	39.58	39.58	39.59	39.58
R	0.62	0.62	0.62	0.62	0.62	0.62
Htheo	42.82	42.76	42.75	42.75	42.76	42.76

Table 4: Numerical OV results for different flock populations, t_{max} = 40iters

OW Design Parameter	OV, fz = 5	OV, fz = 10	OV, fz = 15	OV, fz = 20	OV, fz = 25	OV, fz = 30
A	1.50	1.50	1.50	1.50	1.50	1.50
C	0.45	0.45	0.45	0.45	0.45	0.45
E	0.75	0.75	0.75	0.75	0.75	0.75
F	1.13	1.13	1.13	1.13	1.13	1.13
D	1.24	1.24	1.24	1.24	1.24	1.24
W	39.60	39.58	39.58	39.58	39.58	39.58
R	0.62	0.62	0.62	0.62	0.62	0.62
Htheo	42.79	42.75	42.76	42.76	42.75	42.75

Table 5: Numerical OV results for different flock populations, t_{max} = 50iters

OW Design Parameter	OV, fz = 5	OV, fz = 10	OV, fz = 15	OV, fz = 20	OV, fz = 25	OV, fz = 30
A	1.50	1.50	1.50	1.50	1.50	1.50
C	0.45	0.45	0.45	0.45	0.45	0.45
E	0.75	0.75	0.75	0.75	0.75	0.75
F	1.13	1.13	1.13	1.13	1.13	1.13
D	1.24	1.24	1.24	1.24	1.24	1.24
W	39.60	39.58	39.58	39.58	39.58	39.58
R	0.62	0.62	0.62	0.62	0.62	0.62
Htheo	42.78	42.76	42.76	42.76	42.76	42.76

CONCLUSION

This research investigated the application of a modern metaheuristic technique based on the ability of Crows to explore a good food space called the Crow Search Algorithm (CSA). The algorithm is applied to the design optimization of the OW core diameter, winding width, and in-between-turn-center width for the optimal computation of a theoretical winding height at minimum winding diameter and width tolerances. Considerations were given to the influence of the CSA parameters - the flock size, and the maximal iterations for different scenarios. The potentials of a well-documented linear winding scheme called orthocyclic winding (OW) which is currently gaining grounds in automotive applications are also analyzed. Optimization of the Equal-number-of-turns-per-layer Orthocyclic Winding (ENOTPL-OW) scheme is presented in this study.

From the simulation optimization results, it was shown that it is possible to attain an optimal rewinding policy setting at tmax = 50 liters and for a flock size of 25.

Contributions to Knowledge

The key contributions to knowledge made in this thesis primarily border on the following:

i. Development of objective function models e-Motor Orthocyclic Winding (OW) scheme
ii. Development of a new optimization systems-based model using the Crow Search Algorithm (CSA) for an e-Motor Orthocyclic Winding (OW) scheme.

Implementation of OW optimization simulation program to validate CSA extrinsic population parameters (maximal iterations and flock size).

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