Particle Swarm Optimization with Varied Social Network for Reliable Parameter Estimation in Thermal Analysis of Electrical Machines

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This paper presents a variant of particle swarm optimization (PSO) algorithm, which was developed for a reliable parameter estimation in thermal analysis of electrical machines. The proposed algorithm uses a varied social network, where both number and size of the network (local neighbourhoods) are randomly adjusted during the optimization process. Such approach has been introduced here to assure improved diversity of the PSO and consequently a more reliable and robust search of the solution space. A case study parameter estimation for a reduced-order thermal-equivalent-circuit (TEC) of an electrical machine has been used to demonstrate effectiveness of the proposed method. The analysed black-box parameter estimation relies on the input and output data (demand data) from a short-transient finite-element-analysis (FEA) of a complete machine assembly. The proposed PSO variant has been benchmarked with a selection of the existing PSO algorithms, which employ alternative social network schemes with the network parameters dynamically varied. The statistical data gathered from multiple runs of the PSO-based estimation suggests that the proposed approach offers considerable improvements in terms of accuracy, efficiency, reliability and robustness as compared with the alterative PSO algorithms.

***Index Terms*—Particle swarm optimization, varied social network, parameter estimation, transient thermal analysis, finite element analysis, electrical machines.**

I. Introduction

The social behaviour-based search algorithms found significant interest in the context of electrical machine, design-optimization, control and parameter identification [1]-[4]. The particle swarm optimization (PSO) has been particularly popular here as it offers both simplicity and reliability. There has been a multitude of research devoted to alternative PSOs, where the specific search performance measures like accuracy, efficiency, reliability and robustness were investigated [5]-[8]. In this paper a variant of PSO algorithm with dynamically adjusted social network is presented and compared with a number of more common PSO algorithms, where alternative sociometry is considered [5]-[8]. Here, both structure and size of the PSO neighbourhoods are altered due course of the search process. The proposed PSO has been developed to aid parameter estimation in thermal design-analysis of electrical machines. A reduced-order thermal-equivalent-circuit (TEC) model has been used here to demonstrate efficacy of the analysed PSO-based parameter estimator. Note that the reduced order thermal models of electrical machines are frequently employed, where real-time temperature predictions, complex transient operation and faulty (non-symmetrical) conditions are considered [3].

The initial statistical data gathered from multiple runs of the proposed PSO variant suggests considerable improvements in accuracy, efficiency, reliability and robustness as compared with the alterative PSO algorithms benchmarked in this work.

II. PSO with Varied Social Network

There are various approaches to improve searching performance of the classical PSO with star-social-network (global neighbourhood – *gbest*) like introduction of alternative social constructs with local neighbourhoods – *lbest,* e.g. ring, wheel, pyramid, Von Neumann social networks [5]. Such approach considerably improves diversity of a given swarm of particles and consequently enhances ability to find the global optimum, but usually suffers from lengthier convergence due to slower exchange of information within the swarm [4]-[8]. Some of the techniques to balance the diversity and convergence factors is to introduce a form of disturbance within the swarm like dynamically varied size of neighbourhoods or form of social network among others [5]-[8].

The velocity of each particle for *lbest* PSO is adjusted according to the following equation,

$$v_n = w \cdot v_n + c_1 rand(\quad)\left(p_{best,n} - x_n\right) + c_2 rand(\quad)\left(l_{best,n} - x_n\right) \tag{1}$$

where $rand(\quad)$ returns a number uniformly distributed between 0.0 and 1.0, the inertia weight, w, varies linearly from 0.9 to 0.4 over the course of the run, and exploration and exploitation scaling factors $c_1$and c_2 are equal to 1.49 [4].

In the proposed PSO number of individual neighbourhoods is randomly varied together with social links between individual particles within the swarm. Note that the alternative PSOs assume fixed number of neighbourhoods equal to the swarm size. A new position of the particle in nth dimension follows here the standard from,

$$x_n = x_n + \Delta t \cdot v_n \tag{2}$$

with time step Δt equal to unity.

III. A Case Study

Fig. 1 presents a schematic TEC representation of the analysed electrical machine. The model includes 6 thermal resistances, R_i, and 5 thermal capacitances, C_i, to be estimated using the proposed PSO-based estimator. An input power loss profile ($20s$ on and $20s$ off state) into the winding is used to

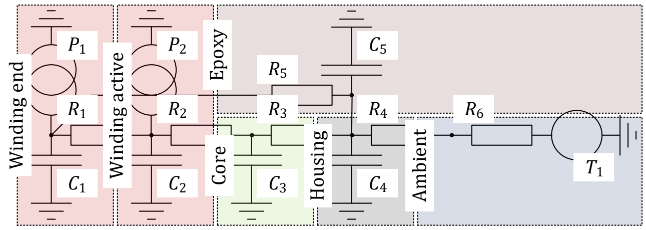

Fig. 1. Schematic representation of the analysed TEC, where R_1 - R_6 are the thermal resistances, C_1- C_2 are the thermal capacitances, $P_1$and P_2 are the input winding power losses and $T_1$is the ambient temperature

generate thermal transients corresponding with the winding end and active subassemblies, core, and housing regions, used as a demand data for the estimation procedure. All model parameters R_i and C_i can change from $1 \cdot 10^{-6}$ to 30, $℃/W$ and $J/℃$ respectively. The swarm size assumed here is equal to 20 particles with number of generations fixed to 100. To collect statistical data associated with PSO searching performance, each of the analysed PSO variants was run 100 times. An error function (averaged standard deviation) from the individual thermal transients was used as an objective function, where the error, $Err(\boldsymbol{x})$, between the demand and estimated data is minimized over the run of the estimation procedure.

IV. Results and Observations

Table I lists statistical data from the estimations using alternative PSOs. Here, 6 variants are considered: 1) PSO and 2) PSO are the conventional algorithms, 3) PSO and 4) PSO use dynamically adjusted ring social network, and 5) PSO and 6) PSO employ randomly generated social constructs, with the later one being the focus of this investigation. The results suggest that 6) PSO offers the best robustness (low variance, $var(Err(\boldsymbol{x}))$) and lowest estimation error among the analysed PSOs, with 3) PSO being the second best. Fig. 2 compares the PSO reliability and efficiency. The proposed 6) PSO offers here the highest reliability, i.e. a percentage of individual PSO runs reaching a given accuracy. The averaged

TABLE I
Statistical Data for Alternative PSO-based Estimators

PSO	$max(Err(\boldsymbol{x}))$	$min(Err(\boldsymbol{x}))$	$mean(Err(\boldsymbol{x})$	$var(Err(\boldsymbol{x}))$
1)	4.4356	0.4756	0.8927	2.0885
2)	2.0102	0.4974	0.7098	0.3493
3)	2.0049	0.4684	0.5953	0.1348
4)	3.8934	0.4716	0.7052	0.9957
5)	1.9047	0.4726	0.6353	0.2141
6)	0.8847	0.4644	0.5259	0.0104

1) PSO with *gbest* (static social network – star)
2) PSO with *lbest* (static social network – ring with neighbourhood size equal to 2)
3) PSO with *lbest* (dynamic social network – ring with neighbourhood size adjusted linearly from 2 to complete swarm due course of the estimation process)
4) PSO with *lbest* (dynamic social network – ring with neighbourhood size randomly adjusted due course of the estimation process)
5) PSO with *lbest* (dynamic social network – random with neighbourhood size adjusted due course of the estimation process)
6) PSO with *lbest* (dynamic social network – random with neighbourhood number and size adjusted due course of the estimation process)

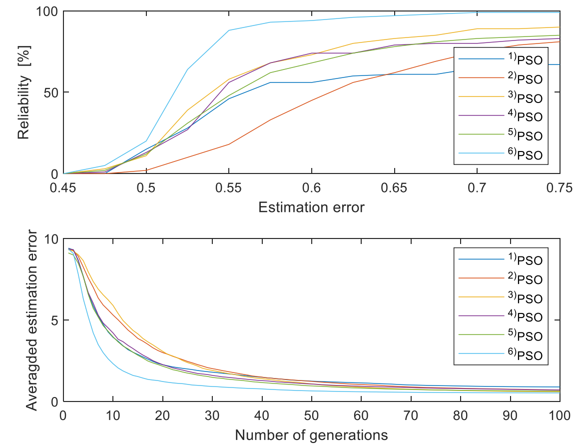

Fig. 2. Selected search performance measures for the alternative PSO-based estimators

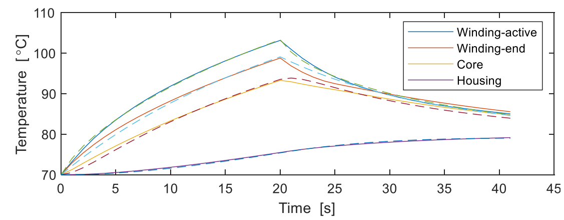

Fig. 3. Demand (solid line) and estimated (dashed line) thermal transients

estimation error refers here to efficiency of PSO, i.e. a number of generation required to rich the specified accuracy. Again, 6) PSO offers here the fastest convergence over 100 individual runs of the PSO-based estimator. Fig. 3 presents an example of thermal transients from the FEA (demand data) and reduced-order TEC (estimated results) showing good correlation. The presented results suggest that the proposed PSO-based estimator (6) PSO) offers all around searching performance improvements, which are particularly desirable in analysis of electrical machines among other applications.

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