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Hybrid EAs for Backup Sensorless Control of PMSM Drives

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Abstract: - This paper presents a robust strategy to increase the reliability of Permanent Magnet Synchronous Motor drives against encoder or resolver failures. If the position sensor fails, the “failure and recovery manager” switches the drive in sensorless mode, i.e., the control system uses the speed and position feedback given by a Sliding-Mode observer in place of the sensor. As the accuracy of the sensorless control depends on the tuning of the observer parameters according to the motor conditions, the Sliding-Mode observer is periodically tuned during the sensor-based control of the drive. A fast and robust tuning of the observer can be obtained by Hybrid Evolutionary Algorithms. This prevents untimely sensored-to-sensorless switching due to speed transients and allows better performances of the sensorless control when the position sensor fails actually. The results carried out prove that the position sensor failures do not affect the drive operation, and proposed HEA outperforms the standard search algorithms.

Key-Words: - Sensorless control, Sliding mode control, Variable speed drives, Evolutionary Algorithms.

1 Introduction

The field-oriented control of Permanent Magnet Synchronous Motor (PMSM) drives needs accurate rotor speed/position information [1]. The speed and position can be measured by sensors, or estimated by observers. Sensorless solutions are very attractive because make cheaper the drive, but due to their lower accuracy, a number of applications still needs sensor-based scheme. However, even if the sensorless algorithm cannot completely replace the sensors, it can works as a backup for sensor failures. The supervisor, “failure and recovery manager”, detects position sensor failures and switches from sensor-based to sensorless control the drive. In this way, the drive can properly operate the motor in sensorless mode, and can alerts the user.

Over the last years, Sliding-Mode (SM) controllers and observers have been largely employed in a.c. drives [2-9] due to their robustness, but their tuning still remains a crucial point to reach optimal performances. In [9], the parameters of an adaptive SM observer were optimized during the sensor-based operation of the drive. Three optimization algorithms, included in the Optimization Toolbox of MATLAB [10], were compared, and the *fminsearch* function which implements the simplex method gave the better performances.

This paper proposes a new Hybrid Evolutionary Algorithm (HEA) as optimization technique. A hybrid method consists of a cooperation of different search methods that inherited the exploitation ability of the local search methods and the explorative ability of the stochastic-guided methods [11]. The results carried out prove that the proposed solution makes shorter and more robust the optimization process.

2 Backup Sensorless Control of SPMSM Drive

The block diagram of the backup sensorless control of a PMSM drive is shown in fig. 1. The SM observer [9] works in parallel with the encoder. The estimates of the observer and the sensor measurement are handled by the “failure and recovery manager” that is in charge of two main tasks. The former is the observer tuning, whilst the latter consists of switching to sensorless control when the sensor fails.

Initially, assuming that the sensor works properly, the observer needs to be tuned because the accuracy of the speed and position estimates of the SM observer [9], $\hat{\omega}_r$ and $\hat{\theta}_r$ respectively, depends on the knowledge of the parameters *R*, *L*, and Ψ which are the stator resistance, stator inductance and PM flux linkage. Usually, the values of these parameters are approximate and change during the drive operations. In order to keep the estimates as accurate as possible, the observer is periodically tuned. As shown in fig. 2, the integral of $|e_\omega| = |\hat{\omega}_r - \omega_r|$ over small periods is used as fitness for the optimization process. There is evidence that the faster the

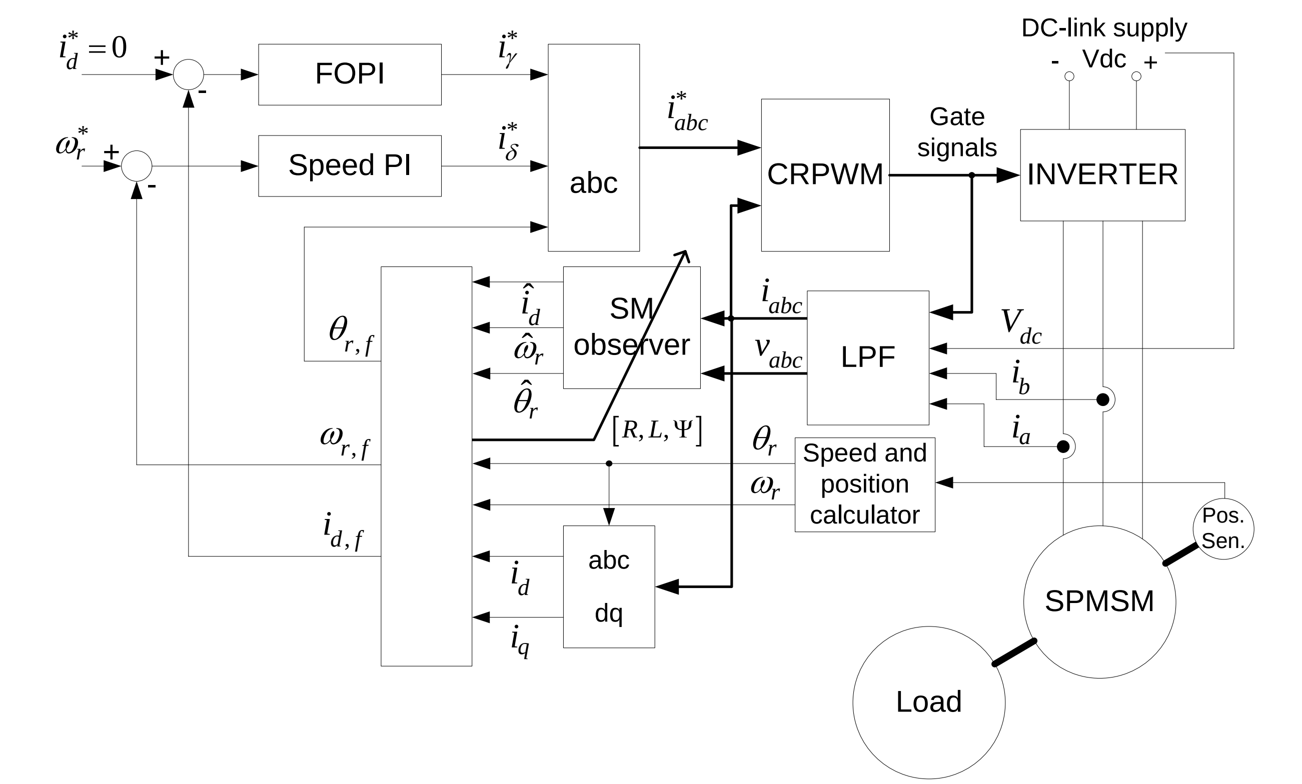

Fig. 1 - Block diagram of the back-up sensorless control of SPMSM drive.

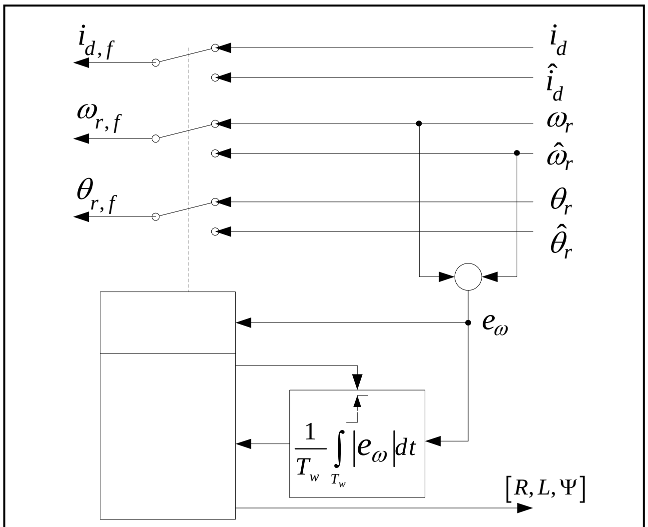

Fig. 2 - Failure and recovery manager.

optimization is, the sooner the sensor failures can be properly detected.

After the tuning, the estimation error is less than 1% in steady-state. In this way the "failure and recovery manager" can switches to the sensorless control when $|e_\omega|$ exceeds a given threshold. Obviously, this threshold has to be set according to the observer performances over a large range of working condition.

4 New Hybrid Evolutionary Algorithm

EAs are guided stochastic search methods that suffer from slow convergence rate. A careful configuration only partly solves such a problem that lies in the non-deterministic nature of evolutionary operators which locate the optimal "hill", i.e., the zone where the optimal solution is, but are not able to quickly refine it. On the contrary, classical methods, often classified as hill-climbing, can efficiently exploit local information to speed up the optimization and properly work when the function to be optimized is smoothed and unimodal; but they often fail in real-world problems that usually are ill-behaved. In order to get the benefits of both the techniques, many hybrid methods were proposed. A hybrid method consists of a combination between different search methods. Although this is a very general definition, it is the only one that can include the huge number of possibilities. These are given not only by the number of search methods, but also by the hybrid architecture, i.e., the way in which the different methods are integrated in a framework to cooperate. As shown in fig. 3, an initial sub-evolution transforms the initial population, pop_{in} into the intermediate population pop_{int}. This stage consists of running the EA. Consequently, the top-ranking individuals are extracted from pop_{int} creating $pop_{top,in}$. Analogously, the medium-ranking individuals form $pop_{med,in}$. The size of $pop_{top,in}$ top-

ranking is chosen between the 10% and 15% of pop_{int}, whilst that of $pop_{med,in}$ is between the 95% and 85%. It has to be noted that $pop_{top,in}$ and $pop_{med,in}$ can be overlapped, that is, can have some individuals in common.
The probabilistic multi-directional simplex method, is the local search method that operates on $pop_{top,in}$ to produce $pop_{top,out}$. Again, the $pop_{med,out}$ is obtained by the aforementioned EA with $pop_{med,in}$ as initial population. Finally, the pop_{out} is obtained by a fitness-based merging of $pop_{top,out}$ and $pop_{med,out}$. The iteration reported in fig. 3 can be repeated until a termination criterion, such as a prefixed number of iterations, is satisfied. The new hybrid architecture better coordinates the global and local search methods in order to save fitness evaluations. The proposed solution rations the use of the local search, and for the same reason, the simplex method has been adopted as local search method.
The simplex method, popularized by Nelder and Mead [12] with their effective version, belongs to the class of the direct search methods whose two main properties are:

- no gradient, or any gradient approximation, can be used,
- only the values of the fitness function can be used.

These properties make the direct search methods an efficient alternative to Newton's, and quasi-Newton methods that are impracticable:

- if the fitness evaluation is very time-consuming and noisy such as when calculated through experimental tests,
- if gradient, Hessian, and first partial derivatives of the fitness function cannot be exactly calculated, and their numerical approximations are too expensive.

5 Simulation Results

This section shows the results regarding the tuning performances given by the proposed HEA and the effectiveness of the back-up sensorless control scheme.
In order to test the performances of the optimization algorithms, we defined two different search spaces. The first, $\mathbf{H_1}$, is a parallelepiped low- and up-bounded between ±30% of the initial guess [R_0, L_0, Ψ_0], where the index 0 indicates the nameplate values. The second, $\mathbf{H_2}$, is a larger parallelepiped because low- and up-bounded between ±70% of the initial guest. The bounds of the search space $\mathbf{H_1}$ has been set supposing reduced parameter variations in normal conditions of work. Vice versa, the search

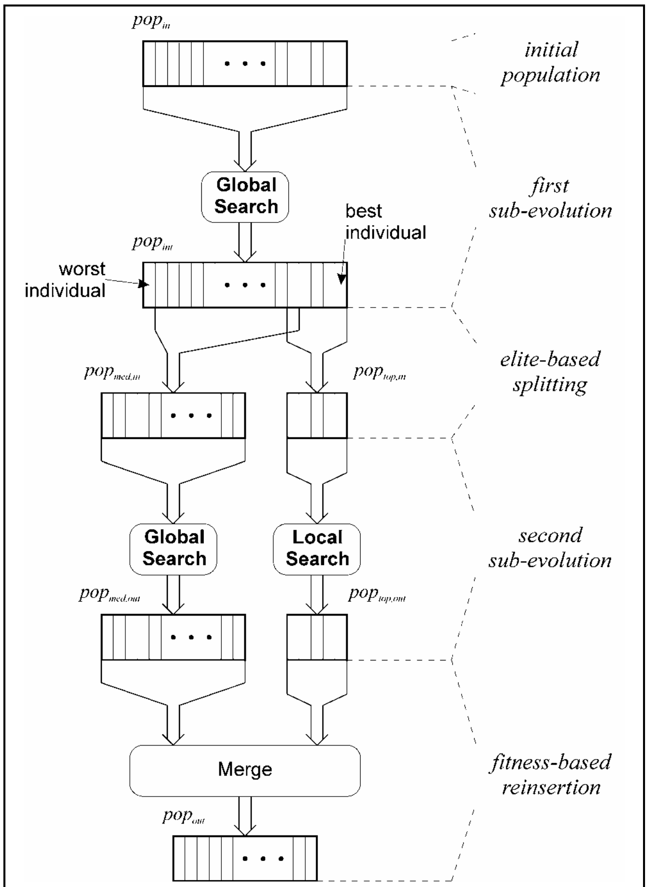

Fig. 3 - Iteration of the proposed Hybrid EA.

space $\mathbf{H_2}$ considers larger ranges for the parameter variations. This leads to a more robust system that needs more time to be tuned.
In fig. 4, the first comparison between the proposed HEA and the fminsearch is illustrated. It refers to the search space $\mathbf{H_1}$, and both the algorithms use a evaluation time window of 0.02 s in which the motor has been operated at the rated speed. The simplex method implemented in fminsearch produces a fitness value equal to 3.31 after 837 evaluations. This result is outperformed by the proposed HEA that not only reaches the same fitness value after 642 evaluations, but further optimizes the observer reaching a fitness value equal to 3.01 after 843 evaluation.
The same experiment has been repeated considering the search space $\mathbf{H_2}$ and the results are shown in fig. 5. There is evidence that the larger search space leads to poor performances of fminsearch. It scores a fitness value equal to 3.91 after 1078 evaluations. It means that the algorithm has not been able to find the same solution as in the previous test, jeopardizing the performances of the whole system. As regards the proposed HEA, it is able to locate the same optimal solution after 1286 evaluations. Moreover it has to be noted that the solutions

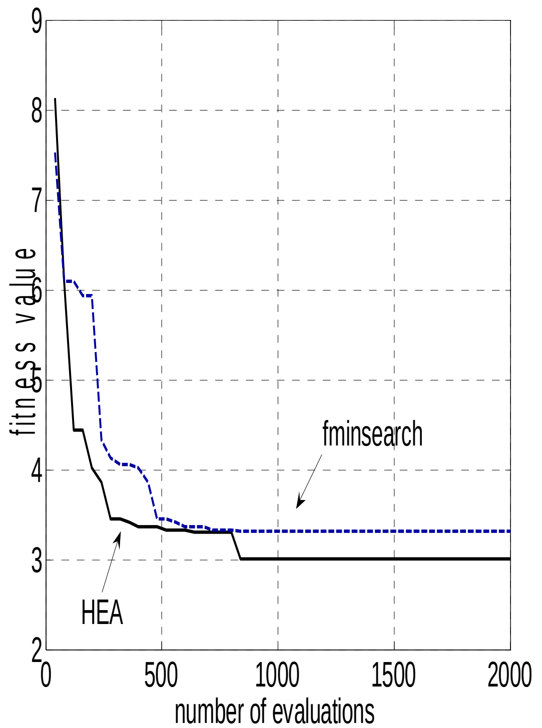

Fig. 4 – Optimization in the search space $\mathbf{H_1}$.

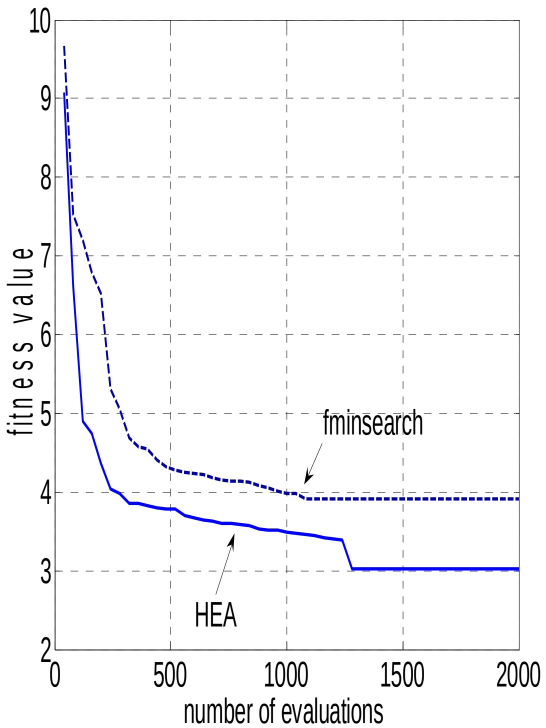

Fig. 5 – Optimization in the search space $\mathbf{H_2}$.

provided after 800 evaluations are good enough to ensure an acceptable behaviour of the drive.
After optimization, the PMSM has been loaded and started to verify the "failure and recovery manager" performance. The motor has been operated at the rated speed (ω_n = 1675 rad/s). The load torque has been removed at time 0.08 s and the position sensor has failed at 0.13 s, then a speed reversal has been operated. The speed response is shown in fig. 6. The starting transient has an overshoot equal to 1.6%. When the load torque is removed, the speed overshoot reaches 2.2%, but the "failure and recovery manager" does not switches. The sensor failure causes a drastic reduction of measured speed. Consequently, the control action tends to accelerate the motor until the failure is detected. This new transient causes a speed overshoot equal to 2.0%. It has to be noted that the detection and recovery transient is very short. In fig. 7 the difference between feedback and estimated speed is shown. When this difference exceeds the alarm threshold there is the commutation from sensor-based to sensorless operation mode, and the feedback speed equals the estimated one. The response of d- and q-axis current components is shown in fig. 8. There is evidence the d-axis current component remains close to zero assuring the field orientation and, in this case, maximum torque/ampere ratio.

From a glance to figures from 4 to 6, one can see that the continuous working is achieved in spite of the sensor fault.

6 Conclusions

In this paper a back-up sensorless control strategy for PMSM drives has been proposed and tested.
The success of the strategy is due to the fast and robust HEA tuning of the adaptive sliding-mode observer.
This solution increases the reliability of the PMSM drive that can overcome sensor failures switching from sensored to sensorless mode. Moreover, the "failure and recovery manager" and the SM observer can be easily embedded in a standard drive because they consist of a light software and do not need any additional hardware.

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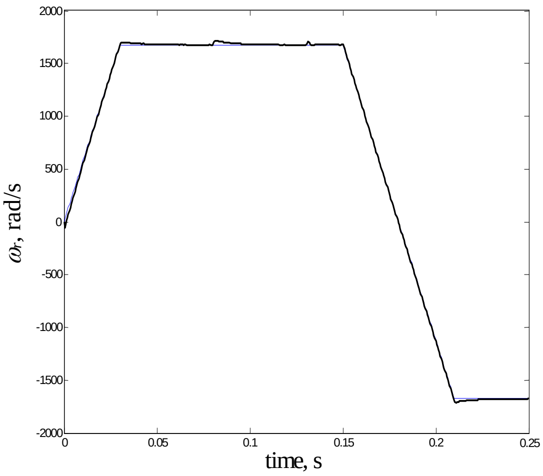

Fig. 6 – Speed response.

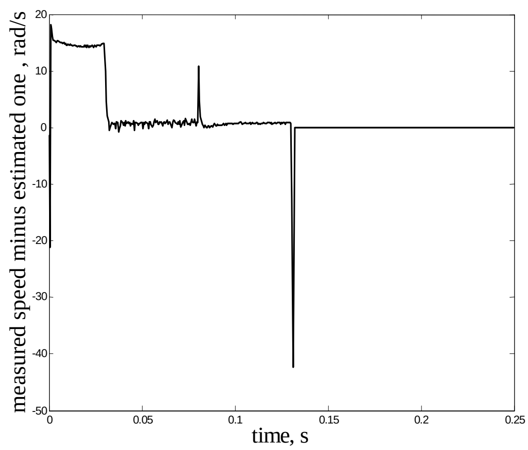

Fig. 7 –Difference between measured and estimated speed.

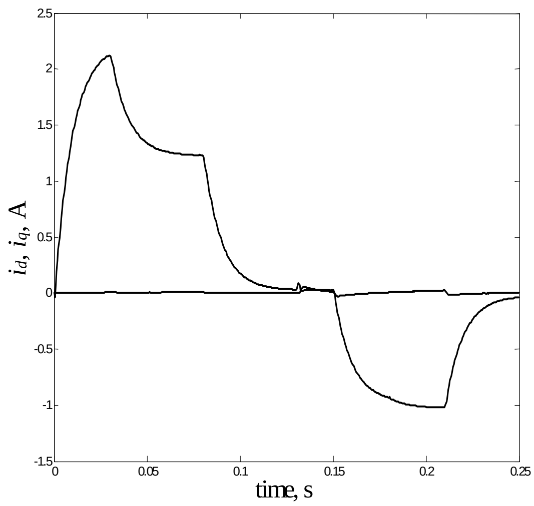

Fig. 7 – d- and q-axis current components.

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