Injection Based Sensorless Performance Optimization of Surface Mounted Permanent Magnet Motor using Particle Swarm

M. Caner, C. Gerada

Abstract—This paper shows the results of an intention to design of surface mounted permanent magnet (SMPM) machines with self-sensing capabilities determining design parameters by Particle Swarm Optimization (PSO). A methodology will be presented which will look at the use of PSO to close up the torque to the highest values as possible and to maximize the self-sensing properties of such machines. A PSO environment has been combined with a finite element analysis (FEA) environment to enable the designer to account for both geometrical and saturation saliencies for an effective determination of the machine’s self-sensing characteristics. The results obtained are satisfactory in terms of torque maximization and self-sensing capability. The sensitivity of the major geometrical parameters of the machine investigated, as well.

Index Terms—Design optimization, Particle swarm method, Sensorless control performance, Surface mounted permanent magnet machine.

I. INTRODUCTION

PERMANENT magnet machines require position tracking for sensorless control. Due to the weak saliency nature of SMPM machines, if the saliency is tracked easily at the stage of motor design, sensorless control can be applied smoothly.

Model-based detection methods [1] are sensitive to machine parameter variations and fail at zero and low speed when the signal to noise ratio of the feedback voltage is very poor. Saliency-based signal injection methods perform better at low and zero speed [2], [3]. However, there are some problems to prevent them more common in their usage. They are dependent on the physical geometry of the machine itself. That makes these methods hard to apply in industrial drives where generalized control strategies compatible with various machine designs from various manufacturers are required.

The aim of any motion or position detection scheme is to track one of these modulating saliencies, which are dependent on the rotor position. It was declared that loading leads a reduction in saliency [4], and double layer structure in SMPM is more suitable for sensorless control [5].

There is a trade-off point between self-sensing and torque capabilities that the point can be obtained by using design optimization methods [6]. Numerous papers related design optimization of SMPM, have been published [7]–[10]. In these studies, optimization was conducted on the analytical model of SMPM and results were verified using FEA. Because obtaining results directly from FEA simulation takes too long, optimization over analytical model has been preferred. However, contemporary computers lessen the time of the optimization with FEA.

PSO is one of the population based stochastic optimization algorithms like GA. It has been successfully applied to design optimization studies to optimize some objectives such as weight, volume reducing and efficiency increase [11], [12]. It was reported in [10] that PSO is more popular and superior to GA for motor design optimization. Also, PSO with the passive congregation (PSOPC) is superior to several types of PSO in terms of search performance in [13].

In this study, FEA based parametric modelling of SMPM machine is conducted and its geometry is optimized using PSO in terms of both torque and self-sensing capabilities. Within this work, the SMPM is considered as a 12slot-10pole structure, which is commonly used due to its relatively high winding factor and low cogging torque and allows fault-tolerant machine design. In addition, the sensitivity of the performance indicators of torque and self-sensing capability is discussed in terms of the major geometrical parameters of the machine.

II. SALIENCY CONDITIONING

The rotor position of an electrical machine can be estimated by modulating the impedance seen from the machine power terminals if there is a form of magnetic saliency dependent on it. This saliency can be either in the rotor’s itself due to the rotor geometry or as a result of iron saturation in the rotor or stator due to the synchronously rotating magnetic flux. This saliency can be tracked by processing the current response to a test voltage signal injection overlaid on the main PWM excitation. In electrical machines, there are a number of saliencies dependent on both the geometry and flux density levels.

The parameters used for representing the saliencies in PM machines are the dq incremental inductances defined in (1).

\[
L'_d = \frac{\partial \psi}{\partial i_d}; \quad L'_q = \frac{\partial \psi}{\partial i_q}; \quad L'_dq = \frac{\partial \psi}{\partial i_d \partial i_q}
\]

(1)

Saliencies resulting from a difference between the incremental inductances in d and q axis are the main factors that influence the sensorless performance for techniques based on high-frequency injection [14]. The three quality criteria are:
\[
max\{\Delta L(\theta, i_q) = L_d(\theta, i_q) - L_q(\theta, i_q)\} \\
min\{ L'_d(\theta, i_q)_{pp}, \ min\{ L'_q(\theta, i_q)_{pp} \} \} \\
min\{ L''_{dq}(\theta, i_q) \}
\]

This paper will consider (2a) and (2b) within the PSO. In Eq. 2b, the subscription “PP” denotes peak to peak values.

### III. PARAMETRIC MODELLING OF SMPM

Electromagnetic analysis of the 12-slot 10-pole three phase SMPM machine design is carried out with FEA-based software. All the machine design has been held with external scripting via Matlab. The outer machine volume and copper loss are constrained for a given convective heat transfer coefficient. The motor design geometry was created with eight variables which were then optimized, according to the different set goals. Table I summarizes the definition of the design limits of these variables according to pre-design optimization results. Fig. 1 shows the placement of these variables on the motor.

<table>
<thead>
<tr>
<th>TABLE I</th>
<th>DESIGN VARIABLES</th>
</tr>
</thead>
<tbody>
<tr>
<td>Split ratio</td>
<td>Sratio</td>
</tr>
<tr>
<td>Tooth width</td>
<td>Tw</td>
</tr>
<tr>
<td>Magnet span</td>
<td>Mspan</td>
</tr>
<tr>
<td>Magnet thickness</td>
<td>Mt</td>
</tr>
<tr>
<td>Stator back iron thickness</td>
<td>Sbi</td>
</tr>
<tr>
<td>Tooth bridge height</td>
<td>Tbh</td>
</tr>
<tr>
<td>Slot opening height</td>
<td>Soh</td>
</tr>
<tr>
<td>Slot opening width</td>
<td>Sop</td>
</tr>
</tbody>
</table>

The outer machine dimensions were constrained for this work. Optimization of the machine’s geometry using the parameters, listed above, were realized for a given convective heat transfer coefficient, the copper losses were fixed. Iron losses were ignored. Some assumptions used for the motor geometries were given below.

- fixed outer radius, 67.5 mm
- fixed slot/pole combinations, 12/10
- fixed air gap length, 1mm
- fixed axial length, 100mm
- fixed copper loss, 165W (in nominal loading)

The PMs are placed along the airfoil of the rotor. And the length of the space between poles can be altered using a magnet span angle. Span angle of pole pair is represented as 3600 in electrically. Each phase consists of four coils. Fractional slot with double layer concentrated winding structure is used.

Appropriate current value has been calculated, in order to achieve constant copper loss per volume while the slot area varies for each design. Square current is directly proportional to copper loss. The copper loss has been calculated by considering slot fill factor. It has been taken as 0.5. The number of turns per coil of the stator phase windings is 34 and 4 coils have been used for each phase.

The PMs, used in this machine, are a NdFe14B type with residual induction, Br at 20C is 1.29 T. M330-35A silicon steel is chosen as the material of stator and rotor iron core components.

A non-linear 2D time-stepping simulation is run for each parameter change, with the current loading scaled for a fixed copper loss to determine the mean torque and on-load torque ripple. Taking the eight design variables as inputs from population-based parameter space, the sensorless performance parameters are calculated according to (2a) and (2b) then used to calculate the fitness value which is necessary for the PSO.

For a better understanding of the values, Table II presents the rated data for the machine and some design assumptions in FEA.

<table>
<thead>
<tr>
<th>TABLE II</th>
<th>THE SMPM MOTOR RATINGS AND FEA SIMULATION PARAMETERS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power, Torque</td>
<td>9.4kW –30Nm</td>
</tr>
<tr>
<td>Voltage, Nominal current</td>
<td>–250 V, 13.5 A 250Hz</td>
</tr>
<tr>
<td>Rotor speed</td>
<td>3000 rpm</td>
</tr>
<tr>
<td>Electrical and mechanical periods</td>
<td>20-4 ms</td>
</tr>
<tr>
<td>Simulation period</td>
<td>0.64 ms</td>
</tr>
<tr>
<td>Resolution (time step used in FEA)</td>
<td>0.04 ms</td>
</tr>
</tbody>
</table>

### IV. PARTICLE SWARM OPTIMIZATION AND CASE STUDIES

Particle swarm optimization algorithm simulates the flock of bird or fish movement while seeking for food around the living environment, has been first proposed in 1995 as a new intelligent optimization algorithm. In this algorithm position and velocity vectors are defined for each particle. Swarm consists of particles and each particle’s start-up value are set randomly between the previously defined lowest and the highest values. A loop is defined in order to handle for each particle in the swarm population for each generation. The algorithm can be summarized as follows.

Within the loop, the PSO algorithm generates a new and improved value (let’s say position) for each search criterion from the previous one. Using fitness evaluation, each particle’s position is compared with the current global best position (Gbest). At first step a candidate solution is given as a starting point. Previous global best and personal best values are updated with current ones at each step. Increasing the velocities of the other particles, it is trying to catch up the best one faster. Finally, at each step, the particles come closer to the solution. This repeats until the loop condition becomes "true". Fig. 2 shows the optimization process of the algorithm.

Passive congregation’s impact is provided by adding a randomly selected particle’s position to the current particle’s velocity vector to obtain PSOPC. PSO and PSOPC are handled by using velocity vectors in (3) and (4) respectively. Both algorithms are based on position information update on the each particle in the swarm (5). Each particle represents a group of parameters need to be optimized.
Releasing the swarm into the search space. 
Start
Definition of Swarm size Generation size Search space of particles Initial positions Initial velocities Initial Gbest Fitness functions

Releasing the swarm into the search space. 
Fitness calculation of each particle using FEA based solution
Fitness evaluation Finding Pbest
Decreasing inertia
If Pbest(i+1)<Gbest(i)
Update Gbest
Update velocities and finding new positions
Max. Generation
End

Fig.2. Optimization process

\[ V_{i+1}^{k+1} = \alpha_i^k \omega_i^k V_i^{k+1} + c_i \beta_i^k (Pbest_i^k - X_i^k) + \ldots + c_i \gamma_i^k (Gbest_i^k - X_i^k) \]  
\[ X_{i+1}^{k+1} = X_i^k + P_{i+1}^{k+1} \] (3) 
\[ X_{i+1}^{k+1} = \omega_i^{k+1} + c_i^{k+1} (Pbest_i^{k+1} - X_i^{k+1}) + \ldots + c_i^{k+1} (Gbest_i^{k+1} - X_i^{k+1}) \] (4) 
\[ X_{i+1}^{k+1} = X_i^{k+1} + \omega_i^{k+1} \] (5)

where \( V \) and \( X \) are velocity and position vectors, \( k \) and \( i \) denote the generation/iteration number and particle/individual numbers respectively. \( \alpha, \beta, \gamma \) and \( \delta \) are random decimals vary between 0-1. Weighting coefficient, \( c_1, c_2 \) and \( c_3 \) are used to determine the importance level of related parts. Pbest is the personal best position of a particle found in each generation. Gbest is the global best position found among all the particles in the swarm so far. Inertia is necessary to control a velocity of a particle while converging optimum point. Its value is gradually decreasing and is determined by a linear equation in (6).

\[ \omega = \omega_{max} - (\omega_{max} - \omega_{min}) \frac{k}{T} \] (6)

where \( k \) denotes the actual iteration, \( T \) is the maximum iteration numbers.

The written PSO and PSOPC softwares were examined on some well-known non-linear functions such as Rastrigin, Michalewicz and Schwefel in Matlab environment. Swarm size and generation number were taken as 20 and 100 respectively in these test studies. According to the comparison results, PSOPC was chosen as an optimization algorithm in this study.

The PSOPC algorithm runs with a Matlab script which is integrated with the 2D FEA-based design software. The values of all the variables used in optimization are kept in memory by using a matrix which also keeps particles’ position and velocity vectors. Three case studies were conducted using three aims.

**Case I:** The design for both maximum continuous output torque and minimum on-load torque ripple has been carried out in (7). This is the typical optimization process for motors.

**Case II:** The sensorless performance only can be determined according to the inductance profile of the machine at a given load without considering the torque performance (8). Saliency and smoothness of the differential self-inductances are the main sensorless performance indicators.

**Case III:** The overall optimization, both aims of the case I and II are considered with seeking a trade-off point (9). That is, SMPM motor geometry has been designed to improve sensorless performance indicators substantially at the expense of a lower torque density.

\[ f_1 = k_T \left( \frac{\bar{T}}{n_1} \right) + k_R \left( \frac{T_r}{n_2} \right) \] (7) 
\[ f_2 = k_S \left( \frac{\Delta L}{n_3} \right) + k_D \left( \frac{L_{dpp}}{n_4} \right) + k_Q \left( \frac{L_{qpp}}{n_5} \right) \] (8) 
\[ f_3 = f_1 + f_2 \] (9)

where \( \bar{T} \), \( \Delta L \) are the average values of the torque and the difference of incremental inductances \( (\bar{T}_d - \bar{T}_q) \) respectively. Hata! Yer işaretleri tam anlamamışız, is peak to peak value of a torque ripple variable. \( L_{dpp} \) and \( L_{qpp} \) indicate peak to peak values as well.

In the nature of fitness, in order to give different importance levels to each part of the equation weighting coefficients are necessary after the equalization of each part. Every part can be divided by certain numbers which are \( n_1 - n_5 \) and their values are 30, 1, 0.6, 0.2 and 0.2 for the equalization. \( k_T, k_R, k_S, k_D \) and \( k_Q \) are used as weightings and their values are 0.95, 0.05, 0.6, 0.2 and 0.2 respectively.

A number of test runs were held after the proposed algorithm was adopted by FEA software. These runs are required to determine the optimum values of generation number, swarm size and limit values of the search space. On the test runs, no significant improvement on results was observed after 20th iteration. In addition, the algorithm did not converge below 15, so generation number was chosen as 20 which is also used as the termination condition. Swarm size is another key factor for the optimization. If swarm size is small, it takes longer to find a solution maybe even not to find it. It is suggested that swarm size should consist of 15 to 25 particles [15]. On the other hand, the tests showed that
the larger swarm size is not necessary. Table III summarizes the parameters with their search space limits chosen for the optimization. Table IV shows the optimized parameters for each design belong to the motor geometry.

TABLE III.
PARAMETERS OF THE PSO ALGORITHM

<table>
<thead>
<tr>
<th>Maximum generation number, [k]</th>
<th>20</th>
</tr>
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<tbody>
<tr>
<td>Swarm size, [r]</td>
<td>16</td>
</tr>
<tr>
<td>Inertia, [o]</td>
<td>0.9 – 0.4</td>
</tr>
<tr>
<td>Weighting factors, [c1, c2, c3]</td>
<td>0.8 0.8 0.6</td>
</tr>
<tr>
<td>Random factor range ( \alpha, \beta, \gamma ) and ( \delta )</td>
<td>0 – 1</td>
</tr>
</tbody>
</table>

TABLE IV.
OPTIMIZED MACHINE RESULTS OF EACH DESIGN

<table>
<thead>
<tr>
<th>Performance Indicators</th>
<th>Design results at x1 load</th>
<th>Design results at x2 load</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A1</td>
<td>A2</td>
</tr>
<tr>
<td>T [Nm]</td>
<td>33.17</td>
<td>33.74</td>
</tr>
<tr>
<td>Tr [Nm]</td>
<td>1.24</td>
<td>1.34</td>
</tr>
<tr>
<td>Lqpp [mH]</td>
<td>0.24</td>
<td>0.27</td>
</tr>
<tr>
<td>Lppp [mH]</td>
<td>0.18</td>
<td>0.23</td>
</tr>
<tr>
<td>AL[mH]</td>
<td>0.94</td>
<td>0.52</td>
</tr>
<tr>
<td>Pcu [W]</td>
<td>165.28</td>
<td>166.62</td>
</tr>
<tr>
<td>Pcu/Area[W/cm²]</td>
<td>0.0039</td>
<td>0.0039</td>
</tr>
<tr>
<td>J [A/m²]</td>
<td>5.75</td>
<td>5.98</td>
</tr>
</tbody>
</table>

V. SENSITIVITY RESULTS OF THE PROPOSED DESIGN

The design C1 can be chosen as a proposed design according to its performance results. In order to see the geometrical parameter sensitivity on performance indicators which were parts of the fitness functions. Figs. 4-11 shows the percentage variation of the five indicators versus change of the each parameter. Here, increased and diminished values of each geometry parameter are used as five and ten percent of the optimized values. These results present an idea of how one might convert the design variables to get better torque and self-sensing capabilities. It can be seen from the figures peak to peak values of \( T_d \) and \( T_v \) are the most sensitive. Also, saliency and average torque indicators almost cannot be improved without compromising on something else.
In this study, a machine design optimization which deals with the difficulties of weak saliency tracking with minimum torque loss at the design stage has been proposed.

Simulation results show that the PSO has made a pretty good spot in terms of overall optimization which cannot be amended easily. It is likewise worth mentioning that these variations also have an impact on the achievable torque and hence an optimization using a fitness function accounting for both the output torque and Sensorless performance should be taken up. The sensitivity results also indicate the validity of the optimization procedure adopted for case III. Although modification of geometry makes a change in inductance ripples differently, it is seen that torque and Sensorless indicators are maximum for optimized geometry shown in horizontal axis as 1.

VI. CONCLUSIONS
VII. REFERENCES


VIII. BIOGRAPHIES

Murat Caner was born in Afyonkarahisar in Turkey, in 1972. He received the Ph.D. degree in electrical engineering from the Yıldız Technical University. He has finished one year for post-doctoral study in permanent magnet design optimization in Power Electronics, Machines and Control Group at the University of Nottingham in 2011.

He began his career as a researcher at The University of Afyon Kocatepe in 1995. His research interests include artificial intelligence, intelligent control techniques, image processing and optimization algorithms. He is currently an Assistant Professor since 2007.

Chris Gerada obtained his PhD in High Performance Electrical Machines at the University of Nottingham in 2005. After this he was appointed as a postdoctoral researcher at the university, until 2008 when he secured a Lectureship in Electrical Machines following which he was subsequently promoted to Associate Professor in 2011 and Professor in 2013. His principal research interest lies in electromagnetic energy conversion in electrical machines and drives, focusing mainly on more-electric transport and distributed energy generation. He has secured major industrial, European and UK grants, authored more than 100 papers and has been awarded a Royal Academy of Engineering Senior Research Fellowship to consolidate research in the field. He is an associate editor of the IEEE IAS Journal and executive member of the UK Magnetic Society Management Committee. He is also vice chair of the electrical machines Committee of the IEEE Industrial Electronics Society.