DOI: 10.1109/TIE.2017.2756599

Social Network Optimization Algorithm for Tubular Permanent Magnet Generator in vehicle energy harvesting

Francesco Grimaccia, Giambattista Gruosso, Marco Mussetta, Alessandro Niccolai, Riccardo E. Zich

Abstract—

Index Terms—

I. Introduction

The recent development in computational capability and the parallel improvement of multi-physic simulation tools has shifted interest towards the modeling and optimization of engineering systems. The optimization of electrical machines, has been one of the hot topics of research in recent years. On one hand the algorithms have become increasingly effective and with a complexity that has grown together with computing capabilities. On the other hand, the availability of complex models for the definition of the objective function, able to assess accurate phenomena. The optimisation procedures range from geometric and performance optimisation up to joint optimizations involving also the economic aspect. Among all those involving multiple goals are the most interesting because they allow to have an overview of the final object, but at the same time are the most complex ones because they give rise to objective functions with sub optimal solutions often equivalent among themselves. The involvement of objectives, often disagreeing among themselves, makes it necessary to identify appropriate methodologies for the construction of objective functions to cater to the most of the requirements. In this context, advanced computational intelligence algorithms can be used to find out the optimized design, involving a large number of physical and geometric parameters, and to maximize the performance of electrical machines and energy-harvesting devices. These procedures are population-based iterative techniques which basically perform an indirect synthesis by evolving the parameters of interest to identify on optimal solution in the design space, through properly defined single and multi-objective fitness functions. The most popular evolutionary algorithms, i.e. genetic algorithm (GA) [1] and particle swarm optimization (PSO) [2] have been combined in the last decade with a broad range of other soft computing techniques, like artificial neural networks [3], fuzzy systems [4], giving birth to a large discipline of hybrid methods which constitute the so-called Computational Intelligence.

Most of these techniques have been used to ottimizazione more or less complex of electric motors and generators, giving origin to a particularly broad and detailed literature [5]–[12]. All these methods are mainly based on iterative procedures with a strong stochastic base, and their performance must be evaluated in terms of speed of convergence and computational burden. In fact, these techniques are suitable when the device structure is complex, as is the case of electrical machine design, which often requires time-consuming and non-linear FEM simulations. To address this issue, surrogate models are used to speed-up global evolutionary search [13]–[15]. A special attention is paid to the study of linear machines and in particular the optimization of Tubular Linear Geneator (TLG), which are taking place in many energy harvesting applications [16]–[18].In this type of problem becomes stringent optimization of the power produced and the reduction of dynamic phenomena, such as end effects and the cogging. The problem requires the solution of different physical domains coupled between them.

In this paper a new population based metaheuristic, named Social Network Optimization (SNO), is proposed for the optimization of an electrical linear generator excited through permanent magnets (PMs), in order to guarantee an effective and faster exploration of the solution domain with respect of traditional techniques.

In the first section, the algorithm, which is quite new in this scenario, will be described and will be validated with a benchmark case showing its effectiveness. Subsequently the optimization problem will be formulated reporting its main equations and then the main results obtained will be analyzed.

II. Social Network Optimization

SNO is a population-based evolutionary algorithm [19]. The aim of this algorithm is to emulate the main characteristics of Social Networks, as shown in Fig. 1.

The population of SNO (candidate solutions of the problem) represent a set of people. Each person lives a real life, in which he lives situations and then these situations are shared on the Social Network.

The real life of each person is also characterized by his character, considered as an inclination to make choices.

Manuscript received Month xx, 2xxx; revised Month xx, xxxx; accepted Month x, xxxx.

F. Grimaccia, M. Mussetta, A.Niccolai and R.E Zich are with Politecnico di Milano, Dipartimento di Energia

G.Gruosso is with Politecnico di Milano, Dipartimento di Elettronica, Informazione e Bioingegneria

(corresponding author to provide phone: xxx-xxx-xxxx; fax: xxx-xxx-xxxx; e-mail: author@ domain.gov).

DOI: 10.1109/TIE.2017.2756599

```
Initialize a random population
Create an empty memory
while not termination criterion do
    Create the new memory
    for all the population do
        if Is an explorer then
            Random change of the character
        else
            Creation of group of friend
            Creation of peer group
            Selection of the influencers
            Interaction between people
        end if
        Change of the situation
        Evaluation of the cost
    end for
end while
```

Fig. 1. Pseudo-code of SNO

The Social Network is the virtual space in which people interact informing the other individual on his status and commenting ("evaluating") the performance of the others. The evaluation of a situation is divided in two parts: the first one is the evaluation by the person that lived the situation, the second one is by some of the other members of the social.

Some people of the Social Network are called explorers, because they are not attracted by other people and their attraction capability is much higher than the one of the average person.

The first iteration population of SNO is initialized randomly: both characters and situations are generated using a uniform distribution of probability in their domain.

The iterative process is limited by a termination criterion chosen among the fitness evaluation of the solution, the stagnation of the algorithm or the number of benchmark function calls.

In the loop, the first process is the creation of a new memory, recalling that the most of lived situations are stored in the memory of the Social Network. The choice of which situation store and which not, is firstly based on the evaluation given to that situation. The second criterion to decide is the "age" of the post. Posts shared in past are more suitably substituted by new posts.

The second loop is the heart of the algorithm: the process of group division, influencer selection and interaction.

People, in SNO, interact in groups: friends groups and peers groups. Groups of friends collect people that have similar situations. The actual situation of a person is compared with the situations memorized in the memory. If these are similar, the situation memorized can influence the person, and so this person and the person who has lived the situation memorized are considered friends. Each person has a group of friends that is different from groups of friends of other people. The similarity between two situations is evaluated as a distance in the space of the candidate solutions.

Groups of peers collect people with the same most predominant feature of the character. Similarly for friends' groups, for peers' groups are compared the actual character of a person with the character of a person who has lived a situation contained in the memory.

All groups change during time: actual situations and characters of people change so also solutions contained in the memory change.

The probability that a person can be chosen as influencer depends on the position in the ranking of the group. In fact, in all groups a ranking is created, where people are ranked by the evaluation of their situation.

Each person has a probability greater than zero to be chosen as influencer. This probability is based with a non-linear relation with the rank of each person in the groups.

After having selected some influencers, people interact with them : the interaction takes into account the tendency of a person to maintain his character, the influence of the influencer and the type of groups from which the influencer is chosen.

The interaction between a person and his influencers can be expressed as:

$$\overline{c}(t+1) = \alpha \cdot \overline{c}(t) + \beta \cdot b \cdot (\overline{s_f - s(t)}) + \gamma \cdot c \cdot (\overline{s_p - s(t)}) \quad (1)$$

where $\overline{c}$ is the character of the person, $\overline{s}$ is the actual situation of this person, α is his inertia, $\overline{s_f}$ is the situation of the influencer of the friends' group and β is his influence, $\overline{s_p}$ is the situation of the influencer of peers' groups and γ is his influence and b and c are two parameters that make a difference between the interaction into peers' groups and in friends' groups.

A. Performance evaluation using TEAM 25 benchmark

The TEAM Problem 25 [20] has been chosen as preliminary benchmark optimization problem in order to compare the performances of SNO with other algorithms. Two of them are standard algorithms: the Genetic Algorithm (GA) [21], and the Particle Swarm Optimization (PSO) [22]. The last algorithm used for the comparison,is an hybrid algorithm [23]: the Genetic Swarm Optimization (GSO) [24].

The problem consists in a model of die press with electromagnet for orientation of magnetic powder. The aim of this test problem is to optimize some geometric parameters to obtain a suitable flux distribution.

As described in [15] the model is assumed as two-dimensional; therefore the cost function to be minimized is:

$$C = \sum_{i=1}^{N} \left\{ (B_{xpi} - B_{x0i})^2 + (B_{ypi} - B_{y0i})^2 \right\}; \quad (2)$$

where B_{xp} and B_{yp} are the components of flux density computed on N sampling points, while the specified values are, respectively:

$$B_{x0} = 0.35 \cdot \sin\theta; \quad (3)$$

$$B_{y0} = 0.35 \cdot \sin\theta; \quad (4)$$

The four algorithms has been tested on this problem, that is evaluated by means of Finite Element simulator [17].

To make possible and fair the comparison between the algorithms, the termination criterion of all the algorithms has

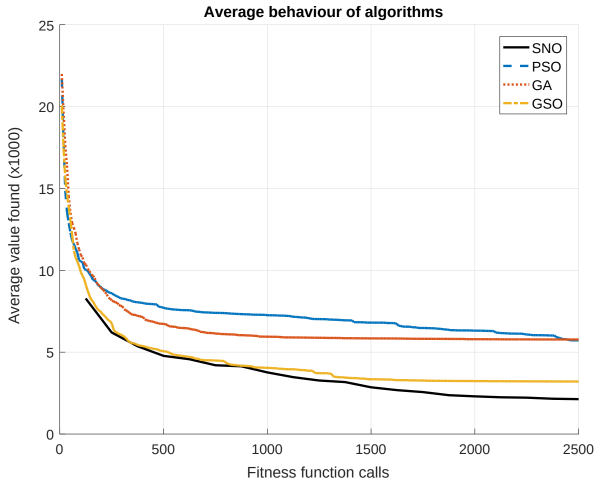

Fig. 2. Comparison between SNO, PSO, GA, GSO on Problem TEAM 25. Average algorithm behaviour

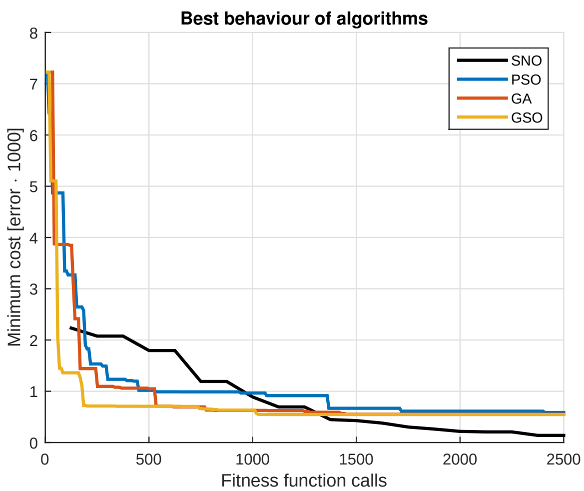

Fig. 3. Comparison between SNO, PSO, GA, GSO on Problem TEAM 25. Best algorithm behaviour

been set to be the total number of fitness function calls. This parameter indicates the computational time allowed for the optimization because, compared to the computational cost of the electromagnetic simulation, the overhead time of the algorithms is negligible. Table I shows the working parameters of the algorithms in terms of population size, iterations and fitness function calls.

TABLE I
WORKING PARAMETER OF THE FOUR ALGORITHMS

Parameter	GA	PSO	GA	SNO
Population size	10	10	10	125
Iterations	250	250	250	20
Fitness function calls	2500	2500	2500	2500

In order to have reliable data, 48 independent trials has been done. The average among the 48 trails cost function values are reported in Figure 2, while in figures 3, and 4 are shown the behaviour of the best and the worst trial.

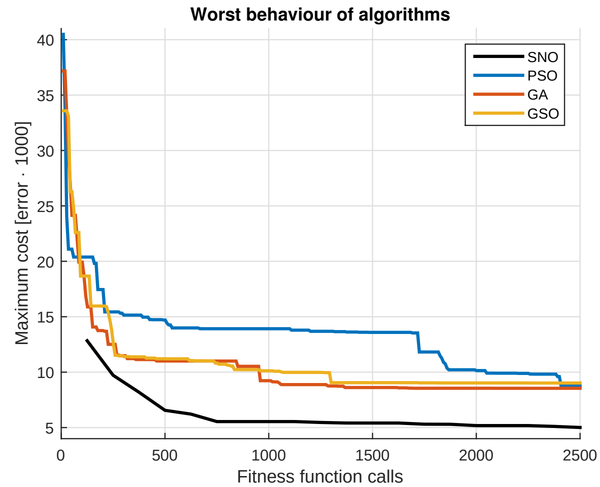

Fig. 4. Comparison between SNO, PSO, GA, GSO on Problem TEAM 25. Worst algorithm behaviour

III. Application to Tubular Permanent Magnet Generator in Vehicle Energy Harvesting

This work focuses on the design of a tubular linear permanent magnet generator, in literature named as "TLPMG".

Tubolar electric generators are electromechanical devices that exploit the relative linear motion between two components (stator and slider) to generate an electromotive force [25] [26].

The main advantages of this kind of electrical machine,is the high power density, compactness and the absence of excitation circuit, which make them an attractive candidate for applications in which performance and reliability are crucial.

In contrast with the advantages exhibited by the permanent magnet machine, it is useful to point out also the drawbacks, that actually represent the limits of such a device in terms of efficiency and working aspects. One of the most relevant downside is represented by the cogging force, a phenomenon that has an high impact on the performances of the device.

A tubular linear permanent magnet generator is made of two main parts: a translator (or prime mover) where magnets are installed, and a stator in which coils are placed. Both can have different structures, implying several differences between them in terms of performances and characteristics. However, in addition to stator and translator, other parts are present in a TPMLG. As reported in Fig. 5 the geometrical dimensions are summarized in two tables: table II shows the free variables (design variable of the optimization problem) and table III shows the dependent variables.

- Sh_L, Shaft length;
- Sh_R, Shaft radius, it is the radius of the shaft to which the slider is connected;
- St_R, Stator outer radius;
- Ag_m, half air gap.

Concerning the preliminary design, firstly we will focus on the design of a periodic machine unit. This unit can be repeated along the axial length depending on the performances we want to achieve.

TABLE II
FREE DESIGN VARIABLES AND DEPENDENT VARIABLES

Free variables	Symbol	unit of measure	Lower bound value	Upper bound value
Number of stator moduli	St_N	[ ]	2	25
Number of slider moduli	Sl_N	[ ]	4	25
Windings height	Wn_H	[% Sh_L/St_N]	0.1	0.9
Stator tooth height	StT_H	[% Sh_L/St_N]	0.1	0.9
Magnet height	Mg_H	[% Sh_L/Sl_N]	0.1	0.9
Slider tooth height	StT_H	[% Sh_L/Sl_N]	0.1	0.9
Half of air gap	Ag_m	[mm]	0.1	0.9
Stator thickness	St_T	[% St_R]	0.4	0.6
Armature thickness	Ar_T	[% St_T]	0.01	0.5
Stator tooth thickness	StT_T	[% St_T]	0.01	0.5
Magnet thickness	Mg_T	[% SlC_T]	0.1	0.9
Slider tooth thickness	SlT_T	[% SlC_T]	0.3	0.9
Winding thickness	Wn_T	[% $St_T - Ar_T - StT_T$]	0.1	0.9

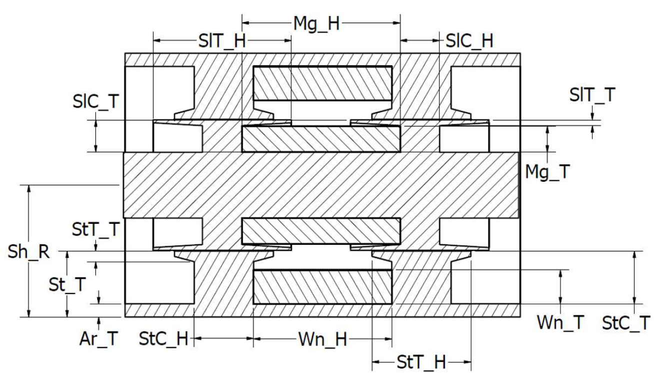

Fig. 5. TPMLG geometry

TABLE III
DEPENDENT VARIABLES

Dependent variables	Symbol	Expression
Stator core thickness	StC_T	$Sh_L/St_N - Wn_H$
Slider core thickness	SlC_T	$St_T - Ar_T - StT_T$
Slider radius	Sl_R	$St_R - St_T - Ag_m - Sh_R$
Slider core height	SlC_H	$Sh_L/Sl_N - Mg_H$

Che macchina elettrica ? trifase, monofase? From an electrical point of view, the machine is a single phase electric generator.

A. Vehicle and road model

In this section the vehicle and the road model used to simulate the vehicle behaviour are described. It is possible to approach the problem of the vehicle comfort using models with different levels of precision [27].

The model here used have three degrees of freedom related to the carbody (the pitch rotation, θ_b, the roll rotation, ϕ_b, and rigid vertical translation of the carbody z_b) and one degrees of freedom for each wheel (z_{fl}, z_{fr}, z_{rl}, and z_{rr}). The problem will be solved using a multibody approach [28], [29].

Piu' che definire le equazioni del modello strada veicolo, che metterei come reference mi focalizzerei su come sono state accoppiate le equazioni meccaniche con quelle elettriche.

For the vehicle simulation, each electric generator can be modelled as an external force field. The force depends on the slip speed and on the relative position between the stator and the slider.

This external force is taken onto consideration in the Lagrange equation in the virtual work of external forces.

The force produced by the generator can be calculated using a power balance: the electrical power is related to the mechanical one by a proper efficiency.

So, for each of the four generators:

$$F = \frac{V \cdot I}{\eta \dot{x}_{slide}} \tag{5}$$

where I is the current flowing in the circuit, V is the potential generated by the generator and η is the efficiency.

The road irregularities has been modeled accordingly to standard ISO8608 [30] that defined the Power Spectral Density (PSD) of the road irregularities.:

$$G_d(n) = G_d(n_0) \cdot (n/n_0)^{-w_i} \tag{6}$$

where G_d is the displacement PSD, n is the spatial frequency, n_0 is the reference spatial frequency and w_i is the exponent of the fitted PSD.

Changing the value of $G_d(n_0)$, it is possible to represent different level of irregularities. Roads are classified by their values of $G_d(n_0)$ in standard ISO8608. Given the PSD, it is possible to find the equation of the displacements [31] [32]. In this optimization process, in order to make the result more robust, two different road irregularities levels have been used.

esiste un grafico di una simulazione elettro meccanica che dice come e' fatta la potenza elettrica?

An example of the electrical output of the simulation is shown in Fig. 6

B. Objective function definition

It is possible to define four benchmark for this multi-objective optimization problem.

Three of them are the standard objectives used to evaluate the suspension performances of the vehicle and the fourth is an index related with the produced power.

The comfort index (CI) is the root mean square (RMS) of the carbody vertical acceleration $\ddot{z}_b$:

$$CI = RMS(\ddot{z}_b) \tag{7}$$

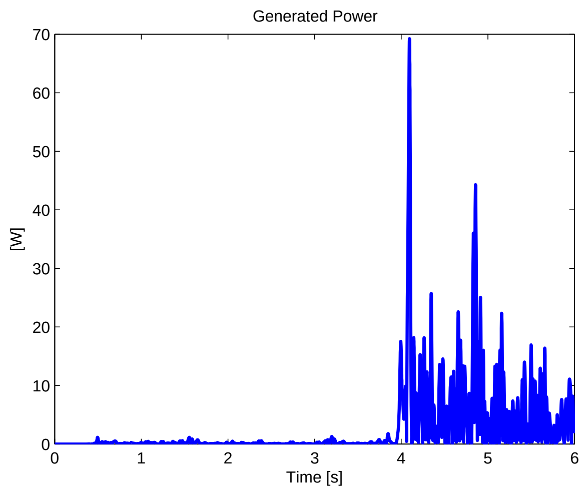

Fig. 6. Example of produced power

The road holding (RH) is the RMS of force exchanged between the wheel and the ground:

$$RH = RMS([K_{cc}] \cdot \overline{x_c}) \tag{8}$$

where K_{cc} is the partition of the stiffness matrix related to the imposed motion and $\overline{x_c}$ is the vector containing the imposed motion.

The working space index (WS) is the RMS of the variation of length of the springs:

$$WS = L_{k-susp} \cdot \overline{x_l} \tag{9}$$

where L_{k-susp} is the partition of the stiffness Jacobian related to the suspension stroke.

For all these indexes the best value is the lower.

Another important performance index in this optimization problem is the power produced by the LiG. In order to have a minimization problem, it has been defined as:

$$PI = \frac{1}{RMS(I \cdot V) + 0.1} \tag{10}$$

where I is the current flowing in the circuit and V is the potential generated by the generator. CIRCUITO EQUIVALENTE? ...O FIGURA DA FEM...

A scalarization approach has been used to face with the multiobjective problem. The scalarization used is the following:

$$c = 4 \cdot \frac{CI}{CI_{base}} + \frac{RH}{RH_{base}} + \frac{WS}{WS_{base}} + 4 \cdot \frac{PI}{PI_{base}} \tag{11}$$

where the values of $(\cdot)_{base}$ are some references values.

C. Optimization procedure

AN - Cambiata ed approfondita

The optimization process is a iterative process in which the optimizer, SNO, selects some candidate solutions.

For each candidate solution, the value of the objective functions have to be evaluated.

The objective function evaluator converts all the candidate solutions into a specific set of geometric values for the generator. This conversion has been done in order to reduce the number of infeasible geometries that the optimizer can find: these solutions reduce the optimization capability of the algorithm.

After having de-codified the candidate solution, a FEM model of the TMPLG is created using a numeric electromagnetic simulator (FEMM4.2). This model will be used in the time simulation of the vehicle to evaluate the linked flux to the coil useful to calculate the electromotive force and consequently the mechanical force.

Having created a model of the generator, it is possible to start the integration of the equations of motion of the vehicle. The equations are non-linear due to the presence of the TMPLG, so it is needed a numerical simulation.

At each time step, the numerical simulation takes as input the road irregularities and the forces generated by the TMPLGs.

The total output of the simulation are the acceleration of the carbody, the positions of the wheels in time and the produced power.

With these data, it is possible to calculate the performance indexes.

The evaluation is summarized in figure 7.

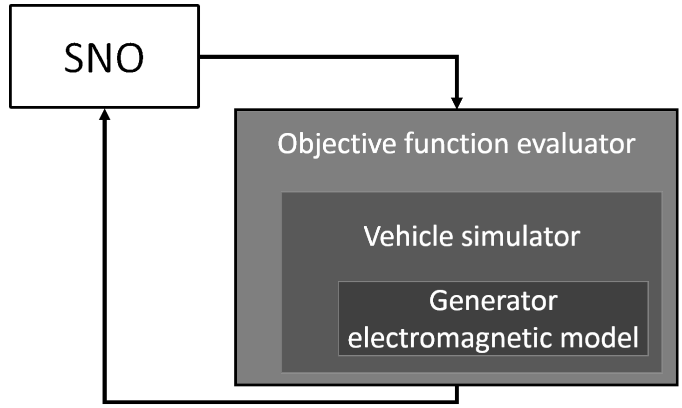

Fig. 7. Optimization process representation

IV. Sensitivity analysis and results

Servono molti piu' risultati, ache dal punto di vista elettrico. Serve una tabella dei dati ottimizzati etc.

Before starting the optimization process, a sensitivity analysis has been performed on the design variables of the TPMLG.

This analysis is aimed to understand which are the most influencing parameters and if there are some non influencing parameters. These parameters can be eliminated from the optimization process. However, the elimination of the parameters can hide some coupling effects that they can have with the other parameters. Moreover the optimization performance are lightly influenced by the number of parameters.

The sensitivity analysis has been performed changing all the variables one at time taking 30 uniformly distributed samples inside the domain of each variable.

From figure 8 it is possible to see the influence of all the parameters obtained from the sensitivity analysis.

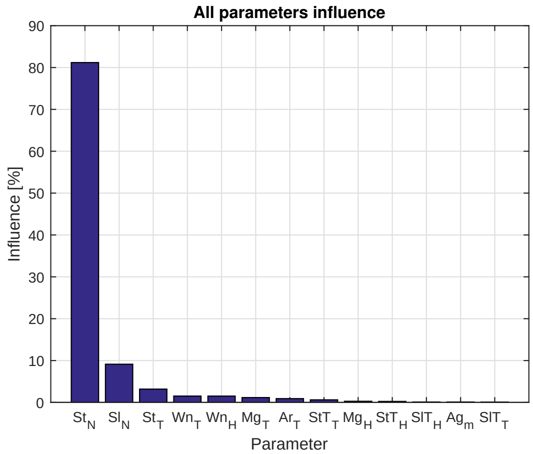

Fig. 8. Parameters influence obtained from the sensitivity analysis

It it possible to see that the number of stator caves is the most influencing parameter (80%) and the second more influencing parameter is the slider number of caves (9%).

These results are expected because almost all the others dimensions are expressed as percentage of these two parameters.

Figure 9 shows the influence of all the other parameters.

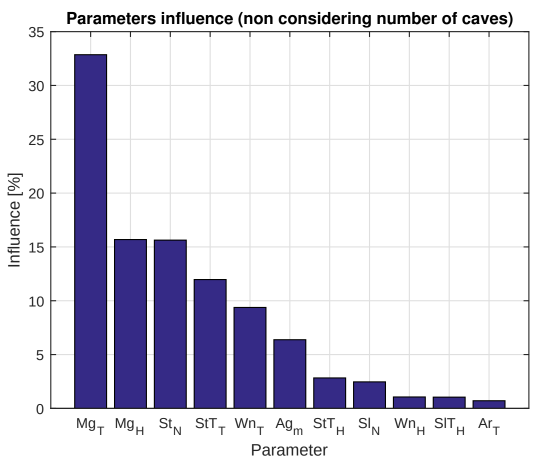

Fig. 9. Some parameters influence obtained from the sensitivity analysis

The convergence curve of SNO is shown in figure 10.

The scaled drawing of the optimized generator is shown in figure 11.

Figure 12 shows the fluxes concatenated to all the windings as a function of the slider position.

The optimal values of the free variables are shown in table IV

From figure 10 it is possible to do some considerations:

- It it possible to see that the complete model is much more difficult to be optimized with respect to the simplified model: this is due to the fact that the complete model has more design variables and the fitness function is much more non-linear
- The optimizer is able at least to improve the initial guess (the random one) and to continue to optimize till the end of the time.

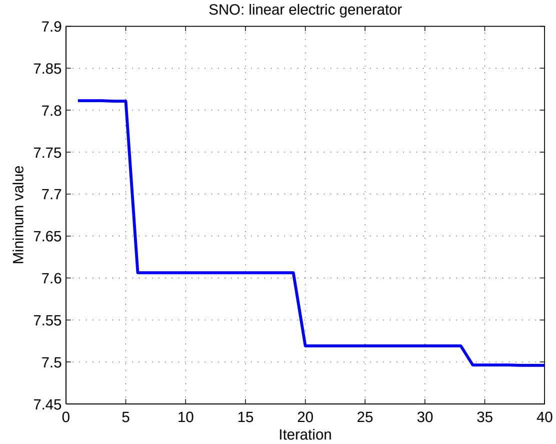

Fig. 10. Convergence curve of SNO on the problem with the complete model of the generator

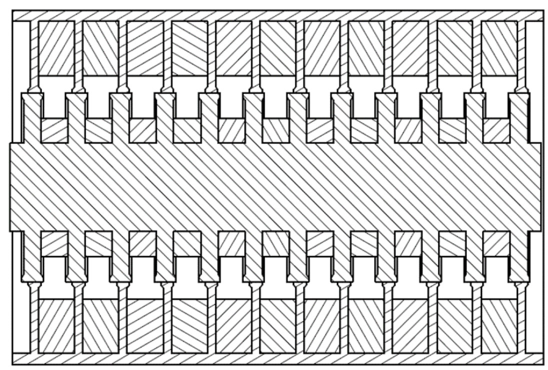

Fig. 11. Scaled optimized generator.

V. Conclusions

Bla bla bla

References

[1] W. Lenwari, M. Sumner, and P. Zanchetta, "The use of genetic algorithms for the design of resonant compensators for active filters," *IEEE Transactions on Industrial Electronics*, vol. 56, no. 8, pp. 2852–2861, Aug. 2009.

TABLE IV
FREE DESIGN VARIABLES OPTIMAL VALUES

Free variables	Symbol	Optimal value
Number of stator moduli	St_N	12
Number of slider moduli	Sl_N	12
Windings height	Wn_H	0.81
Stator tooth height	StT_H	0.10
Magnet height	Mg_H	0.10
Slider tooth height	StT_H	0.61
Half of air gap	Ag_m	0.21
Stator thickness	St_T	0.83
Armature thickness	Ar_T	0.082
Stator tooth thickness	StT_T	0.13
Magnet thickness	Mg_T	0.50
Slider tooth thickness	SlT_T	0.30
Winding thickness	Wn_T	0.46

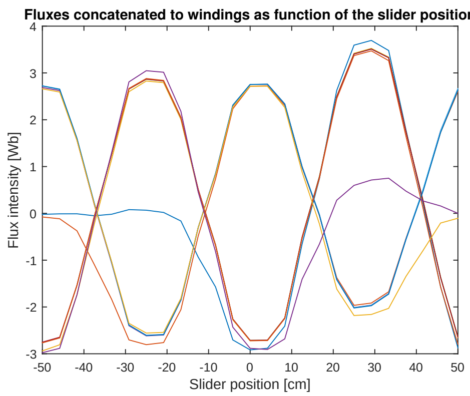

Fig. 12. Fluxes concatenated to windings.

[2] B. Ufnalski, A. Kaszewski, and L. M. Grzesiak, "Particle swarm optimization of the multioscillatory lqr for a three-phase four-wire voltage-source inverter with an lc output filter," *IEEE Transactions on Industrial Electronics*, vol. 62, no. 1, pp. 484–493, Jan. 2015.

[3] D. Y. Li, W. C. Cai, P. Li, Z. J. Jia, H. J. Chen, and Y. D. Song, "Neuroadaptive variable speed control of wind turbine with wind speed estimation," *IEEE Transactions on Industrial Electronics*, vol. 63, no. 12, pp. 7754–7764, Dec. 2016.

[4] M. Q. Duong, F. Grimaccia, S. Leva, M. Mussetta, and R. Zich, "Improving lvrt characteristics in variable-speed wind power generation by means of fuzzy logic," in *2014 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, pp. 332–337, Jul. 2014.

[5] T. Marcic, B. Stumberger, and G. Stumberger, "Differential-evolution-based parameter identification of a line-start ipm synchronous motor," *IEEE Transactions on Industrial Electronics*, vol. 61, no. 11, pp. 5921–5929, Nov. 2014.

[6] M. Sreejeth, M. Singh, and P. Kumar, "Particle swarm optimisation in efficiency improvement of vector controlled surface mounted permanent magnet synchronous motor drive," *IET Power Electronics*, vol. 8, no. 5, pp. 760–769, 2015.

[7] M. Calvini, M. Carpita, A. Formentini, and M. Marchesoni, "Pso-based self-commissioning of electrical motor drives," *IEEE Transactions on Industrial Electronics*, vol. 62, no. 2, pp. 768–776, Feb. 2015.

[8] L. Guo, H. Zhang, M. Galea, J. Li, and C. Gerada, "Multiobjective optimization of a magnetically levitated planar motor with multilayer windings," *IEEE Transactions on Industrial Electronics*, vol. 63, no. 6, pp. 3522–3532, Jun. 2016.

[9] A. Pirisi, M. Mussetta, F. Grimaccia, and R. E. Zich, "Novel speed-bump design and optimization for energy harvesting from traffic," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 4, pp. 1983–1991, Dec. 2013.

[10] A. Fatemi, D. M. Ionel, N. A. O. Demerdash, and T. W. Nehl, "Optimal design of ipm motors with different cooling systems and winding configurations," *IEEE Transactions on Industry Applications*, vol. 52, no. 4, pp. 3041–3049, Jul. 2016.

[11] Y. Wang, D. M. Ionel, V. Rallabandi, M. Jiang, and S. J. Stretz, "Large-scale optimization of synchronous reluctance machines using ce-fea and differential evolution," *IEEE Transactions on Industry Applications*, vol. 52, no. 6, pp. 4699–4709, Nov. 2016.

[12] Y. D. Hong, C. S. Park, and J. H. Kim, "Stable bipedal walking with a vertical center-of-mass motion by an evolutionary optimized central pattern generator," *IEEE Transactions on Industrial Electronics*, vol. 61, no. 5, pp. 2346–2355, May. 2014.

[13] A. C. Zavoianu, E. Lughofer, G. Bramerdorfer, W. Amrhein, and S. Saminger-Platz, "A surrogate-based strategy for multi-objective tolerance analysis in electrical machine design," in *2015 17th International Symposium on Symbolic and Numeric Algorithms for Scientific Computing (SYNASC)*, pp. 195–203, Sep. 2015.

[14] A. Canova, F. Freschi, G. Gruosso, and B. Vusini, "Genetic optimisation of radial eddy current couplings," *COMPEL - The International Journal for Computation and Mathematics in Electrical and Electronic Engineering*, vol. 24, no. 3, pp. 767–783, 2005.

[15] A. Canova, G. Gruosso, and M. Repetto, "Magnetic design optimization and objective function approximation," *IEEE Transactions on Magnetics*, vol. 39, no. 5, pp. 2154–2162, Sep. 2003.

[16] A. Pirisi, M. Mussetta, G. Gruosso, and R. Zich, "An optimized three phase tpm-lig for marine applications," pp. 1712–1717, 2010.

[17] A. Pirisi, M. Mussetta, G. Gruosso, and R. Zich, "Optimization of a linear generator for sea-wave energy conversion by means of a hybrid evolutionary algorithm," 2010.

[18] F. Bizzozero, M. Giassi, G. Gruosso, S. Bozzi, and G. Passoni, "Dynamic model, parameter extraction, and analysis of two topologies of a tubular linear generator for seawave energy production," pp. 433–438, 2014.

[19] A. Niccolai, F. Grimaccia, M. Mussetta, P. Pirinoli, V. H. Bui, and R. E. Zich, "Social network optimization for microwave circuits design," *Progress In Electromagnetics Research C*, vol. 58, pp. 51–60, 2015.

[20] L. Lebensztajn and J. L. Coulomb, "Team workshop problem 25: a multiobjective analysis," *IEEE Transactions on Magnetics*, vol. 40, no. 2, pp. 1402–1405, Mar. 2004.

[21] D. Goldberg, *Genetic Algorithms in Search, Optimization, and Machine Learning*, ser. Artificial Intelligence. Addison-Wesley Publishing Company, 1989.

[22] J. Kennedy, "The particle swarm: social adaptation of knowledge," in *Evolutionary Computation, 1997., IEEE International Conference on*, pp. 303–308, Apr. 1997.

[23] C. Grosan and A. Abraham, "Hybrid evolutionary algorithms: methodologies, architectures, and reviews," in *Hybrid evolutionary algorithms*, pp. 1–17. Springer, 2007.

[24] F. Grimaccia, M. Mussetta, and R. E. Zich, "Genetical swarm optimization: Self-adaptive hybrid evolutionary algorithm for electromagnetics," *IEEE Transactions on Antennas and Propagation*, vol. 55, no. 3, pp. 781–785, Mar. 2007.

[25] W. Li, S. Gao, D. Wu, and X. Zhang, "Design of a linear magnetic-geared free-piston generator for series hybrid electric vehicles," in *2010 IEEE Vehicle Power and Propulsion Conference*, pp. 1–6, Sep. 2010.

[26] C. Ghita, A. I. Chirila, I. D. Deaconu, V. Navrapescu, and D. I. Ilina, "Numerical modeling of the electric linear generators based on the sea waves energy," in *MELECON 2008 - The 14th IEEE Mediterranean Electrotechnical Conference*, pp. 640–645, May. 2008.

[27] E. Pennestrì, P. Valentini, and L. Vita, "Comfort analysis of car occupants: comparison between multibody and finite element models," *International Journal of Vehicle Systems Modelling and Testing*, vol. 1, no. 1-3, pp. 68–78, 2005.

[28] M. Blundell and D. Harty, *The multibody systems approach to vehicle dynamics*. Elsevier, 2004.

[29] F. Cheli and G. Diana, *Advanced dynamics of mechanical systems*. Springer, 2015.

[30] I.-. 1995, "Mechanical vibration-road surface profiles-reporting of measured data," 1995.

[31] M. Agostinacchio, D. Ciampa, and S. Olita, "The vibrations induced by surface irregularities in road pavements – a matlab® approach," *European Transport Research Review*, vol. 6, no. 3, pp. 267–275, 2014.

[32] R. S. Barbosa, "Vehicle vibration response subjected to longwave measured pavement irregularity," *Journal of Mechanical Engineering and Automation*, vol. 2, no. 2, pp. 17–24, 2012.