Kriging Metamodel for Electric Machines: A Drive Cycle Approach

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***Abstract* -- The work presented in this paper proposes a method for rapidly evaluating electric machine performances on drive cycle based on kriging metamodel. The driving cycle is considered through the k-means method to reduce the number of operating points. Thus, a metamodel of the machine's total losses is deduced on the centroids obtained by k-means. It is implemented after an evaluation of a finite element model in MotorCAD. This methodology is applied to design a buried permanent magnet synchronous machine. The optimization over the driving cycle is performed based on this metamodel. Finally, a comparison is made between the results obtained by optimization and the evaluation of these optimal solutions in MotorCAD.**

***Index Terms*-- drive cycle, experimental design, kriging, metamodeling, optimization, permanent magnet synchronous machine, total losses.**

I. Introduction

In order to achieve energy-efficient electric powertrains, it is necessary to dimension all the components on driving cycles. Estimating losses on these cycles requires more or less expensive models in terms of computation time depending on the precision of the model. As an example, in the case of electric motor design, FEA coupled with circuit analysis allows an investigation of the transient motor behavior. It permits to calculate iron losses, AC and DC copper losses, but presents generally long execution time [1]. The complete sizing of the powertrain can therefore be particularly long and complex. In this paper, an approach based on a Kriging metamodel is proposed for the representation of electric machines on the driving cycle. The objective is to substitute a computationally expensive numerical model with a mathematical function that can be quickly evaluated [2].

Thanks to the development of metamodeling techniques such as kriging, polynomial chaos, or neural networks, metamodels have become an attractive solution [3], [4] in different engineering fields. Several authors are interested in using these modeling methods for the design of electrical machines. The application of metamodels for the optimal design of electric machines is wide, for example, neural networks are used to represent the torque waveforms as a function of current amplitude and frequency [5], for the evaluation of electromagnetic performances [6], or as in [7] for the sizing of an induction machine for an automotive application. Although the formulation of the metamodel is complex [8], its use is straightforward and gives the system designer the possibility to exploit a trade-off between accuracy and computation time [9].

The first part of this paper is devoted to studying the reduction of the driving cycle to a certain number of representative operating points. Then, the metamodeling approach is introduced, followed by the application to the case study. This methodology is applied to design a buried PMSM on a WLTC driving cycle through an optimization process. The optimization results are compared with a finite element model to evaluate the accuracy of the metamodels.

II. Drive Cycle Reduction

The representation of the driving cycle in the torque-speed plane of the machine differs from one vehicle to another. Thus, to calculate the torque and speed required to complete a driving cycle, it is necessary to assess the forces acting on the vehicle (aerodynamic force, rolling resistance force, force related to the slope, force related to the acceleration) through the dynamic modeling of the vehicle [10]. After this, electric machine torque and speed can be calculated considering the reducer's gear ratio. An example is shown in Fig. 1, for a WLTC cycle applied to an electric vehicle (the name of the vehicle is not given because of confidentiality matters).

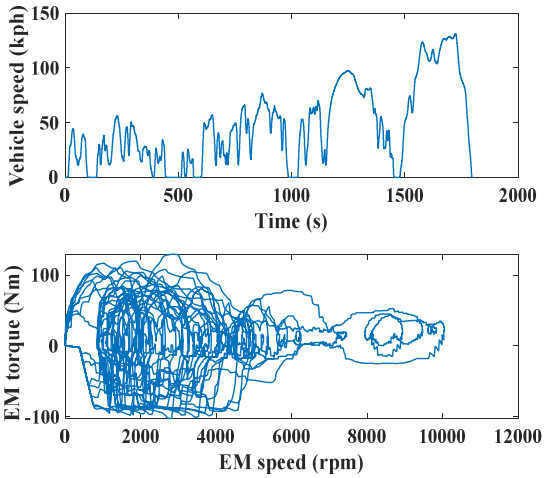

Fig. 1 : Electric machine torque and speed for WLTC cycle

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M. Djami is a PhD candidate with Stellantis in Carrières-sous-Poissy,78955, France, and Laboratoire de Génie Électrique et Électronique de Paris (GeePs), Université Paris-Saclay, CentraleSupélec, Sorbonne Université, CNRS, 91192, Gif-sur-Yvette, France. (mehdi.djami@centralesupelec.fr)

C. Marchand, M. Hage-Hassan, G. Krebs, and P. Dessante are with Laboratoire de Génie Electrique et Electronique de Paris (GeePs), Université Paris-Saclay, CentraleSupélec, Sorbonne Université, CNRS, 91192, Gif sur-Yvette, France

L. A. Belhaj is with Stellantis, Centre Technique de Carrières-sous-Poissy, 78955, Carrières-sous-Poissy, France.

The driving cycles present a significant number of operating points. The difficulty encountered is finding a way to integrate these points in the optimization process of the machine without the prohibitive computation time. There are several driving cycle reduction approaches to reduce the number of operating points [11], [12]. The *k-means* data partitioning method is one of the most accurate methods to perform such a task [11]. It is used to group desired data according to a defined similarity criterion [13]. In our study case, this criterion is the distance between the different operating points of the torque-speed plane.

In this method, the points in the torque-speed plane are grouped into *k* clusters. A centroid is defined for each cluster. The centroid of coordinates (torque, speed) represents the barycenter of all the points contained in this cluster. It is also the most representative of the cluster [14]. This method is applied to the WLTC cycle composed of 18000 operating points in the torque-speed plane of an electric machine. To ensure representative clusters, the cycle must first be normalized. At the initialization of the method, a number *k* of clusters is chosen, here *k=6*. At the first iteration, the centroids are randomly initialized, the operating points of the torque-speed plane are assigned to the nearest centroid cluster, and after the assignment, the mean and distances are recalculated. The centroid of each cluster is calculated by the following equations [14].

$$\Gamma_j = \frac{1}{N_j}\sum_{n=1}^{N_j} \Gamma_{jn} \tag{1}$$

$$\Omega_j = \frac{1}{N_j}\sum_{n=1}^{N_j} \Omega_{jn} \tag{2}$$

Where Γ_j and Ω_j represent the torque and speed values of centroid j, respectively, and N_j is the number of points in cluster j. The process starts again and iterates until each operating point remains in the same cluster.

The clusters obtained for the chosen example are shown in Fig. 2. In the rest of our study, the optimization over the driving cycle will be performed only on the six obtained centroids, thus reducing the number of objective function evaluations.

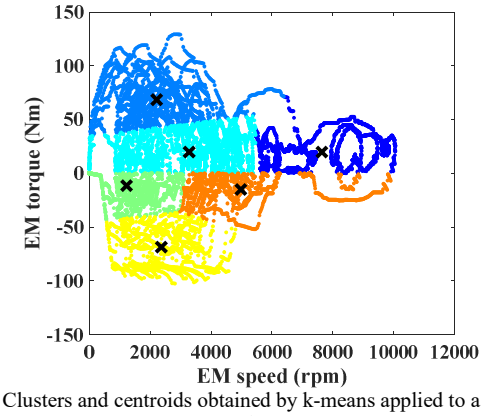

Fig. 2: Clusters and centroids obtained by k-means applied to a WLTC cycle.

The weight w of each centroid represents the total number of operating points in the cluster [15].

III. KRIGING METAMODELING

Metamodels are mathematical approximations of models. They are built from responses at sample sets of design parameters, they reduce the computation time associated with FE simulations. They can be used in different engineering applications due to their precision and fast computation time compared to classical methods like FEA. Here, we use a kriging metamodel [16] for its robustness and accuracy.

Kriging is a stochastic approximation which assumes that the output of the model $M(x)$ is a realization of a Gaussian process (GP) [17]. A kriging metamodel can be described by the following equation [18].

$$M(x) = \beta^T.f(x) + \sigma^2.Z(x,\omega) \tag{3}$$

Where $Z(x,\omega)$ is a Gaussian process of zero mean and unit variance. The first term $\beta^T.f(x)$ is the mean value of the Gaussian process and σ^2 its variance.

In practice, to build a kriging metamodel, the procedure is as follows:

- Select a method for the experimental design: this step is a sample allocation strategy in the design space that aims to maximize the amount of information acquired. The original model is evaluated at these sample points to create the training dataset, which is then used to build the metamodel [19]. These sample points can be created by different sampling methods such as Monte-Carlo, Latin Hypercube Sampling (LHS), and Sobol sequences.

Sobol sequences allow the distribution of the different samples in space by minimizing the distance between each observation. Thus, allowing to keep a good distribution of these samples in space even in the case of high dimensional experimental designs [20]. Fig. 3, compares a two variables experimental design constructed by LHS and Sobol.

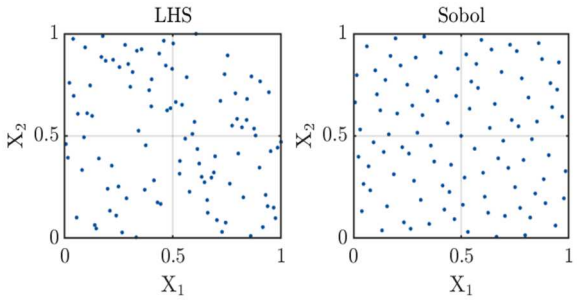

Fig. 3: Two variables experimental design created by LHS and Sobol

- Selecting a functional basis for the trend: the trend refers to the mean of the Gaussian process, i.e., the term $\beta^T.f(x)$ in (1). The kriging metamodel is thus named differently depending on the type of trend used:

- Universal Kriging: assumes that the trend is a linear combination of arbitrary functions (e.g., polynomial functions).

$$\beta^T.f(x) = \sum_{j=0}^{P} \beta_j.f_j(x) \tag{4}$$

- Simple kriging: the trend is given by (5), where f_j is an arbitrary function:

$$\beta^T . f(x) = \sum_{j=1}^{P} f_j(x) \quad (5)$$

- Ordinary kriging: in this case, the trend has a constant value:

$$\beta^T f(x) = \beta_0 \quad (6)$$

- Selecting a correlation function: the correlation function is of primary importance. It contains the assumptions about the approximation function used in the metamodel. It describes the degree of similarity between the sample points from the experimental design and the predicted points. In this sense, samples close to each other should have similar responses [18].

In this paper, ordinary kriging will be used for the trend selection and Matérn function the correlation function as given in (7).

$$R(x,x',\theta,\nu) = \frac{1}{2^{\nu-1}\Gamma(\nu)}\left(2\sqrt{\nu}\frac{|x-x'|}{\theta}\right)^{\nu} \mathrm{K}_{\nu}\left(2\sqrt{\nu}\frac{|x-x'|}{\theta}\right) \quad (7)$$

Where θ is the correlation parameter, $\nu = 5/2$, Γ is the Euler's Gamma function and K_{ν} is the Bessel function [18].

There are also other steps necessary for implementing the kriging metamodel, such as determining the hyperparameters of the correlation function and the choice of the estimation methods necessary to evaluate the accuracy of the metamodel.

IV. Electrical Machine Study Case

A. Geometry Description

As mentioned in the previous section, the metamodel is a substitution model aiming to replace an expensive computational model with a mathematical approximation that allows predicting its behaviour. In our case, the model studied is a synchronous machine with buried permanent magnets (48 slots with eight poles) developed under Ansys MotorCAD; the machine is represented in Fig. 4.

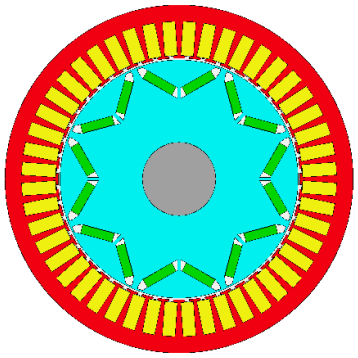

Fig. 4: Reference machine for the study

A kriging metamodel is established to evaluate the total losses as a function of the machine's geometrical dimensions and control parameters. For this, the first step is to select the geometrical variables of the machine, which will serve as inputs for the metamodel. The selected variables and their range of variation are given in Table I.

The range of variation of these variables is established with respect to a reference machine developed at Stellantis [21], whose dimensions are given in Table I.

TABLE 1
VARIATION RANGE FOR THE DIFFERENT VARIABLES OF THE METAMODEL

Parameter	Variation range (mm)	Reference Machine (mm)
x_1: Slot width	[4.5 - 7.5]	4.8
x_2: Slot height	[16 - 20]	17
x_3: Stator outer diameter	[180 - 210]	190
x_4: Magnet thickness	[4 - 7]	5
x_5: Active length	[160 - 210]	160

B. Construction and validation of metamodels

An experimental design is created with Sobol sequences. 270 samples containing the five input parameters are used to cover the domains of variation of each parameter. The database needed to create the metamodel is then obtained by performing FE calculations on MotorCAD for the 6 centroids obtained by *k-means*.

The outputs recovered from MotorCAD per centroid are the control parameters and the total losses. They include iron losses, copper losses (AC and DC losses), and mechanical losses (Fig. 5). MotorCAD simulation includes a black box control strategy. Thus, we propose to establish two metamodels. First one based on geometric parameters, permits the prediction of control parameters (I_s and ψ) (Fig. 6). The second is established as a function of the geometric and control parameters calculated by the first metamodel (Fig. 7). It is used for the prediction of the total losses.

The input vectors X_1 and X_2 are described as $X_1 = (x_1, x_2, x_3, x_4, x_5)$ and $X_2 = (I_s, \psi)$.

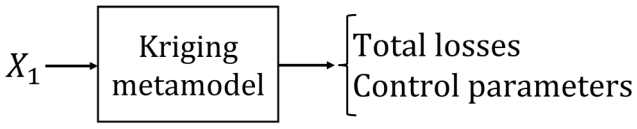

Fig. 5: First evaluation of MotorCAD

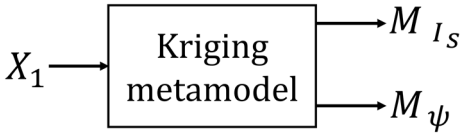

Fig. 6 : Control parameters metamodel

Fig. 7: Losses metamodel

The created metamodels (Fig. 6, and Fig. 7) are validated by evaluating exact and predicted responses at a set of 50 test points that are different from sample points used to create the

metamodels. The comparison between MotorCAD and metamodel calculations for one of the six centroids is shown in Fig 8, Fig. 9, and Fig. 10.
In the case of the control parameter metamodel, the error does not exceed 2% for this centroid as shown in Fig. 8 and Fig. 9, and it is the same for other centroids.

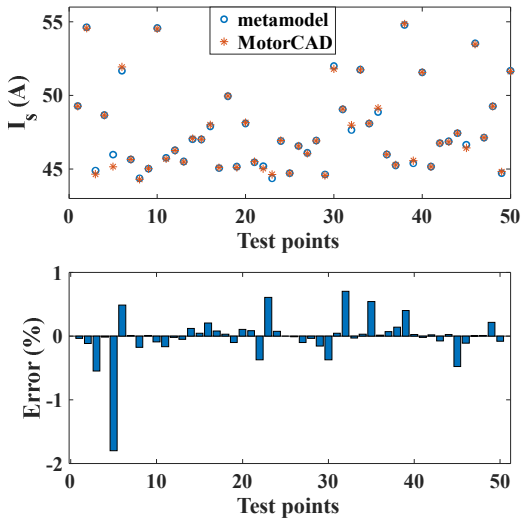

Fig. 8: Evaluation of the precision of stator phase current metamodel

In Fig. 10, the error committed by the metamodel for losses evaluation does not exceed 2% for this centroid. For other centroids, the maximum error for losses prediction is 4%.
This comparison thus validates the metamodeling approach used to evaluate the total losses in the machine on the different centroids. The next step is to use these metamodels to optimize the electric machine over the whole cycle considering only the centroids.

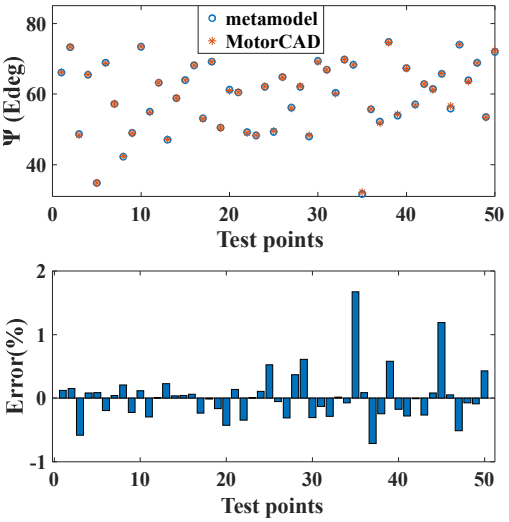

Fig. 9: Evaluation of the precision of phase advance metamodel

V. Optimization over drive cycle

The optimization problem formulated is multi-objective: we seek to minimize the machine's total losses on the driving cycle and mass. A single-objective reformulation treats the problem by minimizing the total losses of the machine on the driving cycle subject to a varying equality constraint on the mass. The *Sequential Quadratic Programming* (SQP) optimization algorithm [14] is adopted to solve the problem using the Matlab function *fmincon*. The optimization problem **P** is formulated as follow:

$$\text{Problem } \mathbf{P}: \begin{cases} Find\ the\ optimal\ values\ of\ \boldsymbol{x}: \\ x^* = min \sum_{i=1}^{6} L_i(x) \\ subjected\ to: \\ Mass(x) = Mass_{target} \\ Mass_{target} = [40\ ;\ 55]\ kg \end{cases} \quad (8)$$

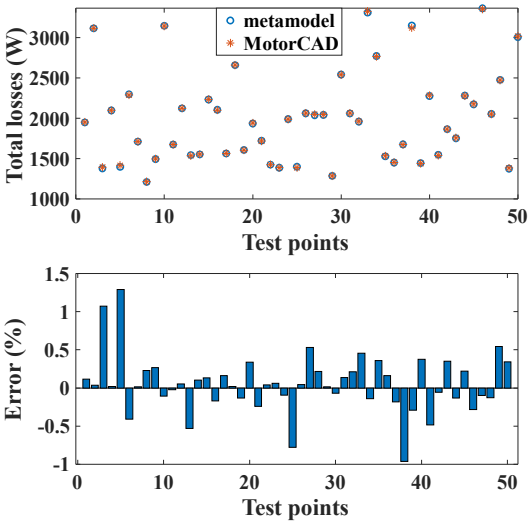

Fig. 10: Evaluation of the precision of losses metamodel

The total loss value is calculated on the centroids according to (9):

$$L_i = w_i . Losses_i \quad (9)$$

w_i is the weight of centroid i, equal to the number of points in cluster i, and $Losses_i$ the value of losses at centroid i. In Table II, the optimization results obtained for different mass values are shown.

TABLE II
OPTIMIZATION PARAMETERS VARIATION FOR DIFFERENT MASSES

Mass (kg)	41	43	44	46
x_1: Slot width (mm)	7,46	7,5	7,47	7,49
x_2: Slot height (mm)	19.9	18.9	19.3	19.5
x_3: Stator outer diameter (mm)	180	199.2	208.2	210
x_4: Magnet thickness (mm)	5.4	4.2	4	4
x_5: Active length (mm)	160	160	160	168.5

The multi-objective optimization elaborates a range of electrical machines with masses varying from 40 kg to 55 kg, In Fig. 11, the cumulative energy losses on driving cycle are given for the different motors size and compared with MotorCAD calculations. Metamodel error evaluation is shown in Fig. 12.
The variation of the machine's mass is due to the different values of the five optimization parameters as shown in Table II. We can see that some parameters varie more than others,

this gives an idea on each parameter importance in the optimization. Here, the stator outer diameter has the biggest impact on mass variation. Notice that the machines with masses higher than 44 kg present higher losses, this is due to the length of the machine which is the parameter having the most variation for these machines.

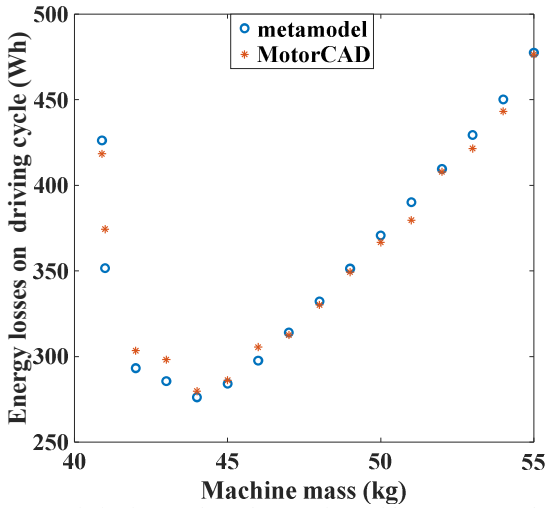

Fig. 11: Optimization results and comparison with MotorCAD calculations

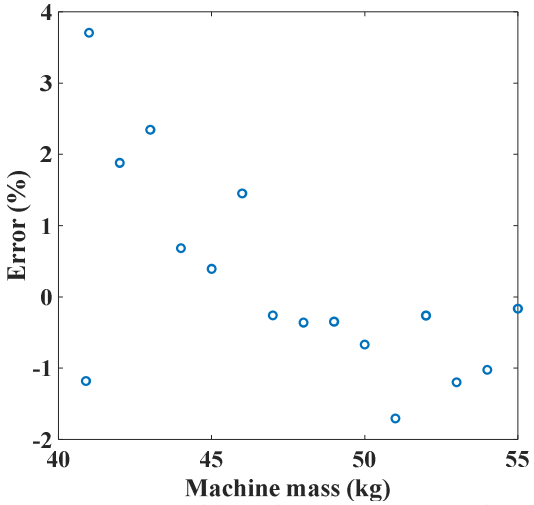

Fig. 12: Metamodel error for the optimization results

The compared results show less than 4% of error for the different machine masses. Thus, validating our proposed approach. The methodology permits a gain in computation time when it's about optimization. Where, 5 minutes are needed to design an electrical machine on a driving cycle.

VI. CONCLUSION

This paper presents the implementation of a driving cycle optimization methodology considering five design variables, based on metamodeling as well as the results for a WLTC application. The results obtained by this methodology have been compared with a computational model under Ansys MotorCAD and show satisfactory results. This method is fast and much less expensive in terms of calculation time, allowing the designer to quickly evaluate the machine's performance according to its size/weight on a complete driving cycle and can therefore be helpful for the first design phases.

The methodology was applied for a V-buried magnet synchronous machine. In future work a generalized approach will be presented for the design of a multirange powertrain. It will consider more design variables for the motor, different machine topologies, and further components as converters and reducers.

VII. ACKNOWLEDGMENT

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IX. BIOGRAPHIES

M. Djami is currently working towards a PhD degree in electrical engineering at the Group of Electrical Engineering of Paris (GeePs laboratory) in collaboration with Stellantis. He received the Engineering degree in Electrical Engineering from Ecole Nationale Polytechnique d’Alger in 2019, and the Master's degree from Université Paris Saclay in 2020. His current research interests include design and optimization of electric powertrains over drive cycle.

M. Hage-Hassan received her B.S. degree in mechanical engineering from the faculty of engineering, Lebanon, Masters in Product Design and Development from Ecole Centrale de Nantes in 2010 and a Ph.D. degree in electrical engineering from University Paris-Saclay in 2014. She is now an Associate Professor at CentraleSupelec. Her current research interests include design and optimization of electric machines and drives.

C. Marchand graduated from the Ecole Normale Supérieure de Cachan, France. He received the Ph.D. and the HDR degrees from the Université Paris-Sud, Paris, France in 1991 and 1999 respectively. He joined the Université Paris-Sud as an Assistant Professor in 1994 and became a Full Professor in 2000. Since 1988, he has been a researcher at the Laboratoire de Génie Electrique de Paris (LGEP) where his research interests are in eddy current nondestructive testing and in the design and control of electrical actuators. Since 2015, he is head of the Group of Electrical Engineering of Paris (GeePs laboratory).

G. Krebs received his Ph.D. degree and Habilitation for Direction of Research respectively in 2006 and 2017, both from Paris Saclay University, France. He is now an Associate Professor at Paris-Saclay University since 2008. His current research interests include design, optimization and finite element analysis of electric machines and drives.

P. Dessante received the Ph.D. degree in applied mathematics and physics from Versailles University, Versailles, France, in 2000, and the HDR (Accreditation to Supervise Research) degree from the University of Paris-Sud (Paris-Saclay), Paris, France, in 2012. He is currently a Professor with CentraleSupélec, Gif-sur-Yvette, France, and a Researcher with the Group of Electrical Engineering of Paris (GeePs laboratory). His current research interests include the simulation and optimization of electrotechnical systems (drive systems and electrical discharges).

L. A. Belhaj was born in Morocco in 1979. She received the electrical engineering degree in 2001 from Polytech Nantes, France. Her PhD: Dynamic modelling and control of coupled alternators in embarked electrical network has been presented in the University of Nantes in 2006. She developed the IE2 asynchronous machines range in Leroy Somer and worked on the alternators refurbishment and control in Jeumont Electric Maintenance in France. Since 2017, she has been working on the design of electrical machines for traction in Groupe PSA, France and is currently the electrical machine expert in Stellantis group.