Support Vector Classifier for Constraints Handling in the Design of Inductors for DC-DC Converters

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Support Vector Classifier for Constraints Handling in the Design of Inductors for DC-DC Converters

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The design of inductors for non-isolated DC-DC converters aims to obtain a required differential inductance value to limit the current ripple, together with low power losses and reduced component size, desired for highly efficient and power-dense converters. However, small size and low losses are often contrasting objectives. In addition, the design solution feasibility must be evaluated by verifying saturation and thermal constraints. This multi-objective optimisation problem of the inductor design can be effectively tackled through population-based algorithms, such as Artificial Immune Systems. As these approaches require the evaluation of many designs through time-consuming procedures, a classifier system trained in advance to recognise non-admissible solutions can support the search for candidate solutions. The adoption of the Support Vector Classifier for the constraints handling of the inductor design problem is here presented and discussed.

***Index Terms*—Buck Converter, Nonlinear Inductors, Data-driven Classification, Multi-objective Optimisation, Support Vector Machine.**

I. INTRODUCTION

THE ever increasing demand for highly efficient and high power-dense power electronics converters makes the design of their inductors challenging [1]. In DC-DC buck converters, the inductor has the role of the dynamic energy storage element, allowing the transition between different operating states of the switching circuit, and it works in a biased steady state: an AC component (current ripple) is superimposed to a DC bias, determined by the load current. The first target of the inductor design is the value of operative differential inductance L_{op}, required to limit the current ripple to the converter specification. In addition, essential features of an inductor are low power losses and reduced component size and weight, aiming to achieve high efficiency and high power density, respectively. However, in a design optimisation procedure, these two goals are contrasting since the core volume reduction can be achieved only by accepting an increase in the component losses. Thus, a multi-objective approach is required to face the inductor design problem, where the decision variables are the main geometric core parameters and the number of turns of the winding. The combination of the design variables must satisfy the operative inductance requirement. In the case of linear operations, the L_{op} is equal to the initial inductance value L_0. However, the DC bias field can lead the operating point of the magnetic material toward saturation, resulting in $L_{\mathrm{op}} < L_0$. Despite limited modelling and control complexities, design configurations operating in partial saturation are considered in the design procedure since they allow further reduction of the core dimension, accepting a limited increase in the total losses [2], [3]. Including the partial saturation operation increases the computational cost of the design problem due to the non-linear nature of the core material. In addition, the thermal limit of the inductor materials must be considered by computing the total losses during the inductor operation and estimating the heat dissipation. Thus, the design problem is configured as a constrained multi-objective design problem, where the total losses and the component dimensions must be reduced, and the constraints on the differential inductance profile and the maximum operating temperature must be satisfied. Optimisation procedures based on meta-heuristic algorithms can tackle this multi-objective problem [4]. These optimisation methods are usually effective in finding the Pareto front [5], but they require the evaluation of many design points, which typically results in time-consuming procedures. Adopting a data-driven surrogate model can reduce the computational cost of evaluating constraint compliance. In this framework, the performances of the Support Vector Machine Classifier (SVC) for the constraints handling are assessed by applying it to the design of an output inductor for a DC-DC buck converter.

II. MULTI-OBJECTIVE INDUCTOR DESIGN

The design optimisation problem considers an inductor with a double-E-shaped core as the one shown in Figure 1. A design configuration is identified by the geometric parameters of the core (A, B, F) and the air gap length g, which take real values in a fixed interval, and the number of turns N.

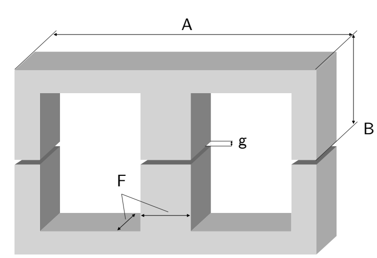
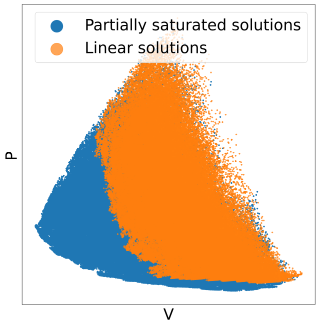
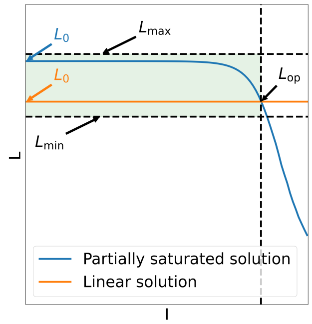


Fig. 1. Geometric parameters considered as design variables in the optimisation of the inductor: width (A), half-height (B), extension of the core (F) and air gap's length (g).



(a)



(b)

Fig. 2. (a) Qualitative comparison of the solutions evaluated considering the operation in linear and in partial saturation conditions, in the space of the total losses and the core volume [7]. (b) Comparison of two design configurations, operating in partial saturation and linear condition. The green box highlights the feasible operating inductance range.

Figure 2a shows a cloud of points representing different design configurations in the objectives space: volume V and losses P, on the x and y axes, respectively. The figure presents a comparison between the solutions obtained considering only the operation in linear conditions (orange dots) and those achievable in partial saturation (blue dots). As shown, the partial saturation operation allows the exploitation of smaller core volumes, which would not result in feasible configurations considering only the linear operation.

The design of partially saturated inductors requires adopting a non-linear model of the device to evaluate the differential inductance profile. A computationally faster but approximated method is the equivalent non-linear reluctance circuit of the component, solved with an iterative procedure. A more accurate design method requires at least a 2D FEM simulation or a 3D FEM simulation to effectively consider the stray flux, the fringing flux, or the skin and proximity effects in the winding. The proposed results are provided considering an equivalent non-linear reluctance model, useful in a preliminary design phase of the power inductor. The non-linear problem is solved through the fixed point (FP) technique [6]. However, the following considerations and remarks can also be applied to the other design procedures.

Figure 2b shows the comparison of two feasible differential inductance profiles for a given operative inductance value, one operating in linear conditions and the other operating in partial saturation. Given the specifications of the converter, the required operative inductance can be computed. In particular, a tolerance range over the prescribed inductance value can be defined.

The loss evaluation can be performed through analytical computations. In particular, the AC winding losses are neglected, while the DC winding losses can be determined by computing the DC resistance of the winding [8]. Concerning the losses of the magnetic core, the improved Generalised Steinmetz Equation (iGSE) allows computing the losses under an arbitrary waveform [9]. For the sake of clarity, it should be noted that the DC magnetic field bias, typical in inductors operating in DC-DC converters, involves an increase in magnetic losses. The parameters of the iGSE can be adjusted as a function of the applied premagnetising field H_{DC} [10]. However, the dependence of the parameters on the DC bias field has to be investigated with experimental measurements at different frequencies, magnetic flux density, and premagnetising field values. In addition, these parameters are generally not reported by manufacturers. This lack of information forces the designer to neglect the effect of the DC bias on the core loss increase, knowing that the estimated value could be wrong. A further requirement for an output inductor of a DC-DC buck converter is the controlled over-temperature during regular operation. The appropriate estimation of the inductor heating requires also knowing the positioning of the other components on the PCB of the converter, and the thermal specifications of the surrounding materials, to implement a thermal finite element simulation. However, a preliminary estimation of the temperature rise caused by the inductor losses can be done considering a natural convection heat transfer condition, with a uniform heat flux density over the outer surface of the core exposed to air. To summarise, the constraints compliance evaluation requires the non-linear differential inductance profile and the operating temperature computation. During a run of the optimisation procedure, much time is spent evaluating configurations that turn out to be unfeasible. To avoid these expensive and unnecessary calculations, a data-driven surrogate model is proposed in this paper to identify the feasibility of a design solution. The model can be used in a pre-selection phase included in the optimisation procedure, making a classifier system decide whether a candidate solution is worth being evaluated [7]. As a case of study, in this paper, the optimised design of an 80 μH inductor in N87 ferrite for a 48-24 V, 10 A, 50 kHz DC-DC buck converter is considered. The multi-objective optimisation procedure is the Vector Immune System (VIS) algorithm [5].

III. THE SUPPORT VECTOR CLASSIFIER FOR COMPLIANCE EVALUATION

The proposed procedure aims at defining if a configuration $\mathbf{P}(\mathbf{x})$, being $\mathbf{x}$ the degree of freedom array, is compliant with design constraints defined as:

(a) Inductance lower bound, $L_{\mathrm{op}}(\mathbf{P}(\mathbf{x})) \geq L_{\min}$;
(b) Inductance upper bound, $L_{\mathrm{op}}(\mathbf{P}(\mathbf{x})) \leq L_{\max}$;
(c) Inductance drop limit, $L_{\mathrm{op}}(\mathbf{P}(\mathbf{x})) \geq k_{\mathrm{sat}} L_0$, with $k_{\mathrm{sat}} \in (0,1)$;
(d) Thermal limit, $T(\mathbf{P}(\mathbf{x})) \leq T_{\max}$;

Figure 3 represents the feasibility regions obtained from an extensive search of the design space by considering every single constraint, while Figure 4 shows the same when considering the intersection of the four constraints. Only three variables are considered in the plots (extension of core F, air gap's length g, and number of turns N) in order to make the design space reproducible in three dimensions. It can be noticed that the resulting feasibility region is narrow and largely nonlinear. This makes the classification task hard.

The classification response should anticipate the evaluation of the configuration's accurate performance, which requires a time-consuming magnetic and thermal analysis, so to avoid

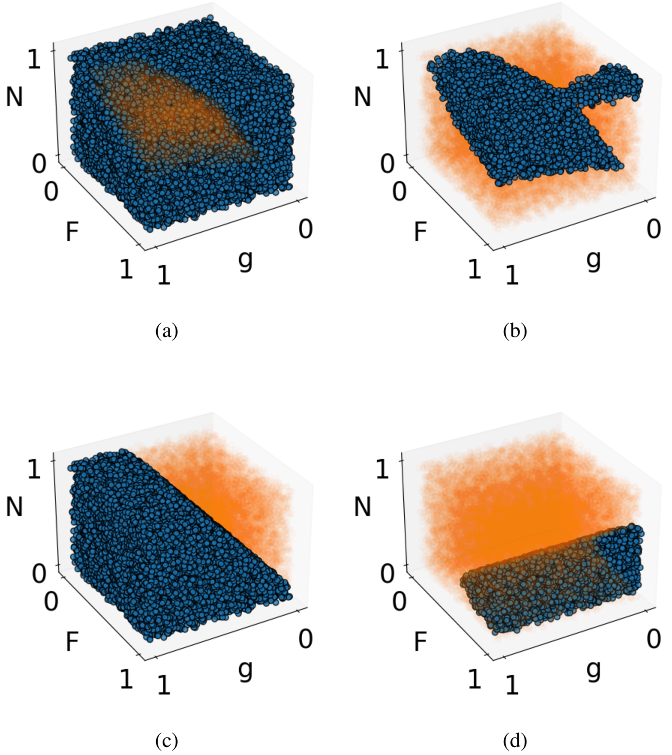


Fig. 3. Comparison of feasible (blue) and unfeasible (orange) configurations in the normalised design variable space. (a) Inductance upper bound. (b) Inductance lower bound. (c) Inductance drop limit. (d) Thermal limit.

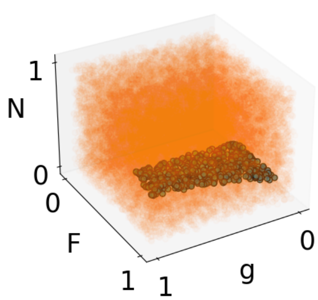


Fig. 4. Comparison of feasible (blue) and unfeasible (orange) configurations, in the normalised design variable space, considering all the constraints on the inductance profile and the thermal limit.

the complete assessment of possibly-unfeasible solutions. The classification problem is identified by 3 features (F, g, N) and two classes (*feasible*, *unfeasible*). The technique chosen is the Support Vector Machine Classifier [11], a machine-learning model for classification and regression which is extremely powerful in solving binary classification problems [12]. The primary objective of SVC is to create a boundary that effectively separates multiple classes in the training set, maximising the margin between them. A significant benefit of SVCs is their ability to identify a subset of support vectors, which are used to find hyperplanes that can ideally separate classes, minimising the classification errors on the training data. The SVC formulation is extremely effective for linearly-separable and not-overlapping classes. But this is not commonly the case for real-life classification problems, such as the one presented in this paper. However, the algorithm can be modified by defining a soft margin, enabling some training points to be misclassified. The SVC can be further adapted to non-linear classification problems through the use of non-linear kernel functions. These functions maps the input space to a higher dimensional one, called feature space, where the problem is linear and can be effectively treated by the SVC. A commonly-used kernel function with SVCs is the Radial Basis Function (RBF). Not going into details of the SVC formulation, taking into account the concepts of soft margins and RBF kernel, two hyper-parameters of SVC can be introduced:

- C, which influences the width of the soft margin, determining the maximum acceptance of classification errors on the training dataset. A higher value of C implies that a smaller margin will be accepted.
- γ, related to the RBF formulation, which determines the distance of influence of a single training sample in the feature space. For large values of γ, the samples need to be very close to each other to be considered in the same class.

Both hyper-parameters influence the model's behaviour by making it closely follow the class boundaries in the training samples (i.e. to overfit), or determining smoother decision surfaces (which instead could lead to underfitting). The next section will discuss the effect of the SVC hyper-parameters on the constraints handling of the inductor design problem.

IV. Results

The application of the SVC to the proposed inductor design problem requires some remarks. The first regards the nature of the dataset used for the training of the classifier and for the evaluation of its performance. A generalised balanced dataset of 2000 design configurations is considered for the training phase. Some details on the generation of the training dataset are provided in [7]. On the other hand, the SVC performances are evaluated on an unbalanced dataset (33% feasible, 67% unfeasible) of about 135000 design configurations, which are the result of a VIS optimisation run. Given the nature of the VIS optimisation [5], these points are obtained both from random generation and local mutation of admissible design configuration. The second remark regards the effect of the classifier on the optimisation procedure: comparing the classifier response and the effective constraints evaluation defines four outputs, constituting the well-known confusion matrix. In the framework of an optimisation algorithm, the effects of the two False outputs are different. While a False Positive (FP) output, which means an unfeasible design configuration misclassified as feasible, reduces the effectiveness of the classifier in reducing the computational time of the design procedure but does not influence the classification output, the effect of a False Negative (FN) output can be significantly detrimental. A FN output is a feasible configuration that is misclassified as unfeasible. It means that a hypothetical optimal design configuration will be wrongly disregarded during

TABLE I
OPTIMAL HYPER-PARAMETERS AND CLASSIFICATION SCORES

Case	C	γ	*TPR*	*FPR*
1	20.7	300.79	0.998	0.014
2	1.13	3.325	1	0.099

TABLE II
CONFUSION MATRIX RESULTS

Case	*TP*	*TN*	*FP*	*FN*
1	39944	69376	21335	4060
2	42851	61851	28461	969

the optimisation procedure, affecting the quality of the Pareto Front. The selection of the SVC hyper-parameters can drive the compromise accepted in the classifier accuracy. A good indicator of a binary classifier performance can be represented by the True Positive Rate (TPR) and the False Positive Rate, defined as

$$TPR = \frac{TP}{TP + FN}, \tag{1}$$

$$FPR = \frac{FP}{TN + FP}, \tag{2}$$

where *TP, TN, FP, FN* are the True Positives, True Negatives, False Positives, and False Negatives, respectively. An ideal classifier will present a $TPR = 1$ and a $FPR = 0$. In a real application, the SVC hyper-parameters can be optimised by searching the TPR - FPR scores nearest to the ideal values. Applying this strategy to the design problem with a grid search in the range 10^{-1} - 10^{3} for C and 10^{-1} - 10^{4} for γ, the values of the SVC hyper-parameters and the classifier scores presented in Table I are obtained. The scores are evaluated by training the SVC on the 50% of the 2000 samples generalised dataset and testing it on the remaining 50%. Then, the performances of the SVC on the 135000 design configurations from the VIS optimisation can be evaluated. The results for the obtained confusion matrix are presented in Table II.

The TPR and FPR of *Case 1* are the nearest to the ideal ones. In this case, the high value of the γ parameter determines an extremely accurate classification of the training samples. In addition, the high γ value makes the influence of the C parameter in modifying the classifier output negligible. These results are interesting since the rate of TN output is considerable, allowing to effectively disregard about 70000 design configurations during the optimisation procedure. However, the high number of FN outputs could strongly deteriorate the quality of the optimisation procedure. Lower values of the C and γ parameters can be selected, as in *Case 2*, allowing to define a smoother model and thus reducing the FN outputs to 969. This outcome is obtained at the expense of a higher FP rate, which implies the evaluation of about 7000 additional unfeasible configurations if compared to *Case 1*. The selection of the most appropriate SVC hyper-parameters depends on the trade-off between the influence on the optimisation accuracy and on the required computational cost.

V. CONCLUSIONS

This paper proposes a preliminary evaluation of the adoption of a Support Vector Machine Classifier for the constraints handling in the design of inductors for DC-DC converters. The presented results support the effectiveness of the SVC in predicting the constraint compliance of the design configurations of power inductors, suggesting that it will help to reduce the computational cost of the design optimisation procedures. An interesting future development is the integration of the training phase of the SVC in the first steps of the optimisation procedure, also considering the hyper-parameters tuning to adapt the classifier performances to the evolution of the available training dataset during the optimisation.

VI. ACKNOWLEDGMENT

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