Intelligent - Web search for EMI filter optimization

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Abstract

This paper proposes an intelligent system that aids the electronic designer to achieve compliance with design constraints exploiting the overwhelming set of components available on the Web. Mainly, designing an input filter for lowering electromagnetic interference (EMI) is still a challenge since the choice of components is subjected to multiple constraints. As a matter of fact, once the components' values are known, the choice depends on the required optimization, such as minimum cost, volume, or size. The Web offers a broad set of devices, but a complete search can result in a time-consuming activity. Besides, the designer's experience often reveals crucial. The proposed system aids the designer in finding components based on the main constraints and performs an optimization. A Machine Learning algorithm learns the designer's choice to be used in future design.

Keywords

Differential Mode Current, EMI Filter, Filter Design, Power Density, Design Tools, Design Optimisation

1. Introduction

The success of an electronic circuit design depends both on the search of components on the market and on the designer's experience. The first issue usually could require a lot of time, while the experience of the designer can be supported through suitable learning systems. In the design of Switched Mode Power Supply (SMPS), it is mandatory, for compliance to high-frequency harmonic standards [1], to suppress Electromagnetic interference (EMI) through a suitable input filter. This circuit, although simple, affects the goodness of the whole project since it increases the weight, the cost and the volume. In particular, the differential-mode (DM) noise mainly affects the major filter part, and the power density of the converter [2]. In an SMPS, the switching frequency of the power device, along with its harmonics, is the leading cause of the harmonic DM spectrum. In addition, a further contribution is given by the new generation of power switching devices, having fast-rising and falling shape of the current value [3], leading to higher switching frequencies. This represents an advantage since it improves power density, and the value of reactive components of power converters (both inductors and capacitors) can be reduced; on the other hand, DM EMI increases, requiring a suitable filter design [4].

The input filter, useful for EMI suppression, is generally composed of inductor-capacitor (LC) based cells, in single or multi-stage configuration. The design procedure of the input filter is well known. It consists in estimating the filter's corner frequency - that is the frequency where the output signal is attenuated to -3dB of the input - and then calculate the product of

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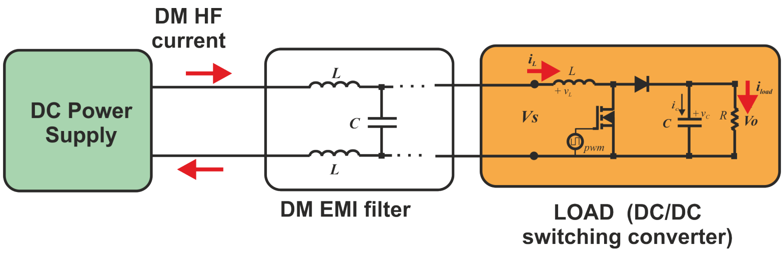

Figure 1: schematics of a power supply equipped with a DM EMI input filter and a DC/DC converter as a load generating EMI.

the inductor and capacitor value. However, after these steps, the designer must choose the suitable filter components satisfying several constraints, such as the minimisation of the cost, or the weight, or the volume occupation. The market offers a wide set of components, which represents an advantage for the designer; at the same time, examining all the possible solutions can be very time-consuming.

In literature some solutions, devised to aid the designer in the project of EMI filters, have been proposed. The design of EMI filters for DC/DC converter is described in [5]; the paper [6] presents an example of filter design considering the power density optimisation. A computer-aided procedure aimed at the automatic design of EMI filters, taking into account the power density for switching power converters, has been proposed in [7]. Few papers adopt intelligent algorithms to optimise filters such as the genetic algorithm (GA) [8] whereas in [9] and [10] the GA is used with particle swarm optimisation for optimising the output filter of a three-phase rectifier or a low pass filter for a Gas Turbine respectively.

The main drawbacks of the above-cited papers is that they operate on a fixed database. The design is therefore forced to check all the components and to compare them until the constraints are satisfied. Besides, the designer's experience is always needed.

It should be underlined that, in such design, after the components available on the market according to the project specifications (e.g., values, max current, etc.) have been identified, a further selection is necessary on the basis of other auxiliary considerations such as availability or manufacturer; then, the final choice is made on the most convenient component for the purposes of the project. These last two steps heavily depend on the designer's experience. This paper proposes a system to automatically search on the market through the Internet, to perform a first selection and optimisation, and finally to support the designer by proposing a solution based on a learning system trained on previous experiences.

The proposed approach is based on three steps implemented in three subsystems. Firstly, there is the definition of an algorithm that can search on the web and represent the characteristics of the components to populate a component database. The second subsystem is based on an optimisation algorithm that selects the suitable components considering the design constraints, and generate a ranked list, based on some features, for example the cost. This component list will be processed by the designer in order to add some more information about its characteristics. The third subsystem is the one that selects from this list the suitable component. This latter subsystem is based on a Machine Learning algorithm that will learn from the past choices made by the designer.

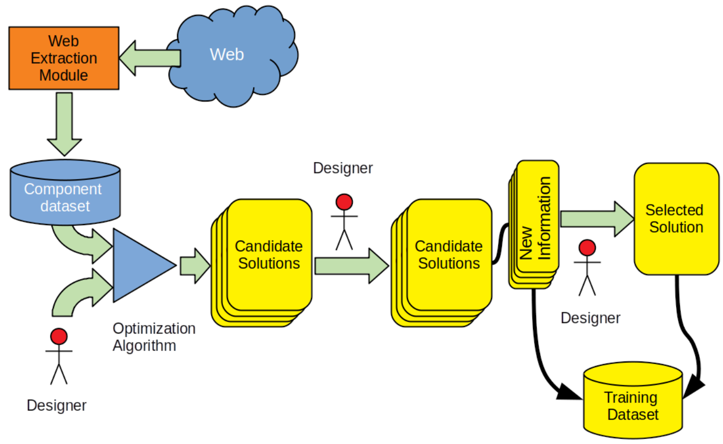

Figure 2: Building the training dataset for the Machine Learning subsystem. The optimisation algorithm propose a set of candidate solutions, and the designer adds the complementary information extracted from the data-sheet of the components. These information together with the chosen component are saved in the training dataset for the Machine Learning (ML) subsystem.

2. The Proposed System

In the proposed system the component choice phase is split in two independent optimisation tasks. The first optimisation step is based on the information memorised in the Component Dataset, these information are available on the web and automatically extracted by the Web Data Extractor Module.

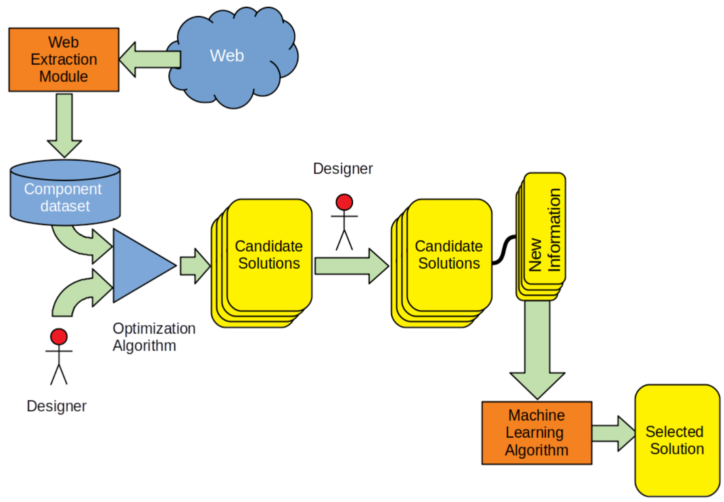

Figure 3: A representation of the work chain of the system. The designer introduces the constraints for the Optimisation Algorithm that selects the suitable components from the component dataset. The designer completes the information with the other obtained from the datasheet and presents the information to the ML subsystem that selects the optimal component.

This step is supported by an optimisation algorithm that will search in the dataset the components that satisfy the main design requirements. The output of this step is a list of suitable components called Candidate Solutions in Figure 2 and 3, ordered by price. The second optimisation step is based on the auxiliary information obtained by the Designer from the component data-sheets. These information are complex to obtain and they are related to some other characteristics such as weight, volume etc. The Designer adds these new information to the list of Candidate Solutions and will start a decision process in order to select the solution. The selected solution, together with the ranked list of Candidate Solutions constitute the training dataset for the ML algorithm. This second optimisation step is automated when the ML algorithm training phase is completed. At the end of the training step the ML algorithm will be able to select the solution on the basis of the New Information extracted by the Designer.

The proposed system is able to support the Designer in component selection task using a two steps procedure. At the beginning the system will select a list of component that fulfil the main project requirements. After that, the Designer will look only at the components in the Candidate Solutions, and will add the required information. The ML algorithm will select from the auxiliary information of the Candidate Solutions the suitable component based on the past choices made by the Designer.

2.1. The Web Data Extractor Module

Exploiting the Web and the Internet in general as a virtually infinite source of information is one of the most effective approaches in supporting the knowledge acquisition process [11][12][13]. Therefore, the first sub-system is an intelligent module that supports the user in searching for and acquiring data on user-selected capacitors and inductors.

The Web Data Extractor Module populates the component dataset that is used for the subsequent processing steps. This solution enables to semi-automatically, and incrementally, build up over time a knowledge base, which can be exploited by the intelligent system to propose suitable future solutions for design requirements.

The module consists of two sub-components. The first one queries the Mouser website[1] through its API and retrieves the list of the available inductors and capacitors along with their main characteristics. The second one is an information extractor module which has been designed to extract information from specific pages of the RS site [2], a well-known electronic components site. In particular, a link to a specific component is inserted, the source of the relative page is analysed in search of the data of interest. Parameters, like *Price, Inductance, Maximum DC current, Mounting type, Maximum DC resistance, Tolerance, Diameter,Height, etc.*, for a given component are extracted and the retrieved data are then be stored in the system's knowledge base.

2.2. The Optimisation Algorithm

The content of the component dataset will be used for the design of the circuit. In this dataset components are represented as a vectors $x \in \Re^N$. During the system design the component

[1] https://www.mouser.it/Passive-Components.

[2] https://www.rs-online.com/

selection phase is supported by the optimisation algorithm. The designer will assign the target and the constraints, and the optimisation algorithm will find the suitable components in the database. The constraints can be various: component dimensions, component weight, price, or availability. The target and the constraints for a project p are expressed as a couple (t, c) where $t \in \Re^T$ and $c \in \Re^C$. The optimisation algorithm helps the designer selecting the component that meets one target at a time; the main targets considered are the minimum price, the minimum volume and minimum weight but they can be more.

Using these targets, the optimisation algorithm will chose a component (or a ranked small set of components) and will output a set of candidate solutions $X \in \Re^N$, $X = \{x_1, x_2, \dots x_k\}$. Looking in a small set of solutions allows the designer to consider other additional constraints of minor importance based on information extracted from the component data-sheet and are not present in the component database. Looking at these information, the designer will make the last move and select the most suitable component x^c. The choice of the designer on a reduced number of components is usually supported by a considerable amount of experience The set of candidate solutions X with their supplementary information and the selected component $x^c \in X$ are loaded in the training data-set and used to train the ML subsystem in Figure 3.

There are many optimisation algorithms suitable for this application, for example genetic algorithms. The only constraint to consider is that the output should be a ranked list of solutions, not a single optimised solution.

2.3. The Machine Learning Algorithm

The learning algorithm learns the design choices made by the human designer, starting from the optimisation results. There are many algorithms that can be used for this application, and a choice is based on the available training data.

Nowadays, a great attention is devoted to neural networks and deep learning. These algorithms have very good performances on almost all application framework but requires a lot of data in the training phase. A deep learning approach can be considered if lots of data are available for training, and many possible neural architectures can be chosen. If few data are available, a deep learning approach is not feasible and other neural algorithms should be considered. An example of this kind of network is the General Regression Network [14], a feed-forward neural network with a single hidden layer where each unit is used to memorise a training couple (x_p^*, x_p^c). This neural network has been used in many fields as classification [15]. This network does not have a training stage, just the memorisation of all the training examples. During the test phase, when an input pattern $x^{*'}$ is presented to the network. Each hidden unit i will contribute to the output with a component weighted by the distance between the input and the training example. During the evaluation task, the ML system will have in input a vector $x^{*'}$ and will output a vector $x^*_{out} \in \Re^N$ that is the result of a regression procedure. The vector x^*_{out} will not contain the code of an actual component; it will have the characteristics of the desired component. To obtain the most similar component, it is necessary to find the x_d vector of characteristics:

$$x_d = \arg\min_k ||x^*_{out} - x^*_k|| \tag{1}$$

obtained by comparing all the elements included in the component dataset to the ideal desired component x^*_{out}.

Figures 2 and 3 show that the system has an continuous interaction with the designer that is involved in many steps of the process. This will make more effective the use of a neuro-fuzzy system that is more transparent than a fully neural system.

3. Case of Study: Design of a DM EMI Filter

The case study consists on designing an optimised filter for a step-up DC/DC converter. The operation of this device is based on a power MOSFET that commutes between ON and OFF state with a switching frequency of 40 kHz. It causes EMI to be minimised with the filter suitably designed [16]. The electric scheme is shown in Fig. 1, where the filter for the differential mode is placed between the supply and the converter as load.

The measurement of EMI and the procedure for choosing the filter components are described in detail in [17]. The EMI spectrum measured before the filter insertion is shown in Figure 4, left side, whereas the spectrum after the use of an EMI filter to comply with the CISPR5 standard is shown in Figure 4, right side. This result is achieved by single-stage LC filter as the one shown in Figure 1; the calculated corner frequency of the filter is about 33.8 kHz. Additional constraints are given by the rated current for the inductor and rated voltage for the capacitor (set to 3 A and 50 V respectively).

The red dot shown in Figure 4 corresponds to the RMS value of the current. It can be noted that filtering operation lowers the amplitude of the harmonics under the Standard limits (in our case the CISPR5). This result can be achieved by several couples of capacitors and inductors and must consider other constraints as already discussed.

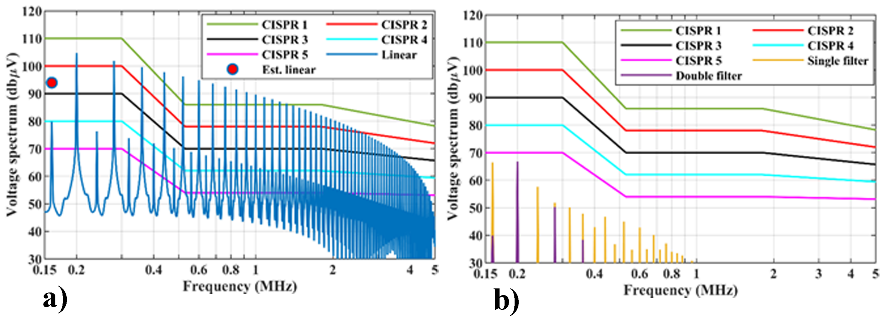

Figure 4: Differential mode spectrum a) before filtering, b) after filtering

As a case study, an input filter is optimised based on its cost as the main constraint. Starting from the corner frequency previously defined, meaning *fc*=33,8 kHz, the search interval for the inductance has been set as 33uH < L < 330uH and for the capacitance as 68nF < C < 680nF. The selection of the values of the components is not trivial. Choosing low inductance values may lead to elements that could interfere with parasitic parameters, while choosing high inductance values may lead to parts that usually are expensive and bulky. Furthermore, such a choice could force the other component to a very small value, leading to the problems mentioned above. The same considerations can be done for the values of the capacitor. Finally, including also the constraints on the maximum current for the inductor and the maximum operating voltage for the capacitor, the web searching algorithm retrieved about 2000 components. After this step, a selection of couples L-C, complying with the corner frequency, has been made. It is worth pointing out that the selected values cannot exactly satisfy the value of the corner frequency since they belong to a set of discrete values depending on the tolerance. Particularly, for a tolerance of 20 percent, the *"E6"* series comprises the following normalised values: *10, 15, 22, 33, 47, 68.* As a consequence, an interval for the frequency corner *fc* has been defined so that the frequency corner calculated based on the chosen couple must satisfy the criterium: $0,9 * fc < fc - calc < 1,05 * fc$, where *fc-calc* is the new frequency corner of the filter defined by the chosen values L-C. The output of the searching algorithm provides the following information: the rated value of the component, its tolerance, the website from which it has been extracted, the manufacturer, the identification code, and the cost. However, additional parameters can be visualised if necessary. The designer can analyse the suggestion of the algorithm; then he can confirm or vary it depending on other parameters to be defined. In our case study, the optimal choice has been compared with the following characteristics: the delivery time and the availability of the component. Figure 5 shows a comparison of the costs among all 29 couples: the cost has a mean of 2.18 euros and a σ value of 1.1; it can be noted that, based on the variance, shown by the grey area, there is a relevant variation of the price among the components.

After this step, the designer verifies if some components have to be excluded. There are several reasons for it: as an example, it is not possible to take into consideration components not available, or with a limited amount of items. Some inductors result with a rated current lower than the desired one, for example, the manufacturers provide a the saturation value of the current, for example 3 A and, as a consequence, a much lower rated current. Besides, some components are excessively bulky or expensive since they are devised for special use only. Furthermore, the first selection showed that, for the chosen application, the inductor's parameters are predominant on the cost and weight of the filter; it is mainly due to the rated current of the inductor. For the above-mentioned reasons, the optimisation can be performed taking into account the inductor only. Four inductors can be considered for the filter design,

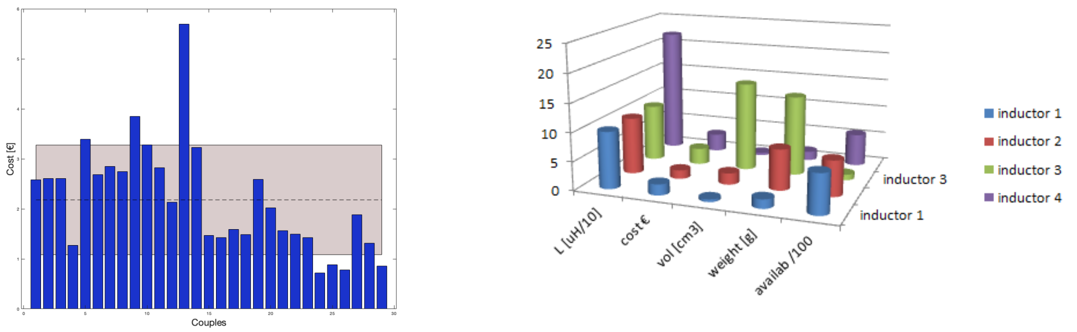

Figure 5: Bar diagram showing the cost of the 29 couples chosen by the algorithm (left), and comparison of the main features of the possible inductors (right).

Table 1
Chacteristics of the selected Inductors

	L [uH]	cost €	vol [cm3]	weight [g]	availability
inductor 1	100	1.92	0,46	1.6	699
inductor 2	100	1.53	2,008	7.2	628
inductor 3	100	2.85	15,582	14	100
inductor 4	220	3.12	0,44	1.58	568

their characteristics are summarized in table 1.

Considering a price criterium, the inductor two is the cheapest component. However, the inductor number one, compared with inductor two, could strongly reduce volume and weight with a slight cost increase. The inductor three is mounted on a bulky package, and it is also expensive; however, it could be selected for heavy-duty applications where the circuit is highly stressed. Finally, the cost of the inductor four is twice compared with the cheapest inductor; on the other hand, it shows a reduced volume and weight. The designer will select the most appropriate component according to the specific project constraints. The choice will be subsequently saved in the system as a knowledge element to be used for the learning process of the ML algorithm.

4. Conclusions

A system for the aided design of input EMI filters has been proposed. The system is composed of three sub-systems working in sequence. The first one is devoted to data extraction from the Web of the components based on the main design constraints (values, rated current or voltage). Then, the optimization algorithm performs a first selection considering the parameter for optimization (such as cost, volume, or weight). Finally, a solution is proposed to the designer based on a machine learning algorithm trained on previous design experience.
The proposed approach minimizes time to search components and takes into account the designer experience for filter design. As future work, the dataset built with this approach will be analyzed to support the definition of fuzzy membership functions.

References

[1] I. E. Commission, et al., Information technology equipment-radio disturbance characteristics-limits and methods of measurement, CISPR 22 (1997).
[2] K. Raggl, T. Nussbaumer, J. W. Kolar, Guideline for a simplified differential-mode emi filter design, IEEE Transactions on Industrial Electronics 57 (2009) 1031–1040.
[3] R. Zhang, W. Chen, R. Yan, J. Liu, Y. Zhou, Z. Shi, Emi prediction of future device gan with reverse conduction characteristic in hvdc system, in: 2020 4th International Conference on HVDC (HVDC), IEEE, 2020, pp. 858–862.
[4] Y. Liu, S. Jiang, H. Wang, G. Wang, J. Yin, J. Peng, Emi filter design of single-phase sic mosfet

inverter with extracted noise source impedance, IEEE Electromagnetic Compatibility Magazine 8 (2019) 45–53.
[5] J.-L. Kotny, T. Duquesne, N. Idir, Design of emi filters for dc-dc converter, in: 2010 IEEE Vehicle Power and Propulsion Conference, IEEE, 2010, pp. 1–6.
[6] G. Ala, G. C. Giaconia, G. Giglia, M. C. Di Piazza, G. Vitale, Design and performance evaluation of a high power-density emi filter for pwm inverter-fed induction-motor drives, IEEE Transactions on Industry Applications 52 (2016) 2397–2404.
[7] G. Giglia, G. Ala, M. Di Piazza, G. Giaconia, M. Luna, G. Vitale, P. Zanchetta, Automatic emi filter design for power electronic converters oriented to high power density, Electronics 7 (2018) 9.
[8] M. Luna, G. La Tona, A. Accetta, M. Pucci, M. C. Di Piazza, An evolutionary emi filter design approach based on in-circuit insertion loss and optimization of power density, Energies 13 (2020) 1957.
[9] W. Sun, Z. Chen, X. Wu, Intelligent optimize design of lcl filter for three-phase voltage-source pwm rectifier, in: 2009 IEEE 6th International Power Electronics and Motion Control Conference, IEEE, 2009, pp. 970–974.
[10] M. Eslami, M. R. Shayesteh, M. Pourahmadi, Optimal design of pid-based low-pass filter for gas turbine using intelligent method, IEEE Access 6 (2018) 15335–15345.
[11] G. Pilato, S. Vitabile, G. Vassallo, V. Conti, F. Sorbello, Web directories as a knowledge base to build a multi-agent system for information sharing, Web Intelligence and Agent Systems: An International Journal 2 (2004) 265–277.
[12] A. Augello, I. Infantino, G. Pilato, F. Vella, Sensing the web for induction of association rules and their composition through ensemble techniques, Procedia Computer Science 169 (2020) 851–859.
[13] A. Cuzzocrea, G. Pilato, A composite framework for supporting user emotion detection based on intelligent taxonomy handling, Logic Journal of the IGPL 29 (2021) 207–219.
[14] D. F. Specht, et al., A general regression neural network, IEEE transactions on neural networks 2 (1991) 568–576.
[15] R. Rizzo, A. Fiannaca, M. La Rosa, A. Urso, The General Regression Neural Network to Classify Barcode and mini-barcode DNA, in: e. a. DI Serio (Ed.), Computational Intelligence Methods for Bioinformatics and Biostatistics, volume 8623, Springer International Publishing, Cham, 2015, pp. 142–155.
[16] N. Mohan, T. M. Undeland, W. P. Robbins, Power electronics: converters, applications, and design, John wiley & sons, 2003.
[17] D. Scirè, G. Lullo, G. Vitale, Emi filter re-design in a smps with inductor in saturation, in: 2021 IEEE 15th International Conference on Compatibility, Power Electronics and Power Engineering (CPE-POWERENG), IEEE, 2021, pp. 1–7.