Summary

The availability of mathematical tools for understanding the actual relationship between the parameters and the outputs of complex dynamical system has become an important resource for the design of next-generation electrical and electronic equipment. The accurate knowledge of the relationship among inputs, outputs and parameters of the systems under analysis can be used to heavily speed up computational expensive design tasks, such as: uncertainty quantification (UQ) and optimization. Indeed, such knowledge can be used to guide the design space exploration and to reduce the number of experiments required by the above tasks.

Unfortunately, in realistic applications, the relationship between the parameters and the outputs of a generic electronic device or circuit is rather complicated and usually not explicit. For the above reason, UQ and optimization are usually performed via *brute force* approaches based on repeated experiments with the so-called computational model (i.e., physical experiments or computer simulations). However, physical experiments can be expensive and time consuming, since they would require the construction of several prototypes. Therefore, during the early design phase, parametric simulations are usually adopted.

In the above scenario, a surrogate model, also known as metamodel, allows to provide a closed-form and fast-to-evaluate approximation of the actual input-output relationship of the computational model. Among the several regression and interpolation techniques developed and used for the surrogate model construction, this dissertation mainly focuses on supervised machine learning (ML) regression techniques. Specifically, state-of-the-art ML regressions, such as: linear expansion of basis functions, artificial neural network (ANN) and kernel-machine regression are briefly presented with the aim of investigating their advantages and drawbacks for the surrogate model construction.

The above analysis shows that ANNs and kernel-machine regressions provide an effective solution for the surrogate model construction in regression problems with a "large" number of input parameters, since they allow mitigating the curse of dimensionality affecting conventional regression techniques based on linear expansion of basis functions. Also, kernel-machine regressions seem to provide the best accuracy with respect to the number of training samples, in regression problems in which *small* number of training samples is available, even if their applicability

is limited to real-valued scalar-output problem. However, for all the regression techniques considered in this dissertation, the computational cost required by the surrogate construction is dominated by the training set generation.

According to the above observations, this dissertation discusses and tries to address some relevant challenges related to the surrogate modeling construction in electronic applications.

First of all, an unconventional training scheme based on prior knowledge based machine learning approaches, in which the surrogate models are trained via a heterogeneous training set combining the predictions of a high- and low-fidelity model, is proposed with the aim of reducing the computational cost for the training set generation.

Then, a generalized mathematical framework is presented to extend the applicability of kernel-machine regressions to complex-valued problems.

Finally, data compression strategies and multi-output kernel formulations are developed with the aim of bridging the gap between ANN structures and kernel-machine regressions for the construction of vector-valued surrogate models.

The effectiveness, the strength and the performance of the above methodologies are investigated and discussed on several application examples by considering the UQ, the optimization and the parametric modeling of realistic electromagnetic structures and electronic devices.