Limitations of genetic programming applied to incipient fault detection: SFRA as example

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***Abstract*—This document deals with the application of genetic programming to the fault detection task, specifically with the power transformer fault detection problem of incipient faults. To this end we use genetic programming to obtain an highly approximated model of the a power transformer. The sweep frequency response analysis test represents the response of the transformer to a discrete variable frequency stimuli. We have been able to obtain a highly precision model which improves the precision of a commercial PG system. This result would be good if we only needed to identify the system. However, for the fault detection task, we should be able to identify the components within the transformer to assert where the fault has taken place. This is because the SFRA test when an incipient fault is present are similar but different as the fault advance. The tree generated for the model after the fault is evolved from the tree defining the power transformer model before the fault. Both trees are similar but the evolution seems to take place in a very specific random place. There is no way we can relate such changes with the physical model of the transformer. This shows the limitations of genetic programming to deal with this task and calls for extensions to the genetic programming paradigm or the merge of paradigms in order to deal with such task.**

***Keywords*-Genetic Programming, SFRA, Power Transformers, Model Generation.**

I. INTRODUCTION

Sweep frequency response analysis (SFRA) has been very successful as a tool to identify incipient faults in power transformers, hereafter we will call the power transformer just transformer. The need of these tools is the result of the new energy markets conditions where these elements are used to the limit leading to potential hazard conditions. An incipient fault is called to a condition which can derive in a fault. Transformer incipient fault diagnostics is an active worldwide research area as safety and economic improvements would be achieved if this task could be solved even at the qualitative level. This problem has been mainly faced with formal models but there is still a very long way to go in this direction[1], [2], [3]. These models are then compared with the real behavior of the transformer leading to some approximations which are valid for that prototype only. The main problem in these kind of models is that they need to have all the information about the parameters of the transformer i.e. they know a priori all the components of the transformer. These models could be called a white box model where we are aware of all the structure and components of the model as show in figure 1

Figure 1. White box model

Furthermore, the transformer model is very complex as it includes, besides lumped components, distributed components within the transformer such as capacitive effects between the windings and the tank as well as inductive effects among the windings, as well as some other distributed parameters. Models for these effects have been proposed in the literature, but there are still work to do in this direction to obtain better results [9], [10].

Nowadays, incipient fault detection in transformers is a complicated task basen mainly on human experience on such tests. Conventional tests such as power factor, TTR, excitation current among others are only effective in the case of declared faults. However in the face of a great number of incipient faults their effectiveness is almost null. To this end several alternative tests have been developed to mainly identify winding/core geometrical changes. Such changes are originated by the axial and radial forces to which the transformer is subject. They are the main origen of most of the incipient faults [4], [5], [6].

II. SFRA

SFRA excites the different transformer operation modes i.e resonance points, which define its geometric structure. To this end a 20V signal in the range between 20Hz to 2MHz is used to excite the transformer and the response is obtained at very well defined connection points. The changes in its geometry will modify the transformer operations modes and therefore the resonance points involved in the frequency

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response. It is important to highlight that a transformer represents a magnetic structure with RLC couplings which involve windings, core and the tank [7], [8].

Incipient failures will, because of its nature, evolve to a declared fault which will result in a transformer permanent damage hence the importance of incipient fault detection as well as the assessment of possible repair or its decommission. In this sense, there has been a worldwide interest to develop a transformer frequency-based mathematical model which in a precise manner allows an identification inside the transformer perhaps using some kind of parameter identification tool. This would allow the right decision making process about the necessity to disconnect it for its inspection and eventual repair [11], [12], [13], [14].

A typical SFRA curve is in Figure 2, where we can observe the highly non-linear behaviour, as a result of the non-linearity of the core as well as the multiple inductive and capacitive couplings among windings, core and tank. Each test has 1046 sampling points.

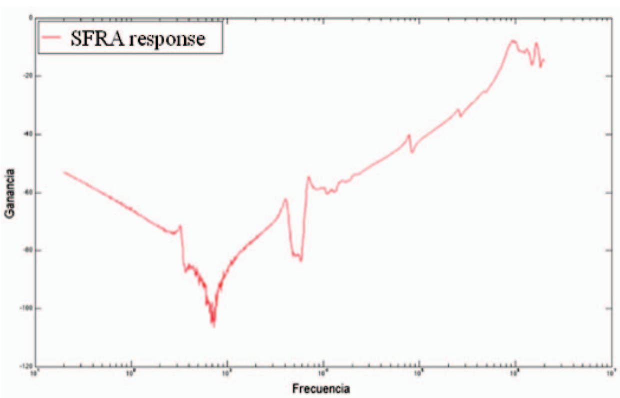

Figure 2. SFRA Typical Response

Based on the experience, it has been possible to identify frequency ranges which are related to the various parts of the transformer structure. These ranges are

- 20Hz-2KHz The fault modes corresponding to core deformations, residual magnetism, short circuits between coils, and winding open circuits.
- 2KHz-20KHz It detects winding displacements and lost of their support.
- 20KHz-400KHz It detects winding deformations and problems in the tap changers.
- 400KHz-2MHz It detects movements on the internal connections cables as well as the tap changer. Furthermore, it detects problems external connections problems mainly with the test equipment.

III. Genetic Programmiing Applied to SFRA

Genetic Programming (GP) has been very successful in modeling highly non linear models such as the one of the transformer. Specifically, the research developed in [15] led to a very precise model of the transformer. The incremental methodology applied there was able to achieve such results. Counting with the transformer mathematical model as well as its parametrization would allow to completely identify the incipient faults inside the transformer, this would make it a must have.

A SFRA test for a particular transformer it is shown in figure 3. As we can observe in figure 3, the model derived using GP faithfully reproduces the response obtained by SFRA. The little differences can be reduced if we allow the GP process evolve. It is important to mention that in this case the evolutive process took five days to reach this model, achieving a 2.3% fitness.

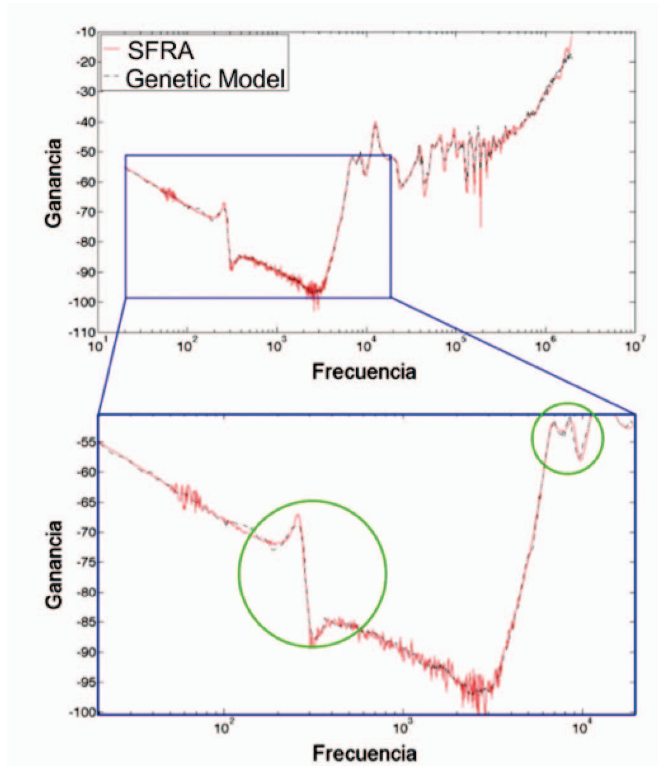

Figure 3. Model obtained using our methodology

In order to validate the developed algorithm we proceed to reproduce the model with a recognized commercial software called Eureqa® whose main task is system identification. We use several configurations for its parameters to control the evolutive process achieving the results shown in Figure 4.

As it can be seen in Figura 4, the results obtained by Eureqa® didn't achieved to reproduce the highly non-linear parts of the response we are looking for. It only obtained a good approximation with soft non linear functions on those ranges. This tell us the model achieved by our system outperforms Eureqa® with highly non-linear models and validates our model. Going back to the model obtained

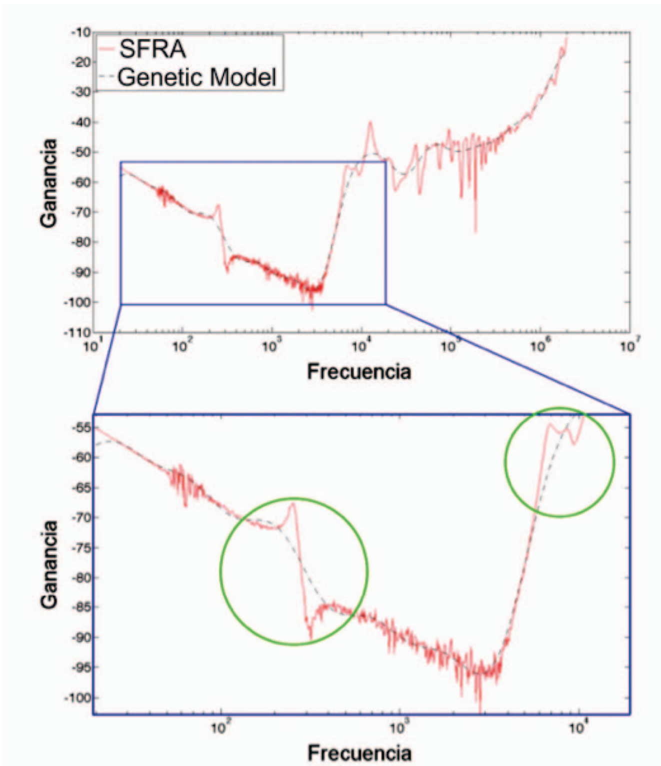

Figure 4. Model obtained using Eureqa

by our system, it is almost identical to the response we are looking for, however, it can not be desegregated to obtain a direct relationship between the internal parts of the transformer and the parts of the model. Furthermore, the way to the parametrization of the transformer is still very long.

With this goal in mind, and to show the potential of GP to identify incipient faults in the transformers we decided to set up an experiment with a transformer where we were very lucky to have a SFRA test both before and after the fault. We will show the SFRA tests, our models for such tests, but mainly the trees derived by GP which supports such models. Here we expect to find some relationships between the states before and after the fault.

Figure 5 shows the faulted transformer where the fault happened at phase C and damaging the corresponding winding.

Figure 6 shows the transformer frequency response with no fault. It is mandatory to clarify this response is quite distinct to the one shown in Figure 2 because in that case the transformer connection corresponds to a Δ connection while this one in Figure-6 corresponds to a Y connection.

Figure 7 shows the tree derived by the faultless transformer model where we can identify two main branches which, however, can't be associated to an specific structural part of the transformer.

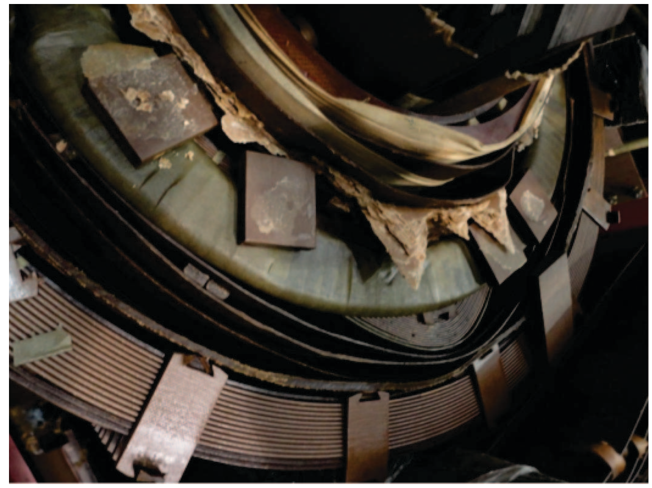

Figure 5. Fault in phase C

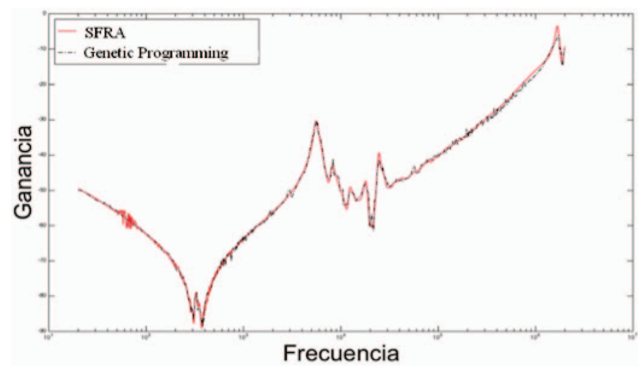

Figure 6. Model before the fault

After the fault, the SFRA test was repeated and the response obtained is show in Figure 8.

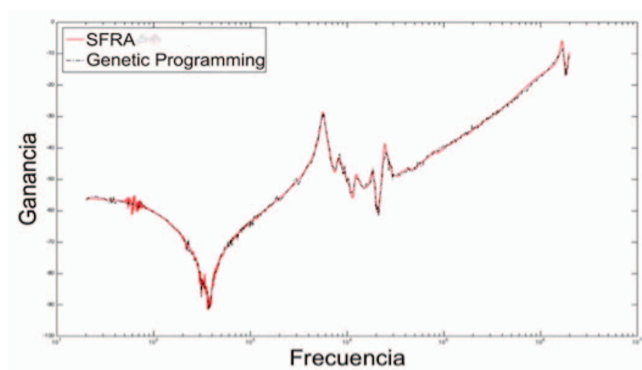

Figure 8. Model after the fault

From Figure 8, the fault on the winding generated a change in the SFRA test, mainly in the 20-400Hz frequency range. It is clear the lost of one resonance around 350Hz, within a range where typically a double resonance exists. We proceed with our GP system to obtain the new model. Then we will identify the changes induced in the model and try to correlate these changes with changes in the tree structure. The tree after the fault is shown in Figure 9 where we can see the fundamental changes are located in part of the right side branches of the tree.

IV. Limitations of GP when applied to parameter identification

As we can see in both trees shown in Figures 7 and 9 the fundamental changes are located in part of the right side branches of the tree. But we are in the same point as before this test. We are not able to discriminate to which parts of the tree belong to the specific parts of the transformer making this task, diagnostics, imposible. Perhaps this is due to the fact that GP can be seen as a black box identification system where we don't know anything about what's inside of the box as shown in Figure 10l

Figure 10. Black box model

GP is adequate for system identification. It is not interested in knowing what's going on within the box. Specifically, it is not interested in which the parameters are, what their relationship is or its structure. Furthermore, PG doesn't know about what is the black box, it could be a transformer o it could be a car. Therefore, transformer diagnostics is not if faced only with GP.

V. The need to adapt GP to fault diagnostic

We have seen GP is an excellent tool for system identification, however for the fault diagnostic task is incomplete. Therefore, we need to reinforce GP with more information. A model which would be somewhere between the black box model where we have no information about the structure or parameters of the system, and the white model where we asume we know everything about the system and therefore a formal model can be derived directly. This model should be a gray box model as shown in Figure 11.

Figure 11. Gray box model

This means, we usually have partial information of the system, maybe not all the information. Moreover, at some point we barely know the structure of the system but not the values of its parameters. This could lead us to the point where for some parts of the model we have no idea about their structure not to say the values. GP must deal with this kind of situations if the fault diagnostic task want to be solved.

VI. Conclusion

In this document we have presented a PG system designed to generate non linear models in a reasonably precise manner. We have compared our system with a commercial one and , at least with highly non linear models, our systems outperformed it. Until now these models have been derived with traditional formal methods but they have not achieve the goal yet, as they need all the information which is a hard task to obtain as there are continuos distributed parameters besides the normal lumped parameters. We have argue that while PG is an excellent tool for the system identification task, its application to the parameter identification task is limited as we can see PG as a blackbox process where no information within the box is needed and therefore it will give no information about such components. New venues must be investigated in order to apply this paradigm. The one we think would have success is the one which integrates the power of PG with the structural information of the system. This document calls for extensions to the genetic programming paradigm or the merge of paradigms in order to deal with such task.

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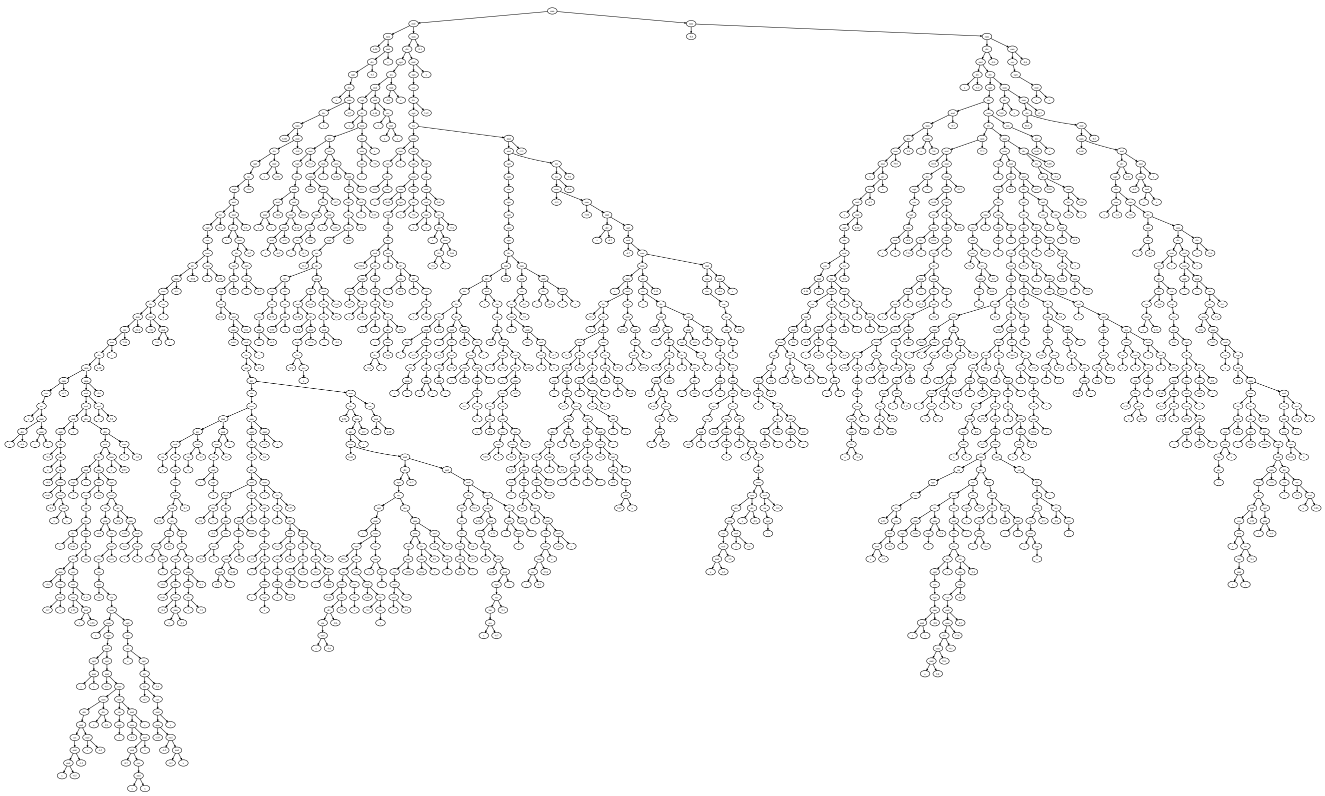

Figure 7. Tree before the fault

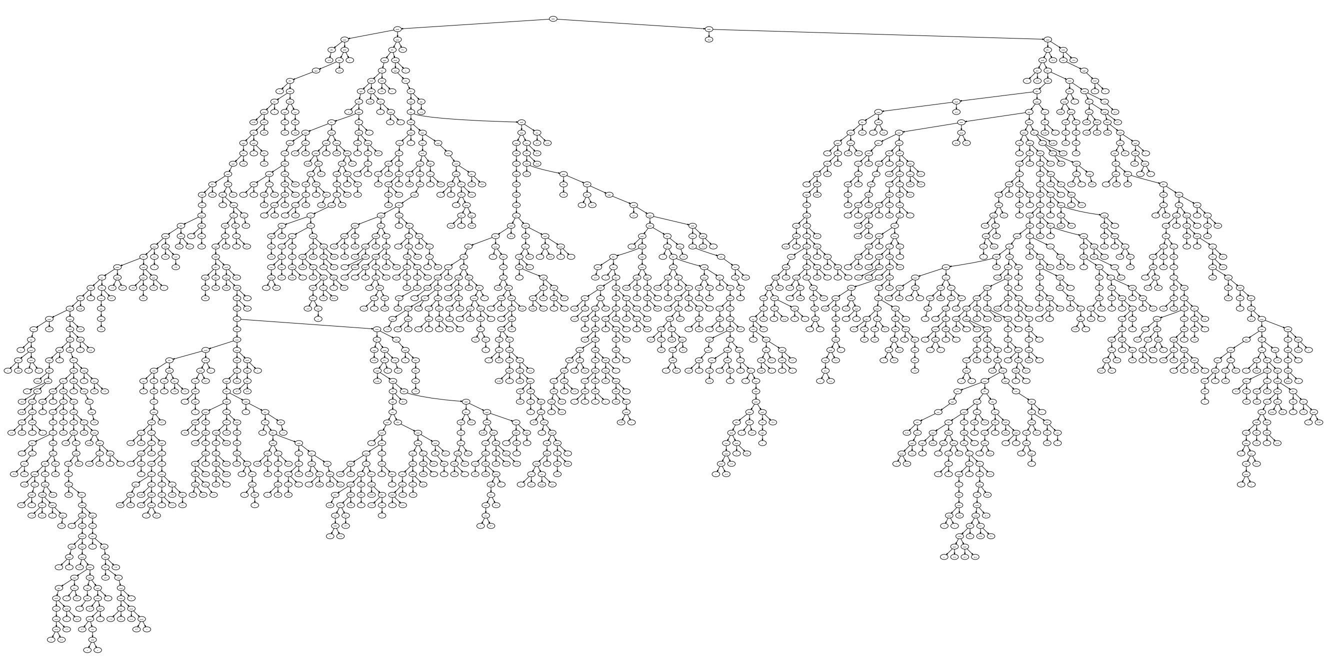

Figure 9. Tree after the fault