Going parametric in EMT studies: EDF methods and tools for input data uncertainties, sensitivity analysis and parameter identification

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Abstract— **This paper presents EDF's approach to input data uncertainty, system variability, sensitivity analysis and parameter identification in EMT studies. After pointing out the limitations of the traditional treatment of these questions, we present the new methods that have been adopted and the tool that has been developed for engineers using EMTP. A final example case illustrates their advantages.**

Keywords: **Parametric studies, parameter uncertainty, scenarios, contingency analysis, sensitivity analysis, optimization, parameter identification, data matching, EMTP, PAMSUITE.**

I. Introduction

In recent years, input data uncertainty in electromagnetic transient (EMT) studies has been a growing concern at EDF. Indeed, worst-case strategies traditionally used to deal with data uncertainties are inefficient and not always conservative. This concern seems to be a global trend, as data uncertainty was one of the important topics at the Discussion Group Meeting of Study Committee C4 at the 2018 CIGRE Session [1].

At EDF, a significant effort has been made lately in order to establish a sound theoretical framework to deal with the problem and to develop a software solution that can be easily used by EMTP users. In addition to data uncertainties, this effort has included three other related problems: system structure variability, sensitivity analysis and parameter identification. As all these problems imply that some of the system parameters have several potential values and/or that a part of the system structure has several variants, we will encompass all of them with the expression *parametric studies*.

This paper aims to share EDF's approach to these problems, both the adopted theoretical methodology and the characteristics of the software solution that has been implemented.

This software implementation is a front-end standalone application that works with EMTP-RV and has been called PAMSUITE (for *Parametric Modelling Suite*). This tool is now extensively used at EDF in all kinds of studies: transformer energization, ferroresonance, geomagnetically induced currents, lightning and switching overvoltages, power quality, power plant stability, and others.

Some of these studies have already been published [2][3][4][5][6]; others will be published in the future. However, due to lack of space, these papers cannot provide the details of the parametric methods and tools that they use. The aim of this paper is also to document them in full detail.

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Paper submitted to the International Conference on Power Systems Transients (IPST2019) in Perpignan, France June 17-20, 2019.

II. Parametric problems: Input data uncertainties, system variability, sensitivity analysis, parameter identification

Ideally, in an EMT study, the physical system under study is well defined, i. e. both the structure of the system and the characteristics of its components are perfectly defined and known.

However, this ideal situation is far from reality. Quite frequently, the model parameter values and/or the model structure are partially undefined. On the one hand, very often the component's characteristics and thus their model parameter values are not exactly known but rather known with some inaccuracy or not known at all; for example, the circuit-breaker closing angle in switching studies or the tower footing resistance in lightning studies; we will call this the *uncertainty* of the system parameters.

On the other hand, the system may present several possible structures; these may be related to contingencies like line or generator outages, but also to different network configurations; we will call this the *variability* of the system structure.

Uncertainty and variability are often linked to another question: the relative influence on the results of each of the parameters and/or configurations, i. e. the *sensitivity analysis*, which may be the main part of the study, for example if the goal is to determine the best investment strategy to reduce fault probability.

Finally, the component's characteristics may be given indirectly, for example through field measurements that do not directly provide the model parameter values; to take advantage of this implicit input data, a *parameter identification* (or *data matching*, or *data assimilation*) process must be implemented in order to extract the relevant information for the system model.

III. Traditional simplifying approach

To cope with the parameter uncertainty, the structure variability and the implicitness of the input data, several strategies have been used in the past. For some very particular types of studies, specific front-end applications using EMTP-like simulators may have been developed, like LIPS for the evaluation of the lightning performance of overhead-lines [7]. However, the majority of EMT studies do not fall into these types and thus the engineer needs to provide a solution from scratch.

In these situations, some advanced engineering teams may have programmed scripts for the particular study case at stake. These scripts run batch simulations of several sets of parameters (for instance [8][9][10][11]). This, however, has practical drawbacks that we will point out in section IV: it applies only to a particular study case, it is very time consuming, it requires advanced skills in programming and statistics and it is prone to errors.

For these reasons, in the vast majority of cases, the usual engineering approach to uncertainty, variability and implicitness of the input data consists in simplifying the problem in order to go from a partially undefined system to a perfectly defined one that can be simulated in an EMT software program. Thus, the following strategies are the most common in engineering studies:

- Neglecting the inaccuracies, the unknowns and the implicit data; using "typical" characteristics for unknown parameter values.
- Studying the system for a limited number of structure configurations and/or parameter sets thought to be most critical, i. e. the worst-case scenarios.

However, the results obtained with these strategies have significant flaws:

- They neglect implicit input data.
- They do not account for all the potential values of the system structure and/or characteristics, and thus they do not allow for a cost-effective decision.
- Their reliability highly depends on the engineer's assumptions regarding the critical configurations and parameter sets, i. e. the engineer's expertise in the field.

Indeed, traditionally, uncertainty and variability in EMT studies have been either neglected or dealt with by considering only worst-case scenarios. Neglecting uncertainty and variability is surely not a good practice but very often neither is considering only worst-case scenarios. On the one hand, it may be difficult or impossible to know in advance the parameter values and/or the system configurations leading to the worst-case scenarios. In fact, the determination of the worst-case scenarios may be easy when the system response against the parameters and/or the configurations is monotonic (either always increasing or always decreasing), but it is difficult when this is not the case. The latter is the most common situation in EMT studies due to resonances, parameter interactions and non-linear behaviors. Of course, failing to properly identify the real worst-case scenarios and drawing conclusions on what are not the worst-case scenarios can lead to system damage.

On the other hand, even if the parameter values and/or system configurations leading to the worst-case scenarios are correctly identified, the mitigation measures undertaken may not be cost-effective, as they may require expensive investments for highly improbable events that could be handled otherwise. For example, 80% or 0.001% fault probabilities don't have the same practical implications and thus shouldn't lead to the same mitigation measure investments [12].

This paper aims to present a practical approach to these problems which avoids the flaws of traditional methods. Due to lack of space, parameter identification will not be described here, but an example of how the problem can be treated with our approach can be seen in [2]. Another approach to parametric batch simulation can be found in [14].

IV. General Features of a Software Program for Parametric EMT Studies

At least three facts explain why uncertainty, variability and implicitness have been usually neglected or dealt with through worst-case assumptions:

- the limited capabilities of usual computers;
- the lack of skills in probability and statistics of power system engineers;
- the lack of software tools for these problems.

Firstly, as we will see, taking into account uncertainty and variability in EMT studies requires performing a large number of simulations (hundreds, thousands), something that was impossible with the speed of past computers. This, however, is no longer the case, as modern computers perform an EMT simulation in seconds or, in the worst cases, minutes. Moreover, nowadays computers have several cores, thus allowing for simulation parallelization and thus reducing the simulation time by a factor close to 1/N, where N is the number of cores of the computer.

Secondly, performing studies that account for the uncertainty and variability of the system implies using techniques in the field of probability and statistics that are usually not or poorly known by power system engineers. A similar remark can be made for parameter identification.

Thirdly, the usual EMT software programs are not able to deal with variants, uncertainties and implicit data. Indeed, some of them allow for batch simulation thanks to native scripting capabilities or by their ability to be run by an external code (see section III). However, this leaves all the hard work to the engineer, who needs to become familiar with the required statistical techniques and then code them in the suitable programming/scripting language. Moreover, even when the engineer has the skills in both statistics and programming, developing a specific program for the problem at stake is very time-consuming and subject to unnoticed programming errors.

These considerations lead to the conclusion that a practical solution for parametric studies is a software program that must

1. not require any user programming/scripting;
2. not require advanced statistical skills (only basic concepts such as mean and standard deviation);
3. parallelize the simulations (as well as the pre-processing of the input data and the post-processing of the simulation results).

Moreover, whereas the traditional EMT outputs are voltage and current waveforms, accounting for system variability and parameter uncertainties means that the study results will be in the form of samples, i. e. statistical distributions. The software program must therefore

4. provide visualization and analysis tools for both types of results: statistical distributions of the whole simulated population and voltage and current waveforms of individual cases.

A final important aspect must be taken into account. Quite often, when performing a study, the engineer performs some kind of pre-processing of the input data and also some post-processing of the simulation results generated by the EMT software program. Sometimes these pre- or post-processing calculations are quite generic, for example the RMS value or the envelope of a voltage waveform; on other occasions, the user performs specific calculations related to his very particular study case. In parametric studies, the software program will be in charge of this for every single simulation; therefore, the software program must

5. include usual pre-processing and post-processing routines as built-in functions;
6. allow user-defined pre-processing and post-processing.

V. Parameter uncertainty

Performing an EMT study requires building a model for the system under study and to calculate the parameter values of the elements of this model. However, quite often these values are not exactly defined; instead, the parameters can take a range of values or follow probability distributions. This is called *parameter uncertainty*.

Of course, even if many parameters are affected by uncertainties, only those whose variation may have an important influence on the output need to be considered. It is of paramount importance not to miss any of these. Discarding in advance uninfluential parameters is tricky and one may discover that a parameter thought to be uninfluential was in fact very important. In case of doubt, the best practice is not to discard any uncertain parameter and to perform a sensitivity analysis that will evaluate the parameters' importance and rank their relative impact (see section VII).

Two types of parameter uncertainty can be distinguished [17]: The first, *epistemic uncertainty* is due to limited knowledge of the characteristics of the equipment, which can be due to a number of reasons: the input data is provided by the manufacturer as a nominal value with a given tolerance/accuracy, or it has been measured on other equipment with similar design, or it has been calculated with approximate analytical methods, or it may have changed since it was measured, etc. Epistemic uncertainty can be reduced if the knowledge of the system is improved, for instance by performing specific measurements. For example, in transformer energization studies, the transformer air-core inductance is a very important parameter usually known with 20-30% accuracy (due to the assumptions of the analytical formulae); in lightning studies, the tower footing resistance value may have a high impact on the results, but this value is never known precisely. In other cases, the engineer has no data at all for some of the system component characteristics. In these cases, "typical" values may be used, but then a high uncertainty must be accounted for (say 30-300% depending on the case).

The second type, *aleatory uncertainty* is due to the intrinsic randomness of the physical phenomenon at stake. For example, in fault studies, the voltage angle at the fault inception is an important parameter that can take any value (θ=0-360°). In switching studies (capacitor, lines, cables…), the circuit-breaker (CB) closing angle over the power-frequency period and the pole closing span ($t_A \neq t_B \neq t_C$) are very important factors, but their values change randomly at each CB operation. In transformer energization studies, the CB closing times are key factors, and so is the transformer residual flux, which changes at each energization as well [15][16]. In lightning studies, the strike current amplitude and waveform parameters vary randomly as well [18][19].

As we have previously seen, when the model parameters are affected by some uncertainty, a traditional strategy is to study the worst-case scenarios. However, we have seen that this strategy may lead to equipment damage or decisions that are not cost-effective. The rigorous way to deal with parameter uncertainty is to perform a probabilistic study, i. e. to adopt *a risk-based approach*. The output of such a study are the statistical distributions of the variables of interest and, if a particular event is at stake, the probability (or risk) of occurrence of this event, for example a fault, equipment damage or system collapse.

For this, we must first model the parameter uncertainties with suitable probability distributions, and then apply an uncertainty propagation algorithm to the EMT model to compute the output probability distributions [17].

A. Parameter uncertainty modelling

The uncertainty of each uncertain parameter must be quantified and modeled by a probability distribution. For many parameters, a continuous uniform distribution will be considered as there is no reason to favor one or another value in the uncertainty range, i. e., all the possible values are equally probable (a triangular distribution could also be used if the central value is considered the most probable). This distribution is defined by its minimum and maximum values [a,b]. In the previous examples, this distribution could model the tower footing resistance, the fault inception angle, the CB closing angle, the transformer residual flux and air-core inductance. Other uncertain parameters follow special probability distributions linked to the physical phenomenon they model; for these, the field literature provides the characteristic values of the probability distributions: for example, CB pole closing span follows a Gaussian distribution [15][16], whereas lightning strike current amplitude and waveform parameters follow log-normal distributions [18][19].

B. Uncertainty propagation

Uncertainty propagation techniques provide a way to compute the output signals probability distributions given the probability distributions of the parameters. The best known and robust technique is the Monte Carlo method [20][21], which is the one implemented in our software tool. Other techniques exist that may allow for a higher convergence speed, but they are limited to a small number of parameters and they often provide less statistical error control. Some of them have been compared for transformer energization studies in [16]. Whichever the propagation technique, the output signals probability distributions are computed by sampling the uncertainty space defined by the uncertain parameters, performing the EMT simulations for these parameter sets, and computing the corresponding outputs signals (that may require the post-processing of the simulation results we have talked about before).

The output of the propagation process are the cumulative distribution functions (CDF) of the output signals. For example, if the output signal is a voltage at the terminals of a transformer, the algorithm will provide the probability of exceeding any voltage value. An example is shown in Fig. 3a for the voltage drop at a transformer energization.

However, the output signals probability distributions are only estimates, whose reliability increases with the number of simulations performed. As a consequence, an indication must be provided to the user about the reliability of the results so they can decide on the number of simulations to be performed. In our software implementation, this is done by providing convergence graphs and confidence intervals, which are powerful and reliable indicators [21]. An example is shown in Fig. 2 for the probability of exceeding 5% RMS voltage drop at a transformer energization; this figure shows that after 8000 simulations, the probability is estimated at about 12% with a 1% confidence interval width.

VI. System variability

System variability refers to the fact that the system under scrutiny does not have a unique structure, and neither does the system model. The multiplicity of model structures that need to be considered may be due to contingencies like line or generator outages, which imply keeping/removing the corresponding elements in the model; but also to lighting strikes or ground faults, which imply connecting the lightning current source or the fault model to different points of the system model. But contingencies are not the only situation where one needs to consider several model structures: very often, the system under study can operate in several configurations, for example a substation, and the study (for example, a TRV study) needs to consider all of them. Finally, a very particular case of structure multiplicity is that of model comparison: in this case, the user wants to compare several component models (for example the CIGRE, Heidler, and biramp lightning current models).

In practice, system variability is modelled in several ways: different network configurations are due to the state of the switches that model the circuit-breakers, which can be open or closed; outages are also modelled by switches that connect or disconnect the lines or generators; ground faults are modelled by a switch that connects a node of the model to the ground, the potential fault nodes being defined by a list; the same applies to lightning strike locations, which are modelled by a current source connected to one of the nodes of a list defining the potential impact points; finally, alternate models are introduced by connecting one of them to the appropriate node.

In all these cases, the variability is modelled by an element that takes a value out of a list of potential values: {open, closed} for switches, {node$_1$, node$_2$, … node$_N$} for faults and lightning strikes, {model$_1$, model $_2$, … model $_N$} for alternate models. Each of these sets of potential values can be treated as a parameter defined by a discrete uniform distribution. Then, if each parameter has n_k potential values, the total number of possible model structures is $\Pi n_k = n_1 \cdot n_2 \cdot n_3 \cdot ...$

System variations can therefore be studied exhaustively, in other words, it is possible to simulate all the potential system variations if the total number of required simulations, Πn_k, is computationally affordable.

However, sometimes this is not the case and Πn_k is too high. In this case, an uncertainty propagation technique must be used to estimate the output of interest, for example the system reliability.

VII. Sensitivity analysis

In a sensitivity analysis study, the goal is to determine the relative influence of the uncertain parameters on the output signals or on the probability of the event at stake (on the risk). Sensitivity analysis allows for better understanding of the behaviour of the system under study; but most importantly, if this behaviour is unsuitable (faults, equipment damage…), sensitivity analysis gives indications for action, as it shows where (if possible) we should intervene to change this behaviour. This action might be modifying the system configuration or changing the equipment, but it may also be to perform field measurements in order to reduce epistemic uncertainties and thus better estimate the probability of the event at stake [12].

Action should target the system elements associated with the parameters that influence the most the output, and avoid wasting time with those associated with the parameters that have little influence. Several sensitivity analysis techniques exist to identify these target parameters [22][23][16]. Some techniques provide numerical indices that estimate the influence of each parameter (and sometimes its interactions); other techniques show the impact of the parameters and their interactions in a graphical way. Our software implementation includes the Morris and Sobol sensitivity indices (numerical), and the scatter and cobweb plots (graphical). An example is given in section VIII.

VIII. Example case

In this section we will present an example of parametric study performed with our software implementation of the previous techniques. Due to lack of space, only parameter uncertainty and sensitivity analysis will be considered.

The system under study is represented in Fig. 1. It consists in the energization of the 250 MVA YNd11 150/33 kV transformer of an offshore wind farm connected to the 150 kV grid though a 35 km long submarine AC cable. The events under scrutiny are the RMS voltage drop at the point of common coupling and the resonant temporary overvoltages (TOV) at the transformer terminals. As an illustration, we will assume that the grid operator is concerned by a voltage drop higher than 5% (grid power quality), and that the wind farm operator is concerned by temporary overvoltages higher than 1.3 per unit (transformer insulation damage). The goal of the study is to determine the maximum potential values of the RMS voltage drop and the TOV, as well as the probability of exceeding the preceding threshold limits (5% and 1.3 pu).

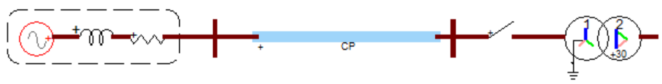

Fig. 1: Study System

The supply grid is modelled by a Thevenin equivalent circuit. As only the per unit length cable sequence parameters are available, the Bergeron model is used. The transformer is modelled with idTRAN [6].

A number of parameter uncertainties will be considered. According to the grid operator, the short-circuit power of the supply grid may vary between 4 and 8 GVA. The cable parameters have been obtained by computer simulation; we will consider an accuracy of 5% for the positive sequence parameters and 30% for the negative sequence parameters; the higher value for the latter is due to the fact that they are much more difficult to estimate by simulation. The circuit-breaker poles may close any time over the 50 Hz power-frequency period and there is a small pole span among the three closing times; this pole span will be modelled by a Gaussian dispersion as suggested in [15]. As for the transformer, its air-core inductance value has been obtained by simplified formulae and thus we will consider a 30% accuracy. Moreover, as the transformer capacitances to ground are not known, we will consider they are in the range of 1 and 3 nF [24]. Finally, the transformer residual fluxes may vary between zero and 80% of the rated flux, with the phase pattern suggested in [15] depending on the de-energization angle. Altogether, there are 14 uncertain parameters. According to section V.A, these parameter uncertainties are modelled in PAMSUITE as shown in Table 1.

In order to compare the deterministic worst-case scenario strategy to the probabilistic strategy, we have considered six potential a priori worst-cases that an experienced engineer could think of [15]: the lowest air-core inductance; the maximum residual flux; the CB closing simultaneously at zero (cases "A") or maximum voltage (cases "B") of phase A with the same sign as the residual flux; the R and L of the cable at their mean (cases "1"), max (cases "2") or min ("cases "3") value.

Table 2 shows the results obtained for the potential a priori worst cases and the results provided by PAMSUITE for a Monte Carlo run of 8000 simulations.

Compared to the results provided by PAMSUITE, all the potential worst-case scenarios underestimate the three outputs of interest: the maximum inrush current, the RMS voltage drop, and the TOV.

Table 1: Parameter uncertainty models for the example case
("U" stands for uniform distribution, "N" for Gaussian distribution)

Supply network	Circuit breaker
S_{sh} ~ U[4,8] GVA	t_A ~ U[100,120] ms
	Δt_B ~ N(0,5) ms
Cable	Δt_C ~ N(0,5) ms
$\Delta_{cable\ R1}$ ~ U[-5,5]%	
$\Delta_{cable\ R0}$ ~ U[-30,30]%	Transformer
$\Delta_{cable\ L1}$ ~ U[-5,5]%	$\Delta L_{air\text{-}core}$ ~ U[-30,30]%
$\Delta_{cable\ L0}$ ~ U[-30,30]%	C ~ U[1,3] nF
$\Delta_{cable\ C1}$ ~ U[-5,5]%	$\lambda_0 = \lambda_r \cdot$ U[0,80] %
$\Delta_{cable\ C0}$ ~ U[-30,30]%	θ_d = U[0,2π]

With the following dependent parameter definitions:
$t_B = t_A + \Delta t_B$; $t_C = t_A + \Delta t_C$; $\lambda_k = \lambda_0 \cdot \cos(\theta_d + (k-1) \cdot 2\pi/3)$, k={A,B,C}
$RLC_{cable} = RLC_{cable,rated} + \Delta RLC_{cable}$, RLC_{cable}={R_1,R_0,L_1,L_0,C_1,C_0}

Table 2: Worst case results

	Potential "a priori" worst cases						PAM-SUITE worst case
	CB close at zero V			CB close at max V			
	A1	A2	A3	B1	B2	B3	
Current max (kA)	5.6	5.5	**5.6**	4.1	3.9	4.0	**6.2**
RMS drop max (%)	9.9	9.4	**10.4**	8.4	8.1	8.7	**11.5**
TOV max (pu)	1.41	1.34	**1.43**	1.32	1.32	1.42	**1.49**

However, for the supply grid and the offshore plant operators, the most important figure is not the maximum voltage drop or TOV, but the probability of exceeding the threshold limits. These figures are provided by the software implementation: the probability of exceeding a 5% RMS voltage drop is about 11.5%; the probability of exceeding 1.3 pu TOV is about 1.9%. As an illustration, for the RMS voltage drop, Fig. 3a shows the cumulative distribution function and Fig. 2 the convergence graph for the probability of exceeding 5%, the confidence interval of the estimated probability becoming narrower as the simulation process goes on.

As for the sensitivity analysis, Fig. 3b shows the computed Sobol sensitivity indices for the probability of exceeding the TOV limit. Among the epistemic parameters, this figure shows that several of the cable parameters and the transformer capacitance do not have any significant impact, therefore time should not be wasted trying to gather better knowledge of them. On the contrary, the transformer air-core inductance, the short-circuit power of the network and the capacitive cable parameters are very influential; therefore, their accuracy could be improved to get more accurate results (the other influential parameters are aleatory, thus nothing can be done).

Note that this probabilistic study has been done with little extra time: setting up the case in PAMSUITE took 20 minutes and the results figures shown here are directly copy-pasted from the software interface. The simulation process to run the 8000 simulations (automatic, no intervention of the user) took 1.5 hours using 10 cores in parallel in a computer with an Intel Xeon E5-2630 12-core 2.60 GHz processor (400 ms simulated time with 20 ms time step).

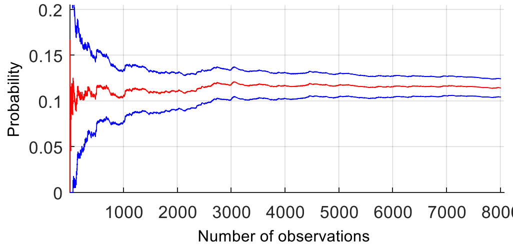

Fig. 2: RMS voltage drop probability of exceeding 5%, depending on the number of simulations, with a confidence interval

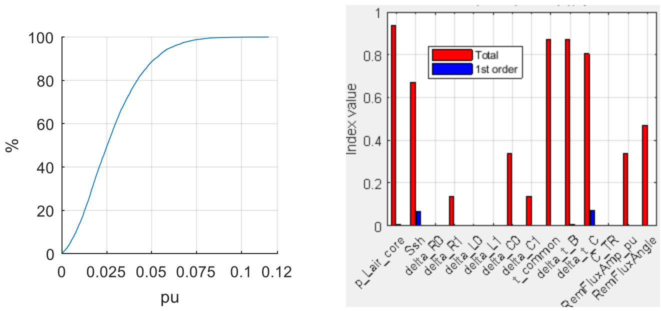

Fig. 3: (a) RMS voltage drop CDF;
(b) Sobol sensitivity indices for exceeding the TOV limit

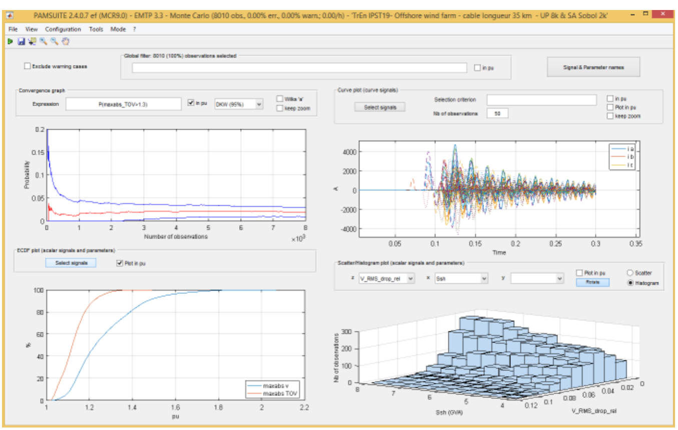

Fig. 4: PAMSUITE Simulation & Analysis user interface

IX. Conclusions

The advantages of using parametric simulation in EMT studies, in particular of probabilistic simulation, have been shown. This approach allows to take into account the relative quality of the input data and to consider all the potential configurations of the system under study. The traditional approach consisting in the simulation of several scenarios thought to be the worst cases and discarding uncertainties and implicit data should be avoided, as nowadays computers allow for the use of advanced simulation techniques that provide rigorous, reliable and much richer results. In addition, they are less dependent on the experience and expertise of the engineer in charge of the study. For this, new software tools need to be developed that provide the means to apply the parametric approach easily and quickly; “going parametric” shouldn’t take more than 30 minutes additional time.

X. References

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