Stochastic Assessment of Voltage Dips Caused by Transformer Energization

J. S. Peng, H.Y. Li, Z.D. Wang, F. Ghassemi, and P. Jarman

Abstract—Energization of large power transformers may cause significant voltage dips, of which the severity largely depends on a number of parameters, including circuit breaker closing time, transformer core residual flux and core saturation characteristic, and network conditions. Since most of the parameters are of stochastic nature, Monte Carlo simulation is conducted in this paper to stochastically assess the voltage dips caused by transformer energization in a 400 kV grid, using a network model developed and validated against field measurements. A dip frequency pattern was identified and it was found to be sensitive to residual flux distribution but insensitive to closing offset time distribution. Out of 1000 stochastic runs, the probability of reaching the worst case dip magnitude (estimated under the commonly agreed worst energization condition) was found to be lower than 0.5%; about 80% of the dips are likely to be with magnitudes lower than 0.6 pu of the worst case. Nevertheless, there are dips with magnitudes exceeding the worst case dip magnitude, indicating the inadequacy of deterministic assessment approach by using the commonly agreed worst energization condition.

Index Terms—Electromagnetic Transient Program (EMTP), transformer energization, voltage dips, stochastic estimation

I. INTRODUCTION

Transformer energization may result in significant inrush current causing adverse impacts on transformer itself (loss-of-life, mechanical damage to transformer winding) and power system operation (reduced power quality, false operation of protection devices and temporary overvoltages) [1-3]. Severity of these impacts is determined by several key parameters which can be classified as external and internal for the transformer: external parameters include the circuit breaker closing time, strength of the supply source; and internal parameters include residual flux and saturation characteristics of the transformer core [4].

The power quality issue affected by transformer energization manifests itself mainly in the form of voltage dip (sag) which is defined in IEC 61000-4-30 as “a temporary reduction of the voltage magnitude at a point in the electrical system below a threshold”. Voltage dips caused by transformer energization can be especially severe in those systems where the network impedance between the source and the energized transformer is high [5], and they are characterized by being non-rectangular, long duration of recovery and non-symmetrical (each phase has a dip magnitude different from others due to different degrees of saturation) [6]. Tripping of equipment and trigger of low voltage alarms caused by such kind of voltage dips were reported in [7] and [8], respectively.

Aided by Electromagnetic Transients Program (EMTP), simulations have been conducted to assess the potential voltage dips caused by transformer energization in various networks. In [9], voltage dips caused by energizing a 315 MVA generator step-up (GSU) transformer in the 138 kV BC Hydro system was studied; voltage dips resulted from energization of a 124 MVA transformer in the 154 kV Korea power system was investigated in [10]; voltage dips caused by energizing a 500 MVA transformers in a 132 kV network was addressed in [11]. In addition, voltage dips caused by energization of medium-voltage wind turbine transformers were studied in [12-16] to check grid code compliance. All of these studies utilized the commonly agreed worst energization condition, i.e. energizing a transformer at the voltage zero crossing of one phase and its corresponding residual flux set to be with maximum magnitude and polarity in line with flux build-up, to predict the maximum possible voltage dip magnitude.

However, since the circuit breaker closing time, transformer core residual flux as well as system conditions are normally of stochastic nature, the assessments performed using the deterministic approach as mentioned above could underestimate the outcome or at least unable to give the probability distribution of the occurrence of inrush transients, therefore, cannot assist the realistic estimation of their adverse impacts on the system. Hence, recently, a number of studies were devoted to study the impacts of parameter uncertainties on the calculation of transformer energization transients [17-19].

In this paper, voltage dips caused by energizing a large GSU transformer in a 400 kV grid is stochastically evaluated. A network model of the grid is developed in ATP/EMTP and validated against field measurement results. Monte Carlo simulation is conducted to stochastically assess the frequency of occurrence of different voltage dip magnitudes; in addition, the influences of the probability distributions of the stochastic parameters on the estimation of dip frequency are also analyzed and compared.

II. SYSTEM UNDER STUDY

As shown in Fig. 1, the system under study is the same as the one presented in [8], which consists of 11 substations linked by 400 kV double circuit transmission lines with lengths ranging from 21 to 97.54 km. Some of the substations are
connected with reactive power support devices. A power plant is located near substation K. Through power feeder 1, GSU transformers T2 (345 MVA, 400/19 kV, YNd1) and T3 (415 MVA, 400/21 kV, YNd1) are connected to the busbar of substation K via CB2; through power feeder 2, GSU transformer T1 (345 MVA, 400/19 kV, YNd1) is connected via CB3. In order to start the power plant, the auxiliary plant needs to obtain power supply from the main grid and therefore requires energization of the GSU transformers before connecting the generators.

![Fig. 1 Schematic diagram of the system under study](image)

### III. NETWORK MODELING AND VALIDATION

The network model developed and validated in [8] was used as the basis for the stochastic simulation. The modeling of the system is briefly described as follows: system equivalent sources were represented by ideal voltage source connected in series with Thevenin equivalent impedances; transmission line was represented by Bergeron model; all the loads and shunt devices, such as capacitor banks, were modeled by constant impedances and they were directly connected to the 400 kV busbars; transformers modeling mainly considered winding resistances, leakage inductances and transformer core saturation characteristics, and this was realized by the use of an admittance matrix based model (BCTRAN) with delta-formed hysteretic inductors (type-96) externally connected to the low-voltage winding terminal of the BCTRN model.

To validate the accuracy of the developed network model, various simulation scenarios have been conducted against field measurements [8], here an example is shown which involves simultaneous energization of T2 and T3 while T1 was disconnected. Closing time were interpreted from the voltage waveforms observed at power feeder 1: phase C was energized first at 5 ms behind the negative-going zero crossing of phase C line-to-ground voltage; relative to the energization instant of phase C, the other two phases were energized both with a delay of 1.1 ms. Residual fluxes in both T2 and T3 were initialized to -0.385 pu, 0.55 pu and -0.165 pu of the peak nominal flux for phase A, B and C, respectively.

The simulated currents and voltages on power feeder 1, currents at the feeder I-K and the RMS voltage variation at substation I are plotted against field measured waveforms in Fig. 2, Fig. 3, Fig. 4 and Fig. 5, respectively. As can be seen, the simulated and the measured waveforms match each other well.

![Fig. 2 Voltage variation on power feeder 1 (simulation versus measurement)](image)

![Fig. 3 Current variation on power feeder 1 (simulation versus measurement)](image)

![Fig. 4 Current variation on power feeder K-I (simulation versus measurement)](image)

![Fig. 5 RMS voltage variation on substation I (simulation versus measurement)](image)

### IV. STOCHASTIC SIMULATION METHOD

Monte Carlo method is employed for the stochastic simulation. The method is a procedure of iteratively performing stochastic sampling experiments with a system model [19]. In each experiment, the values of the stochastic variables consisted in the system model are re-sampled from their corresponding distribution functions, based on which, a simulation is conducted to estimate the system performance. Through performing a large number of statistical sampling experiments, the response of a system to the stochastic variables can be approximately obtained. The more experiments being performed, the more accurate the approximation can be achieved towards the real performance of the system.
Monte Carlo simulation requires a large number of simulations where the only difference between each case is a stochastic variation of a few random parameters. Manually carrying out such a simulation (editing and running the ATP program) requires tremendous efforts and may easily cause mistakes. It is therefore preferable to automate such a simulation process. An ATP-MATLAB simulation platform was specifically established for automating the Monte-Carlo simulation. It coordinates the advantages of both packages: ATP executes the transient simulation; MATLAB is used to generate and modify the values of the stochastic variables as the inputs for simulation, control Monte Carlo simulation and process the simulation results. It allows arbitrary number of simulation runs to be carried out.

V. DETERMINE STOCHASTIC PARAMETERS

In this section, the potential stochastic parameters and their generating process are discussed.

A. Stochastic Parameters

In general, when the closure of a circuit breaker is uncontrollable, the signal to initiate breaker closing is stochastic with respect to the ac voltage wave; in addition, the breaker three phase poles do not close simultaneously, but with some closing time scatters which may vary with time and maintenance [20]. Hence, the circuit breaker closing time is featured by the stochastic signalling time to order the closure of three poles and the stochastic closing time span between the three poles.

Transformer residual flux is largely influenced by the ring down process initiated by transformer de-energization [21]. Resulted from this process, the residual flux in the transformer core can be influenced by a number of factors including de-energization instants, circuit breaker arc chopping characteristics, transformer core material, winding capacitances and other system capacitance connected to the transformer [2]. The uncertain properties of transformer residual flux however can be categorized by two folds: one is the magnitudes of residual flux in three phases and the other one is their distribution among three phases. Up to date, knowledge about these two aspects include: the magnitude of residual flux can be as high as 85% of the peak nominal flux; the sum of three phase residual fluxes of a three phase transformer must equal to zero [2, 21].

Furthermore, the amount of loads connected to the system could have daily and seasonal variations. Similarly, the source strength may vary with system configurations and generation connections. Therefore, both of these two parameters are of stochastic feature to certain extent.

B. Quantification of Stochastic Parameters

For the above-mentioned stochastic parameters, each can be quantified by a range defined by minus or plus certain percentages of a nominal value; in addition, the range can be described by a probability distribution using Uniform, Gaussian, Exponential or any other distribution function. Utilizing the approach suggested in [19], modeling of the stochastic closing time follows the procedure shown in Fig. 5. First, a common order time T_cot, which is the same for three poles of the circuit breaker, is defined by a range and a probability distribution; normally, the common closing time range is of one power frequency cycle and is characterized by Uniform distribution. Second, the maximum closing time span (MCTS), i.e. the time interval between the first pole and the last pole to close, is defined; the MCTS is used in the third step to define the range of the offset time for each pole T_offset_i (i represents phase A, B or C); the range is assumed to be from –MCTS/2 to +MCTS/2, referencing the T_cot; in addition, a probability distribution is assigned to define the offset time range. Finally, the closing time of each pole is determined by the summation of T_cot and T_offset_i which are stochastically generated based on their corresponding ranges and distributions.

For generating three-phase residual fluxes, it is commonly assumed that: the residual flux of each phase is in a range whose absolute maximum value is no more than the peak nominal flux; the three-phase residual fluxes should sum to zero. With these assumptions, the three-phase residual fluxes are generated through the procedure shown in Fig. 6. As can be seen, the first step is to define the maximum residual flux Resi_max (normally in terms of the percentage of the peak nominal flux) to determine the residual flux range (i.e. from – Resi_max to +Resi_max); in the second step, a probability distribution is assigned to characterize the residual flux range; in the third step, based on the range and probability distribution, two residual flux values Resi_1 and Resi_2 are randomly generated; then, a check loop is called upon to verify whether the absolute value of the sum of Resi_1 and Resi_2 is smaller than Resi_max; if not, go back to the second step; if yes, proceed to the fourth step to calculate Resi_3; finally, Resi_1, Resi_2 and Resi_3 are randomly assigned to phase A, B and C, respectively.

Both procedures were programmed in MATLAB to generate the stochastic circuit breaker closing time and transformer core residual flux as the inputs for ATP to carry out transient calculations.

![Fig. 5 Procedure for generating stochastic circuit breaker closing time](image)
The stochastic assessment contains a number of case studies which are shown in Table I.

<table>
<thead>
<tr>
<th>Case</th>
<th>Closing offset time (ms)</th>
<th>Residual flux Distribution</th>
<th>Energized Transformer / Network condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>±2.5</td>
<td>Gaussian</td>
<td>Only T1 is energized</td>
</tr>
<tr>
<td>S2</td>
<td>0</td>
<td>Exponential</td>
<td>Network condition is fixed</td>
</tr>
<tr>
<td>S3</td>
<td>±5</td>
<td>Exponential1</td>
<td></td>
</tr>
<tr>
<td>S4</td>
<td></td>
<td>Exponential2</td>
<td></td>
</tr>
<tr>
<td>S5</td>
<td></td>
<td>Gaussian</td>
<td></td>
</tr>
<tr>
<td>S6</td>
<td>±2.5</td>
<td>Uniform</td>
<td></td>
</tr>
<tr>
<td>S7</td>
<td></td>
<td></td>
<td>T2 &amp; T3 are energized Fixed network condition</td>
</tr>
<tr>
<td>S8</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S9</td>
<td>±2.5</td>
<td>Gaussian</td>
<td></td>
</tr>
<tr>
<td>S10</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S11</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

A base case for the stochastic estimation, named as Case S1, is calculated to identify the general dip frequency pattern; it considers energizing only one GSU transformer (T1) with the closing time and residual flux treated as random parameters and system condition (e.g., system loading and source strength) fixed.

Influence of closing time span on the general dip frequency pattern is studied in Case S2, S3, S4 and S5; specifically, Case S2 and S3 consider the influence of the magnitude of MCTS, Case S4 and S5 study the influence of the offset time distribution. Influence of residual flux distribution on the general dip frequency pattern is studied in Case S6, S7 and S8. Furthermore, influence of the variation of system condition including substation loading and source strength is considered in Case S9. In Case S10 and S11, the dip frequency patterns result from simultaneously energizing two transformers are assessed and compared with that obtained in the base case.

For all the case studies, the range of the common order time is one cycle defined by Uniform distribution and the range of residual flux is between -0.8 pu and +0.8 pu of the nominal peak flux. Results obtained from each case study were processed by MATLAB using histogram to show the dip frequency.

VII. RESULTS AND ANALYSIS

In the results analysis, the dip magnitude (9.6%, named here as WDM1) observed at substation I (shown in Fig. 1) in the case of energizing T1 under the commonly agreed worst energization condition is selected as the base value to be referred to by all the dip magnitudes obtained from Case S1 to S9. Similarly, the dip magnitude (18.4%, named here as WDM2) observed at substation I in the case of energizing T2 and T3 under the commonly agreed worst energization condition is used as the base value for scaling all the dip magnitudes obtained from Case S10 to S11.

A. General Dip Frequency Pattern

In Case S1, the offset time of each pole was considered to follow a Gaussian distribution whose mean is zero (i.e., three poles tend to be closed simultaneously) and whose standard deviation is MCTS/6 (the MCTS was assumed to be 5 ms). As for the residual flux, it was assumed to be characterized by a Uniform distribution. After carrying out 1000 stochastic simulation runs, the frequency of voltage dips in three phases at substation I was obtained and it is shown in Fig. 7. As can be seen, the dip frequency pattern of each phase are almost identical to each other, indicating that the dip frequency pattern observed on one of the phases can represent those observed on the other two phases. Therefore, analysis of the simulation results can be focused on one phase and the phase chosen here is phase C.

By observing the dip frequency of phase C at substation I, it can be seen: over 80% of dips are with magnitudes less than 0.6 pu of WDM1; no more than 6% dips are with magnitudes larger than 0.8 pu of WDM1; only about 0.2% of voltage dips are with magnitudes larger than the WDM1 and their magnitudes are about 1.1 pu of WDM1. This larger dip magnitude suggests that calculation based on the commonly agreed worst energization condition (which assumes zero closing offset time) may underestimate the worst dip magnitude by 0.1 pu.

The dip frequency with such pattern can be attributed to the fact that, for any value of residual flux which would significantly increase the voltage dip severity, there exists a counteracting switching time that results in minimum inrush current, in another word the probability is rather small for the combination of closing time to be right at the voltage zero crossing and the residual fluxes to be large and with polarities...
in the same direction of the flux build-up.

Furthermore, to test whether 1000 runs is sufficient, dip frequency pattern out of 5000 runs of Case S1 were obtained and plotted in Fig. 8. Comparing with the dip frequency pattern obtained from 1000 runs, the differences between them are very small, indicating that it is sufficient to make the subsequent studies based on 1000 runs.

![Fig. 7 Frequency of dip magnitude of each phase at substation I out of 1000 stochastic runs](image)

**B. Influence of Closing Time Span Range**

The magnitude of MCTS may vary between circuit breakers. This variation may affect the outcome of the dip frequency pattern identified in the base case. To address this concern, two case studies were conducted: one with zero closing time span (Case S2) and the other one with 10 ms MCTS (Case S3). For both cases, the distributions of closing time span and residual flux are the same as those used in the Case S1. Similar to Case S1, 1000 runs were made for Case S2 and Case S3 to predict the dip frequency patterns of phase C at substation I; these two patterns are compared with that obtained from Case S1 in Fig. 9. As can be seen, there is not much difference between one another. This indicates that the dip frequency pattern is not sensitive to the variation of the magnitude of MCTS.

**C. Influence of Closing Offset Time Distribution**

Closing offset time with Gaussian distribution should be common because circuit breaker poles tend to be closed simultaneously [19]. However, circuit breakers can be of different characteristics due to different operating mechanism, frequency of maintenance and level of wearing. Therefore, closing offset time might be characterized by other distributions. Here, two more closing offset time distributions, Uniform and Exponential, were considered in Case S4 and S5 to study the influence of closing offset time distribution on the dip frequency pattern. Both distributions were established within a range of ±2.5 ms. Compared to Gaussian distribution in Case S1, the samples of large offset time are greatly increased in Case S4 and S5, particularly in the case of Exponential distribution which was designed to make more closing offset time samples concentrated on the ends of the range. In Fig. 10, the dip frequency patterns of phase C at substation I estimated based on Uniform and Exponential offset time distribution are compared with that obtained in Case S1. As can be seen, the dip frequency patterns are very similar to one another; this indicates that the dip frequency pattern is not sensitive to the distribution of closing offset time.

![Fig. 9 Frequency of dip magnitude of each phase at substation I under different closing time span magnitude](image)

**D. Influence of Residual Flux Distribution**

Up to date, little knowledge is known about the residual flux distribution in the transformer core. This uncertainty makes it necessary to study the influence of residual flux distribution on the dip frequency pattern. Stochastic estimation of voltage dip frequency was conducted based on other residual flux distributions including Gaussian (Case S6) and Exponential (Case S7 and Case S8). The Exponential distribution is of two types: the Exponential_1 was designed to make more residual flux samples concentrate on the maximum ends of the range; the Exponential_2 was designed to make more residual flux samples concentrate near zero.

In Fig. 11, the dip frequency patterns observed on phase C at substation I were generated under the above three residual flux distributions, which were compared with that obtained.
under the base case. As can be seen, the dip frequency pattern resulted from Gaussian residual flux distribution is relatively the same with that given by Case S1; in the case of Exponential, the frequency of dips with magnitudes less than 0.6 pu of WDM1 is increased to about 90%, whilst the frequency of dips with magnitudes larger than 0.8 pu of WDM1 is reduced to less than 2%; residual flux with Exponential_2 distribution increases the frequency of dips between 0.8 and 1 pu of WDM1 from 5% to 11%, but it does not result in substantial increase of the dips with magnitudes exceeding 1 pu of WDM1. These findings suggest that the dip frequency pattern is sensitive to the distribution of residual flux. For transformers prone to retain residual flux of high magnitudes, the frequency of dips with magnitude close to that of the worst case voltage dip is higher.

**E. Influence of System Condition Variation**

In the real system, the source strength and system loading might also vary in a certain range. The influence of this variation on the dip frequency pattern was studied in Case S9. As shown in Table II, the variation of source strength is modeled by ±25% variation of the base case fault level; the source impedance angle varies between 75° and 85°; the variation of system loading is modeled by ±25% variation of half nominal loading and with its power factor varies between 0.9 and 0.999 (inductive). All of the variations were assumed to follow Uniform distribution. The variation of residual flux and closing time were set to be the same as that in Case S1.

In Fig. 12, the dip frequency pattern observed on phase C at substation I was calculated and compared with that of Case S1. As can be seen, the two patterns are very similar to each other. This indicates that, the dip frequency pattern estimated by Case S1 is not sensitive to the ±25% variation of system condition.

**F. Influence of aggregated energization**

In previous case studies, the energization only involves one transformer. In certain circumstances, aggregation of several transformers being energized at the same time can occur. Therefore, the dip frequency pattern resulted from such aggregated energization was further analyzed by regarding the simultaneous energization of GSU transformers T2 and T3 in the network under studied, which involves two cases: one is Case S10 in which the residual fluxes of both transformers were assumed to be the same; the other one is Case S11 in which the residual fluxes of both transformers are independent. Note that, for both cases, the modeling of the closing time and residual flux is the same as in Case S1 in terms of their ranges and distributions. The dip frequency patterns for both cases were obtained by carrying out 1000 runs. The dip frequency pattern of phase C at substation I obtained from Case S10 simulation is compared with that of Case S1 in Fig. 13. In Fig. 14, similar comparison between Case S11 and Case S1 is given. It can be seen that: if the transformers being energized simultaneously are of the same residual flux, the dip frequency pattern is identical to that observed in the case of energizing one transformer only; if the transformers are of stochastically assigned residual fluxes independent from each other, the frequency of dips with magnitudes between 0.2 and 0.6 pu of worst case dip magnitude is increased, whilst the frequency of dips with other magnitudes decreased, which indicates that the likelihood of reaching the worst case dip magnitude is reduced.

**TABLE II**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Range</th>
<th>Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Source strength</td>
<td>±25% of the original fault level</td>
<td>Uniform</td>
</tr>
<tr>
<td>Impedance angle</td>
<td>75°-85°</td>
<td>Uniform</td>
</tr>
<tr>
<td>System loading</td>
<td>±25% of half nominal loading</td>
<td>Uniform</td>
</tr>
<tr>
<td>Load power factor</td>
<td>0.9-0.999 inductive</td>
<td>Uniform</td>
</tr>
</tbody>
</table>

![Fig. 11 Frequency of voltage dips in phase C at substation I under different residual flux distributions](image)

![Fig. 12 Frequency of dip magnitude of each phase at substation I under variation of system condition](image)

![Fig. 13 Frequency of voltage dips in phase C at substation I of Case S10 contrasting with that of Case 1](image)
National Grid for the financial and technical support. The Manchester Fund Research Impact Scholarship of The

Fig. 14 Frequency of voltage dips in phase C at substation I of Case S11 contrasting with that of Case 1

VIII. CONCLUSION

In this paper, Monte Carlo simulation has been conducted to stochastically assess the voltage dips caused by transformer energization in a 400 kV grid, using a network model developed and validated against field measurements. The simulation was automated by an ATP-MATLAB interface which uses ATP to handle transient calculation and MATLAB to generate simulation inputs, control Monte Carlo runs and process results.

A dip frequency pattern was produced over 1000 stochastic runs and it was found to be sensitive to the distribution of residual flux but insensitive to the distribution of closing offset time. This suggests that it is important to model the residual flux distribution in transformer core while closing offset time distribution can be of less concern. In addition, it was shown that the dip frequency pattern is insensitive to the system condition when varying in a range of ±25% of the base case condition.

Usually it is believed that the worst voltage dip magnitude can be deterministically estimated by energizing a transformer under the commonly agreed worst energization condition. The stochastic studies conducted in this paper however show that the probability of reaching such a dip magnitude is lower than 0.5%, indicating that the worst case scenario is unlikely to occur in a system. In fact, about 80% of the dips are likely to be with magnitudes lower than 0.6 pu of the worst case. Nevertheless, there are dips with magnitudes exceeding the worst case dip magnitude, indicating the inadequacy of deterministic assessment approach by using the commonly agreed worst energization condition.

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X. REFERENCES


