Detection Event Inception Point Algorithms Based on Instantaneous Point-on-wave Measurements

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***Abstract* – Nowadays, the algorithms of the windowed digital signal processing are widely used for the development and introduction of the phasor measurement units. The specific feature of these algorithms is the presence of spikes at the beginning of the transient process due to the inclusion of both steady-state and transient processes into a window span. As a result, the error of the electric mode parameters acquisition during the data accumulation period rises. This effect can be mitigated by shifting the window to points after the beginning of the transient process. In this paper, we present an effective algorithm for real-time determination of the inception point of the transient process. The algorithm was tested on model-generated and real signal samples. The criterion is suggested for precision enhancement of the algorithm by utilizing beginning points of transient processes of phased and linear voltages and phased currents. The error of prediction for the real samples testing does not exceed 0.001 seconds.**

Keywords* – *point-on-wave, point of inception, power system disturbances

I. Introduction

The progress in the area of phasor measurement units (PMU) has led to the introduction of methods for electric mode determination based on the theory of digital signal processing and to standards specifying requirements for those devices. Methods of electric mode parameters determination are widely based on discrete Fourier transform, Proni method, Kalman filtering, Hilbert transformation. The specific feature of window-based methods is the considerable increase of parameter determination error at the inception point of the transient process due to the presence of both steady-state and transient signals in the window span. The example of the spike on the frequency series obtained with the sliding window method is shown in Fig. 1; the spike duration corresponds to the window span.

The occurrence of such spikes can falsely trigger the system's relay protection, emergency mode, or cause the wrong switch of operating mode. This effect can be mitigated by shifting the window of parameter calculation algorithm to points following the point of the spike, i.e. to points after the inception point.

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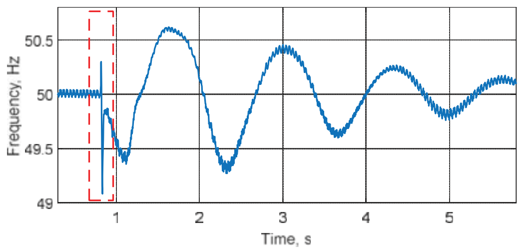

Fig. 1. The example of the spike at the inception point of the transient process for a sliding window frequency determination data.

II. Review of Inception Point Determination Methods

The task of determination of transient process inception point is linked to the thinning of the period of a voltage dip, for determination of which a method is standardized by [7] based on mean square voltage estimation from the main harmonic. In [8] a similar method is suggested, however, the estimate of the mean square of the signal is done on the half-period of the main harmonic with the value capped to ±10 % from the allowable range. For the search of the transient process end, the allowable band can be lowered because post-emergency mode can have lower voltage levels due to power system faults. These methods can be effectively utilized for electrical energy quality parameter determination, but also can be unfit for tasks of emergency control of power systems due to considerable delays and insufficient precision.

With the expansion of PMU a row of methods for emergency and operating mode control was developed, aimed for determining transient process inception with high precision and low delay. In [9] authors suggest a method, based on the the discrete wavelet transformation (DWT) coefficients analysis. Coefficients of DWT are constant for the settled process, the beginning of the transient process is accompanied with an increase in coefficient values from the appearance of high-frequency residues in current and voltage spectra. The DWT is applied to each signal phase, and inception time is determined by the search of peaks in DWT coefficients. The inception time is registered if DWT coefficients differ for more than 3 times the standard deviation from the mean. The main difficulty in DWT is with the selection of the mother wavelet's type and form. The use of short mother wavelet allows to decrease the delay in inception point determination with increased precision error and vice versa for the long mother wavelet. This difficulty limits the applicability of the method for real-time calculations. Besides, the DWT applicability is challenging for slow-changing parameters of the electric signal.

For better adaptability of the inception point determination, authors in [10] used a widely known method of d-q transformation, which allows us to bring three vector components of the current/voltage to the orthogonal q-d basis. The determination of the inception point of the transient process is done by tracking the point of value of voltage direct-axis component leaving the allowed region of values. This method can identify three-phase symmetric disturbances in real-time and determine with high precision transient process's inception and ending. As was shown in [10], the q-d method allows us to determine the inception and ending times for the symmetric disturbances, but the significant loss of precision takes place for asymmetric disturbances.

In [11] the method based on orthogonal peak detection was suggested. This method assumes the rotation of the main harmonic of the current/voltage signals to 90 degrees and amplitude analysis of the analytical signal. The use of the method in real-time is limited by the necessary for the calculation delay of ¼ of the main harmonic period.

Authors of [12] suggested analyzing the signal form to the determination of the inception point. The method is based on forecasting the instantaneous current/voltage values, and the inception time is registered at the point of the error of forecasting exceeding 10 % of the registered value. This method is highly precise in the inception point determination and achieves better results for the higher discretization frequencies of initial data. However, the ending point of the transient process determined by the method can have an error for transient processes accompanied by the phase shift. One more contrary to the method is the false identification of the transient process's initiation from the deformations of the current/voltage curve form.

Despite a considerable amount of publications in the area, it should be noted the gap in the research of methods application for emergency control in real-time. The main requirements posed to the emergency control systems are robustness, adaptability, and fast response time. Each of the reviewed methods satisfies only a part of the requirements. In this paper, it is suggested algorithm for inception point determination for real-time application.

III. Algorithm of Inception Point Determination

The algorithm is based on forecasting extrema points on the interval of offset by 2nd-degree polynomial:

- For the determined learning interval, extrema coordinates are obtained by the sliding parabola.
- The polynomial is fit to the extremes coordinates data with mean square error loss [15-17].

$$x(t) = a(t)t^2 + b(t)t + c(t) \tag{1}$$

- The mean squared error differences of registered and predicted signal levels are calculated for the training interval;
- The signal level is forecasted on the offset interval with the use of model (1) coefficients;
- The difference between forecasted and registered signal is calculated for each time step;
- If the registered value is 3 standard deviations than the expected value, the time step is marked as inception point.

The amounts of retrospective and forecasted extremes are the tunable parameters of the algorithm. Fig. 2 shows the flowchart of the algorithm.

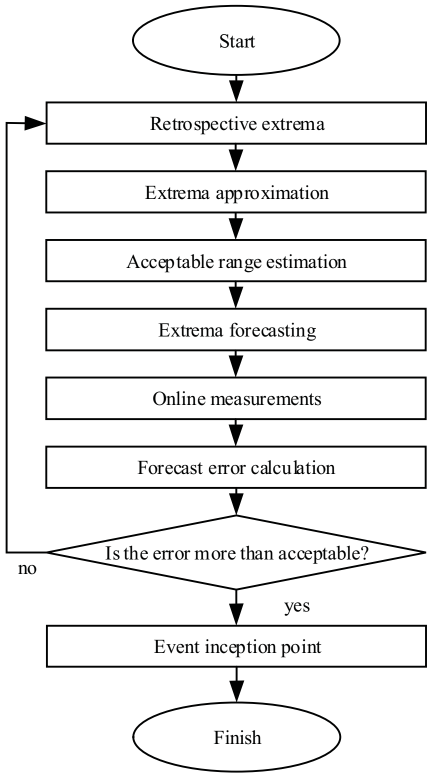

Fig. 2. Flowchart of inception point determination algorithm.

IV. Case Study

The algorithm was tested on the following data types:

- Mathematically modeled voltage signal with the transient process at 0.1 s and an amplitude decrease of 40 % and frequency variation of 1.6 Hz,
- Signals obtained from three-phase at short circuit modeled on electrodynamic model with transient process inception at 0.834 s. The timestamp of inception point was obtained with DWT method described in [18].

Fig. 3-6 designations are: EV – the expected value, SD – the standard deviation, DELTA – the difference between forecasted and registered value.

A. *Modeled signal*

Fig. 3 shows the result of the inception point determination.

For the determination of the inception point of the process shows in Fig. 3 the learning interval is 5 extremes and the prediction interval is 2 extremes, the predicted inception point value is 0.105 s and the error is 0.005 s.

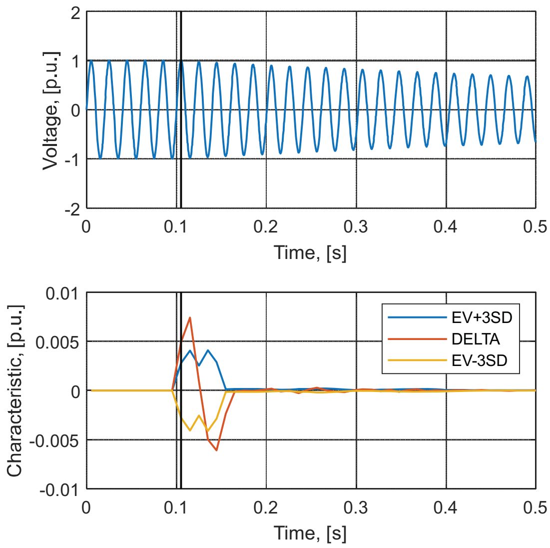

Fig. 3. Algorithm test on modeled signal.

B. *Physical signal*

Fig. 4 shows the result of inception point determination for the physical signal of the electro mechanic transient process.

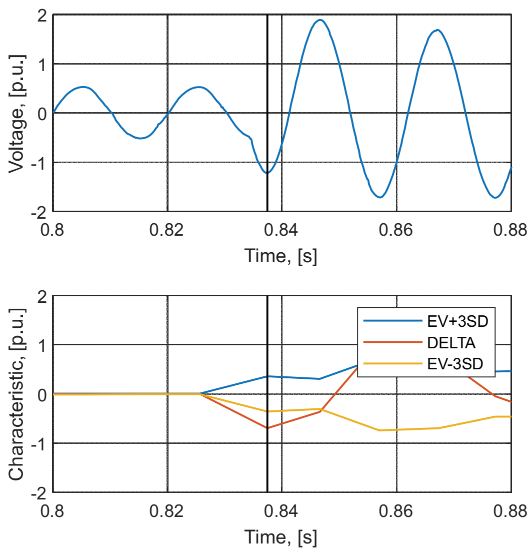

Fig. 4. Algorithm test on pysical signal.

For the determination of the inception point of the process shows in Fig. 4 the learning interval is 6 extremes, the prediction interval is 2 extremes, the predicted inception point value is 0.837 s and the error is 0.003 s.

Combined analysis of the phase signals of linear voltages and currents can be used to increase the algorithm's precision:

$$t_{IP} = \min\left(t_{Ua};t_{Ub};t_{Uc};t_{Uab};t_{Ubc};t_{Uca};t_{Ia};t_{Ib};t_{Ic};t_{Iab};t_{Ibc};t_{Ica}\right), \quad (2)$$

where t_{IP} – the inception point of the transient process; t_{Ua}, t_{Ub} , t_{Uc} – inception points for phases *A*, *B*, *C*; t_{UaB}, t_{UbC} , t_{UcA} – inception points in linear voltages; t_{Ia}, t_{Ib} , t_{Ic} – inception points for phase currents, t_{Iab}, t_{Ibc} , t_{Ica} – inception points for linear currents.

Fig. 5 shows the results of the inception points determination with the use of criterion (2). The inception points are shown as a black line. Table I summarizes the results of inception point determination.

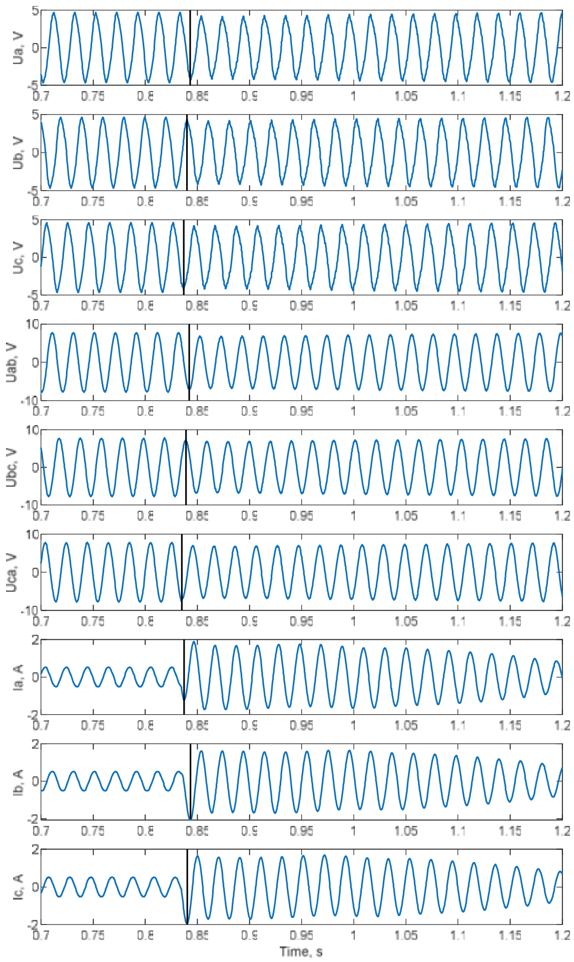

Fig. 5. Results of inception point determination with the use of criterion (2).

TABLE I. INCEPTION POINT DETERMINATION RESULTS

No.	Signal	Predicted inception point, s	Error of prediction, s
1	Ua	0.843	0.009
2	Ub	0.840	0.006
3	Uc	0.837	0.003
4	Uab	0.842	0.008
5	Ubc	0.839	0.005
6	Uca	0.835	0.001
7	Ia	0.837	0.003
8	Ib	0.842	0.008
9	Ic	0.840	0.006

According to (2):

$$t_{IP} = t_{Uca} = 0.835 \text{ s}$$

Fig. 6 shows the signal of CA voltage signal and inception points predicted with the proposed algorithm and DTW method in [18].

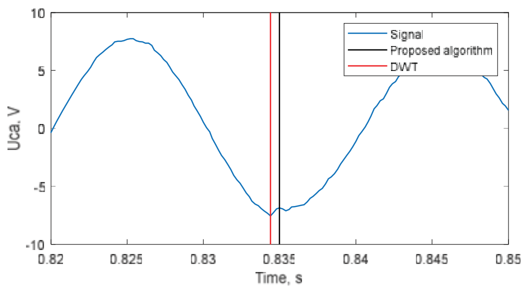

Fig. 6. The comparison of reference and predicted by algorithm inception points.

The data in Table I shows the error of 0.001 s of inception point determination with the use of criterion (2).

V. CONCLUSION

In this paper, we suggest the algorithm for inception point determination based on extrema forecasting. The tunable parameters of the algorithm are amounts of extremes in learning data and the amount of forecasted extremes. The inception point is registered if the registered value exceeds the forecasted value by 3 standard deviations, and depending on the requirements on response time and precision the threshold value difference can be set to a constant. The criterion (2) is suggested to enhance the algorithm's precision, requiring the parallel determination of inception points for nine signals (phase and linear voltages and phase currents) and the selection of the minimum value.

The algorithm was tested in mathematically modeled signal and physical signals. Errors of inception point determination are 0.005 s for modeled signal and 0.001 s for the physical signal with the use of criterion (2).

REFERENCES

[1] IEEE Standard for Synchrophasor Measurements for Power Systems, in IEEE Std C37.118.1-2011 (Revision of IEEE Std C37.118-2005) , vol., no., pp.1-61, 28 Dec. 2011.

[2] C. M. Orallo, I. Caruaati, J. Strack, S. Maestri and P. G. Donato, "Comparative Analysis of DFT-Based Synchrophasor Estimators,"2018 Argentine Conference on Automatic Control (AADECA), Buenos Aires, 2018, pp. 1-6.

[3] J. A. de la O Serna, "Synchrophasor Estimation Using Prony's Method, " in IEEE Transactions on Instrumentation and Measurement, vol. 62, no. 8, pp. 2119-2128, Aug. 2013.

[4] M. S. Sachdev, H. C. Wood, and N. G. Johnson, "Kalman filtering applied to power system measurements for relaying," IEEE Trans. Power Apparatus Syst., vol. 104, no. 12, pp. 3565–3573, Dec. 1985.

[5] A. S. Berdin, D. I. Bliznyuk and P. Y. Kovalenko, "Estimating the instantaneous values of the state parameters during electromechanical transients," 2015 Interna-tional Siberian Conference on Control and Communications (SIBCON), Omsk, 2015, pp. 1 - 6.

[6] J. Depablos, V. Centeno, A. G. Phadke and M. Ingram, "Comparative testing of synchronized phasor measurement units," IEEE Power Engineering Society General Meeting, 2004., Denver, CO, 2004, pp. 948-954 Vol.1

[7] IEEE Guide for Voltage Sag Indices, IEEE Std. 1564-2014, March 2014.

[8] J. Barros and E. Perez, "Limitations in the use of rms value in power quality analysis," in Instr. Meas. Tech. Conf., 2006.

[9] F. Costa and J. Driesen, "Assessment of voltage sag indices based on scaling and wavelet coefficient energy analysis," IEEE Trans. PowerDeliv., vol. 28, pp. 336–346, Jan. 2013.

[10] Z. Fan and X. Liu, "A novel universal grid voltage sag detection algorithm," in Power Engineering and Automation Conf., 2012.

[11] Y. Wang, X. Xiao, and M. Bollen, "Challenges in the calculation methods of point-on-wave characteristics for voltage dips," in Int. Conf. Harm. and Quality of Power, 2016.

[12] H. Chu, H. Jou, and C. Huang, "Transient response of a peak voltage detector for sinusoidal signals," IEEE Trans. Ind. Elec., vol. 39, 1992.

[13] M. Pavella, D. Ernst, and D. Ruiz-Vega, "Transient Stability of Power Systems: A Unified Approach to Assessment and Control", Norwell, Kluwer, 2000.

[14] D. Bliznyuk, P. Kovalenko and V. Mukhin, "The Technique for Accelerated Evaluation of the Instantaneous Values of Power System Performance Parameters," 2019 IEEE 60th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON), Riga, Latvia, 2019, pp. 1-6.

[15] V. N. Fomin, "Mathematical theory of learning recognition systems", 236 p., 1976.

[16] P. Y. Kovalenko, M. D. Senyuk, V. I. Mukhin and A. A. Korelina, "Synchronous Frequency Calculation Based on Synchrophasor Measurements," 2019 International Conference on Electrotechnical Complexes and Systems (ICOECS), Ufa, Russia, 2019, pp. 1-4.

[17] A. S. Berdin, D. I. Bliznyuk and P. Y. Kovalenko, "Estimating the instantaneous values of the state parameters during electromechanical transients," 2015 International Siberian Conference on Control and Communications (SIBCON), Omsk, 2015, pp. 1-6.

[18] A. F. Bastos, S. Santoso and G. Todeschini, "Comparison of Methods for Determining Inception and Recovery Points of Voltage Variation Events," 2018 IEEE Power & Energy Society General Meeting (PESGM), Portland, OR, 2018, pp. 1-5.