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Prediction of Short-Term Voltage Instability Using a Digital Faster Than Real-Time Replica

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***Abstract*—Predictive analysis of post fault system dynamic behavior can be a vital resource for better control and reliability improvement of the overall system. This article presents methods for predictive analysis of Fault Induced Dynamic Voltage Recovery (FIDVR) event using a faster than real-time digital replica of a power system. The methods proposed include use of quick algorithms for detection of FIDVR events and metrics for predicting dynamic behavior of the power system impacted by the detected FIDVR event. We show that, using a digital faster than real-time replica, the FIDVR event can be detected in required time and that the transient voltage deviation index (TVDI) can be quickly calculated.**

Keywords – Fault Induced Dynamic Voltage Recovery (FIDVR), Phasor Measurement Unit (PMU), Short-Term Voltage Instability (STVI), Voltage Stability Indices (VSI), Faster Than Real-Time Digital Replica (FTRTDR), Transient Voltage Deviation Index (TVDI).

I. Introduction

Modern power systems are operating close to limits with the increased penetration of renewable energy resources and growing demand for electricity. Intelligent online dynamic security assessment methods play a pivotal role in the operation of such systems. Short-Term Voltage Instability (STVI) detection is one such method for online dynamic security assessment. The STVI phenomena, e.g. FIDVR, occurs in these systems with increased penetration of induction motors and electronic devices. The time frame of its occurrence is in the order of a few seconds. Hence, STVI is a growing concern of a power system operator, who requires effective methods for its assessment within a very short timescale.

Conventional voltage stability assessment is mostly based on static methods that typically use the static power flow equations. Such an approach has proved adequate for effective monitoring of the long term voltage stability of the power systems and many Voltage Stability Indices (VSI) are developed for this propose [1]. A few recent works in literature have addressed the problem of monitoring STVI using methods such as hierarchical intelligent systems [2], a synchrophasor based short-term voltage stability indicator [3] and a time series shapelet classification based method [4]. However most of these indices are less adequate for online monitoring of STVI and only a very few address the prediction of it.

For the mitigation of STVI problems such as FIDVR using demand side management solutions, it is of utmost importance to have a predictive assessment of the phenomenon. Load shedding is a promising demand side management solution to the FIDVR mitigation problem and few recent works in the literature address this problem using methods such as under voltage load shedding using kinetic energy [5] and under speed load shedding [6]. An FIDVR phenomenon [7] is usually triggered by severe faults such as transmission line outage, short circuit in a critical load and other equipment damages or accidents. If the fault clearance exceeds more than 3 cycles, the corresponding voltage sag induces stalling behavior in induction motors which leads to delayed voltage recovery occurring in a time frame of few seconds, most often less than 30 seconds. Hence, it is important to have a mechanism to detect the faults triggering the FIDVR event. Many frameworks have been developed in literature such as synchro-measurement application development platform [8], GridOPTICS [9] which serves as a tool for Phasor Measurement Unit (PMU) data management and can be used with intelligent algorithms as a mechanism for fault detection. Once the fault duration that could initiate an FIDVR event is detected we can simulate an FIDVR phenomenon in a time domain simulation tool and analyse the impact of the post fault dynamic behavior and how it affects the system stability. The main challenge of using time domain simulation as online stability assessment tool is the computational time required for the same. Many recent references [10]–[12] have shown the possibility of having faster than real-time dynamic simulations with some using custom made software solutions [10], [11] and others using commercial software solutions [12]. The advantages of having commercial software is that it enables accurate post fault dynamic analysis in the most up-to-date system models that are maintained by the system operators. The work presented in this paper combines the advantages of a new framework for PMU data management and faster than real-time dynamic simulations.

In this paper, we propose the use of a digital replica of a power system that can accurately and efficiently model the system dynamics and predict the FIDVR event. The main benefit of using digital replica [13], [14] is that the control action for the real system can be implemented based on faster than real-time impact analysis on the digital replica. The key feature of this approach is fast calculation of TVDI, which is proposed as a metric to predict an FIDVR event and as means for quantifying the impact of this event on reliable operation of the power system. The underlying methodology that allows fast impact and stability assessment is the ultra-fast time domain simulation of an accurate system model. The present work uses Python API for PowerFactory software to obtain faster than real-time capability. The high level of details that can be achieved using the PowerFactory models for system simulation allow us to accurately describe the FIDVR event propagation and ultra fast simulation allows us to take action fast enough to prevent possible damage from the FIDVR event.

The rest of the article is divided into three main sections. Section II gives the basic description of the faster than real-time digital replica together with subsections explaining the detection and prediction algorithm used for the prediction of an FIDVR event. Section III presents the simulation results with the focus on the detection and prediction algorithm. Section IV concludes the paper with a discussion and future scope of the work.

II. Faster Than Real-Time Digital Replica

A faster than real-time digital replica (FTRTDR), as shown in Fig. 1, is proposed using a Python based master algorithm. In the proposed architecture, the real system supplies measurement points to the FTRTDR.

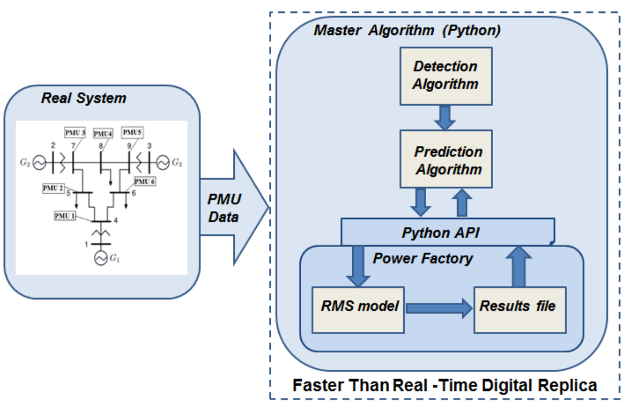


Fig. 1: Architecture of the FTRTDR

The master algorithm contains detection and prediction algorithms for fault detection and post fault dynamic behavior prediction. The main purpose of the detection algorithm for the present study is to detect topological changes that lead to the occurrence of STVI event and hence detection algorithms should be computationally efficient to enable detection in the minimum possible time. The prediction algorithm is activated with the detection of an event by the detection algorithm. The prediction algorithm can start a faster than real time, time domain simulation of the test network. This simulation provides the post fault dynamic behavior information of the test system in faster than real-time corresponding to the detected fault. The prediction algorithm then processes this post fault dynamic behavior information and hence make better prediction on the system behavior to provide control actions to the real system. The following subsections further explain the detection and prediction algorithms used.

1) Detection Algorithm: The main purpose of the detection algorithm is to detect any topological changes that can lead to the occurrence of an FIVDR event from the PMU data infeed. In the present study, we confine ourselves to detection of faults such as line outage fault and three-phase short circuit fault. Our focus is to detect the time of occurrence of a fault, which is of utmost importance as it determines the post fault dynamic behavior of FIDVR event in a power system. We use the Quickest Change Detection (QCD) using the Cumulative Sum (CuSum) algorithm developed in [16] as our detection algorithm. The sequence of statistic of each line in a network is computed as in [16] as,

$$W_{(m,n)}[k+1] = \left(W_{(m,n)}[k] + log \frac{f^{\sigma}_{(m,n)}(\Delta\theta[k+1])}{f_0(\Delta\theta[k+1])} \right)^+ \quad (1)$$

where $W_{(m,n)}[0] = 0$, (m,n) denotes to line connecting bus m and bus n in a transmission network and k denotes the k^{th} measurement sample. The second term of the sum in the equation relates to the determination of log likelihood ratio with respect to the fault. The scalability of the QCD based detection method is well explored in [16] with systems as big as IEEE 118-bus test system, and hence, this paper does not focus much on exploring the same.

2) Prediction Algorithm: The prediction algorithm consists of the following steps:

- Start the faster than real-time time domain simulation with the latest topological change detected using the detection algorithm.
- Process the data in the ElmRes object and calculate the chosen metric values. For the present study, we use the Transient Voltage Deviation Index (TVDI) developed in [2] as our metric. The TVDI is calculated as,

$$TVDI_{i,t} = \begin{cases} \frac{|V_{i,t} - V_{i,0}|}{V_{i,0}}, & if \frac{|V_{i,t} - V_{i,0}|}{V_{i,0}} \leq \mu \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

  where $V_{i,t}$ denotes the voltage magnitude of bus i at time t, which is obtained from the faster than real-time time domain simulation, and μ is the threshold to define unacceptable voltage deviation level, which is set as 20% for the present study.
- Use this metric to choose the best corrective action (e.g. the most appropriate UVLS scheme),
- Communicate the control actions to the equipment in the field (e.g. voltage relay).

$(x)^+ = x$ if $x \geq 0$, otherwise $(x)^+ = 0$

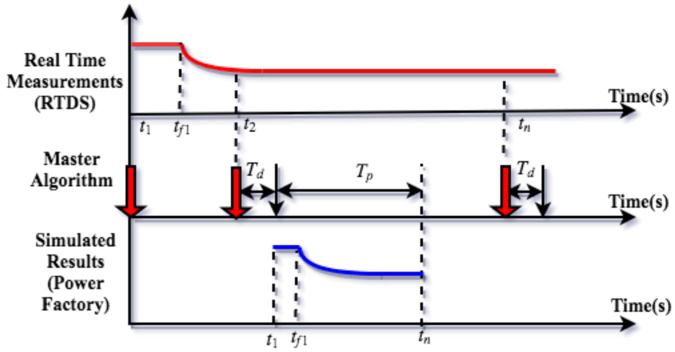


Fig. 2: Timing diagram of FTRTDR with three levels: 1) Real system (real-time measurements), 2) Detection and prediction in the master algorithm, and 3) PowerFactory replica simulation results

3) Implementation: To validate the FTRTDR concept, the real system is represented with an ElectroMagnetic Transient (EMT) simulation of the test network simulated in the Real-Time Digital Simulator (RTDS) with RSCAD software. The PMUs are implementated using the soft-PMU models in the RSCAD software and output of which is transferred to the master algorithm via TCP/IP socket connection. This setup emulates the in-feed of measurement data to the control room. Once the FTRTDR is deployed in the field such setup can be replaced by actual on-line stream of measurement data. The measurement data considered for the present study includes magnitudes of voltages and currents, together with phase angles and frequency.

The faster than real time, time domain simulation of the test network is done using Digsilent PowerFactory software.The simulated test network model is an RMS/phasor model and it is re-configurable to different post fault scenarios. The faster than real time, time domain simulation is possible by running the PowerFactory software in *engine mode*, i.e. the Python API based execution of the simulation runs. The simulation results are stored as an ElmRes object [17], which consists of values of all the variables monitored during the simulation in a tabular form as time series data. The number of monitored variables plays a crucial role in the performance of the digital replica as the PowerFactory software takes additional time to process and store them.

Fig. 2 illustrates the timing diagram of the FTRTDR. The first part of the diagram represents dynamic behavior of the real system in real-time. The second part represent the operation of master algorithm and the third part shows the simulated results in PowerFactory. The master algorithm receives measurement data as data samples at a particular sampling rate for a particular time window $(t_2 - t_1)$. For the present study this time window is chosen as 1 second and sampling rate is chosen as 60 samples per second which is a practically possible data sampling rate using PMUs. The detection algorithm executes at the end of every time window with the time taken for detection of a event represent as T_d. Once an event is detected, the prediction algorithm executes a faster than real-time PowerFactory simulation in time T_p. The simulation result over the time T_p corresponds to the dynamic behavior of the real system from time t_1 to t_n. Thus if the time T_p is short enough, the simulation results can be used for the prediction of the post fault dynamic behavior of the real system.

All simulations (except RTDS) are run from a personal computer (DELL i7, 2.6 GHz(4 CPU's), 8 GB RAM). The RMS simulation model takes the total of $3.07sec$ in a IEEE 9-bus system considered. The paper [18] discusses the scalability of the proposed method for different test systems. It further shows that the proper selection of the factors such as type of simulation, step-size and the number of monitored variables of PowerFactory simulation model enables the possibility of having a faster than real-time PowerFactory simulation.

III. Simulation Results

This section is divided into three subsections, the first subsection explains the short term instability event modeling, the second section explains the results of implementation of QCD as the detection algorithm and third section explains the results of prediction algorithm implementation using the TVSI index. The IEEE 9-bus system is used as the test system in this paper. The Fig. 3 shows the PMU locations in the test system and this system is simulated in RTDS as the representation of the real world.

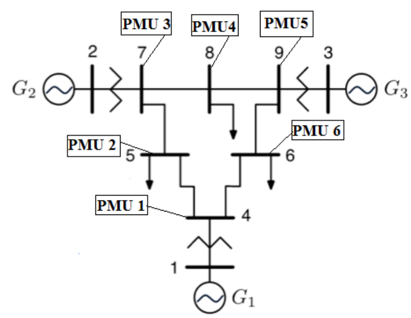


Fig. 3: IEEE 9-bus system with PMU

A. Modeling of FIDVR event

Here we explain how the FIDVR event is added in the IEEE 9-bus system. Load at Bus 5 is replaced with the composite load model as shown in Fig. 4. The FIDVR event is primarily caused by the composite load model in response to the three-phase fault that is not cleared in less than 3 cycles. The CLM model is created in resemblance to the model from [20] and the parameters of different components are mostly obtained from [21]. Some parameters are modified for the sake of better illustration of the FIDVR behavior. The Fig. 5 shows an FIDVR event in IEEE 9-bus simulated using PowerFactory

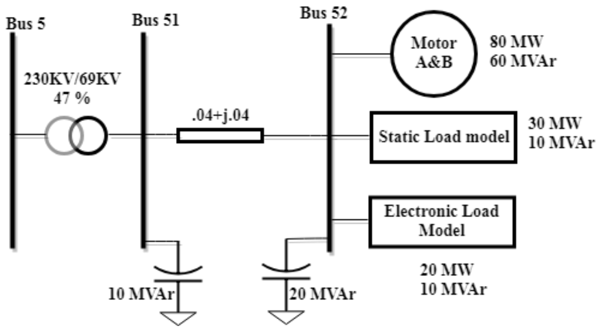


Fig. 4: Composite load model as specified in [20]

software for 5 seconds. The FIDVR event is triggered by short circuit happening in the bus 5 at 0.2 seconds and cleared in 0.3 seconds. It can be noticed from the Fig. 5 that the post fault dynamic voltage of bus 5 has severe deviation.

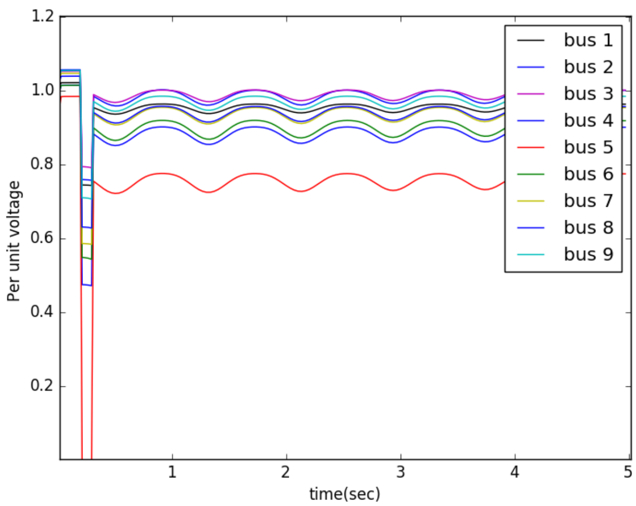
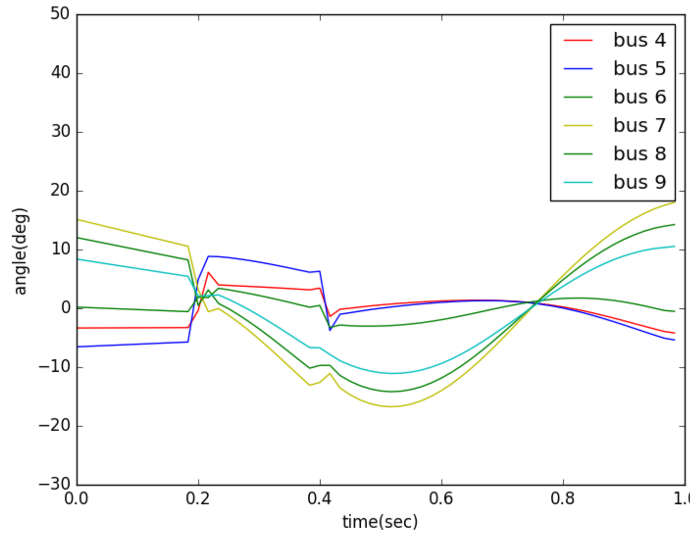


Fig. 5: Bus voltages of IEEE 9-bus system during an FIDVR event

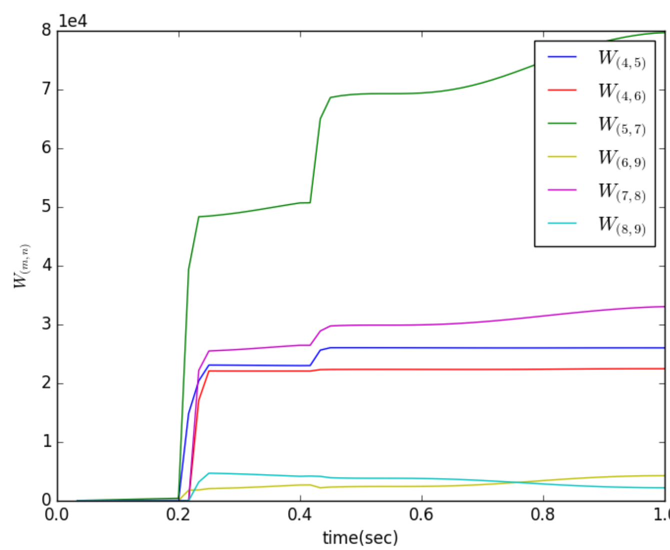
B. Detection algorithm Implementation

This section explains how the QCD algorithm [16] is used as the detection algorithm for the detection of two events namely the outage of line and a three-phase short circuit event. QCD also helps in determening the duration of events. The QCD algorithm uses the angle values as input and for the present study we have considered infeed data sample rates of 30 samples per second and 60 samples per second. First the sequence of statistics $W_{(m,n)}$ for each line (m,n) is calculated for a period of one second and then the variations in the slope values are used to detect the existence of an event and its duration. The Fig. 6 shows outage of line event with outage of line $(5,7)$ happening in 0.2 seconds followed by its reconnection happening after 0.4 seconds. The Fig. 6a shows the angle values corresponding to the line outage and second part shows the $W_{(m,n)}$ value calculated.

The detection algorithm can detect the event by processing the slope values of $W_{(m,n)}$ computed for the entire time-window. It can be noted from fig. 6b that the slope values of $W_{(5,7)}$ is highest during the initial occurrence of the line outage at 0.2 seconds and during the reconnection at 0.4 seconds. Thus a fault happening can be detected and isolated as the outage of line with corresponding duration of occurrence analyzing the slope values of $W_{(m,n)}$.



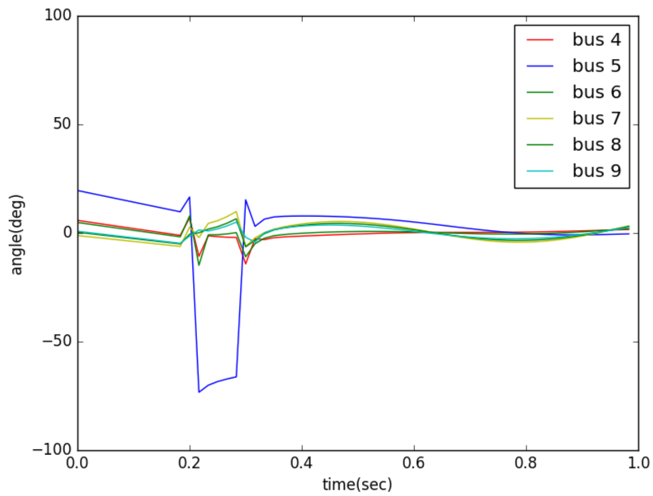
(a) Measured angle values.



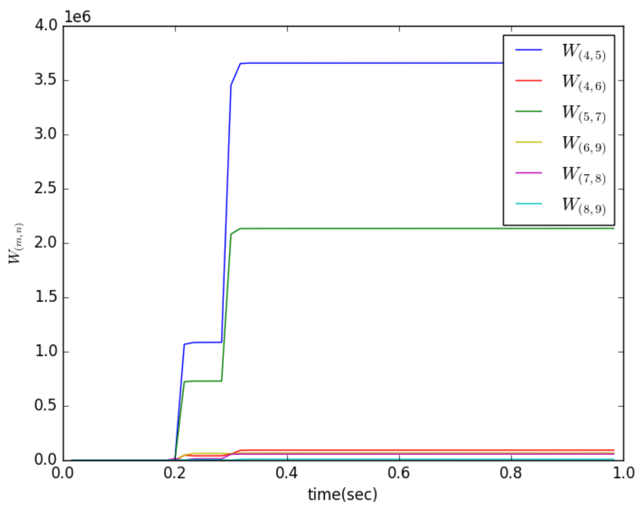
(b) $W_{(m,n)}$ values calculated.

Fig. 6: Outage of line (5,7).

The Fig. 7 corresponds to a three-phase short circuit event occurring at Bus 5 at 0.2 seconds and cleared at 0.3 seconds. The Fig. 7a shows the angle values corresponding to the three-phase short circuit event and second part shows the $W_{(m,n)}$ value calculated. In the case of a three-phase short circuit event occurring at a bus, the slope of $W_{(m,n)}$ of the lines connected to that bus will be the highest during the fault time and the time of fault clearance. It can be noted from fig. 7b that by processing the values of $W_{(4,5)}$ and $W_{(5,7)}$ computed for the entire time-window, the detection algorithm can detect the event with the duration of its occurrence.



(a) Measured angle values.



(b) $W_{(m,n)}$ values calculated.

Fig. 7: Three-phase short circuit in Bus 5.

The time taken for the detection algorithm execution depends on the sampling rate and time window considered. For the present study the time window considered is one second. It is noted that the time taken for execution of detection algorithm is 0.0312 seconds for the sampling rate of 30 samples per second and 0.0467 seconds for the sampling rate of 60 samples per second by using the personal computer specification explained in Section II. The time taken for execution of detection algorithm should be less than the time taken to receive one data sample to make sure every sample gets included in the on-the-fly-execution of the detection algorithm. This is possible if the sampling rate of 30 samples per second is used. In such case, all samples are included in the detection algorithm. To manage the detection with the sampling rate of 60 samples per second or more, a system with higher computational power is needed.

C. Prediction algorithm Implementation

This section illustrates how the prediction algorithm uses faster than real-time simulation results along with fault duration information to predict the impact of an FIDVR event. Since a three-phase short circuit fault at Bus 5 is longer than 60 milliseconds (3 cycles), as shown in Fig. 7, it triggers an FIDVR event. Once the event is detected, the prediction algorithm starts the simulation of 5 seconds of the same event in PowerFactory model. The results are retrieved as voltage values corresponding to bus affected with the three-phase short circuit fault. The Fig. 8 shows the 5 second simulation results for the voltage of Bus 5 for different three-phase short circuit fault durations in the PowerFactory model. The Fig. 9 shows TVDI value computed corresponding to the voltage values in the first part. The final value of TVDI after a 5 second simulation can be used as a metric to analyze the impact of the FIDVR event and to determine the appropriate control action such an under voltage load shedding scheme.

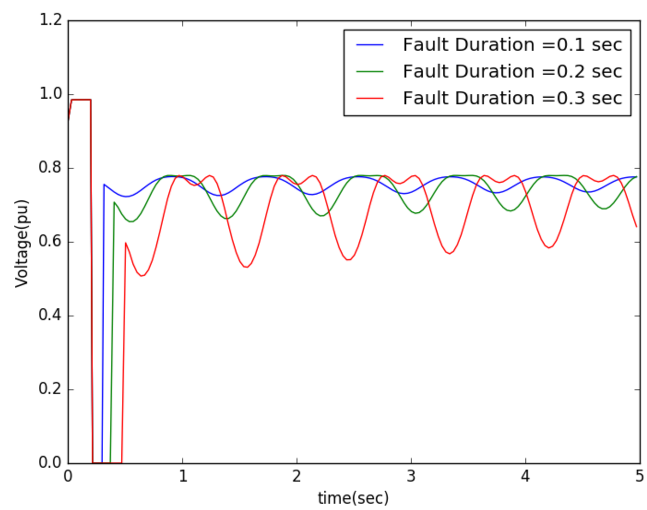


Fig. 8: Bus 5 voltage for FIDVR events with different fault durations.

For the test system modeled in PowerFactory with all the composite load models, the time taken for initialization of the simulator is 3.05 seconds and the time take for dynamic RMS simulation is 1.17 seconds. If the initialization of the simulator is done ahead of time, then the time taken for the dynamic simulation is short enough to be able to compute the TVDI value much faster. As shown is [19], the time taken for tripping of loads in a GOOSE message based load shedding is in the range of 67-100 milliseconds. Taking 100 milliseconds as the upper bound, the time passed from event detection to load shedding is within 1.27 seconds from the occurrence of the fault in the real system. Thus the particular FIDVR event can be detected and corresponding UVLS scheme can be implemented in the real system in the order of seconds from the actual occurrence of the fault.

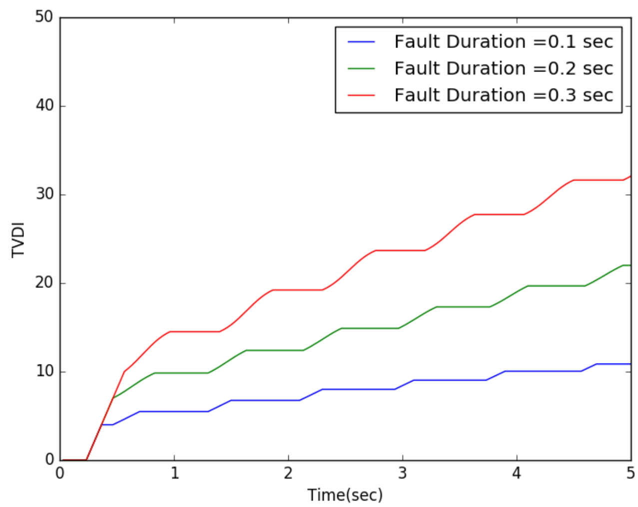


Fig. 9: TVDI calculation for FIDVR events with different fault durations.

IV. Conclusion and Future Work

The paper presents a faster than real-time digital replica that can be used a tool to detect an FIDVR event and to predict its impact on the system transient behavior. Detection for an FIDVR event is done using the QCD algorithm, which is used to detect the three-phase short circuit fault with fault duration greater than three cycles and this can be seen in fig. 7b. The fig. 9 illustrate how the TVDI value calculated can be used as a metric to evaluate the impact of the FIDVR event.

To improve the methodology even further, we look at how the TVDI index value calculation can be used to propose better under voltage load shedding schemes for the mitigation of FIDVR event detected.

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