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Adaptive differential relay coordination for PV DC microgrid using a new kernel based time-frequency transform

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ABSTRACT

A discrete differential current based unit protection and fault distance estimation is proposed for a 100 kW Photovoltaic (PV) based Multi-Terminal Direct Current (MTDC) microgrid. Relay coordination and adaptive relay settings are presented in terms of PV arc and DC cable faults. To distinguish PV arc and DC cable faults without nuisance tripping event, an improved energy density based time-frequency transform is presented in this paper. A new frequency filtering Kernel based Discrete Time Frequency Transform (KDTFT) is proposed for effective fault detection. DC microgrid protection is essential area to be research focus due to lack of precise grid codes/standards. Pole-pole (PP) and pole-ground (PG): positive/negative faults are the most counted operational threats for DC microgrids. As PV is considered to be integrated as primary DG via DC cables, highly resistive DC arc faults (series, parallel: cross-string, intra-string) are also focused in this paper. The independent PV arc protection is designed as backup to arc-fault circuit interrupters (AFCIs). The efficacy of proposed protection measure is considered in terms of percentage error for fault distance estimation and Circuit Breakers trip time (Ts). The adequacy study is presented while considering DC load diversity.

1. Introduction

To cope with the thriving energy requirement the present electrical distribution systems are towards improvement to a bidirectional active network solution, where the idea of microgrid comes into picture [1,2]. In present era Direct Current (DC) based micrgrids are become realistic due to electronics based consumers' expansion [3] as well as DC operated DGs like PV, fuel cell, etc. Among various DG applications Photovoltaic (PV) with auxiliary storage/generators are become popular for microgrid solutions lately. Effective DC microgrid operation is possible by incorporating optimal converter control/management and coordination with protection measures [4].

DC distribution networks are advantageous as compared to conventional AC grids in terms of enhanced power flow ability (i.e. enhance power flow by √2 times [5]), reduced power losses (i.e. smaller distance DC cables are free from skin effect) and fast protection switching ([6]). Besides being beneficial over AC mocrogrids, low voltage Multi-Terminal DC (MTDC) distribution networks are craving for fault protection provisions like well-defined protection standards [6], expensiveness of fast, power electronics DC circuit breakers (CBs) [7]. Pole-pole (PP) and Pole-ground (PG → positive pole to ground and NPG → negative pole to ground) are the two major fault challenges for a low voltage DC microgrid [5–7]. The PP type faults are common protection risks, but the PG/NPG events are complicated in nature (especially when DC arc faults are considered) and pose erroneous detection problem. A PV based DG is more prone to DC arcing issues [8,9] due to the PV array construction in series/parallel manner.

For any PV structure different possible arc fault events (i.e. series, parallel: cross-string, intra-string and arcing ground) are recorded [8]. In existing literature Time-Domain Reflectometry (TDR), Earth Capacitance Measurement (ECM) etc. are few well established techniques to locate PV arc faults [9]. In accordance with the Article 690.11: National Electrical Code (NEC), 2011 [10], Arc-fault circuit interrupter (AFCI) apparatus is suggested to be installed as protection measure, with grid interactive PV system greater than 80 V (rated). Commonly followed protection configurations [11] are from Underwriters Laboratory (UL: 1699B), “Photovoltaic DC Arc-Fault Circuit Protection (STP: standard technical panel)”. AFCIs are primarily implemented for series arc fault protection. Parallel (i.e. cross-string and intra-string) and ground arcs are required backup/supervisory arc protection for PV based microgrid. There is a need to protect/monitor fault occurrence at PV side and to provide adaptive relay settings according to PV injection level during fault, to rest of the distribution network. The fault detection techniques can be segregated into four major classes based on the domains to

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analyze the fault current characteristic: Time-domain, Frequency-domain, Time scale and Time Frequency domain [12]. Time domain analysis is based on inconsistency in current signature, where trip signal to DC CBs are generated by using CuSum [6], Mathematical Morphology Gradient [13], etc. Active impedance estimation (AIE) [14], probe power unit (PPU) [15] are studied for DC cable fault protection. These methods are effective due to less computation burden, but erroneous during PV arc fault consideration. Time scale (wavelet transform) based DC fault protection is reported in [16]. DC cable faults depict significant fault current amplitude but DC arc faults show noisy low amplitude current. Due to the narrow high frequency support, less interpretable feature resolution it is challenging to design an effective fault protection scheme out of [16] while considering different types of arc faults. TF responses [17] are popular choice when accuracy is needed to achieve from overlapped signal response. Time-frequency response (TFR) based protection strategy is more promising for a PV based DC microgrid, where fault detection is challenging due to overlapping nature of fault current magnitude (time domain analysis for DC cable faults) and wide frequency spectrum (PV arc faults). As both low/high frequency fault currents are involved, a new frequency filtering Kernel based Discrete Time Frequency Transform (KDTFT) is proposed in this paper. The frequency selection feature of proposed KDTFT is effective to reduce computational burden (fast detection), and thus become more attractive for DC microgrid applications. The fault location identification is achieved by a non iterative (fast calculation) direct Moore Penrose pseudo-inverse/MPI [18] technique. The frequency spectral analysis of proposed KDTFT is considered to detect PV side arcs, due to the difficulty of their low amplitude detection thresholds. Independent PV protection leads to DGs disconnection and detection threshold variation at rest of the DC network side. To cope with this issue relay coordination (between PV arc and DC cable faults) is presented by Piecewise Spline Lidstone Polynomial Interpolation, PSLPI [19], where adaptive relay setting (fault identification thresholds) for present DC network is achieved.

A differential current oriented rapid fault detection and accurate fault location identification for PV incorporated MTDC microgrid is proposed in this paper. Independent PV arc protection (backup to AFCI) and relay coordination according to it, for DC cable faults is implemented by proposed time frequency transform (KDTFT). After emphasizing the recent trends and motivation of DC network protection study in Section 1, the KDTFT formulation and its spectral energy calculation is discussed in Section 2. In Section 3 the proposed unit protection is presented in terms of DC cable parametric equivalence. Independent PV arc fault protection scheme is discussed in this section. Spectral energy (magnitude, frequency) based fault detection and adaptive relay coordination concept (PSLP interpolation) between PV arc and DC cables are presented in Section 4. Fast and accurate fault distance calculation by MPI (non-iterative) approach is discussed in this section. A comprehensive case study is conferred in Section 5, where the effectiveness validation of proposed TFR is validated in MATLAB and TMS320 C6713 DSP platform. Efficacy and the agility of the proposed method are evidenced based on two basic parameters: fault distance estimation (in terms of percentage error, ϵ in %) and fastness in fault detection (in terms of CBs' trip time, Ts), respectively.

2. Spectral energy calculation for fault detection

The microgrid operation exhibits nonlinear time varying (NTV) nature as compared with conventional grids. Further PV based DG integration makes the system NTV response added with uncertainties, nonlinear and non-stationary time frequency solution. For a DC microgrid, various fault characteristics display noisy (various frequency components) pattern, especially for arc faults. This scenario leads to a more complex protection challenge for DC feeders, while nuisance tripping taking place due to PV side arc faults (high frequency, low amplitude). Detection of these faults are effective by identifying the amplitude (for DC cable faults: PP, PG/NPG) and frequency (for PV arcs) variations by a suitable TFR. Conventional TFRs (i.e. Discrete Wavelet Transform/DWT [16], S-transform [17], chirplet transform [24], etc.) are effective for estimation of amplitude/frequency components of any DC current signal. But they are ineffective to identify various PV arc faults (i.e. series, parallel: intra-string, cross-string) from frequency components of fault current. A kernel function based DTFT is adopted as a solution to this complexity, where Morlet Kernel function is opted for its strong energy concentration (by higher dimensional feature mapping). To identify arc faults accurately and to provide protection coordination adequately for DC feeders feature mapping function (to discriminate different frequency scales) of kernel algorithm is incorporated as frequency rotational and shifting operators in proposed KDTFT. The spectral energy elaboration proposed by kernel mechanism helps detecting different arc fault events from minimum of their noise signature. The fastness and accuracy is ensured for proposed KDTFT by less computational frequency stack formation and decision making from vicinity of frequency components.

For a time series $x(t)$, sampled with an interval of T seconds to get N numbers of samples (i.e. for any window instance), the KDTFT can be defined as:

$$KDTFT\left(jT, \frac{n}{NT}\right) = \sum_{k=0}^{N-1} z(kT)\, w\left[(j-k)T, \frac{n}{NT}\right] \exp\left(-\frac{jPkn}{N}\right) \tag{1}$$

where $j = 0,1, \ldots, N-1$ is time point indexing, $n = 0,1, \ldots, (N/2) - 1$ is frequency point indexing, and k is the time domain shift for the given time series. A convolution is considered with discrete time series, $x\,(kT)$ and window function (i.e. modified Gaussian window [17]), w as:

$$w\left(jT, \frac{n}{NT}\right) = \frac{a + b\left|\frac{n}{NT}\right|^c}{r\sqrt{P}} \exp\left[(jT)^2\left(a + b\left|\frac{n}{NT}\right|^c\right)^2\right] \tag{2}$$

where r and b are named as scaling coefficients to control the number of uncertainty response in a window; a and c are the positive constants contribution to damped hidden frequencies. P is periodicity coefficient for DC signals (the value is considered near to zero as DC has no periodicity). The kernel expanded discrete time series signal (z) in Eq. (1) can be defined as:

$$z(kT) = X(kT)\ \Phi_G^R((j,k)\ T)\ \Phi_G^{t_0}((j,k)\ T) \tag{3}$$

where Φ_G^R and $\Phi_G^{t_0}$ are frequency rotational and shifting functions, derived from a kernel function (K_G). $X(kT)$ is calculated as Discrete Fourier Transform (DFT) of the actual sampled (i.e. DC currents' time-series components) signal $x(nT)$ by Fast Fourier Transform (FFT) algorithm as:

$$X_k = \sum_{n=1}^{N} x_n \exp\left(-iP\frac{kn}{N}\right) = \sum_{n=1}^{N} x_n \left[\cos\left(P\frac{kn}{N}\right) - i\ \sin\left(P\frac{kn}{N}\right)\right] \tag{4}$$

here $i = \sqrt{-1}$. An integrable kernel expression K_G is derived by *Lebesgue Measure*, and is considered for rotation of Φ_G^R by $\tan^{-1}[K_G] \in L^2(R)$ in time-frequency plane; and frequency shift of $\Phi_G^{t_0}$ by $K_G(t_0, T)$ for each time instance. These rotational and shift functions are expressed as:

$$\Phi_G^R\ ((j,k)\ T) = \exp\left[-i\left(\sum_{j=1}^{N} \frac{1}{j} K_G\ (X_{jT}, X_{kT})\ kT\right)\right] \tag{5}$$

$$\Phi_G^{t_0}\ ((j,k)\ T) = \exp\ [iT\ (K_G\ (X\ (j-t_0),\ X\ (j-k)))] \tag{6}$$

These kernel based higher dimensional operators are become $[\Phi_G^R]_{M\times N}$ and $[\Phi_G^{t_0}]_{M\times N}$ for N number of samples for any particular window instance. For each k^{th} interval for any single window a *Morlet kernel* based instantaneous patterns are obtained from $X\,(k)$ as: