Cable Diagnostics with Power Line Modems for Smart Grid Monitoring

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Abstract—Remote monitoring of electrical cable conditions is an essential characteristic of the next-generation smart grid, which features the ability to consistently surveil and control the grid infrastructure. In this paper, we propose a technique that harnesses power line modems (PLMs) as sensors for monitoring cable health. We envisage that all or most of these PLMs have already been deployed for data communication purposes and focus on the distribution grid or neighborhood area networks in the smart grid. For such a setting, we propose a machine learning (ML) based framework for automatic cable diagnostics by continuously monitoring the cable status to identify, assess, and locate possible degradations. As part of our technique, we also synthesize state-of-the-art reflectometry methods within the PLMs to extract beneficial features for effective performance of our proposed ML solution. Simulation results demonstrate the effectiveness of our solution under different aging conditions and varying load configurations. Finally, we reflect on our proposed diagnostics method by evaluating its robustness and comparing it with existing alternatives.

Index Terms—Smart grid monitoring, cable diagnostics, aging, power line communications, reflectometry, machine learning.

I. INTRODUCTION

The smart grid uses information and communication technology to provide utilities with complete visibility and pervasive control over their assets and services [1]. As a predominant constituent of utility assets, underground cables are widely deployed in both transmission and distribution systems due to their aesthetics, robustness to weather conditions, and reduced impact on the environment [3], [4]. Cable in-service failures lead to potentially dangerous situations and severe economic losses [5]. Thus, various cable diagnostics schemes have been developed in the past to employ preventive measures before an in-service failure [5] Ch. 6], [7] Ch. 4).

As cables age, the dielectric properties of the insulations continuously deteriorate, which can be monitored to infer cable health conditions [8] Ch. 2, Ch. 7], [9], [10]. Conventionally, sensors with high sampling rates are installed to gather necessary information from the voltage and current measurements [11], [12], [13] Ch. 4]. Alternatively, we propose a cable diagnostics scheme using power line modems (PLMs), which are installed across the smart grid for data communications to enable advanced grid control operations [14–18]. We exploit the principle that cable dielectric property changes manifest themselves as variations in the communication channels estimated inside legacy PLMs. By monitoring these channel variations, we reuse PLMs to infer cable health conditions. Our proposed solution can be implemented together with contemporary diagnostics methods, or be applied independently to achieve a cost-effective grid diagnostics scheme.

A. Contributions

In this paper, we propose a machine learning (ML) based framework for automated cable diagnostics. We develop a multi-step cable health monitoring scheme to progressively detect, assess, and locate cable degradations. For our investigations and evaluations, we use a cable aging model from the literature [19], [20], refine it for faithful emulation of realistic cable degradations, and further apply it to generate power line communication (PLC) channels using a bottom-up approach to extract features for training and testing our machine. Several such machines can be trained for a variety of diagnostics tasks and can be loaded onto the PLMs remotely to perform online cable diagnostics.

A review of conventional diagnostics methods shows us that joint time-frequency domain reflectometry (JTFDR) provides promising results in cable anomaly detection and localization by combining the benefits from both time domain reflectometry (TDR) and frequency domain reflectometry (FDR) [21]. Thus, we explore the possibility of extracting additional features from JTFDR for use in our ML solution, since the performance of our trained machine is contingent on the quality of the fed features. However, conventional JTFDR requires bulky and expensive external devices as well as experienced technicians to be dispatched onsite. To address this overhead, we devise a method to synthesize JTFDR solely using PLMs by applying the in-band full duplex (IBFD) communication functionality [22], [23]. IBFD-enabled PLMs continuously estimate the self-interference (SI) for echo cancellation. In the context of PLC, SI predominantly consists of the reflected signal components [22]. Thus, the received waveform obtained through TDR is essentially the SI channel impulse response. Following this, we process the estimated SI channel state information to synthesize the results of JFTDR within the IBFD-PLMs. Thereby, we extract additional features from such a PLM-JTFDR technique to train a machine that can operate with improved performance, which is confirmed through our simulation results.

Further, to judge the effectiveness of our proposed solution under real-world scenarios, we critically evaluate its robustness by emulating non-idealities that could be encountered during...
practical deployment and testing its performance under such conditions.

B. Outline

The rest of the paper is organized as follows. In Section II we introduce the modeling of cable degradation, including its growth and the dielectric property change it causes within the insulation. We then describe the procedure to generate PLC channels subject to a particular degradation condition under a considered network topology in Section III. In Section IV we introduce our proposed ML framework for automated cable diagnostics, including PLM-JTFDR for feature selection. We present the simulation results in Section V and discuss the potential challenges for our proposed solution and compare it with prior works in Section VI. Conclusions are drawn in Section VII. Specifics of PLM-JTFDR are relegated to the Appendix.

Nomenclature: Throughout this paper, we use $\Re(x)$ and $\Im(x)$ to indicate the real and imaginary parts of a complex number $x$. We denote a uniform random distribution between $a$ and $b$ as $\mathcal{U}(a,b)$.

II. CABLE AGING MODEL

Based on the insulation material used, power cables are classified into laminated and extruded types [6, Ch. 6.2.3]. While laminated cables suffer mainly from thermal degradations, extruded ones are mostly susceptible to electrical aging, i.e., developing water-treeing (WT) and electrical-treeing [24]. In this paper, we focus on investigating the cable aging caused by WT degradations, since WT is a prominent cause for premature failures of extruded cables [23, 6, Ch. 6]. In addition, focusing on WT degradations has the added benefit that many works in the literature, e.g., [19, 20], have developed a deterministic model for WT growth and thoroughly investigated the dielectric properties of WT-degraded extruded cross-linked polyethylene (XLPE) insulation, which is widely deployed in low- and medium-voltage (MV) cables [3, 4, 26].

A. Cable Aging Profile

Investigations into the nature of WT in cable insulations have shown that under normal operating conditions, power cables develop near-uniform WT degradations across their length as they age [10, 19]. However, water ingress or local defects may lead to salient localized WT degradations [19]. Therefore, for faithful emulation, we model the aging condition along the cable with an aging profile as shown in Fig. 1. The cable section develops a homogeneous WT degradation along its length with thickness $y_{homo}$, within the total insulation thickness of $y_{insul}$. In addition, a section of the cable, of length $\ell_{WT}$, may also be subject to a localized WT degradation of thickness $y_{local}$.

The growth of $y_{homo}$ can be related to the elapsed service time, $t_{sr}$, as

$$y_{homo} = \left( \frac{\alpha_0 v_0 f_0^2 \epsilon_0}{Y} \Re\left\{ \epsilon_w^{-\frac{1}{2}} \right\} \right)^{\frac{1}{\alpha}} t_{sr},$$

(1)

where $F$ is the operating electric field strength (see Section III). The remaining parameters are all listed in Table I along with their values that we use in our model. Thus, an estimated value of $y_{homo}$ can be used to obtain an equivalent age, $t_{eq}$, of a degraded cable, which can be computed as

$$t_{eq} = \sqrt{\frac{Y}{\alpha_0 v_0 f_0^2 \epsilon_0 Y_{homo}^{\frac{1}{2}}}}.$$

(2)

This equivalent age provides an intuitive indication into the WT degradation severity that the cable has experienced.

B. Dielectric Properties of WT Degraded Cables

The dielectric properties of WT degraded XLPE insulation material have been investigated in the literature, e.g., in [20, 29]. The relative permittivity of WT degraded XLPE insulation (shown as the shaded region in Fig. 1) can be computed as [29, Eq. 1]$

\epsilon_{WT} = \epsilon_{PE} \left( 1 + \frac{q_w (\epsilon_w - \epsilon_{PE})}{D(1 - q_w)(\epsilon_w - \epsilon_{PE})} \right),$

(3)

where the relative permittivity of water is given by $\epsilon_w = 81 - \frac{\sigma_w}{2\pi f_0}$, for any operating frequency $f$. Please refer to

Note that the properties of XLPE insulation material vary with the manufacturing process and depend on various factors including its density and crystallinity [27]. The parameters listed in Table I are values obtained under typical situations and serve as nominal parameters.

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**TABLE I**

| CABLE AGEING MODEL PARAMETERS [19, 20, 23, 29] P. 794 |
|--------------------------------------------------------|
| **Parameter**                          | **Value**          |
| Diffusion constant of water into the dielectric ($\alpha_0$) | $1.44 \times 10^4$ |
| Size of the free-volume voids ($v_0$)               | $2.5 \times 10^{-28}$ m$^3$ |
| Mains frequency on the line ($f_0$)                 | 60 Hz             |
| Absolute permittivity ($\epsilon_0$)                | $8.8 \times 10^{-12}$ F/m |
| Relative permittivity of non-degraded XLPE ($\epsilon_{PE}$) | $2.3 - 0.001\j$ |
| Dielectric mechanical yield strength ($Y$)           | $2 \times 10^7$ Pa |
| Depolarization factor ($D$)                         | $\frac{1}{2}$      |
| Absolute water content in the WT region ($q_w$)      | 0.06              |
| Conductivity of water ($\sigma_w$)                   | 0.22 S            |

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Fig. 1. Longitudinal section of a cable insulation illustrating the cable aging profile. The shaded region indicates the portion of the insulation subjected to WT degradation while the unshaded region consists of the intact sections of the insulation and the conductor-insulation interface.
Table 1 for descriptions and values of all other parameters. For the overall cross section of XLPE insulation with both WT degraded and intact regions, the equivalent relative permittivity can be computed using the series dielectrics model as [20, Eq. 6.3],
\[
\epsilon_{\text{total}} = \left( \frac{y}{r_{\text{insul}}} \epsilon_{WT} + \frac{r_{\text{insul}} - y}{r_{\text{insul}}} \epsilon_{\text{PE}} \right)^{-1}, \tag{4}
\]
where \( y \) is the WT degradation depth.

To further determine and establish degradation severities, we define the WT degradation severity as \( \gamma \triangleq \frac{r_{\text{insul}}}{y} \). For a cross section with localized WT degradation (region A in Fig. 1), we have \( y = y_{\text{local}} \) and \( \gamma_{\text{local}} = \frac{r_{\text{insul}}}{y_{\text{local}}} \). For other cross sections without localized WT degradation (region B in Fig. 1), we have \( y = y_{\text{homo}} \) and define \( \gamma_{\text{homo}} = \frac{r_{\text{insul}}}{y_{\text{homo}}} \).

III. PLC CHANNEL MODEL

The change in relative permittivity of the insulation material also results in a change in the PLC channel frequency response (CFR). To accurately capture this effect, we adopt the bottom-up approach of modeling PLC CFRs in our investigation [31]. Each section along the cable with the same degradation severity can be viewed as a uniform line with electrically small cross-sectional dimensions, in which condition PLC signals are transmitted in the quasi-transverse-electromagnetic (quasi-TEM) propagation mode, and the PLC channel can be modeled with the multi-conductor transmission line (MTL) theory [32, Ch. 1]. Finally, we concatenate the modeling of each of these sections to obtain the overall CFR. By using the WT degradation model of (4) in the MTL per-unit-length (PUL) parameter computations [11], we model the PLC channel for cable sections with arbitrary degradation severity. For the software implementation, we feed the computed PUL parameters to an open source PLC channel emulator of [33] to generate PLC channels.

A. Network Topology and Loads

Typical MV distribution networks consist of few intermediate branches and can be divided into smaller \( T \) and chain networks [34]. Therefore, for a realistic grid emulation, we consider a \( T \)-network with three PLMs, as shown in Fig. 2, with possible network extensions beyond each of the PLMs. Without loss of generality, we consider a symmetrical topology with an equal separation distance of 500 m between each PLM and the branch point (BP) [35]. Further, we also place a 500 m transmission line between each PLM and any further branch extensions (BEs). To emulate a range of realistic network extensions, we consider equivalent load impedances randomly chosen in \( \mathcal{Z}(0,50) + j\cdot\mathcal{Z}(-50,50) \) \( \Omega \) between each pair of conductors.

B. PLC Channel Generation

We use the PLC channel emulator of [33] to generate PLC channels in the frequency range of \( 2 – 30 \) MHz with a frequency resolution of \( \Delta f = 24,414 \) kHz in accordance with the HomePlug GreenPHY (HPGP) PLC standard that is tailored for smart-grid applications [36]. The channel generator of [33] provides the end-to-end CFR, \( H_f \), as well as the access line impedance, \( Z_{in} \). Using \( Z_{in} \), we compute the SI channel transfer function, \( H_{SI} \), with an IBFD analog hybrid impedance of \( 100 \Omega [22, Eq. 31] \). We use both \( H_f \) and \( H_{SI} \) for our ML solution since an IBFD-enabled PLM inherently estimates both these parameters for communications purposes. In this work, we consider \( H_f \) and \( H_{SI} \) to be perfectly estimated by the PLMs in order to focus specifically on determining the potential of using CFR variations to estimate cable degradations.

C. Cable Settings

To obtain the PLC CFRs, we consider the XLPE multi-core cable N2XSEY [37], with equidistant conductor separations of \( d_{\text{cond}} = 15.88 \) mm, equal conductor radii \( r_{\text{cond}} = 3.99 \) mm and a maximum rated voltage \( V_0 = 12 \) kV. We then apply an approximate cylindrical geometry to compute the electric field under \( V_0 \) at a distance \( r_{\text{cond}} \) from the center of the conductor [38, Eq. 1], where the electric field strength is at its maximum and is most prone for WT inception [38], as
\[
F_{\text{max}} = \frac{V_0}{r_{\text{cond}} \ln \left( \frac{d_{\text{cond}}}{2r_{\text{cond}}} \right)}. \tag{5}
\]
Considering an expected maximum service time of \( t_{\text{max}} = 30 \) years [6, Ch. 6] in (1), we derive the maximum homogeneous degradation severity, \( \gamma_{\text{homo}}(\gamma_{\text{local}}) = 0.0481 \) under nominal conditions. Therefore, in our evaluations, we confine \( \gamma_{\text{homo}} \leq 0.05 \), and to clearly distinguish salient localized WT degradation, we let \( \gamma_{\text{local}} \geq 0.1 \).

IV. ML FRAMEWORK FOR CABLE AGING INFERENCE

In this section, we introduce our proposed aging inference procedure in Fig. 3 where we progressively perform cable degradation type classification, degradation severity assessment, and, in case of a localized degradation, the location prediction. We first identify the type of aging profile to determine if the cable has undergone a localized degradation. Consider a representative distribution network as shown in Fig. 2. If no localized degradation is present in any of the six branches, we identify...
the cable aging profile to be homogeneous throughout. In such a case, we predict its associated homogeneous degradation severity, and quantify the value in terms of an equivalent cable age, $t_{eq}$ (see (2) and Table I). On the other hand, when the presence of a localized degradation is predicted, we first determine the branch on which it resides. Next, we use a pair of PLMs, including the PLM closest to the localized degradation, to assess its severity, $\gamma_{\text{local}}$, as well as locate its two ends.

B. Machine Learning Techniques

We formulate the problems of aging profile type identification and branch localization as supervised classification, and the problems of degradation localization and aging severity assessment as regression. For both classification and regression, we use two sets of ML techniques, support vector machine (SVM) and boosting, due to their superior overall performance [1], [39], [40]. For each of the procedures shown in Fig. 3 we train separate machines, which can be remotely loaded onto the PLMs for automated cable diagnostics.

C. Feature Selection

For each of the ML tasks, selecting the features set is crucial for a successful ML performance. We have shown in our prior works [1], [39] that cable degradations cause higher dielectric losses and thus greater attenuation in $H_l$ across the frequency band. Therefore, we include the $m$th-order moments ($m \in \{1, 2, 3, 4\}$) of $|H_l|$ in our feature library to train our machine. Additionally, various studies in the literature, e.g., [20], [39], [41], have shown that degradations reduce the velocity of wave propagation in the degraded section of the cable. Thus, we also include the locations and amplitudes of the peaks in the channel impulse response, $h_l$, and the $m$th-order moments ($m \in \{1, 2, 3, 4\}$) of $\angle H_l$ in our feature library.

Furthermore, reflectometry methods, such as JTFDR, provide meaningful results for detecting and locating cable anomalies [21]. Hence, we also extract features from JTFDR waveforms. However, conventional JTFDR requires bulky and expensive external devices (e.g., arbitrary waveform generator and high sampling rate sensors). To counter this overhead, we propose the use of PLMs to synthesize the result of JTFDR by enabling the IBFD functionality [22], [23]. We use the SI channel estimate, $H_{SI}$, that is inherently computed inside IBFD-PLMs for echo cancellation, which essentially indicates the multipath channel traversed by the transmitted signal reflected into the receiver path. We detail the procedures involved in synthesizing PLM-JTFDR in the Appendix. Through this procedure, we use the peak amplitudes and locations of the synthesized JTFDR results as additional features for ML. In Section V we show through numerical results that PLM-JTFDR provides cleaner waveforms for extracting features when compared to directly using the SI channel that is estimated by the IBFD-PLMs.

V. SIMULATION RESULTS

In this section, we provide simulation results of our proposed solution. First, we present the results of PLM-JTFDR to show its ability in contributing helpful features to the ML algorithm. We then demonstrate the effectiveness of our ML solution through numerical evaluations for automated cable health condition monitoring. Throughout our simulations, we apply the network topology shown in Fig. 2 and the cable aging model and PLC channel characterization described in Section II and Section III respectively.

A. PLM-JTFDR

We first run PLM-JTFDR with an aging profile that contains a localized degradation located between TX and BP. We set the localized degradation to be of the minimum degradation severity $\min(\gamma_{\text{local}}) = 0.1$ to evaluate the sensitivity of our scheme even to mild degradations. We arbitrarily set a 166 m long degradation to be present between 211 m and 377 m from the transmitter. The resultant PLM-JTFDR waveforms obtained for this setup is shown in Fig. 4. For comparison, we also show $-|H_{SI}|$ alongside.

The peak locations in Fig. 4 are seen to be at $n_A = 0$, $n_B = 129$, $n_C = 232$, $n_D = 305$. Since we are aware of the network topology a-priori, i.e., that BP is $l_0 = 500$ m

\[ \frac{1}{2} \text{For illustration clarity, we only show the first 300 time samples of the signal normalized with respect to the magnitude of its first peak.} \]
away from TX and that \( n_D \) indicates the reflection from BP, we can compute the two ends of the localized degradation to be \( \ell_{0\text{NB}}/n_D = 211 \text{ m} \) and \( \ell_{0\text{NE}}/n_D = 380 \text{ m} \) apart from TX, respectively. While we predict the start location of the degradation accurately, the slight disagreement in locating the degradation end point can be attributed to the slower wave propagation speed in the localized degradation region. For a section of cable with \( \epsilon_{\text{total}} \) (see (4)), the wave propagation velocity can be computed as

\[
v = \frac{1}{\sqrt{\mu \epsilon(\epsilon_{\text{total}})}} \tag{6}
\]

When \( \gamma_{\text{local}} \gg \gamma_{\text{homo}} \), \( v \) at the region with a localized WT degradation is noticeably different from other regions. This is also shown in [20, 39, 41], where fault or degradation localization in severely aged service cables yields significant deviance from their true values. However, this minor discrepancy is noticeably negligible and does not present any adverse effects on our eventual diagnostics goal.

We notice from Fig. 4 that \( h_{\text{JTFDR}} \) is smoother and its peaks are more prominent than \( h_{\text{SI}} \). Therefore, compared to directly using \( h_{\text{SI}} \) for cable diagnostics, PLM-JTFDR has superior sensitivity and performance to detect less salient localized WT degradations.

B. Simulation Settings for Evaluating our ML Framework

For the rest of our simulations, we set \( \gamma_{\text{homo}} \sim \mathcal{N}(0, 0.05) \), \( \gamma_{\text{local}} \sim \mathcal{N}(0.1, 1) \), \( \ell_{\text{WT}} \sim \mathcal{N}(100, 300) \) m, and the center of the localized WT degradation randomly located within 100 m from the center of a branch in Fig. 2.

The performance of ML algorithms is dependent on the number of training samples, \( n_{\text{TR}} \), we use. While a lower \( n_{\text{TR}} \) could be inadequate to sufficiently train the machine, its performance also saturates beyond a certain \( n_{\text{TR}} \). In our simulations, we choose \( n_{\text{TR}} \) such that the machine attains its maximum performance level. Such a methodology is representative of practical implementations, since we execute the training phase off-site, where we are not constrained by the actual value of \( n_{\text{TR}} \) we choose to use. We then test our trained machines with an arbitrary number of test samples, \( n_{\text{TE}} \), in each of our ML tasks. We choose \( n_{\text{TE}} \) such that a clear performance trend is discernible. Since \( n_{\text{TR}} \) and \( n_{\text{TE}} \) vary for each of the ML tasks, we specify our chosen tuple \( (n_{\text{TR}}, n_{\text{TE}}) \) with all our results.

C. Aging Profile Type Classification and Branch Location

1) Phase-1: In the first phase, we use the \( i \)th PLM, \( p_i \), \( i \in \{1, 2, 3\} \) to identify whether a localized WT degradation resides either between \( p_i - \text{BP} \) or between \( p_i - \text{BE}_i \). The result of this exercise for varying \( \gamma_{\text{local}} \) is shown in Fig. 5. We observe in Fig. 5 that using \( h_{\text{JTFDR}} \) to extract features provides near-perfect detection with negligible false alarm (FA) rates across all values of \( \gamma_{\text{local}} \), while using \( h_{\text{SI}} \) provides unsatisfactory detection especially at lower \( \gamma_{\text{local}} \), with either SVM with radial basis function (RBF) kernel or the adaptive boosting (AdaBoost) as our considered ML algorithms. The improved performance is expected due to the nature of \( h_{\text{JTFDR}} \) in comparison to that of \( h_{\text{SI}} \), i.e., more prominent peaks and a smoother floor in \( h_{\text{JTFDR}} \), as discussed in Section V-A. Therefore, the result of Fig. 5 shows that the detection performance can be significantly improved by adopting PLM-JTFDR into the ML framework.

2) Phase-2: Once a localized WT degradation is detected between \( p_i - \text{BP} \) or \( p_i - \text{BE}_i \), we let \( p_j \) \( (j \in \{1, 2, 3\}, j \neq i) \) confirm whether the degradation resides between \( p_i \) and BP. The detection results for this phase is shown in Fig. 6. At first, we use the same feature-set for this task as that used in Phase-1. We observe in Fig. 6(a) that this results in detection rates that are less than desirable, especially for lower values of \( \gamma_{\text{local}} \). However, by adding additional features, such as the variance of \( h_{\text{JTFDR}} \), the detection rates can be substantially improved across all values of \( \gamma_{\text{local}} \) as seen in Fig. 6(b).

D. Homogeneous Ageing Severity Assessment

When Phase-1 of aging profile type classification determines a homogeneous aging profile, we use the least squares boosting (LSBoost) to train a machine for the prediction of the degradation severity level. Specifically, we train and test with different homogeneous degradation severities quantified by their equivalent age as computed in (2). To emulate realistic
degradations, we limit \( t \sim \mathbb{N}(0, 32.5) \) years in our simulations [6, Ch. 6]. The equivalent age prediction performance is shown in Fig. 7(a). We observe that the estimated age closely matches the actual age. Furthermore, the prediction accuracy is considerably improved when compared to the state-of-the-art [1], as we now use not only \( H_1 \), but also \( H_{SI} \).

E. Localized Degradation Severity Assessment

Next, we consider the condition where the classifier indicates the presence of a localized degradation, to assess its severity. To this end, we train an LSBoost regressor with a degradation randomly located between \( TX - BP \), since we rely on the node closest to the degradation for assessment. The prediction results are presented in Fig. 7(b). Similar to the performance gains seen in Section V-D, our results show significant improvement in prediction accuracy when compared to the state-of-the-art [1], due to the additional insight obtained from features extracted with the IBFD functionality.

F. Localized Degradation Location

Thus far, we have predicted the type of degradation present and its severity. As our final diagnostics stage, we attempt to locate the salient localized cable degradation so that further efforts in preventing an in-service fault can be concentrated. Locating a localized degradation consists of determining the positions of its two ends. For this purpose, we follow the procedure of first determining its starting point, or the target point, and then estimating the degradation length. For the localization of the target point, we train an SVM for regression with linear kernel. The results of predicting the target location can be seen in Fig. 8(a). We notice that the prediction accuracy is near perfect with negligible variance of individual predictions from the fitted curve. This accurate target location prediction is made possible due to the peak location clarity in \( h_{JTFDR} \).

Next, we predict the length of the degradation to identify its end point. However, we found that the length prediction was highly inaccurate with any ML algorithm. Therefore, we device a workaround to this challenge by instead predicting the product \( \ell_{WT} \cdot \gamma_{local} \), which can be predicted with high accuracy, and then using our previously predicted values of \( \gamma_{local} \) (in Fig. 7(b)) to determine \( \ell_{WT} \). The prediction results for \( \ell_{WT} \cdot \gamma_{local} \) is shown in Fig. 8(b), where we clearly notice that the fitted curve of the predictions is a straight line with unit slope and nearly passing through the origin, thereby confirming the high accuracy of our results.

VI. DISCUSSION

In this section, we provide a brief discussion on our proposed solution by comparing it with prior arts and exploring its robustness in non-ideal settings.

A. Related Work

1) Reflectometry Methods: Utilities typically use reflectometry methods, such as TDR, FDR, or JTFDR, for detecting faults and degradations on the line [21], [42]–[44]. While our solution includes the use of the same underlying principle to enhance our proposed ML framework, we synthesize the results of JTFDR using the already existing PLMs that inherently estimate the SI channel for IBFD operation. Therefore, no additional dedicated components are required as in conventional reflectometry methods. Further, by incorporating the reflectometry methods into a ML framework, we are able to comprehensively infer the cable health conditions, which conventional methods are unable to achieve.

2) Fault localization: Several prior works have proposed and developed solutions to use PLMs for fault localization, for e.g., [11], [45]–[47]. Apart from these works facing practical limitations, such as, say, requiring a reference CFR measurement for any given load condition, detecting the presence of a fault on the main line is a reactionary response to a service failure. In contrast, we develop solutions in our work to estimate cable degradations in order to take preventive measures to avoid a fault. Furthermore, assessing cable degradations is also non-trivial when compared to fault detection as the signal reflections tend to be more obscure, as seen in Fig. 8.
3) ML Techniques: ML-based data-driven methods have also been previously used for cable diagnostics, albeit without using PLC. [48] provides a substantial literature review on fault diagnosis using data-driven methods. Further, [41] and [49] also provide techniques to use SVM for cable diagnostics. However, similar to the methods described in Section VI-A2, these solutions predominantly focus only on fault diagnostics, and also do not involve using PLMs.

B. Robustness to Non-idealities

Although the WT model we use in (5) is representative of realistic WT degradations, we explored the robustness of our solution to possible behavior deviations that could be seen in practically encountered WT degradations. To this end, we evaluated our solution by training our machine to associate the behavior of WT degradations with the model of (3), and then testing its performance by applying real-world WT degradation measurements reported in [20, Ch. 6]. The results of this exercise can be seen in Fig. 9. For illustration purposes, we present the result of two evaluations we performed, one each with and without a localized degradation. First, we predict the equivalent age of a cable that is subjected to homogeneous WT degradation. In comparison to similar results obtained earlier in Fig. 7(a), we observe in Fig. 9 that the prediction performance is noticeably affected, as expected. However, our machine is robust enough to provide a satisfactory performance with near unity slope of the fitted line and low individual prediction variance. Next, we focus on analyzing a localized degradation, where we predict its target location, as in Fig. 8(a). In this case, we notice in Fig. 9(b) that the prediction results are still accurate, since locating a degradation mainly relies on the peak locations caused due to a discontinuity. The prominent peaks and smooth floor of our proposed PLM-JTFDR make detecting and locating such discontinuities fairly robust to the accuracy of the WT model used.

The framework presented in our work also inspires future engineering endeavors, e.g., investigating the extent of the impact of channel estimation errors on the prediction accuracy, and examining the robustness of our solution when trained with one form of degradation and tested on cables subject to multiple types of degradations and various other non-idealities (e.g., bending of cable or cable splicings).

VII. Conclusions

In this paper, we have proposed methods to re-use PLMs available across the smart grid distribution network to also monitor cable health conditions. We propose an ML framework for automated cable aging inference. By adopting a multi-step strategy, we progressively detect, assess, and localize cable degradations. Further, we enhance this solution by using PLMs to synthesize the results of conventional JTFDR, and incorporate the features extracted from PLM-JTFDR in our proposed ML framework to significantly improve its capability and performance. The machine uploaded on the power line modems can be updated as often as required with online firmware upgrades. Our proposed technique provides utilities with a low-cost solution that enables them to harness power line modems as not only communication devices, but also as pervasive grid sensors to continuously monitor the status of the cables, and take precautionary measures to avoid cable in-service failures and resultant power outages.

APPENDIX

PLM-JTFDR

Conventional JTFDR involves transmitting a Gaussian enveloped chirp sequence, $s_{gc}(t) = g(t) \cdot c(t)$, where $g(t)$ and $c(t)$ are the Gaussian-shaped and the chirp sequences, respectively, and subsequently sampling and processing the reflected signal, $\rho(t)$, to diagnose cable anomalies [21]. To emulate this procedure in the IBFD-enabled PLMs, we convolve a pre-generated $s_{gc}(t)$ with the estimated SI impulse response, $h_{SI}(t)$, to produce the equivalent received JTFDR signal, $\hat{\rho}(t)$, as

$$\hat{\rho}(t) = (s_{gc} * h_{SI})(t),$$

where ‘*’ indicates the linear convolution operation. We then process $\hat{\rho}(t)$ as in conventional JTFDR to obtain locations and magnitudes of peaks in the resultant final waveform, $h_{JTFDR}$.
for detecting and locating any possible cable degradations. Specifically, we compute the cross-correlation signal, $u(t)$, as

$$u(t) = \int_{-\infty}^{\infty} s_{ge}(\tau) \hat{p}(t+\tau) d\tau,$$

and then pass $|u(t)|$ through a low-pass filter for envelope detection. We also summarize the operating procedure in Fig. 10.

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