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Real-time Deep Neural Networks for internet-enabled arc-fault detection

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A B S T R A C T

We examine methods for detecting and disrupting electronic arc faults, proposing an approach leveraging Internet of Things connectivity, artificial intelligence, and adaptive learning. We develop Deep Neural Networks (DNNs) taking Fourier coefficients, Mel-Frequency Cepstrum data, and Wavelet features as input for differentiating normal from malignant current measurements. We further discuss how hardware-accelerated signal capture facilitates real-time classification, enabling our classifier to reach 99.95% accuracy for binary classification and 95.61% for multi-device classification, with trigger-to-trip latency under 220 ms. Finally, we discuss how IoT supports aggregate and user-specific risk models and suggest how future versions of this system might effectively supervise multiple circuits.

1. Arc detection matters

Electrical circuits harbor silent and serious risks. Conductors flex, break, and oxidize; insulation abrades, and interconnects, switches and terminals degrade. Wires are routed in hard-to-inspect areas between walls, ignored until problems manifest. One such problem is arcing, an unintended, luminous and sustained discharge of electricity in conductive, ionized gas between two regions of varied electrical potential.

Arcs may be series or parallel. Series arcs occur when a conductor is unintentionally broken, *e.g.* from a loose connector, a poorly-made splice, or an accidental nick or cut. Parallel arcs occur between hot and neutral or ground, or neutral and ground. Though parallel arcs burn hotter, series arcs have the potential to burn between 5000 and 15,000 °C (Gregory and Scott, 1998), expelling molten liquid capable of starting fires.

Since 1998, specialized devices called Arc Fault Circuit Interrupters (AFCIs) (Gregory et al., 2003) have helped mitigate fire risks. These systems interrupt faulty circuits, but err on the side of over-sensitivity, disconnecting benign devices like vacuums or computers. We propose leveraging advances in sensing, connectivity, inference and action in order to build an intelligent, cost-effective Internet-of-Things enabled arc-fault detector capable of learning new definitions, similar to a virus scanner.

To prove this concept's feasibility, we examine low-power, AC series arcs, which provide worst-case training data. AC faults are difficult to classify because the circuit's connected load limits the arc's maximum current (Li et al., 2003; Gregory and Scott, 1998), reducing the signal-to-noise ratio. Series faults pose a high likelihood of confusion with benign appliances such as DC motors, and by testing with low-power circuits, (<15 A @ 120 VAC), our algorithms will readily extend to higher-power arcs.

This paper proposes fault detection using an adaptive deep neural network trained using real data. Such a system provides a future-proof and scalable system for arc classification, maintaining sensitivity while reducing unintended interruptions. Connectivity allows device and fault "definitions" to be aggregated at scale, while on-board computation and connectivity enables operating characteristic measurements and remote control. More than describing a smart AFCI's implementation, however, this paper highlights the opportunity latent in bringing AI and connectivity into "mundane" devices, such as those found in infrastructure.

2. Existing arc detectors

Contemporary arc detectors leave much to be desired from the perspective of cost, immunity to false positives (unnecessary interruption), response time, and upgradability.

AFCIs may rely upon analog circuits, application-specific integrated circuits (ASICs), field-programmable gate arrays (FPGAs), or optical and electromagnetic techniques to detect arcs. Device sensitivities and reaction times (25–250 ms) vary (Johnson et al., 2013; Li and Li, 2005).

Low-cost analog detection is most prevalent, but it suffers from high false positive rates (Li et al., 2003; Liu et al., 2008). Mechanical approaches are initially more reliable, but costly and degrade over time (Liu et al., 2008).

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Algorithmic detectors face different challenges. Arcs are dynamic, and detection efficacy varies as the cathode erodes (Gregory et al., 2003). Appliances may share characteristics with arcs, including current shoulders, a change in amplitude, or an increased rate of current rise (Gregory et al., 2003), leading to misclassification.

Some arc detectors utilize machine learning to improve classification accuracy. For example, researchers have applied neural networks to identify abnormal operation without a priori arc models. These approaches yield between 95% and 99% accuracy using small feature vectors for training and testing, though it is unclear how resilient these approaches are to nuisance detection (Ma and Guan, 2011; Liu et al., 2011; Kai et al., 2016).

More generally, algorithmic arc detection is a form of dynamic process transient fault detection. Roverso (2002) describes one approach to dynamic fault detection using bagged recurrent neural networks, windowed wavelet feature generation, and task (fault) decomposition (Roverso, 2002). However, this approach might require costly hardware to deploy in real-time.

Hidden Markov Models (HMMs) learn time-dependent spatial and temporal patterns to identify state transitions from normal to abnormal plant operation. Kwon et al. (2002) Similar HMMs identify individual appliances from combined electrical loads, but require supervised model creation and long inter-state transitions not conducive to the fast (>1 Hz) realtime operation required to protect against arc-related fires (Zia et al., 2011).

Computer-controlled AFCI's running these algorithms may rely upon features including Fourier coefficients, wavelets, and use techniques such as band-pass filtering to eliminate harmonics and baseline current from measurements (Liu et al., 2008; Cheng et al., 2010; Li et al., 2009). Other approaches derive features by correlating multiple information sources, for example by relating differential current ($\frac{di}{dt}$) to absolute current ($|i|$), which improves separability of nuisance tripping from fault tripping. These approaches may detect early arcing with up to 98% accuracy (Yang et al., 2016).

Some AFCIs create additional value to drive adoption. Ming et al. (2009) developed a system using Controller Area Network (CAN) to connect sensors a single host computer for classification (Ming et al., 2009). Koziy et al. (2013) proposed integrating detectors into smart meters (Koziy et al., 2013).

Most AFCIs rely on predefined and immutable arc definitions, leading to nuisance interruption. Developing an AFCI with adaptive and remotely-updatable definitions would provide additional utility relative to conventional approaches. Such an approach allows for common-Cloud signature aggregation to minimize nuisance disconnects while facilitating new insights (what is plugged in?) and remote control (turning off a stove while vacationing).

3. Hypothesis

Current waveforms differ between arcing and normally-operating circuits. Unlike the current traces from a resistive circuit, arc fault waveforms typically have shoulders because the arc does not flow current until sufficient voltage across the gap returns following a zero current condition (excitation and reignition). Gregory and Scott (1998) and Li and Li (2005). Representative normal and arcing traces from an electronic stovetop and ozone (arc) generator can be seen in Figs. 1 and 2.

Listening to these signals as audio, we could differentiate between resistive and arcing signals. We therefore hypothesized that audio processing techniques may be used to classify normal and faulty circuits. Audio-based classification has been successfully applied to the development of automotive diagnostic systems (Siegel et al., 2016, 2017). However, these approaches rely on physical or statistical models. Deep learning techniques might instead allow for normal and abnormal classification without an a-priori hypothesis, and would scale to support the volume of data generated by connected devices.

In the following sections, we test a neural network using audio features to identify circuit operating states.

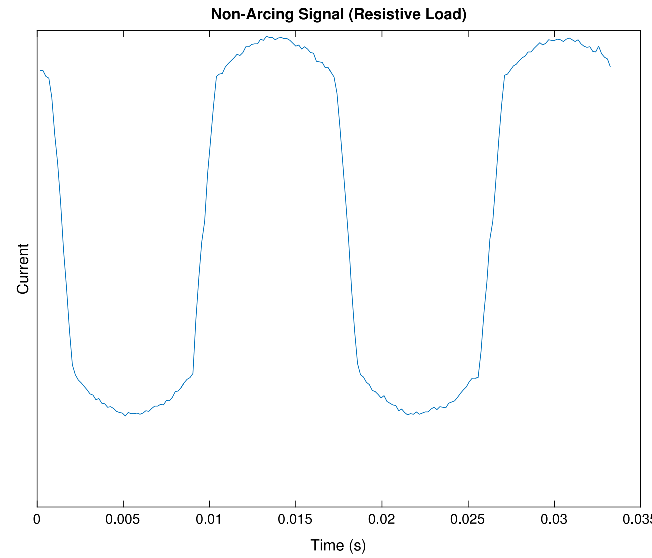

Fig. 1. This figure shows a typical smooth and periodic current trace for a resistive electrical load.

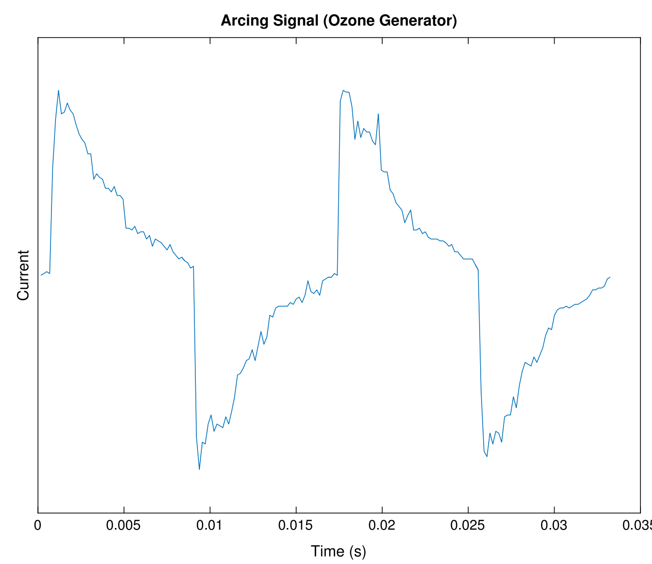

Fig. 2. In this arcing current trace, note the shoulders as the electrical potential climbs before creating an arc.

4. Experimental setup

Typical arc fault detector training data comprises arcs, nuisance trips, and normal circuits. Arc testing approaches including guillotine, carbonized path, wet arc, and loose terminals. Nuisance trip sources, designed to test false positive rejection, include motor loads, dimmers, and computers (Li et al., 2003). For normal circuits, resistive elements are used.

Earlier papers' training and testing would provide a uniform baseline for evaluation but the data were unavailable. Further, these data sets neglect multi-state classification, which is a key capability of our solution.

We instead generated data from an electric stove-top burner, an iMac computer, a fan, and an ozone generator. The burner simulates an ideal resistive circuit, the iMac switching power supply introduces noise, and the fan's DC motor arcs by design. The ozone generator represents a continuous series fault, as it relies on a high-voltage discharge to cause