ELECOMP CAPSTONE
VIRTUAL SUMMIT
FRIDAY, MAY 8, 2020

THE UNIVERSITY OF RHODE ISLAND

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FaultLine

Power Signature Analysis for Fault Detection and Predictive Maintenance

Acumentrics
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Project Motivation

All electronic devices require power to operate, a value which can be derived from voltage and current. Power consumption varies over time depending on the intended action to be performed by the device. By analyzing the power consumption, one can identify specific electrical characteristics in a device over time. Learning this unique 'power signature' allows the user the ability to identify abnormal device behavior and can be used to prevent catastrophic failure. Due to the deployment of Acumentrics' systems in secure environments, data collection cannot occur in the field. Therefore, failure analysis occurs upon the return of the system to the company. Similar to earthquake prediction - accomplished by analyzing characteristics at notable fault lines - the goal of the project is to be proactive instead of reactive. By leveraging machine learning, our team hopes to be able to predict electromechanical failures.

Key Accomplishments

Appliance Selection: A fan was selected as our target appliance due to its low-cost, easily inducible electromechanical faults, and complex power load. Since the appliance has both real and complex power components, the power signature of the device will be more unique.

Fault Mode Induction: In order to train the ML model it was necessary to induce unique fault modes into the target appliance. Over the course of the two semesters, our team induced three fault modes within the target appliance. First one increasing the load to the motor where five quarters were attached to one blade. Second decreasing the load where a single blade was removed from the fan. The last one was burning the motor by holding the blades still for thirty seconds, repeated for 20 iterations.

Integrated Circuit (IC) Selection: After thorough research, the analog ADE7880 IC was selected for its functionality, compatibility, and accuracy. With advanced power analysis features and single/poly-phase data acquisition, the chip was an ideal choice for its high precision energy monitoring calculations that are necessary to determine unique power signatures.

ML Model Selection: A Recurrent Neural Network (RNN) was selected for our application to enable effective training on the power data. RNNs are capable of learning relationships within temporal data; given an input data series, the model is capable of learning the effect of previous entries on the currently processed value. For power data, the underlying characteristics of the signature can be understood by a RNN. However, instead of training on temporal data, the input can be converted to the frequency domain with Fast Fourier Transforms. By converting domains, the total amount of input data is decreased without negatively affecting the accuracy. To train on the non-temporal data, an alternative model was utilized, an Artificial Neural Network.

ML Training Setup Formation: A process was developed to train an ML model with the ADE7880 data. The process includes visualizing the input data, preparing the input data for the model, facilitation of the training process (via TensorFlow), and evaluation of the resulting trained model **(Fig. 3)**.

Development of the Data Collection Unit (DCU): In order to initially achieve the ABO, a system was designed to read and collect data from the ADE7880; the system utilizes the evaluation board, current sense transformers, and 3.3V power supply to calculate power data from the fan analog inputs **(Fig. 2)**. However, the system was unable to properly collect and log ADE7880 data.

Implementation of the ADE7880 Communication (ADEC) Library: To communicate between the ADE7880 and the Raspberry Pi, an IC communication library was developed; the library utilizes the Linux kernel spidev library to send and receive SPI transactions at rates of 2.5 MHz. The library API provides the functionality to read/write to ADE7880 registers, lock/unlock the Digital Signal Processor of the ADE7880, save/load a set of pre-defined calibration registers to/from a CSV, and collect data from a set of pre-defined register values.

Development of the Fault Detection Unit (FDU): Due to the shortcomings of the DCU, an improved system, the FDU, was developed. The system had two major goals: real-time data collection and real-time inference. To achieve these goals, the DCU's evaluation board was adapted into a custom PCB. This board provides the capability to not only feed the appliance's analog inputs to the ADE7880 but also providing a Raspberry Pi interface to read the register data **(Fig. 1)**. Depending on the set mode, the Raspberry Pi can append the data to an output CSV or feed it to an embedded ML model. The resulting fault prediction is then displayed on a set of LEDs **(Fig. 4)**.

Anticipated Best Outcome

The Anticipated Best Outcome is:

- A functional prototype capable of modeling a single connected device and detecting abnormalities in behavior
- The system must be non-intrusive and rely solely on the power signature of the connected device
- The system must be capable of real-time data collection as well as real-time model inference.

Project Outcome

The Anticipated Best Outcome was achieved

Figures

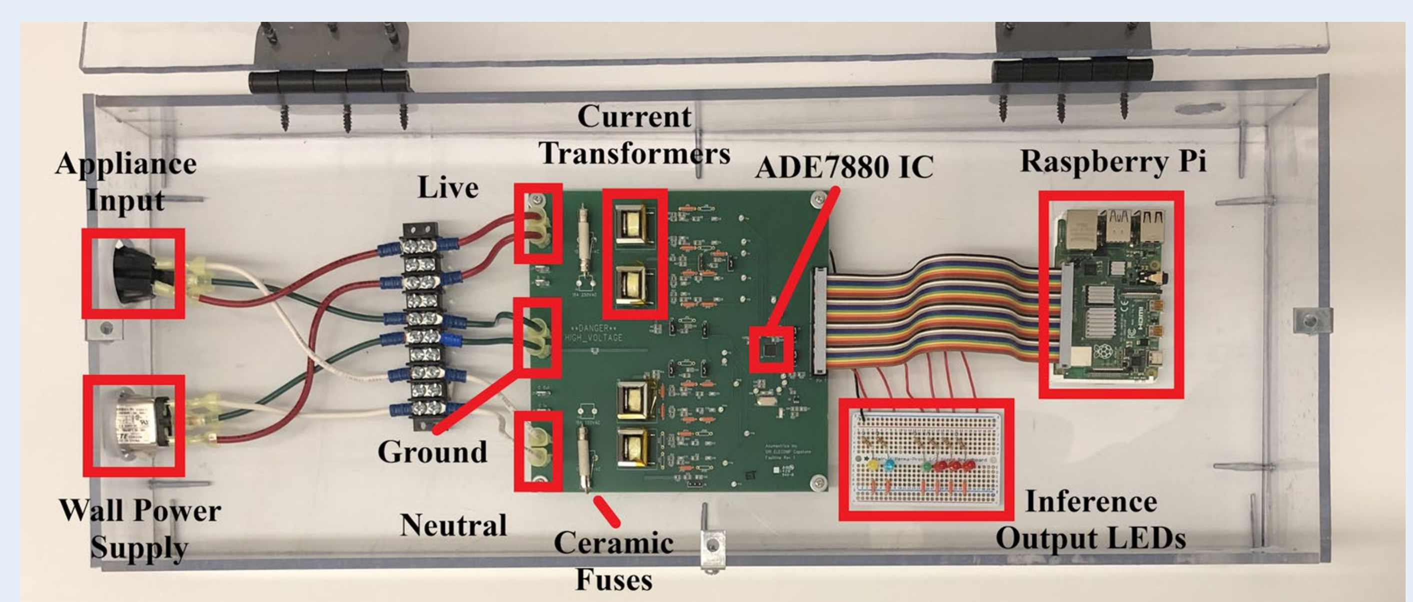

Fig.1: Fault Detection Unit Assembly

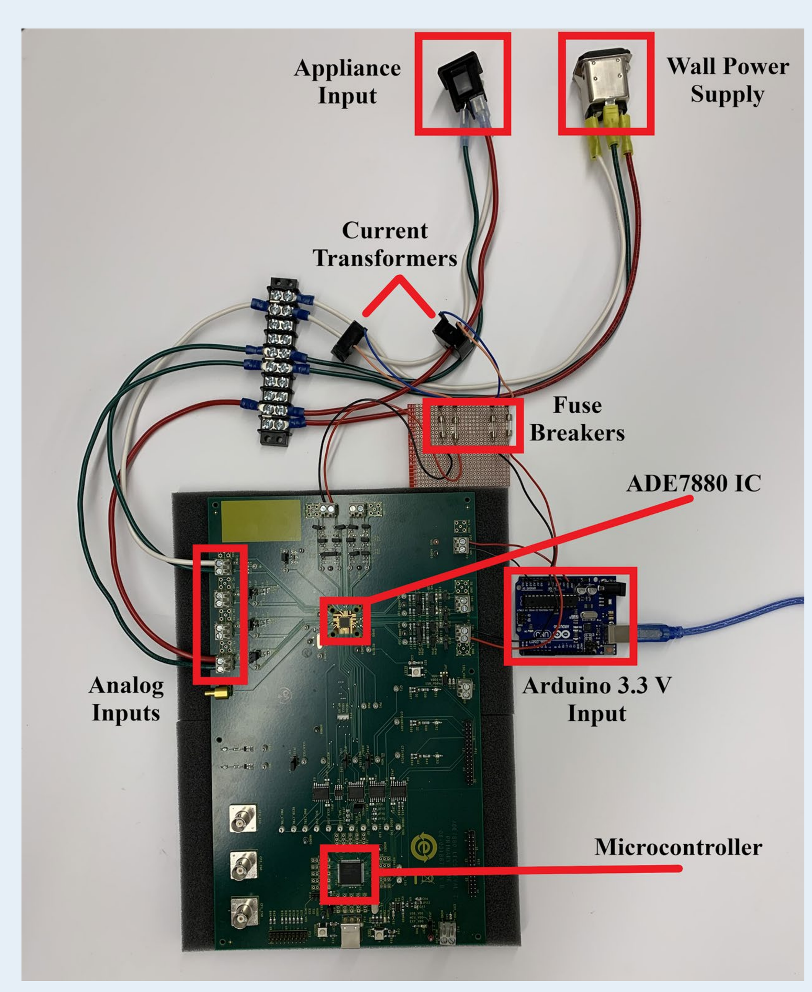

Fig.2: Data Collection Unit Assembly

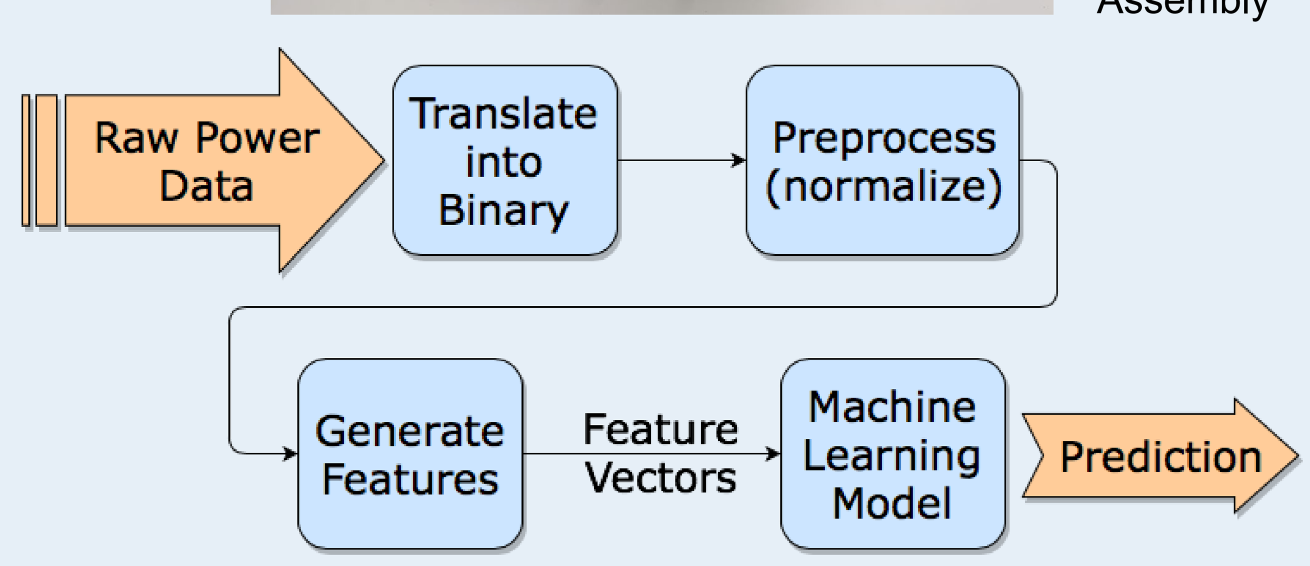

Fig.3: Machine Learning Inference Process

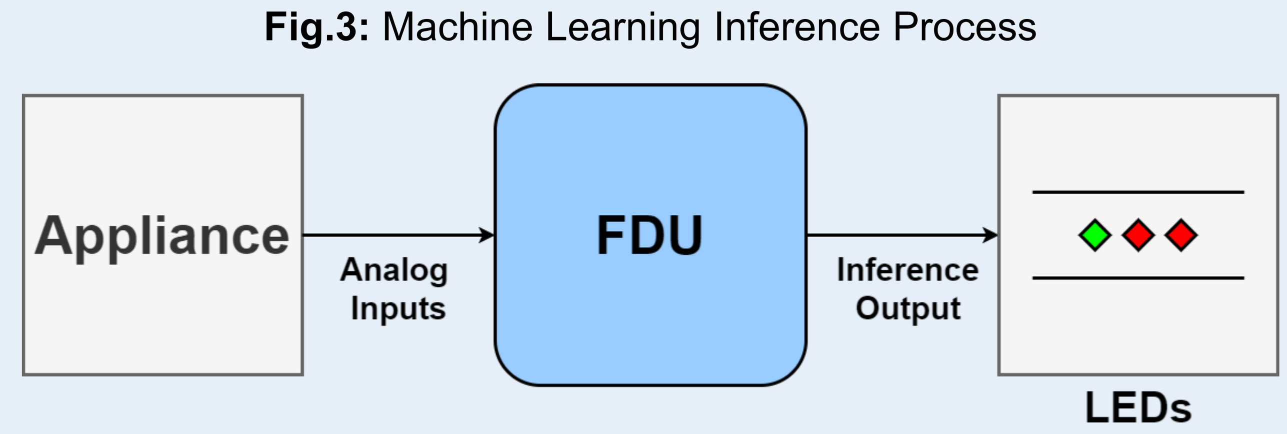

Fig.4: FDU System Overview

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