DutyCycle Analysis using Time Series data for off road vehicles

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Abstract—The integration of machine data into vehicle design research and development has been a prevalent practice in the automotive industry in recent years. This field has experienced rapid growth and maturation, evolving from basic exploratory data analysis to the utilization of data in machine learning and advanced analytics. While data science applications are commonly discussed in the on-road vehicle sector, the off-road automotive industry is also embracing these technologies.

In the Construction and Forestry, the utilization of telematics data from machines in design and development has reached unprecedented levels. There is a growing demand for collecting data at higher frequencies and resolutions. One notable application involves collecting data in a time series format to derive machine duty cycles. Duty cycle analysis involves classifying sequences of sensor-recorded data into distinct machine operations.

In the area of Deep Learning, Recurrent Neural Networks (RNNs) stand out for their ability to learn from sequential data. Long Short-Term Memory (LSTM), a type of RNN, is adept at learning internal representations of time series data and retaining information across lengthy input sequences. A trained LSTM model can predict machine operations for each time step in the sequence data. This derived duty cycle information can be further analyzed and used as input for various applications.

One practical application of this classified data is anomaly detection in machine operations. For instance, differences in operation times between novice and experienced operators can be identified. Such data can help assess operator and machine efficiency, leading to informed decision-making and performance optimization.

Keywords—Duty Cycle, Time series data, Machine Learning, LSTM models, RNN

INTRODUCTION

The data explosion is driving the automotive industry to new heights. In recent times we have witnessed rapid development over the last decade in the space from of using data just to make informed decisions to using data to enhance vehicle safety, IoT, increased uptime with predictive analytics and much more. We also see how self-driving vehicles in very near future would be a common thing around us and it will dramatically change the automotive industry. A few years ago, this was a distant fantasy and was most commonly seen in fiction. The very basic raw material to realize such technology advancements is ‘data’. In off-road vehicles too the usage of data has significantly grown over the past few years. So much is the data generation that the industry has already shifted from using on prem servers for storing data to using cloud servers for storing and managing large amounts of data. There has also been a paradigm shift in data processing, computations and it has evolved significantly. Processing a huge amount of data or training models on huge data sets is no longer a barrier in achieving data science objectives.

In automotive industry there are various streams in which data analytics is used. For example, building smarter machines, applying advanced analytics across manufacturing value chain, customer behavior analytics, marketing spend management, Supply chain management and predictive analytics for product quality management.

This paper talks about use of data collected from off highway vehicles for Engineering research and development. The focus is on deriving machine duty cycle with the data from Construction and Forestry machines. The data in talk here is of higher frequency and resolution and primarily in a time series format. The Wikipedia definition of time series is that it is a series of data points indexed (or listed or graphed) in time order. Most commonly, a time series is a sequence taken at successive equally spaced points in time. Thus, a sequence of discrete time data [1].

A duty cycle is the fraction of one period in which a signal or system is active. Simply put a duty cycle defines how much a vehicle is used in each mode of operation. The information of duty cycle can further help determine critical vehicle operation statistics. [2] These statistics can be used to determine vehicle efficiency and will help determine any anomalies which increase fuel costs of the vehicle.

While deriving a duty cycle for a vehicle or several vehicles, we must remember that every machine operation would not have
exact same profile. Which means every duty cycle would be different but at a broad level each duty cycle for a certain set of operation would fit under certain ranges or clusters. If we translate these operations in terms of data a certain operation of machine would fit under certain cluster of data. This is where it opens trails to perform some machine learning classification analysis on the data. And when the data is available in time series format it becomes a problem of classifying sequences in the data considering the time indexing of the data.

In Deep Learning, Recurrent Neural Networks (RNN) excels in learning from sequential data. LSTM is a type of recurrent neural network that can learn an internal representation of the time series data and remember over long sequences of input data. This paper will talk in detail about LSTM and how to can use it to derive duty cycle of machines from the data.

Duty Cycle Analysis
The study was conducted on an excavator machine. Excavator [3] are heavy construction equipment consisting of a boom, dipper (or stick), bucket and cab on a rotating platform. The cab sits atop a undercarriage with tracks. All movement and functions of a hydraulic excavator are accomplished through use of hydraulic fluid, with hydraulic cylinders and hydraulic motors. Excavators are used in many ways:

- Digging or trenches
- Digging holes
- Material handling
- Demolition
- Mining
- River dredging
- Driving piles
- Loading trucks
- Snow removal

categorized the work states under below basic operations of the machine.
- Dig
- Adjust to Dig
- Dump
- Adjust to Dump
- Travel

When we collect data from the machine while the machine is in above work states, certain characteristics in the data could be extracted which determines the current mode. For each mode there could be unique characteristics in the data which change. And when we have the data is the times series format, those characteristics do vary with respect to time in each mode of operation. The machine learning models can be explored to determine these characteristics in the data and classify the data for each mode. Details on the machine learning model are explained below.

Long Short-Term Memory
Long Short-Term Memory networks usually just called LSTM is a Recurrent Neural Network (RNN). [4] It can learn an internal representation of the time series data and remember over long sequences of input data. It is well-suited to learn from experience to classify, process and predict time series when there are very long-time lags of unknown size between important events. The LSTM cell (memory cell) is a specifically designed unit of logic that help reduce the vanishing gradient problem sufficiently to make recurrent neural networks more useful for long-term memory tasks. A memory cell which can maintain its state over time, consisting of an explicit memory and gating units which regulate the information flow into and out of the memory. A memory cell is composed of four main elements: an input gate, a neuron with a self-recurrent connection, a forget gate and an output gate. The self-recurrent connection has a weight of 1.0 and ensures that, barring any outside interference, the state of a memory cell can remain constant from one-time step to another. The gates serve to modulate the interactions between the memory cell itself and its environment. The input controls what new information is added to cell state from current input. On the other hand, the output gate can allow the state of the memory cell to have an effect on other neurons or prevent it. Finally, the forget gate can modulate the memory cell’s self-recurrent connection, allowing the cell to remember or forget its previous state, as needed.

Figure- 1 Deere Excavator
In all the above operations the excavator operates in certain work states or iterates between certain duty cycles. We
Following equations show how a layer of memory cells is updated at every timestep. We assume there are h hidden units and that the minibatch is of size n. Thus, the input is Xt and the hidden state of the last time step is Ht−1. Wxi, Wxf, Wxo and Whi, Whf, Who are weight parameters and bi, bf, bo are bias parameters. The gates are defined as follows: the input gate is It, the forget gate is Ft, and the output gate is Ot. [5]

It is the input gate, Ĉt the candidate value for the states of the memory cells at time [6]

\[
It = \sigma (Xt Wxi+ Ht−1 Whi + bi) \quad (1)
\]

\[
\hat{C}t = \tanh (Xt Wxc+ Ht−1 Whc + bc) \quad (2)
\]

\[
Ft = \sigma (Xt Wxf + Ht−1 Whf + bf) \quad (3)
\]

\[
Ct = Ft \ast Ct−1+ It \ast \hat{C}t \quad (4)
\]

With the new state of the memory cells, compute the value of their output gates and their outputs:

\[
Ot = \sigma (Xt Wxo+ Ht−1 Who + Vo Ct + bo) \quad (5)
\]

\[
Ht = Ot \ast \tanh (Ct) \quad (6)
\]

Duty cycle is the problem of classifying sequences of data recorded by sensor into known well-defined machine operations. For the excavator machine, the sequence of operations is Dig, Adjust to Dig, Dump, Adjust to Dump and Travel States. To analyze the duty cycle of excavator is a classical sequence classification problem and suitable to deal with the LSTM. Given Pilot pressures and Propel pressures on time series we use a sliding window with a length of N values to extract input data for the LSTM. The input data for the LSTM is a time series data of different pressures values such as Left/Right Drive forward pressure, Boom Raise/Lower pressure, Arm In/Out pressures and swing Left/Right pressures. In order to form a richer representation of the data, our model has two LSTM layers. We connected the output of the LSTM and form a new Feature vector. Finally, the feature vector is classified by a multi classifier. [7]

LSTM For Duty Cycle Analysis

We started with exploratory data analysis (EDA) approach to summarize the main characteristics of dataset. The number of observations belonging to Travel class is significantly lower than those belonging to the other classes. See the Figure-3 for Imbalanced data. We handled data imbalance problem using increasing the frequency of the minority class. See Figure-4 for balanced data.
The pressures values were normalized to have zero mean and unit standard variance. We have plotted pressures values against time on x-axis. See in the plot ‘Figure-5 Plot for time series data in Travel Operation’ which indicates left drive propel pressure and right drive propel pressure are playing role in determining travel state of the machines and other signal values are not significant.

Thus, the LSTM-based model achieves classification accuracy of 80%. To analyze the results in more detail, we show the confusion matrix for the validation datasets. The confusion matrices indicate that many of the prediction error are due to confusion between these two machine operations: “Adjust to Dig”, “Dump”. This is because these two activities are relatively similar. Our training metrics are not smooth and fluctuations because of small data sizes but if we use larger data, we improve accuracy of predication.

We split the data into train and test sets. Training data used to train the model to learn and remember internal representation data and test set is for validation of our model. Train the LSTM-model as mentioned above and observe loss and accuracy values over the N iteration. Over the training iterations the model decreases the loss and increase the accuracy. See Figure-6 to understand the training LSTM Model.

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