IMPLEMENTATION OF DEEP LEARNING TO PREVENT PEAK-DRIVEN POWER OUTAGES WITHIN MANUFACTURING SYSTEMS

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Abstract:

In this paper, a solution to effective energy consumption monitoring of fast-response energy systems in industrial environments was deployed, while the research focuses on the manner and intensity of energy use in the observed system as a consequence of nonlinearity in the dynamic systems performance, with the aim to predict the near future relatively accurately. Paper addresses the quite common but still an inevitable case for majority of manufacturing systems where constant jumps in peak loads on several machines simultaneously lead to the situation that the entire system remains without power supply. This paper proposes a deep learning method, based on enhanced recurrent neural network (*RNN*), more precisely LSTM network (*Long Short-Term Memory*) to effectively predict future machine state in terms of energy consumption five steps ahead. The data sets were obtained for eight machines in one CNC metal-forming center on a monthly level on a one second sampling rate by the means of previously developed IoT device.

Keywords: manufacturing, energy consumption, IoT, deep learning, LSTM.

1. Introduction

The manufacturing sector has a critical role in the general economy's supply chain, as being recognized as an indispensable component that ensures delivery of goods and services to other economy sectors. However, frequent power failures, driven by process machine operations as is the case within CNC machining processes, are sometimes inevitable, because the switching capacities of machines are often many times higher in capacity than in the case with switches in electrical cabinets for powering the process itself. Due to this reason, frequent power outages can occur, bringing operations to a screeching halt and contributing to a productivity, revenue and material losses. Specifically, power outages force production systems to deal with production lines pushed to a sudden stagnation. This further manifests in inability to produce and assemble goods, increase in downtime that eventually affects supply chains to shut down altogether.

Traditionally, this problem was being solved eventually by improving managing of electrical layout, relying on backup generators, frequent testing to prevent faulty behaviors, and so on. Moreover, with regular, time-based maintenance intervals, production machinery are often subjected to maintenance although no actual need for such activity exists, while components, tools and accompanying elements are superseded as soon as their operation time expires or is close to expiry [1]. In many cases, those components could still be utilized. On the other hand, there are cases in which specific components reach an operating threshold before the regular time-based maintenance schedule and, before failure, perform faulty tasks that trigger the problem occurrence in other fields, such as increasing the current intensity of the motors, which leads to power outages due to excessive simultaneous loading. In response to previously mentioned, some studies recognized that near real-time processing of energy data could directly indicate certain anomalies in components, tools and overall machine operation [2-4], while the exponential rise of IoT and AI breakthroughs could support manufacturing systems to understand the vast amount of data fast and utilize generated information to predict and prevent downtime.

2. Observed system overview and proposed solution

For the purposes of analysis, the production system for metal forming and CNC processing was observed. This system represents a machine park specialized in the automotive and aerospace industries, with a focus on the production of machine parts, elements, components, assemblies and subassemblies in flexible and scalable processing. The collection of data on the current intensity was performed with the deployment of previously developed IoT device [5] which schema and outlook are given in Fig. 1.

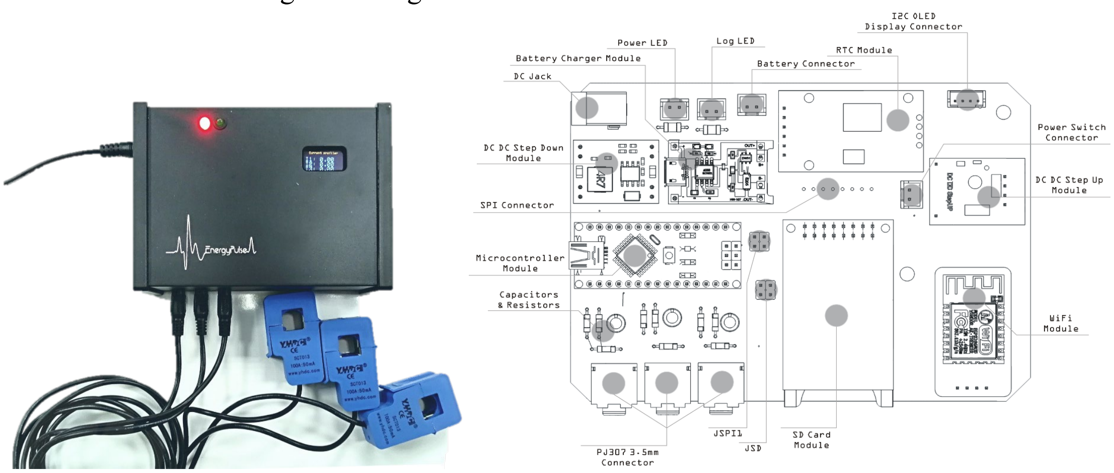


Fig. 1. IoT device for data acquisition [5]

The data were recorded for one operating month with one second sampling rate. Table 1 provides a review on data volume and structure.

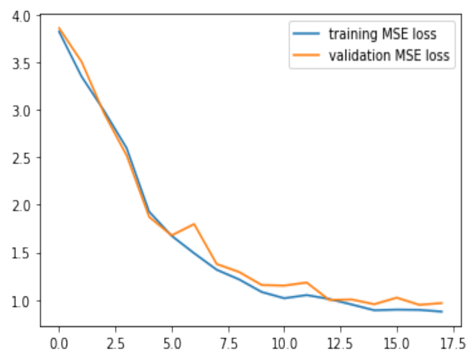
No.	Machine designation	Machine type	No. samples	Sample structure
1	HAAS SL 20 HE	lathe	2.694.778	[Date, Time, S1, S2, S3, T] (date, time, current 1, current 2, current 3, temperature)
2	HAAS SL 20 THE (1)		2.480.446	
3	HAAS SL 20 THE (2)		2.587.392	
4	HAAS ST 20 Y		2.573.452	
5	SCHMID VMC-800P	mill	171.592	
6	SCHMID VMC-500P		2.571.390	
7	Pinnacle VMC1100S		1.342.193	
8	Kasto SBA-260AU	saw	2.393.416	

Table 1. Acquired data volume and structure

2.1 Deep learning model

When it comes to fast and accurate forecasting based on time series as a primary tool in the field of energy-based predictive maintenance, LSTM (*Long Short Term Memory networks*) models turned out to fit among the most suitable choices [6]. The main reason lays behind the fact that LSTMs are designed with the aim to avoid the long-term dependency problem, while remembering information for long periods of time is actually their default behavior, and not something they struggle to figure out [7].

The model task is to be able to predict the next five steps based on a given time series, i.e. in this case the sequence of 30 values, based on which it should predict the next 5. The model structure considers 2 LSTM with Relu and 5 Dense layers with linear activation. ADAM is defined as an optimizer, and losses are monitored through MSE and MAE. Model is set to save the best only epoch in terms of MSE on validation data (Vmse) with patience = 3 and minimum delta = 0.001. Training and validation were performed on a subsample of CNC milling machine energy consumption dataset in a ratio 80/20, respectively. Model evaluation was carried out on a CNC lathing machine energy consumption dataset. After 17 epochs, the model reached the best possible result within current architecture, with MSE = 0.9454 (Fig. 2).




```
model = Sequential(name='lstm_5steps')
model.add(LSTM(512, activation='relu', return_se-
quences=True, input_shape=(lag, 1), name="lstm_0"))
model.add(LSTM(512, activation='relu', name='lstm_1'))
model.add(Dense(256, name='dense_0'))
model.add(Dense(128, name='dense_1'))
model.add(Dense(64, name='dense_2'))
model.add(Dense(32, name='dense_3'))
model.add(Dense(predict_steps, name='dense_4'))
model.compile(optimizer='adam', loss='mse', metrics=['mae'])
early_stop = EarlyStopping(monitor='val_loss', pa-
tience=3, min_delta=0.01)
save_checkpoint = ModelCheck-
point(save_weights_only=False, save_best_only=True, filepath=
'pinnacle_model_5steps_bst.h5' )
```

Fig. 2. Loss function monitoring for training and test dataset and model architecture

The generated model can predict the given future state (based on the previous 30, it can predict 5 steps in the future), on the validation set of data for the Pinnacle VMC 1100S machine with MSE = 0.9454. This model shows acceptable results due to its complexity, while an increase in MSE is expected for each subsequent increase in forecasting steps.

2.2 Solution integration into manufacturing system

The solution integration into the observed manufacturing system is illustratively given in Fig. 3. Each process machine was equipped with a previously mentioned IoT device to acquire and publish data. The communication is provided via MQTT protocol and data are stored on the server DB. LSTM model is also located on the server, while the user dashboards are provided via web app supported by Grafana services.

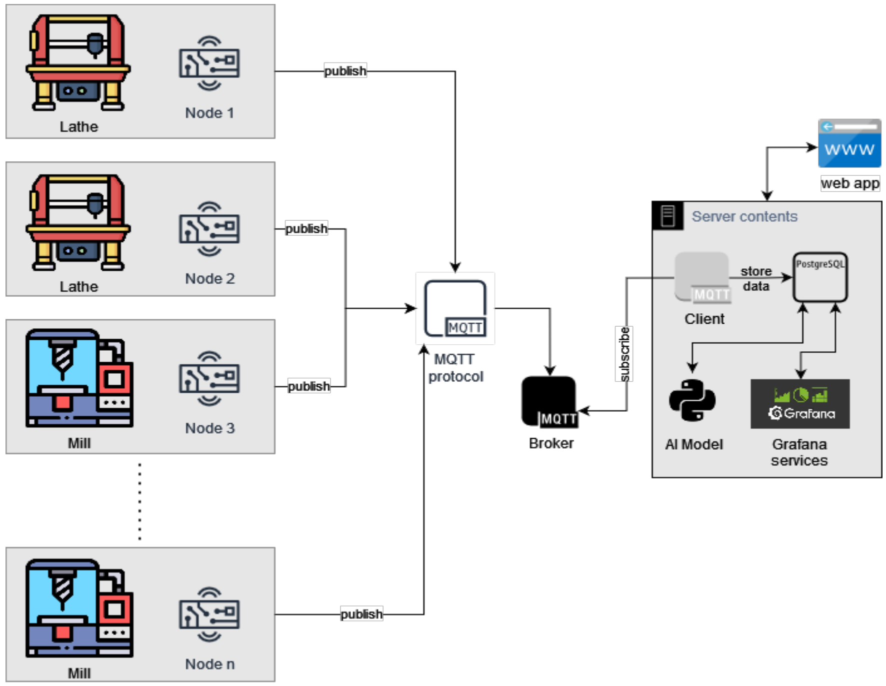


Fig. 3. Solution implementation diagram

Within this environment, developed AI model could help in real-time detection of anomalies in terms of increase of power consumption for each machine as well as to point out the increasing frequency of peak loads occurrence for each specific case.

3. Conclusions

The proposed solution represent a real industrial case that combines integration of IoT and AI with the aim to improve overall production efficiency by eliminating downtimes due to power outages caused by inadequate maintenance procedures. Beside this, real-time monitoring enables its user to effectively track suspicious events and prevent problem escalations.

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