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Machine learning framework for energy management in smart manufacturing

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ABSTRACT

The dynamic nature of manufacturing production environments, along with numerous machines, their unique activity states, and mutual interactions render challenges to energy monitoring at a machine level. To this aim, a machine learning framework is presented, to predict the machine-specific load profiles via energy disaggregation, and these machine-specific load profiles are in turn used to predict the machine's activity state as well as their respective production capacities. Various supervised machine learning algorithms such as GBDT, XGBoost, LightGBM, LSTM and BLSTM were evaluated on their capacities to predict load profiles and production capacities of four machines investigated in this study. LightGBM and EnBLSTM were identified as the respective best performing algorithms with an average MAE and RMSE of 0.035 and 0.105 for disaggregation studies and 1.64 and 11.41 for production capacity estimation. Four unsupervised machine learning algorithms, namely K-means, minibatch K-means, HMM and GMM were evaluated to cluster the machines activity states from their disaggregated load, where the GMM algorithm had a superior performance with the V score and Fowlkes-Mallows index of 0.85 and 0.98, respectively. The framework and methodology developed in this study are purely data-driven, cross-deployable and serve as promising catalyst to foster smart energy management practices and sustainable productions in the manufacturing industry.

Keywords: smart energy management, energy disaggregation, smart manufacturing, machine learning, big data, data-driven analytics

NONMENCLATURE

Abbreviations	
BLSTM	Bidirectional Long Term Short Memory
CPPS	Cyber Physical Production Systems
FM Index	Fowlkes Mallow Index
GMM	Gaussian Mixture Model
HMM	Hidden Markov Models
LightGBM	Light Gradient Boosting Machines
LSTM	Long Term Short Memory
LT	Laser Trimmer
LW	Laser Welder
MAE	Mean Absolute Error
ML	Machine Learning
RMSE	Root Mean Square Error
XGBoost	Extreme Gradient Boost

1. INTRODUCTION

Determining and understanding energy use at every stage of the manufacturing process is critical for optimizing manufacturing processes in order to reduce energy consumption (1,2). Thus metering and analysis of energy load profiles in manufacturing shop floors is imperative to track consumption, evaluate potential energy savings, and reduce environmental impacts (1). Given the significance of energy profiling and management in manufacturing industries, notable works have been accomplished in recent times. Rodrigues et al. (3) analyzed electrical energy consumption in a manufacturing system, of a complete process as well as that of individual machines, by coupling discrete event simulation (DES) with optimization tools. Seow et al. (4) developed a methodology to model energy flows within a manufacturing setting using both direct and indirect energy consumption data and computed a breakdown of energy at each step during production of a single product. Herrmann et al. (5) devised an energy-oriented manufacturing simulation platform to provide a flexible, scalable and modular simulation environment. However, given the dynamic nature of manufacturing production environments, along with the presence of numerous machines, their intricate interactions and various activity states, estimating and understanding the energy profiles for each process and at a more granular machine level is challenging, either due to lack of disaggregated load profiles, or methodological knowledge or generic techniques to accomplish the same (6,7).

In this study, we propose a generic methodology to estimate the load profiles of individual machines in a production environment via energy disaggregation fostered by supervised machine learning. The machine-specific load profiles are in turn used to predict the machine's activity state as well as their respective production capacities. The primary essence of the study is to bring forth not just conceptually, but also demonstrate– on how the vision of *Industry 4.0* fostered by industrial big data and machine learning can be realized for smart energy management in production environments (8). The Model Factory at the Singapore Institute of Manufacturing Technology (SIMTech) which is an actual pilot-scale production environment, supports platforms such as Cyber Physical Production Systems (8) was chosen as an ideal testbed for this study.

2. MATERIALS AND METHODS

2.1 Data acquisition

The primary source of data used for modelling purpose and reported throughout the paper was sourced from the Model Factory at SIMTech. Four machines in the Model Factory, namely, laser welder (LW), laser trimmer (LT), oven 1 and oven 2, were identified and selected, to log machine-specific data via satec PM135 sensors.

For each of the four machines, the following information were logged: individual electrical load profile in watts (W), production throughput (quantity), operational states (1 = *off*, 2 = *production* and 3 = *idle*) at a frequency of 1 minute (high frequency) for a duration of 15 months spanning from October 2017 to December 2018. Once the individual load profiles of the 4 individual machines were obtained, they were summed up to formulate a new variable called "*cumulative load"* (watts) for each timestamp in the dataset. Given the demonstrative nature of the study an assumption was made that, the calculated cumulative load would mimic and represent the aggregate load (central power) requirement.

2.2 Energy disaggregation

Conventionally, the algorithms used to study energy disaggregation can be broadly classified into hidden markov models (HMM), deep learning and machine learning models (8,9). To this aim, we compared and evaluated various state-of the art algorithms such as GBDT, XGBoost, LightGBM, LSTM, BLSTM and their ensemble form i.e. ensemble LSTM and BLSTM (henceforth referred as EnLSTM and EnBLSTM respectively) to determine their ability to disaggregate the central power supply to the machine-specific load-profiles i.e. individual load profiles for laser welder, laser trimmer, oven 1 and oven 2 in this study.

The *cumulative load* profile was defined as the input feature whereas the individual load profiles of were the target labels and the entire data was first split into a training and testing dataset with 80:20 ratio. The training data was then fit onto the aforementioned algorithms, and their hyperparameters were tuned using the Bayesian optimization (10) strategy. For each combination of hyperparameters, 3 models were trained and evaluated using the folds of the training data dictated by the time series 3-fold cross validation method. Once the optimal hyperparameters for each of the algorithms were identified during the training phase, the algorithms with the same configuration were used in the test phase, to predict the machine-specific disaggregated load and compared with the actual disaggregated load and, both mean absolute error (MAE) and root mean square error (RMSE) (11) were considered as an evaluation criterion, as these metrics are widely used for time-series data.

2.3 Activity mode clustering

An understanding of the machine-specific activity mode can provide insights on value-added and non-value-added energy. To this cause, the disaggregated load profiles of the individual machines as listed in section 2.2 were subjected to four unsupervised-clustering algorithms, namely mini-batch K-means, K-means, hidden markov model (HMM) and Gaussian mixture model (GMM) to predict their respective activity-states, where the following labels were used: cluster 1 = *off*, cluster 2 = *on* (production) and cluster 3 = *idle* state.

A simple grid search based tuning method was employed to tune the above-mentioned clustering algorithms. During the tuning stage, the hyperparameter combinations with higher V score and Fowlkes Mallow (FM) index were chosen (12). In the account of a tie in the V scores and Fowlkes mallow scores among the several hyperparameters set, the combination that was least computationally intensive (in terms of faster execution time) was selected as the best performing algorithm.

2.4 Production estimation

Machine learning methodologies can aid production estimation (in terms of quantity of batches or single product; which is essential for production planning and scheduling) by learning from disaggregated load profiles at a machine level- a classical example of predictive analytics. Thus, the disaggregated load profiles of the four machines were used as input features to predict their respective production capacities.

Table 1. Machine specific details

Equipment	Status	Active State	Load Range (W)	Quantity*	Batch time (mins)
LW	Off	1	0		
	Production	2	0.019-0.740	1	< 1
	Idle	3	0.33-0.790		
LT	Off	1	0		
	Production	2	0.002-0.860	1	< 1
	Idle	3	0.162-0.860		
Oven 1	Off	1	0		
	Production	2	0.054-5.340	60	35
	Idle	3	0.406-5.102		
Oven 2	Off	1	0		
	Production	2	0.051-5.702	60	35
	Idle	3	0.390-5.018		

For all the four machines investigated in this study, the disaggregated load profiles for each of the machines, recorded at minute-level intervals, were transformed to cumulative load profile in Watts (W) to an hourly basis i.e. *cumulative load profile per hour*. Four such unique profiles were created w.r.t to each of the machines, and were labelled as input features for production estimation. Similarly, the original individual production quantity for each of the machines was transformed to *cumulative production quantity per hour* and was labelled as target features. The following algorithms, namely, XGBoost, LightGBM, LSTM, BLSTM and EnLSTM and EnBLSTM were evaluated for their comparative performance and their hyperparameters tuned using the Bayesian optimization strategy. **Table 1** presents the details of the machine-specific activity-states and their corresponding typical load ranges along with number of samples processed during production.

3. RESULTS

3.1 Energy disaggregation

For each of the algorithms evaluated, the hyperparameters were tuned using the Bayesian optimization strategy to find the best set of configurations for each of the respective models, such that they would yield greater accuracy in their prediction performance and the algorithms with the same configuration were used in the test phase, to predict the machine-specific disaggregated load and compared with the actual disaggregated load.

Table 2 represents the MAE and RMSE values for each of the algorithm evaluated and are ranked in order from least to highest.

Table 2. Comparative evaluation of algorithms based on MAE and RMSE values

Ranking	Algorithm	MAE (W)	Algorithm	RMSE (W)
1	LightGBM	0.035	EnBLSTM	0.101
2	XGBoost	0.036	EnLSTM	0.103
3	EnBLSTM	0.039	XGBoost	0.106
4	BLSTM	0.040	LightGBM	0.106
5	EnLSTM	0.041	BLSTM	0.110
6	LSTM	0.049	LSTM	0.117

A trade-off chart (not included) was developed to capture the combined effects of the MAE and RMSE on the model accuracy, where the combined performance of the top three algorithms, as identified by the MAE-RMSE trade-off chart in decreasing order was LightGBM > EnBLSTM > XGBoost. **Figure 1** represents the cumulative load profile along with disaggregated profiles for each of the machines as predicted by the LightGBM model in the test process.

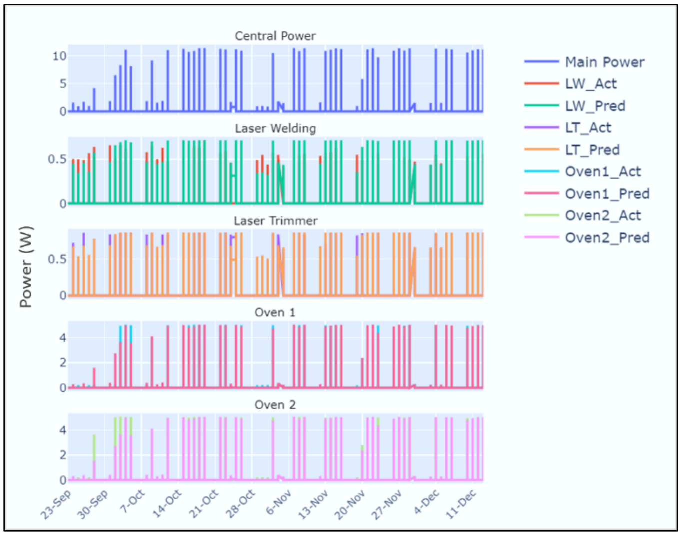

Figure 1. Disaggregated load profiles of the individual machines on the test dataset using LightGBM algorithm yielded an average MAE and RMSE of 0.0351 and 0.105

3.2 *Activity-state clustering*

The comparative evaluation of the four algorithms for activity state determination as presented in **Table 3**. It was observed that the GMM produced the best clusters in terms of highest V score, Fowlkes-Mallows index while also being computationally less intensive. Interestingly, there was an evident difference in clustering performance between the probability based (GMM and HMM) and distance-based clustering (K-means and minibatch K-means), and it was observed that the probability-based algorithms outperformed the latter in terms of higher V score and Fowlkes-Mallows index. Another interesting observation was that, if only the time taken for model convergence was considered, the minibatch K-Means was the best performing algorithm while the HMM was the poorest. Figure 2 represents the cluster plots for oven 2 and laser trimmer as predicted by the GMM algorithm

Table 3. Comparative evaluation of the clustering algorithms to determine machine-specific activity states

Machine	Algorithm	V score	FM Index	Execution Time
Laser Trimmer	Mini Batch K-means	0.785	0.968	**1.205**
	Kmeans	0.785	0.968	1.556
	HMM	0.833	0.978	19.198
	GMM	**0.833**	**0.978**	**1.35**
Laser Welder	Mini Batch K-means	0.793	0.974	2.311
	Kmeans	0.793	0.976	2.388
	HMM	0.812	0.981	20.474
	GMM	**0.830**	**0.984**	2.572
Oven 1	Mini Batch K-means	0.634	0.915	**1.427**
	Kmeans	0.634	0.915	1.947
	HMM	0.834	0.98	19.442
	GMM	**0.878**	**0.982**	2.438
Oven 2	Mini Batch K-means	0.634	0.915	**1.427**
	Kmeans	0.634	0.915	1.947
	HMM	0.834	0.98	19.442
	GMM	**0.878**	**0.982**	2.438

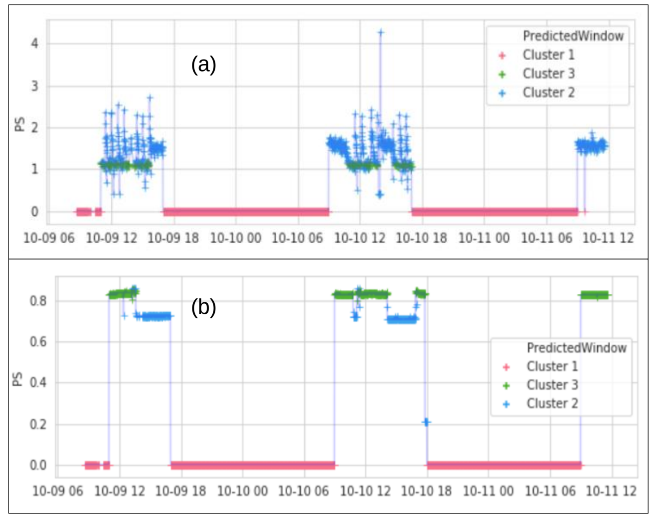

Figure 2. Cluster plots for (a) Oven 2 (b) Laser Trimmer based on GMM

3.3 *Production estimation*

Post the hyperparameter tuning, the algorithms with the optimal configuration were compared and evaluated to predict the production quantities for each of the four machines on the test data and the results are presented in **Table 4**. Based on the MAE and RMSE values determined from the prediction, it was observed that the algorithms could be further classified into 3 subgroups i.e. Ensemble Neural Networks, XGBoost, and Neural Networks. The EnBLSTM had the best model performance given their least MAE and RMSE values. In general, ensemble neural networks (EnLSTM and EnBLSTM) performed much better than the neural network models (LSTM and BLSTM) as evidently seen from their lower MAE and RMSE compared to the latter. **Figure 3** represents the actual and predicted production quantities for each of the machines as predicted by the EnBLSTM algorithm on the test data.

Table 4. Comparative evaluation of algorithms for production estimation based on average MAE and RMSE

Ranking	Algorithm	MAE (n*)	RMSE (n*)
1	EnBLSTM	1.639	11.40
2	EnLSTM	1.641	11.41
3	XGBoost	1.892	11.61
4	LSTM	2.254	12.48
5	BLSTM	2.301	12.64

n*: Production quantity (batches in the case of oven 1 and 2 and individual units for laser trimmer and welder)

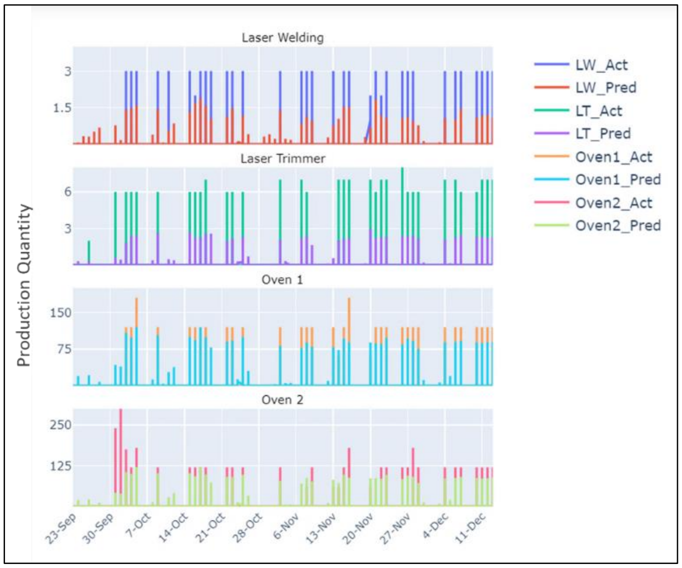

Figure 3. Production plots for the machines based on EnBLSTM

4. CONCLUSION

The transformation of the manufacturing industry towards a more energy efficient and sustainable one is faced with plentiful challenges – where the lack of methodological knowledge or generic techniques to accomplish the same is highlighted. To address the same cause, this paper brings to forth, a generic framework for energy management in manufacturing environments, which is purely data-driven. The feasibility of ML algorithms to predict machine-specific load profile was evaluated, which can be further used to quantify other essential parameters (such as activity states and production quantity estimation), fostering the drive towards the transformation of sustainable, smart and energy-efficient production planning and operations. Given the fact that all the supervised and unsupervised ML models developed in this study served their intended purpose, our future investigations would be twofold: to expand and evaluate the cross-deployment of the energy disaggregation studies aimed to more machines and also consider machine-machine interactions.

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