Towards an efficient and interpretable Machine Learning approach for Energy Prediction in Industrial Buildings: A case study in the Steel Industry

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***Abstract*— Energy consumption worldwide has increased significantly over the past few decades due to increasing population and economic growth. Efficient building energy consumption prediction plays an important role in energy planning, management, and conservation in smart buildings. This paper presents a new machine learning (ML) approach for the prediction of energy consumption in industrial buildings. It presents a trade-off between the performance and the interpretability of ML models which are major issues for building energy prediction using ML. The applicability of the proposed approach is demonstrated by a real case study to predict energy consumption in the steel industry. It shows that the Random Forest (RF) model provides the most effective prediction results, and the permutation feature importance helps the steel industry experts to better understand the judgments of the model. Hence, it will assist them to optimize energy consumption and make the most appropriate decision in industrial buildings.**

Keywords*— *Energy prediction, IoT, machine learning, smart industry buildings, interpretation, efficiency.

I. INTRODUCTION

Energy is considered an essential factor in economic and social development. Over the past few decades, the energy problem is becoming more and more serious, due to the advancements in electricity-dependent machinery. Hence, the actual energy consumption of the building is one of the important links in the field of building energy conservation. Therefore, the energy prediction of machine tools plays an irreplaceable role in energy planning, management, and conservation in the manufacturing industry [1]. According to [2], the prediction of building energy consumption is crucial for improved decision-making towards reducing energy consumption and CO2 emissions, because it can assist in evaluating different building design alternatives and building operation strategies (in terms of their energy efficiency) and improving demand and supply management.

Traditional building energy prediction methods fail to fully consider the complex characteristics of building energy consumption, resulting in unsatisfactory prediction results [3] [4]. At present, the integration of the latest technologies including the Internet of Things (IoT) and data analytics in energy prediction can optimize and enhance energy usage and distribution in smart buildings.

Several IoT-based energy prediction solutions were proposed by different researchers [5, 6, 7, 8, 9, 10]. Most of these approaches did not address the considered IoT architecture like in [5, 6, 7], which leads to a lack of detail about the implementation of the proposed solution. However, some existing approaches [8, 9, 10] describe the used IoT architecture to give an overview of the application of IoT technology in building energy prediction.

These approaches are generally based on different ML algorithms (such as decision trees, k-Nearest Neighbors, support vector machines, random forests, etc.) to predict energy consumption in smart buildings. They have been used successfully in several cases, but they still have two major problems: (a) the gap between actual and predicted energy consumption and (b) the misunderstanding by domain experts of model predictions.

Indeed, the first challenge facing ML techniques is to offer an accurate and efficient prediction, which is important for energy trading companies. In fact, accuracy directly translates into profits: the more accurate and efficient the prediction, the more money they make [5]. The second challenge is the interpretability of ML models. The most successful ones are black-box models, i.e., whose inner workings are not clear, such as deep learning, random forest, SVM, etc. However, domain experts are reluctant to adopt these models because they cannot interpret their predictions and verify their reliability.

This study aims to address both issues. We propose a novel ML approach for predicting energy consumption in industrial buildings. It presents a trade-off between performance and interpretability. The performance is ensured by a data preprocessing phase to make the real-world usable by any ML algorithm and to ensure a good performance of the ML models. Interpretability is obtained by determining the most important features as well as those that are unnecessary using the permutation feature importance method.

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The applicability of the proposed approach is demonstrated through a real case study to predict energy consumption in the steel industry. We compared the prediction performance and training time of eight ML techniques of different types (stand-alone, ensemble, and deep learning). Then, we proposed a global interpretation step to allow steel industry experts to better understand the models' judgments.

The remainder of this paper is organized as follows: Section II provides preliminaries. Section III presents the related works on ML for building energy prediction. The proposed approach is exposed in section IV. We present a real case study to predict energy consumption in the smart steel industry using efficient, accurate, and interpretable ML models. Section V provides results and discussion before presenting the conclusion drawn from this work in Section VI.

II. PRELIMINARIES

To understand our approach, knowledge about IoT-based architecture for energy prediction in smart industry buildings is very important. Indeed, the IoT architecture describes the steps of acquisition, transfer, and analysis of data to measure and predict energy consumption. It allows effective communication between power distributors and customers by predicting future power use, which can make industry building more efficient and satisfy the changing energy demand.

In the following, we present the IoT architecture considered in our energy prediction approach. It consists of four layers, as shown in Fig.1:

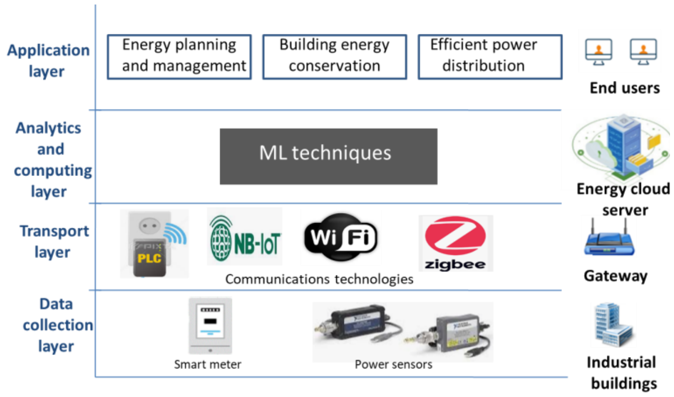

Fig1. IoT-based architecture for energy prediction in industrial buildings.

- **Layer 1: Data collection**

It is the first layer of the architecture. It consists mainly of acquiring data from many sensors and transducers and processing them in real time. Such data contain information concerning energy consumption, energy demand, energy amount, and power quality, produced in each node of the power grid which must be made available to allow the electric grid to manage properly and efficiently the energy flow. Therefore, the traditional power meters used in the power grid have been at first conceived as sensing systems able to provide data concerning the energy consumption in terms of active power used to bill the consumption of the final electric user. At present, modern smart power meters add further features and functionalities such as the possibility to control and measure remotely consumption. Furthermore, it uses improved metrics to measure the quality of the current and voltage signals, which can optimize power management on the grid [11]. It also offers the possibility to take decisions based on measures.

The smart power meter allows users to get information on active, reactive, and apparent power, power factor, voltage, current Total Harmonic Distorsion (THD), peak power, and instantaneous power values [12]. Therefore, the aim of the new smart power grid is not just only to evaluate accurately the power consumption of each user but rather to efficiently route the energy flows paying attention to user demand and quality requirements.

- **Layer 2: Transport**

It sends the collected data from the previous layer to the energy cloud server for further storage and analysis. It uses different communication technologies, both wireless and wired. Several factors must be considered to decide on communication technology to use in Smart Grid and smart metering. Requirements include aspects such as geographical topography, technical and operational requirements, and cost. Therefore, wireless technologies, such as 5G (NB-IoT), WiMAX (IEEE 802.16), ZigBee (IEEE 802.15.4), and Z-Wave (IEEE 802.15.4), Wi-Fi (IEEE 802.11), and LoRa, have some advantages over wired communication. They are less costly to implement in complex infrastructure, easy to install in some areas, and provide connectivity in inaccessible areas. Wired communications, such as Power Line Communication (PLC), Fiber Optical and Ethernet, will not necessarily struggle with interference issues as wireless solutions may do. Both types of communication technologies are necessary to transfer data from smart power meters to energy cloud servers.

- **Layer 3: Analytics and computing**

The collected and transferred data are then prepared and analyzed using different ML techniques for energy consumption prediction. Research works based on these techniques will be discussed in detail and compared in section III. It should be noted that our proposed approach is defined in this layer. It is based on several machine learning techniques for predicting building energy consumption. It will be described in section IV.

- **Layer 4: Application**

It is the topmost layer in the architecture. It interacts with end users for further analysis and decision-making. It applies the data process results from the data analytics and computing layer and offers building users various services such as energy planning and management, building energy conservation, energy-saving strategy formulation, and a more efficient and reliable functioning power distribution system. It also includes the building's future power needed estimation. Hence, the prediction of energy consumption is important to maintain stability between the demand and supply of electricity in smart buildings. In the next section, we will study some recent ML methods used for the prediction of energy consumption in smart buildings.

III. RELATED WORK: USING MACHINE LEARNING FOR BUILDING ENERGY CONSUMPTION PREDICTION

As mentioned previously, our proposed approach is defined in the 'Analytics and computing layer' which is based on several machine learning techniques for predicting building energy consumption. Therefore, we have considered several research works that include machine learning (ML), the internet of things (IoT), and building energy management communities. Instead of focusing on specific conferences and journals, we have performed keywords-based queries like 'building energy consumption prediction', 'machine learning, 'deep learning', 'data analytics', 'interpretable machine learning' and 'internet of things'. We have discarded papers published before 2016 as we wanted to focus on recent works. These keyword-based queries returned more than 100 research papers. We read their abstracts and selected those which presented smart buildings' energy consumption prediction using ML techniques. Of the remaining papers, we focused on approaches that seemed appropriate to our research questions. Following this methodology, we selected 10 papers that we analyzed in depth in Table 1.

TABLE I. SELECTED APPROACHES USING ML FOR ENERGY CONSUMPTION PREDICTION

Ref.	c1	c2	c3	c4	c5	c6	c7	c8
[13]	✓	✓	✓	*	SVM	✓	S	*
[14]	*	*	*	*	LR	*	S	-
[15]	✓	✓	✓	*	XGBoost, SVM, and kNN	✓	E	✓
[16]	*	*	*	*	MLP	✓	D	✓
[17]	*	*	*	*	Extreme learning machines	✓	D	*
[18]	*	✓	✓	*	MLP	✓	D	*
[19]	*	*	✓	*	General LR, Regression tree, SVM, KNN and CUBIST	✓	S	✓
[20]	✓	✓	*	*	MLP, kNN and SVM	✓	D, S	*
[21]	✓	✓	✓	*	Catboost, XGBoost, and MLP	✓	E	*
[22]	✓	✓	✓	*	MLP, GB, DNN, RF, Stacking, kNN, SVM, DT and LR	*	E, S, D	*

(✓) Yes, (*) No

We compare the selected solutions according to three main criteria: *(a)* the data processing mechanisms implied by each work, (b*)* the ML technique(s), and (c) the interpretation method employed by the work. We give special attention to the following steps in data pre-processing: cleaning (**c1**), data conversion (**c2**), feature extraction and selection (**c3**), data augmentation (**c4**), the ML algorithm(s) (**c5**), the hyperparameters tuning (**c6**) and the type of ML method (**c7**) (ensemble learning method (E), stand-alone method (S) or deep learning method (D)). We also reported whether the authors used an interpretation method to explain the models' predictions (**c8**).

We can notice from Table 1 that the researchers of the selected works present several methods based on different ML algorithms among which four are the most used, namely Support Vector Machine (SVM), k-nearest neighbors (kNN), Naive Bayes (NB), and Multilayer perceptron (MLP). The first three algorithms are represented as standalone methods because they train a single model to predict building energy consumption while the fourth algorithm (MLP) is a deep neural network. Another observation we can make is the other works use ensemble methods that combine the prediction of different models that are built with different algorithms like in [15, 21, 22] or ensemble methods that combine the predictions of several models built with the same algorithm namely the decision tree, such as the random forest (RF) and the gradient boosting (GB) used in [22].

Despite the variety of the used algorithms, the gap between actual and predicted energy consumption remains a problem. This problem may be due to an overfitting problem of the model which fits the training data too well but is unable to accurately predict the unseen test data. Indeed, the efficiency of an energy prediction method does not only depend on the chosen algorithm and its hyperparameters but there are also other important factors such as ensuring a good quality of training data. The raw data obtained from IoTs are usually noisy, scattered, and even incomplete. As we can see from Table 1, the steps of data cleaning, data conversion, data selection, and data augmentation are not presented in all works. Although, these steps are important to guarantee good data quality.

Another challenge faced by ML techniques is the interpretation problem. Indeed, most of the successful ML models are black-box models, i.e., models that lack clarity about their internal workings, such as deep learning, RF, SVM, etc. This makes domain experts reluctant to adopt these models because they cannot interpret their predictions and check their reliability. Most of the existing works focus only on the performance of ML models but ignore the interpretation of these models. As we can see from Table 1, only the [15, 16, 19] works address this problem.

Based on these observations, we propose a novel approach using eight different machine learning algorithms (standalone, ensemble, and deep learning) to predict energy consumption in industrial buildings. Furthermore, unlike most existing works, we give equal importance to performance and interpretation. Performance is ensured through a data-preprocessing phase and interpretation is achieved by an interpretation phase.

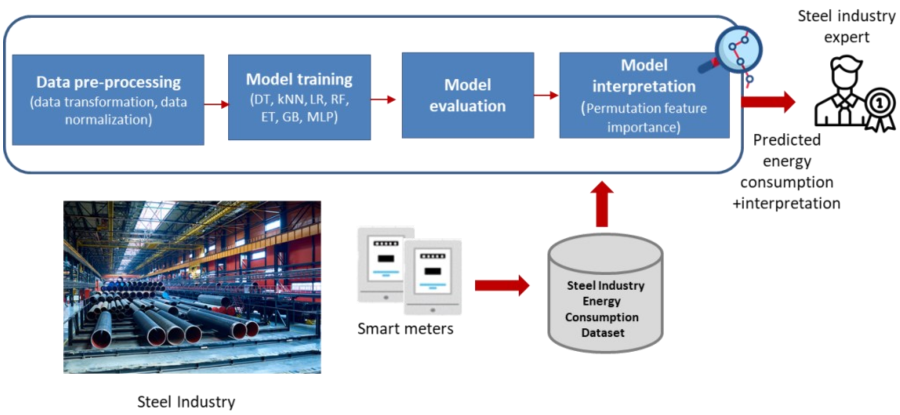

Fig2. The proposed approach.

We use a very recent dataset to evaluate and compare machine learning models to predict energy consumption in industrial buildings.

Our contribution is exposed in the next section.

IV. Proposed Approach

In this section, we introduce a novel machine-learning approach to predict energy consumption in industrial buildings. The approach consists of five main phases namely: data collection, data pre-processing, model training, model evaluation, and model interpretation as shown in Fig2.

A. Phase 1. Dataset description

One of the challenges of ML-based energy prediction methods is the lack of large and public data sets that present energy consumption for industry buildings [23]. In this context, we used the Steel Industry Energy Consumption Dataset [19]. It is one of the most recently published datasets that incorporate energy consumption data collected using multiple IoT devices from a smart small-scale steel industry in South Korea. The steel industry produces several types of coils, steel plates, and iron plates. The collected data is recorded every 15 minutes and is then stored in a cloud-based system. Data is collected for 12 months.

The dataset includes 35040 instances described by eleven features such as lagging and leading current reactive power, lagging and leading current power factor, carbon dioxide emissions (tCO2), load types, timestamp, number of seconds from midnight for each day, period, or weekday position (Week status) and day of the week. Industry energy consumption is the target variable that ML models must predict. Table 2 shows these features with their measurements and value types.

B. Phase 2. Data pre-processing

The goal of this second phase is to make IoT data exploitable by any machine learning algorithm as this data is real-world data. It is very important to improve the representation and the quality of the dataset before starting any data analysis process. This ensures the good performance of ML models.

Therefore, to improve the representation and the quality of the Steel Industry Energy Consumption Dataset, we rely on two steps: data transformation, and data normalization (see Fig2.). It should be noted that the data records are all complete, it doesn't contain missing attribute values. Therefore, we do not need a data cleaning step to remove outliers and process missing data.

1) Data transformation

The data to be analyzed consists of two types: numerical data and categorical data (see Table 2). Most ML models require that the categorical data must be in a numeric format to work properly. Therefore, the goal of this step is to convert data from symbolic into a numeric format.

TABLE II. Description of the Dataset Features

Feature	Measurement	Type
Industry Energy Consumption	KWh	numeric
Lagging Current Reactive Power	kVarh	numeric
Leading Current Reactive Power	kVarh	numeric
tCO2(CO2)	Ppm	numeric
Lagging Current Power Factor	%	numeric
Leading Current Power Factor	%	numeric
Number of Seconds from Midnight	s	numeric
Week status	Weekend (0) or a Weekday(1)	categorical
Day of week	Sunday, Monday, Saturday…	categorical
Load Type	Light load, medium load, maximum load	categorical
Timestamp	day/month/year hour: minute	categorical

In our dataset, each instance is represented by seven numerical features and four categorical features namely 'WeekStatus', 'Day_of_week', 'Load_type' and 'Timestamp'. In this step, we propose to replace 'Timestamp' feature with five numeric features: 'Timestamp_year', 'Timestamp_month', 'Timestamp_day', 'Timestamp_hour', and 'Timestamp_minute'.

We also convert 'WeekStatus', 'Day_of_week' and 'Load_type' to three numerical features using the 'LabelEncoding' function from the Scikit-learn library [20]. It consists in assigning an integer value to each categorical value. For example, the 'LoadType' feature which can have three possible values: light load, medium load, or maximum load is converted to one numeric value: 0 for a light load, 1 for medium load, and 2 for maximum load.

2) Data normalization

This step is applied to avoid biases when the feature values belong to very different scales. Indeed, many studies have shown the importance of data normalization to improve the quality of the data and, consequently, the performance of learning algorithms [24].

In our dataset, some features vary between 0 and 1, while others can reach infinite values. Therefore, we normalized these features using the Min-Max normalization defined in equation 1. It scales the un-normalized data within the range of 0 to 1.

$$X_{normalized} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where $X_{normalized}$ is the normalization result, and X is the initial value. Here, X_{min} and X_{max} denote the minimum and the maximum values of each feature, respectively. For normalization, we used the 'MinMaxScaler' function from the Scikit-learn library [20].

C. Phase 3. Model training

In the previous phase, we presented the data pre-processing phase. In this section, we trained and tested eight regression-based machine learning algorithms to predict the steel industry energy consumption. We selected different types of algorithms (standalone, ensemble, and deep *neural network)* to cover all the algorithms that are already used in the literature (see section III):

- *Standalone algorithms* such as Decision Tree (DT) and k-Nearest Neighbors (kNN), Support Vector Machine (SVM), and Linear Regression (LR).
- *Ensemble algorithms* such as Random Forest (RF), extra tree (ET), and Gradient Boosting (GB).
- *Deep Neural Network algorithms* such as deep neural multilayer perceptron (MLP).

We used the Scikit-learn library implementation of these algorithms. 70% of the total data is used for model training and 30% for testing. Before training these algorithms, it is important to select the right hyperparameters since they have a significant effect on the performance of machine learning models. There are mainly two types of hyperparameter optimization methods, namely manual search and automatic search. For this study, we used the default values specified by Scikit-learn because they work reasonably well. It should be noted that hyperparameters can be set using an automatic search using grid or random search, but these methods are slow and expensive. The deep neural network model is based on a deep neural MLP with three hidden layers, each containing 64 neurons. The 'RELU' activation and 'Adam' optimizer were utilized. Random forest (RF) and extra tree (ET) were developed with 100 estimators. The Gradient Boosting (GB) was developed using 100 estimators and squared error as loss function. k-Nearest Neighbors (kNN) was developed with five neighbors.

D. Phase 4. Model evaluation

To evaluate the performance of the trained models, we used the following performance metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), R-Squared and training time, described below:

- **Mean Absolute Error (MAE)** is a useful measure used with regression models. It is the mean of the absolute values of the individual prediction errors on all instances in the test set. Each prediction error is the difference between the true value and the predicted value for the instance. The closer the measure is to zero, the better the performance, while the higher the measure, the worse the performance.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \left|y_{pred,i} - y_i\right| \quad (2)$$

- n denotes the number of observations in the test set,
- y_i represents the actual value,
- $y_{pred,i}$ indicates the predicted value.

- **Mean Squared Error (MSE)** is the square root of the mean of the squared error values between the predicted values and the actual values. The closer the measure is to zero, the better the performance, while the higher the measure, the worse the performance.

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (y_{pred,i} - y_i)^2 \quad (3)$$

- **R-squared (R^2)** is a measure of the prediction quality of a regression model. It is also known as the coefficient of determination. It displays the extent to which the data fits the model. The best outcome of R^2 is 1.0.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - y_{pred,i})^2}{\sum_{i=1}^{n} (y_i - \underline{y})^2} \quad (4)$$

- $\underline{y}$ denotes the mean of measurements.

E. Phase 5. Model interpretation

In the previous phase, we compared the models based on performance measures and training time. But we did not evaluate these models concerning the human expert's understanding. In some cases, the domain expert is unable to interpret and trust the predictions of the models. As a result, he or she will be reluctant to adopt them. Indeed, machine learning algorithms can be classified into two types according to their explicability: white-box algorithms and black-box algorithms.

White-box algorithms create interpretable models, such as decision tree, linear regression, and kNN that have observable behaviors and features, as well as relationships between influential features and output predictions. These models provide results that can be easily interpreted by a human expert, but the performance is not very satisfactory.

Black-box algorithms create opaque models such as deep learning, random forest, extra tree, and gradient boosting. They provide good performance, but they are opaque in terms of interpretation [22]. They are not able to interpret their decisions to human experts because they lack clarity about their inner workings.

To solve this problem, we apply an interpretation method called 'Permutation Feature Importance' [25] to explain model predictions. It is an interpretation method that works with any ML model (standalone, ensemble, or deep neural network). It is independent of the ML model used (model model-agnostic method). It provides a global interpretation of the model by determining the most important features as well as the unnecessary ones. It computes an importance score for each feature of a data set after fitting a model. This importance score measures the sensitivity of a model to random permutations of this feature values. In other words, it determines whether a feature *f* is important based on the deviation of a model performance. This deviation is measured by an evaluation metric (e.g., mean squared error) after a random permutation of the feature values. Indeed, if *f* is not useful in predicting the expected outcome, then permuting its values will not reduce the performance of a model. These steps are described below:

- Getting a trained model, a set of test data, and an evaluation measure (e.g., R-squared).
- For each feature of the test data, randomly shuffle its values and evaluate the performance of the model on the modified test set (e.g., R-squared).
- In the end, it returns a list of features and their associated scores, sorted in descending order.

For a mathematical explanation of the Permutation Feature Importance method, see [26].

V. RESULT AND DISCUSSION

In this section, we present a comparison of the eight ML models trained and tested on the Steel Industry Energy Consumption Dataset according to their performance and training times. Then, we show the most important features of each model to help the domain expert in interpreting the predictions of each model.

Table III shows the performance of all models based on the three performance measures: mean absolute error (MAE), mean square error (MSE), R-squared. Models with values closer to zero for MAE and MSE and with values closer to one for $R^2$are the better predictive models.

TABLE III. PERFORMANCE RESULT FOR EACH MODEL.

	Model	*MAE*	*MSE*	*R-squared*
Standalone models	LR	2.593	20.647	0.980
	DT	0.578	2.061	0.998
	kNN	2.803	29.626	0.972
	SVM	2.392	20.930	0.978
Ensemble models	RF	**0.368**	**1.055**	**0.999**
	ET	0.412	1.178	0.998
	GB	1.718	8.595	0.992
Deep neural network model	MLP	0.612	1.382	0.998

Bold represents the best performance.

As can be seen in Table 3, the RF is considered the most effective model for the steel industry energy consumption. It produces the lowest RMSE and MAE values and the highest R^2value. The ET model, which has not been much used in the field of energy prediction (see Table 1) emerged as the second-best predictive model. The DT model appeared in third place and the MLP model which is known to have good results comes in the fourth position.

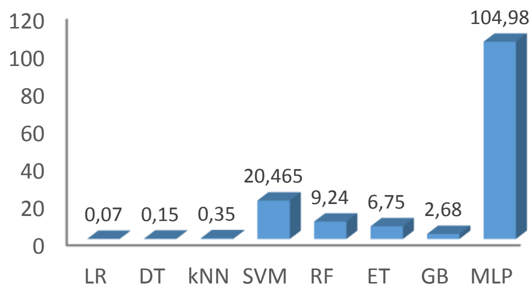

Fig3. Training time for each model.

Fig. 3 presents the training time of the trained models. The results show that the LR model outperforms the other models with a training time of 0.07s followed by the DT with a training time of 0.15s. The MLP model has the worst training time, although it has a good performance. Furthermore, we can see that the RF and ET models have suitable training time and the best performance. For this reason, we focus on these two models in the following paragraphs. We then present their interpretations.

We now focus on a global interpretation of the RF and ET models by determining the most important features as well as those that are unnecessary using the permutation feature importance method. Fig.4 and Fig.5 show the top 20 features for the RF and ET model, respectively. The R-squared (R^2) is used as an evaluation measure to calculate the weight of each feature. Each row in Fig. 4 and Fig. 5 represents a feature and its weight, which indicates the extent to which the performance of the model increases/decreases because of the random mixing of feature values. The more intense the green color, the higher the weight value. The features are thus classified according to their associated weight, in descending order.

Weight	Feature
0.9765 ± 0.0038	CO2(tCO2)
0.0150 ± 0.0039	Lagging_Current_Reactive.Power_kVarh
0.0048 ± 0.0004	Lagging_Current_Power_Factor
0.0012 ± 0.0002	Leading_Current_Power_Factor
0.0010 ± 0.0004	NSM
0.0004 ± 0.0002	Timestamp_month
0.0004 ± 0.0002	Leading_Current_Reactive_Power_kVarh
0.0003 ± 0.0002	Timestamp_day
0.0002 ± 0.0001	Load_Type
0.0001 ± 0.0002	Timestamp_hour
0.0001 ± 0.0001	WeekStatus
0.0001 ± 0.0001	Day_of_week
0.0001 ± 0.0000	Timestamp_minute
0 ± 0.0000	Timestamp_year

Fig4. Feature importance for RF model based on permutation feature importance.

In Fig. 4, we see that 'CO2 (tCO2)' has the highest weight with +0.9765. This means that when we randomly change the values of this feature, the performance of the RF model increases by +0.9765. The value after the plus-minus sign is the uncertainty value. It should be noted that for the RF model all features turn out to be important because there is no negative value for the weight of a feature.

Similarly, we can notice from Fig.5 that ‘CO2 (tCO2)’ has the highest weight with 0.7621. This means that when we randomly shuffle the values of this feature, the performance of the ET model increases by 0.7621. We can also notice a strong contribution from two other features: ‘Lagging_Current_Reactive.Power_kVarh’ and ‘Load_Type’.

By comparing the ten most important features extracted from the two models: (‘CO2(tCO2)’, ‘Lagging_Current_Reactive.Power_kVarh’, ‘Lagging_Current_Power_Factor’, ‘Leading_Current_Power_Factor’, ‘NSN’, ‘Timesstamp_month’, ‘Leading_Current_Reactive.Power_kVarh’, ‘Timesstamp_day’, ‘Load type’, ‘Timesstamp_hour’), we observe that all of them are identical although their ranking is different.

Weight	Feature
0.7621 ± 0.5803	CO2(tCO2)
0.1636 ± 0.5366	Lagging_Current_Reactive.Power_kVarh
0.0410 ± 0.2144	Load_Type
0.0159 ± 0.1092	Lagging_Current_Power_Factor
0.0069 ± 0.0728	Timestamp_hour
0.0055 ± 0.0537	Leading_Current_Power_Factor
0.0023 ± 0.0367	NSM
0.0010 ± 0.0009	Timestamp_month
0.0006 ± 0.0006	Leading_Current_Reactive_Power_kVarh
0.0004 ± 0.0006	Timestamp_day
0.0003 ± 0.0003	WeekStatus
0.0002 ± 0.0001	Day_of_week
0.0002 ± 0.0002	Timestamp_minute
0 ± 0.0000	Timestamp_year

Fig5. Feature importance for ET model based on permutation feature importance.

We can also notice that the variable ‘Timestamp_year’ has no impact on the steel industry energy consumption and that some date/time variables like ‘WeekStatus’, ‘Day_of_week’ and ‘Timestamp_minute’ have a very low impact.

Through this interpretation phase, steel industry experts can better understand the models' judgments. Specifically, they can determine which features have a significant impact on energy consumption and which features do not. This will allow them to verify the predictions of the models, and it will increase their confidence and help them better understand the steel industry. Thus, they will make the best decisions to optimize energy planning, and management and enhance the energy distribution strategy.

VI. CONCLUSION AND FUTURE WORKS

Nowadays, monitoring energy consumption in manufacturing plants is essential to reduce energy waste. Reducing energy waste can be achieved through the prediction of future energy consumption, which will allow decision and policymakers to think about some changes for optimizing energy planning, management, and improving energy distribution strategies, and reducing CO2.

One way to approach this challenge is to use ML algorithms for the prediction of energy consumption in industrial buildings. Indeed, various techniques are used in the literature. However, two major problems hinder the use of these methods: (a) the gap between actual and predicted energy consumption and (b) the misunderstanding by domain experts of model predictions. Therefore, this study aims to address both issues.

A new ML approach for predicting energy consumption in industrial buildings is proposed in this paper. It presents a trade-off between the performance and interpretability of ML models. The performance is ensured by a data preprocessing phase to make the real-world usable by any ML algorithm and to ensure a good performance of the ML models. Interpretability is obtained by determining the most important features as well as those that are unnecessary using the permutation feature importance method.

The applicability of the proposed solution is demonstrated through a real case study to predict energy consumption in the steel industry. We compared the prediction performance and training time of eight ML techniques of different types (stand-alone, ensemble, and deep learning) and then we proposed a global interpretation step so that steel industry experts can better understand the models' judgments.

In summary, the most relevant lessons learned from this experiment could be useful for future real-world applications: RF model produces the most efficient and accurate prediction results for the steel industry experts that they can trust. Confidence is gained by showing them which features are important for the entire dataset. This information is also useful to help them make the most appropriate decisions to optimize energy planning, and management and improve the energy distribution strategy. We will continue to explore this path in the future to improve the proposed approach by exploring other model-agnostic interpretation methods with applications in other smart industries.

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