Electricity Consumption Forecast in an Industry Facility to Support Production Planning Update in Short Time

Daniel Ramos, Pedro Faria, Zita Vale
Polytechnic of Porto
Porto, Portugal
dados@isep.ipp.pt , pnf@isep.ipp.pt, zav@isep.ipp.pt

Regina Correia
SISTRADE
Porto, Portugal
regina.correia@sistrade.com

Abstract— **The global environmental concerns raise the need to decrease energy, namely electricity consumption. Energy consumption can be reduced by improving energy efficiency and by improving the optimization of energy management in each context. These opportunities are very relevant in buildings and industry facilities. In order to improve the optimized energy management, adequate forecasting tools are needed regarding the load consumption patterns in each building. In the present paper, two forecasting technics, namely neural networks, and support vector machine, are used to predict the consumption of an industry facility for each 5 minutes. The proposed model finds the best method in order to be used in a later stage regarding the updated of production planning. The size of historic data is also discussed. The case study includes one-week test data and more than one-year train data.**

Keywords— Industry facility, load forecast, production planning.

I. Introduction

The electricity sector is facing several challenges due to the concerns on environmental issues. The efficient use of electricity can be improved with the support of smart grids (Faria et al. 2019). In fact, in the context of smart grids, consumers can receive incentives for reducing the electricity consumption in certain periods; is the so-called concept of Demand Response (DR). While in some DR programs the consumers receive incentives, in other programs, price signals are sent to consumers in real-time so they can adapt the consumption, reducing electricity bill [1, 2].For a building or facility, at commercial, domestic, or industrial level, to improve their participation in such programs, adequate planning of the targeted tasks and respective energy consumption forecast are needed. In the end, the available resources use will be optimized, and the energy bill will be reduced by adapting the consumption to the available opportunities in smart grids. As an example, focusing on industrial facility, a real-time automatic energy forecast can be performed with data belonging to a facility in the context of production line in order to optimize the energy management. Different artificial intelligence technics can be used.

Artificial Neural Networks (ANN) represent a model with neurons and weights linked together by using a multilayer model that starts on an input layer, generating from that point hidden layers, until the obtaining of the output layer. Another technic, a Support Vector Machine (SVM) maps data in the large resource space by adopting non-linear mapping develops linear regression in the resource space [3].

This work has received funding from Portugal 2020 under SPEAR project (NORTE-01-0247-FEDER-040224), the scope of ITEA3 project SPEAR 16001 and from FEDER Funds through COMPETE program and from National Funds through (FCT) under the project UIDB/00760/2020, and CEECIND/02887/2017..

978-1-7281-7455-6/20/$31.00 ©2020 IEEE

These algorithms were tested in other applications in the energy domain area including short time load forecasting (STLF). An ANN model is proposed with training on hourly data in order to forecast electric load of NEPOOL region, in [4]. A SVM Model is proposed in order to study the reliability of the technique in wind speed forecasting and power generation forecasting, in [5]. A research takes place to compare the performance of ANN and SVM algorithms in the context of load forecasting performed for 2 models first for maximal load of forecasting day and second acting as hourly load predictor in [6]. During the event NPower Forecasting Challenge 2015, the BigDEAL team proposed a methodology that uses several techniques including ANN in order to predict daily energy usage of a group of costumers [7]. The 7th International Conference on Modern Circuits and Systems Technologies (MOCAST) study the biological systems and natural phenomena chaotic behavior in order to predict their future behavior. ANN and SVM are listed among the techniques used to perform the predictions [8].

In the present paper, the proposed methodology has been implemented in python language, considering two forecasting methods, namely Artificial Neural Networks (ANN) and Support Vector Machine (SVM). These methods, in the proposed methodology, support the update of the operation schedule in an industrial facility according to the most recent and accurate available forecast results. The developed method, as described in section 2, includes all the data streaming and cleaning implemented, which deals with rather relevant amounts of missing data. The energy forecast is done for each 5 minutes, while different sizes of input data are tested and compared for both the ANN and the SVM approaches.

After this introduction the method described in Section 2, the case-study is described in Section 3, while results are presented in Section 4, and Section 5 present the most relevant conclusions of the paper.

II. Proposed Methodology

In this section, it is described the different phases of the proposed methodology, including data streaming, cleaning and correction, training and forecast execution, and schedule update, according to Fig. 1. Data cleaning required several steps to make data cohesive allowing algorithms in later phases to build solutions for the business problem with less errors.

First, it is known that the production line has active participation all days belonging to a grand majority of weeks excluding Sunday. That means that entry records belonging to Sunday are not typical, so they are deleted and excluded from the week's profile. The reason why most weeks can be included in the historic of data is because there is a minority of weeks with presence of days with unreliable data. This happens due to the holidays' existence and accumulated consumptions, the result of missing period records with unrecovered data. So, these weeks should be discarded as well. Although alternative decisions concerning the labeling of holidays in the data structure may be useful to provide more complete knowledge on long term forecasts, the fact that the forecast are established for short term leads to the observation that this additional information in this case leads to overfitting. Therefore, the decision to discard holidays is instead taken place.

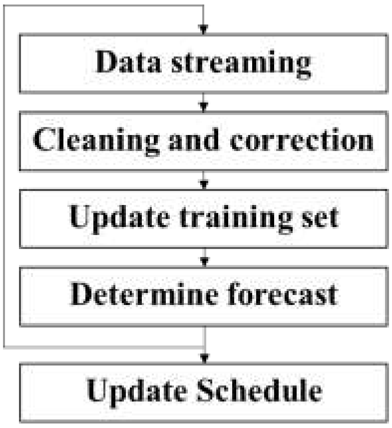

Fig. 1. Proposed methodology for forecast and production planning update.

Furthermore, there are many inconsistencies in the records entries. Being the production registered from five to five minutes data clean should organize those records in ways that there is always one record associated to all five minutes from each day. By other words, all days should have always 288 records each one corresponding to five minutes. Scenarios with several observations of production line belonging to a five minutes slot should be summed to keep the 288 periods per day. There are also a few exceptions in which there are some entries with five minutes missing. This issue is overcome by creating the missing recording and establishing that the consumption value associated to the 5 minutes in question is the same of the previous record. Additionally, spikes can be observed while plotting the data. These values take erroneous profile to the data, so it is extremely important to correct these mistakes. To keep all the 5 minutes observations, the values with spike detections are replace by the average of the previous and the next iterations. The errors calculations provide some awareness about the deviation of the observed values in the predictions from the actual values. These errors are used in order to check the performance of each one of the algorithms. This study applies the weighted absolute percentage error (WAPE), taking into account that this is a measure of prediction accuracy of forecasting very useful on regression problems such as this one. Eq. 1 shows WAPE for each one of the algorithms.

$$WAPE = \frac{\sum_{i=1}^{n} Ca}{\sum_{i=1}^{n} Cp} \tag{1}$$

- $WAPE$ – weight absolute percentage error
- $\sum_{i=1}^{n} Ca$ – sum of actual consumptions (Ca) for a total of observations (n) each iteration according to index (i)
- $\sum_{i=1}^{n} Cp$ – sum of predicted consumptions (Cp) for a total of observations (n) each iteration according to index (i)

The conversion from real consumptions to the absolute values is unnecessary, because there is the guarantee that those values are nonnegative. Furthermore, the reason why WAPE is calculated and not the mean absolute percentage error (MAPE) is because the latter calculates the ratio for each iteration being the actual consumption in the denominator. Therefore, there is a risk of a real consumption being null and the division being impossible. To avoid this issue, WAPE is used instead as an alternative for MAPE. Additional metrics were discussed to be tested although they were discarded in the case for good reasons. To highlight that metrics regarding non percentage results like the mean absolute error (MAE) are not the intended in the cases studies as the same will not provide the errors inside a scale of all possible cases. Metrics regarding square roots of squared errors like Root Mean Squared Percentage Error (RMSPE) lead to the observation that in this scenario with much uncertainty it has a downfall that affects the forecasts. This metric has the disadvantage that it does not treat each error the same, hence giving more importance to the biggest errors.

After determining the forecast of energy consumption for each 5 minutes, which includes the decision on the size of input data set, the most recent, updated, and accurate energy forecast is obtained. After that, the motivation is to provide this information to the facility energy manager in order to update the planning of the production according to the energy consumption and the available distributed generation and the electricity prices in real-time.

III. CASE STUDY

In this study, the goal is to study the forecast algorithms performance counting with the simulation graphs and results. Data relies on the week's profiles being always associated to a five minutes slice being these registers of 5 minutes always sequentially. The forecast is performed for all 5 minutes target slices present from 8 to 13 April on 2019 (last week of April 2019 without holidays), as seen in Fig. 2.

This case will study the algorithms performance and compare them testing different simulations using alternatively from 10 to 15 inputs. The output is always one taking into account that the user only wants to know the prediction for a 5 minutes slice. The structure featured for ANN in this case study consists in a feed forward network representing a multilayer model composed by neurons and weights linked together. This structure is featured by one input layer with 10 to 15 neurons, followed by 2 hidden layers of 64 neurons each, ending in an output layer with a single output. The amount of neurons in the input layer hold consumptions data placed in sequential periods. These provide a total of 10 to 15 neurons depending on the extent of consumption data provided to the input. The output layer has only one value which is the consumption that takes place after the last input. The network architecture is composed by 2 hidden layers with 64 neurons each in order to provide with enough reliability (taking into account the amount of inputs) during the rules creation, relevant step in the learning process which determine the rules that turn the input in its respective output. Furthermore, the epochs of ANN were defined with an amount of 500 iterations, which means ANN will keep training the model 500 times or by other words optimize the rules 500 times. To highlight that a callback is implemented where the model will stop training as soon as not reaching improvements in the 500 iterations. The learning function used in the training process was the gradient descent algorithm. The learning rate was defined with 0.001, a very small rate considering the necessity to reduce the loss of information.

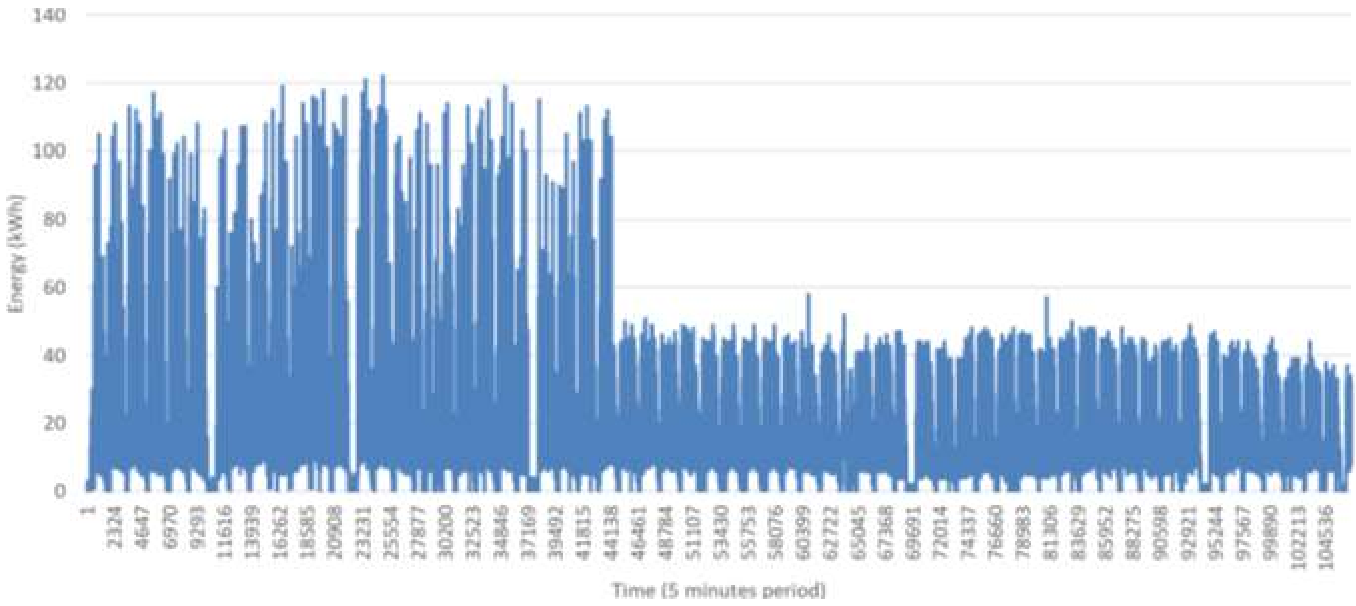

Fig. 2. Consumption data in the complete data set.

SVM uses the k-nearest neighbours algorithm associated to 5 nearest neighbours. RF uses 1000 forest trees and the state of random samples when building trees set to 42. Fig. 2 shows the historic with the data consumption from 5 to five minutes from early 2018 to 6 February 2019. Each one of these inputs corresponds a 5 minutes slice that gives the sequence to the previous 5 minutes belonging to the previous input. The output corresponds to the 5 minutes prediction that gives the sequence to the previous five minutes belonging to the last input. Let's keep in mind that each day has 288 periods (5 minutes periods), so that gives 1440 periods per week

IV. RESULTS

In this section are presented the results obtained with the application of the proposed methodology to the selected case-study. In sub-section A are presented the results regarding the one-week data forecast. In subsection B are presented the results regarding daily forecast.

A. *One Week Forecast*

The forecasts for one target week were tested with different algorithms which include artificial neural networks and support vector machine. Furthermore, these forecasts were tested with different simulations that distinguish themselves in the data structure which is defined by the input with a fixed number of entries (consumptions that represent a sequence of 5 minutes time slots) that map the output (targeted consumption belonging to the next five minutes that gives the sequence that was left by the last input).

Table I evaluates the algorithms performance with different simulations that rely on the number of entries from 8 to 13 April on 2019 (last week of April 2019 without holidays). In general, both algorithms present low errors being these errors lower for ANN. Furthermore, it is inferred that Table I shows a nonlinear behavior taking into account that there is not a proportion between the number of entries and the errors presented for each algorithm. Within ANN, the data with 11, 12 and 14 entries give low errors; regarding SVM, data with 15 entries gives low errors. The facility consumption activities and predictions from 8 to 13 April on 2019 (last week of April 2019 without holidays) are presented in Figure 3. It can be seen that the simulation tests show a similar behaviour during the whole process. On first step the energy remains null, following to rise up exponentially from period 87 until before the period 130.

TABLE I. WAPE RESULTS FOR EACH METHOD WITH DIFFERENT ENTRIES

Entries	WAPE (ANN)	WAPE (SVM)	round, WAPE (ANN)	round, WAPE (SVM)
10	0.128	0.139	0.13	0.14
11	0.117	0.139	0.12	0.14
12	0.124	0.140	0.12	0.14
13	0.132	0.139	0.13	0.14
14	0.117	0.139	0.12	0.14
15	0.131	0.135	0.13	0.13

From this point on, the consumptions start to alternatively decrease and increase with a nonlinear behaviour. To emphasize that SVM tends to change from value to value much faster than ANN. Despite the similarities, the graphs also show some differences with algorithms ANN and SVM even though the nonlinear behaviour from Monday to Saturday is constant.

Starting by ANN, between periods 1076 and 1119 while reaching a local minimum spike with 10, 11, 12, 13 and 14 inputs; with 15 inputs the consumptions reaches several local minimum spikes. Just after period 1420, for 10 and 11 inputs, the consumptions decrease and increases alternatively with nonlinear behaviour; while for 12, 13 and 14 inputs the consumption does not show much difference; 15 inputs show a behaviour even more nonlinear than 10 and 11 inputs.

Following to SVM, on period [87, 130], a consumption spike is visible for 11 inputs.

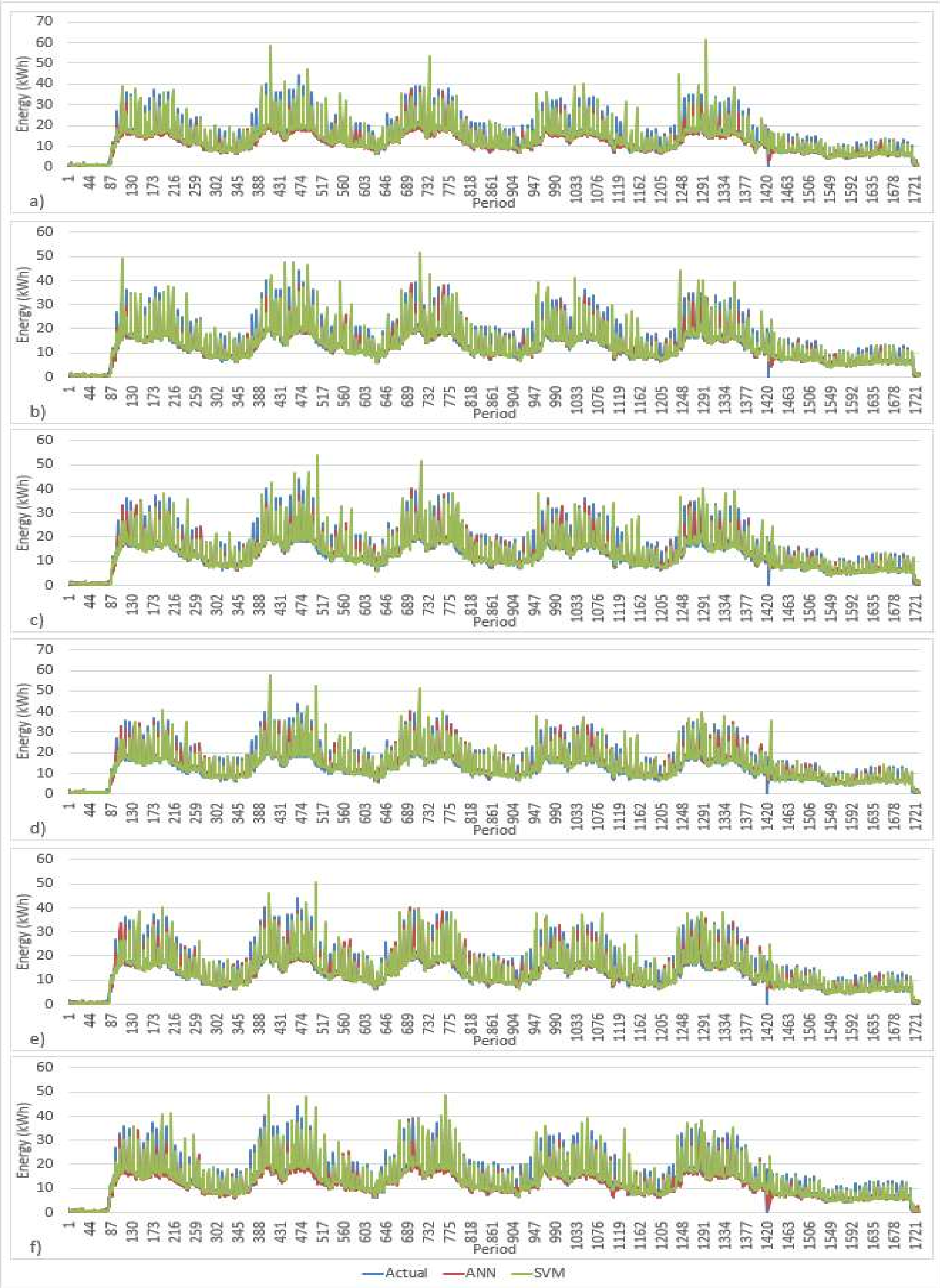

Fig. 3. Obtained forecasts with each method and with different entries: a) 10 entries, … f) 15 entries.

On period [173, 216], both for 13 and for 14 inputs 1 spike is visible to pass by 40; while with 15 inputs 2 spikes following the same condition are visible; for 10, 11 and 12 inputs no spikes pass by 40.

On interval [216, 259], for 10 inputs a spike is visible less than 30 KWh; for 11, 12 and 13 inputs a spike is visible less than 40 KWh; for 15 inputs 2 spikes are visible; with 14 inputs a spike is detected just after t=259. On interval [259, 345], for 10, 11 and 12 inputs, there is tendential for more local maximum spikes than for inputs 13 and 14. On interval [646, 818], 14 inputs is the only case which it is not visible spikes presence. Just after 1420, a spike is visible in all cases except for 10 inputs.

B. *Daily results*

Figure 4 shows analytics graphs that focus on the errors WAPE provided by the predictions of each one of the algorithms in study from 8 to 13 April on 2019 (last week of April 2019 without holidays). These errors are tested with different simulations (alternating the number of entries) and analyzed in detail for each day of week (Monday to Saturday) in order to understand how the line consumption behaves for each day of week.

First of all, it is clear that errors tend to remain lower in ANN than SVM. Both ANN and SVM errors behave differently looking for all case scenarios. Despite this, both algorithms agree that in Wednesday the consumption remains a lower bound value compared to the whole set of consumptions during the entire week. Observing the errors variation with 10 and 13 entries, ANN errors are lower for Tuesdays and Wednesdays, higher for Mondays and Thursdays while they tend to grow up in the rest of the week. Observing the errors variation with 11 and 12 entries, ANN errors are lower for Wednesdays, higher for Mondays, Tuesdays and Thursdays while they tend to grow up in the rest of the week. Now with ANN and 14 inputs, errors remain lower for Mondays, Tuesdays and Wednesdays and tend to grow up during the rest of the week.

About ANN and 15 inputs, errors remain lower for Tuesday and Wednesday, higher for Mondays and tend to grow up during the rest of the week. For ANN in the majority of case scenarios errors tend to grow up in the rest of the week. In complement to this, errors variation is unpredictable in the beginning of the week and the error behavior variation during that time relies from case to case. In SVM, errors variation behaves very differently according to the number of entries. The only certain that is established is that Wednesday consumptions represents lower bound consumption in comparison with the whole set of days and that from Wednesday to Thursday there is an error increase. Although it can be concluded that the error significantly depends on the week day it has been decided not include the week day as an input.

The reason is that the non-work days of the factory production activities largely depend from particular management decisions which quite often change official holidays in order to make the production more efficient while ensuring the workers rest time.

Looking at Fig. 4, it can be seen that the day with lower WAPE values is day 3. Also, the number of entries has relevant impact on this day results. In order to analyze this day, Fig. 5 presents the results of day three. During the whole process, ANN and SVM predictions tend to remain near the real consumptions. However, a few exceptions can be placed in question. Near the 61st period, it is clear SVM predicted consumptions do not grow up in the same instant as the real counterpart. Furthermore, the consumption increase differences are inconsistent.

Another inconsistence example is present in period]121,133[in which the real consumption tends to significantly grow up, while ANN predicted consumption increase is just not enough and SVM prediction increase is not satisfactory. Near the end of the day, real consumptions tend to remain low, while ANN and SVM predicted consumptions mistakenly perform a significantly increase, creating a spike in the process.

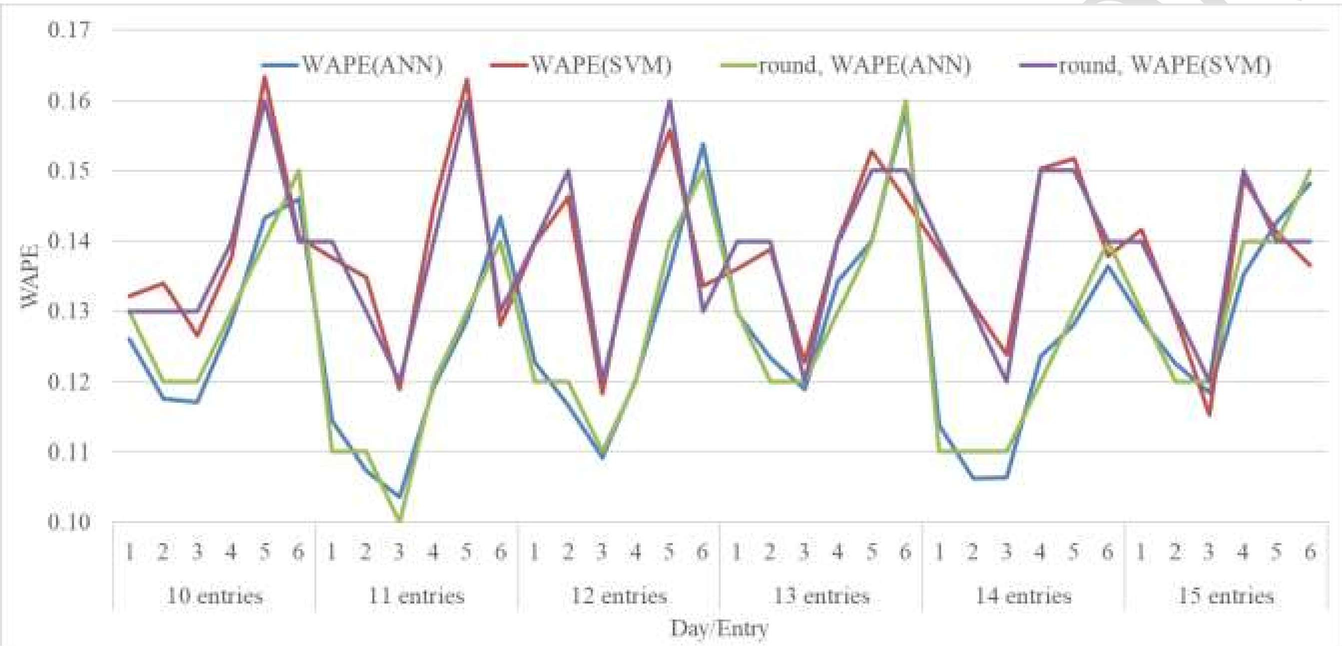

Fig. 4. Daily result erros for each one of 6 one week days and entries from 10 to 15.

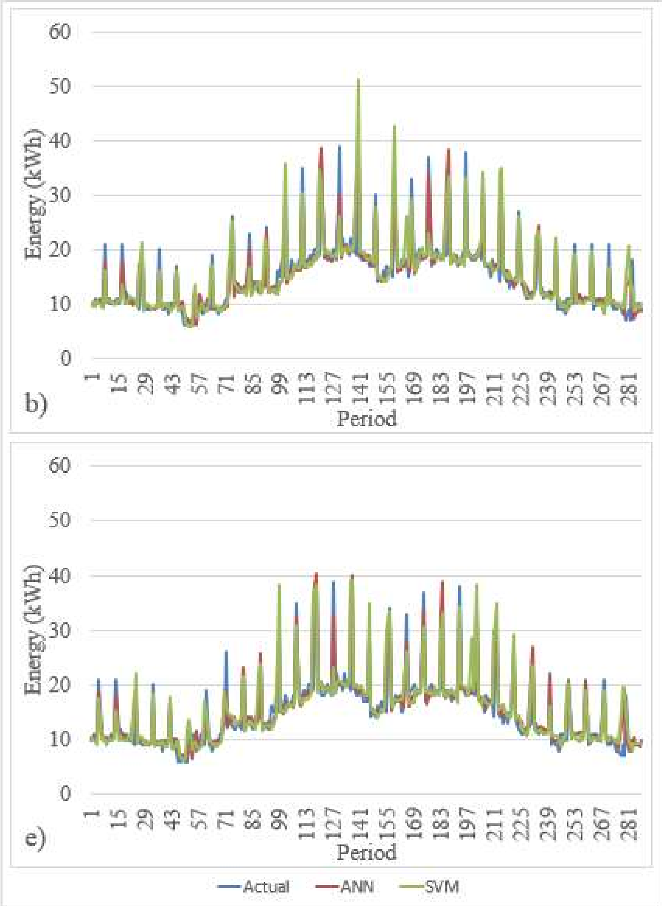

Fig. 5. Daily results, for day 3, with ANN and SVM methods: b) 11 entries, e) 14 entries.

V. CONCLUSIONS

This paper proposes an automatic energy consumption forecasting according to an industrial facility context with forecast targets aimed for a five minutes time slice. The forecasts are supported by 2 algorithms (Artificial Neural Networks) using the python programming language. The results present acceptable errors, hence, data is trustable to be used on future work.

The system stores all the results in an excel file including the graphs with predictions and real consumption comparison and the WAPE error calculated for each one of the algorithms. Tests and results show that the performance is better for ANN. It is important to highlight that different simulations were tested which rely on the quantity of inputs that map the output. All the simulations presented acceptable errors being the impact with less or higher number of inputs low on both algorithms varying less for SVM.

With the provided results, it has been able to decide what are the most adequate methods and input data sets in order to provide input to update the operation scheduling.

REFERENCES

[1] P. Faria, and Z. Vale, "A Demand Response Approach to Scheduling Constrained Load Shifting. Energies," MDPI, vol. 12, 2019, pp. 1752.

[2] P. Faria, and Z. Vale, "Demand response in electrical energy supply: An optimal real time pricing approach," Energy. Elsevier Ltd, vol. 36, 2011, pp. 5374–5384.

[3] A. Jozi, D. Ramos, L. Gomes, P. Faria, T. Pinto, Z. Vale, "Demonstration of an Energy Consumption Forecasting System for Energy Management in Buildings", Progress in Artificial Intelligence, EPIA, Lecture Notes in Computer Science, vol 11804, 2019, Springer, Cham.

[4] S. Singh, S. Hussain, and M. Bazaz, "Short term load forecasting using artificial neural network," Fourth International Conference on Image Information Processing (ICIIP), Shimla, 2017, pp. 1-5.

[5] Z. Zhu, D. Zhou, and Z. Fan, "Short term forecast of wind power generation based on SVM with pattern matching" IEEE International Energy Conference (ENERGYCON), Leuven, 2016, pp. 1-6.

[6] A. Selakov, and et al., "A comparative analysis of SVM and ANN based hybrid model for short term load forecasting," IEEE PES T&D, Orlando, FL, 2012, pp. 1-5.

[7] J. Xie, B. Liu, X. Lyu, T. Hong, D. Basterfield, "Combining load forecasts from independent experts," North American Power Symposium (NAPS), Charlotte, NC, 2015, pp. 1-5.

[8] A. Pano-Azucena, E. Tlelo-Cuautle, X. Tan, "Prediction of chaotic time series by using ANNs, ANFIS and SVMs", 7th International Conference on Modern Circuits and Systems Technologies (MOCAST), Thessaloniki, 2018, pp. 1-4.