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Reinforcement Learning of a Multi-Agent System for the Forecasting of Electricity Consumption

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Abstract

The management activities of buildings have been readapting strategies over the years to be more efficient on the use and supply of electricity power. The uncertainties presented in the consumption profile and user behaviour create difficulties where it is hard to determine an optimal energy management strategy. These can be overcome with schedule prediction tasks that anticipate possible power consumption scenarios contextualized in a large sequence of small periods. The predictions accuracy relies on a large historic of data obtained from smart grids devices. This is simplified to a case study that deals with demand response issues and methods used for the prediction activities. The case study is formulated according to aspects influencing the predictions accuracy including the data reliability and the size of the historic of data.

This dissertation goal is a contextual analysis of forecasting algorithms. The proposed approach makes use of decision trees to identify when (in which context) each forecasting algorithm is more accurate. Then reinforcement learning is applied as an alternate strategy to learn the most accurate algorithm in different context. The contextual analysis of forecasting is studied according to a sequence of steps integrated in a multiagent system known as MARLEC (MultiAgent system with Reinforcement Learning for forecasting electricity consumption). This multiagent system evaluates which forecasting algorithm is the most appropriate in different contexts according to two alternatives: Artificial Neural Networks and K-Nearest Neighbours. These evidence different pros and cons that result in more or less accurate forecasts scheduled for the different short periods of the day. An error analysis is useful to analyse the prediction accuracy of different forecasting algorithms. Four error metrics are considered in these studies to assess the quality of each method results, namely SMAPE, MAPE, MAE and RMSE.

Keywords: decision trees, electricity sector, forecasting algorithms, management strategy, optimization, reinforcement learning.

Resumo

As atividades de gestão de edifícios têm readequado estratégias ao longo dos anos para serem mais eficientes no uso e fornecimento de energia elétrica. As incertezas apresentadas no perfil de consumo e no comportamento do usuário criam dificuldades onde é difícil determinar uma estratégia ótima de gestão de energia. Isso pode ser superado com tarefas de previsão de programação que antecipam possíveis cenários de consumo de energia contextualizados numa longa sequência de períodos curtos. A precisão das previsões depende de um grande histórico de dados obtidos a partir de dispositivos de redes inteligentes. Isto é simplificado para um caso de estudo que lida com problemas de resposta à demanda e métodos usados para as atividades de previsão. O estudo de caso é formulado de acordo com aspectos que influenciam a precisão das previsões, incluindo a confiabilidade dos dados e o tamanho do histórico de dados.

O objetivo desta dissertação é uma análise contextual de algoritmos de previsão. A abordagem proposta faz uso de árvores de decisão para identificar quando (em qual contexto) cada algoritmo de previsão é mais preciso. Em seguida, a aprendizagem por reforço é aplicada como uma estratégia alternativa para aprender o algoritmo mais preciso em diferentes contextos. A análise contextual da previsão é estudada de acordo com uma sequência de etapas integradas num sistema multiagente conhecido como MARLEC (Sistema MultiAgente com Aprendizagem por Reforço para previsão do consumo de eletricidade). Este sistema multiagente avalia qual algoritmo de previsão é o mais adequado em diferentes contextos de acordo com duas alternativas: Redes Neuronais Artificiais e Vizinho mais Próximo. Essas evidenciam diferentes prós e contras que resultam em previsões mais ou menos precisas programadas para os diferentes períodos curtos do dia. Uma análise de erro é útil para analisar a precisão da previsão de diferentes algoritmos de previsão. Quatro métricas de erro são consideradas nestes estudos para avaliar a qualidade dos resultados de cada método, nomeadamente SMAPE, MAPE, MAE e RMSE.

Palavras-chave: algoritmos de previsão, aprendizagem por reforço, árvores de decisão, estratégia de gestão, otimização, setor elétrico

Glossary

ANN	Artificial Neural Networks
GECAD	Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development
KNN	K-Nearest Neighbours
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MARLEC	MultiAgent system with Reinforcement Learning for forecasting electricity consumption
RMSE	Root Mean Squared Error
SMAPE	Symmetric Mean Absolute Percentage Error

Contents

1. Introduction and objectives

The energy management of a building that acquires and monitors real time data involves the participation, collaboration and exhaustive work from researchers, decision makers and experts from data science or machine learning fields. The uncertainties presented in the electric energy consumption profile generate controversies and doubts on how to reach the optimal energy management strategy. Using the adequate methods to forecast the electric energy consumption is crucial to support the energy management decisions and can largely contribute to more environmentally sustainable buildings and to lower energy costs.

Several aspects should be considered to improve the forecasting accuracy thus obtaining electric energy consumption patterns closer to the reality. The data reliability and the dimension of the historic dataset are very relevant aspects that have huge impact on the accuracy of predictions. The exclusion of untrustful electric energy consumption data and the consideration of additional sensors data showing high correlation patterns with the power consumption should be considered to obtain accurate forecasts.

As electric energy management decisions can impact on and depend from several entities, people and appliances in a building, multiagent systems are a good option to model the different players and provide energy managers and users with adequate decision support [30]. The learning process of these agents is an important aspect. Different learning techniques should be tested and wisely used, as experimental works show that there is not a single technique able to provide the users with the best results under a wide range of contexts. Reinforcement learning is very valuable in these situations as it enables agents to learn from past actions thus allowing the change of behavior capability and the switching between cooperative and adversarial behavior [32], [33], [42], [43], [44]. This provides an evaluation of the more suitable forecasting for different contexts. The actions and decisions are based on the feedback of observations of the agents and on the use of rewards for previous actions. In the case of electric energy consumption forecasting, reinforcement learning can be used to select the most suitable forecasting model for each particular context, based on the historic performance of different forecasting models in different past contexts. The reinforcement learning methods have aspects with pros and cons that influence the final reward obtained.

This dissertation aims at conceiving and implementing models for electric energy consumption forecasting that can be used to support decisions regarding energy management in a building, based on two types of problems. The first consists in forecasting the building electric energy consumption for each five minutes period. The second consists in evaluating which forecasting algorithm is the most appropriate for different five minutes periods. The second goal was initially achieved with a decision tree model that evaluates if the selected forecasting algorithm is the best in a particular context in which it has been used. The dissertation proposes an alternative approach to the second goal using a multiagent system with reinforcement learning. The multiagent system decides which forecasting algorithm is more appropriate in different five minutes contexts with the support of Multiagent Bandit algorithm assuming the building as the agent that decides the forecasting algorithm as different agents more appropriate for each five minutes decision.

The organization where the work was developed, GECAD - Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development, provided the data required for the dissertation. GECAD is specialized on the development of scientific research on Intelligent Systems and on their application to Power and Energy Systems. It has relevant real-time monitoring infrastructures that feed large datasets. The access to real time data and to the long historic of data provided by GECAD were very important to test and validate the models proposed in this dissertation.

Part of the results of this dissertation have already been published, namely in [1], [2] and [3]. Accordingly, in [3] forecasting activities are performed for a target week with the support of Artificial Neural Networks and K-Nearest Neighbours and an historic of data being the forecasts enhanced with sensors data and retraining windows that update new data while discarding previously data. In [2] a decision tree supports rules that select forecasting algorithms applications for different periods of five minutes explaining afterwards if these selections were suitable or controversy. In [3] an application of reinforcement learning application researches which forecasting algorithm is more suitable for different periods of five minutes based on previously experience. This evaluates the forecasting algorithm decisions based a reward criterion and a feedback with new observations.

After this introduction, section 2 makes a literature review with relevant publications associated to the dissertation fields. Section 3 presents the proposed solution, detailing the respective methodology. Section 4 concisely presents the relevant aspects related with monitoring and historic datasets. Section 5 addresses the tests and the obtained results and the respective analysis. Finally, section 6 presents the conclusions of the work and some suggestions for its future development.

2. Literature Review

The literature review is structured on several sub-sections according to the relevant topics and methods used in this dissertation. Sub-section 2.1 addresses demand response and smart grids. Sub-section 2.2 explains the forecasting approaches. Sub-section 2.3 describes works regarding Multi-agent Systems and reinforcement learning applications. Sub-section 2.4 presents a concise evaluation of forecasting algorithms.

2.1 Demand Response and Smart Grids

The electricity sector recognizes the value of demand response for the markets efficiency [4]. This is possible by creating demand response programs that enable the consumers to adapt their consumption in taking the consumers profile into account and reducing the operation costs [5]. This process is accompanied by load reductions determined through optimal solutions which influence the retailers' profit [6]. Another factor that enhances the markets' efficiency is contextualized in the domain of smart grids highlighting the distributed generation for grid reliability [4]. It is further noted that distributed generation can enable high efficiency, the reduction of transmission and distribution losses, the support of local power grid and the improvement of the system stability. The smart grid technology is required to deal with the increasing of demand response noted in a worldwide scale [7]. The integration of energy resources with smart grids technologies particularly in short term application has shown to result in more efficient solutions [8]. Proposed smart grids approaches implementing demand response programs are used for power transaction in the electricity market [9]. Uncertainties present in electricity consumption profiles make demand response control and the reduction of electricity usage difficult as evidenced in [10]. Dynamic pricing is promising to overcome some of the difficulties motivating customers to change their consumption patterns. The benefit of electricity management is explained in [11] as it is relevant for social growth as the consumption prediction tasks are fundamental in economic development. The prediction of energy consumption in a building is a task that considers occupants behavior in [12] as means to understand the occupant behavior impact on the building energy consumption.

2.2 Forecasting approaches

The adequate modelling and forecasting of electricity consumption in buildings are crucial to obtain energy efficiency and can be done relying on data-driven techniques and machine learning forecasts methods [13]. Approaches using Artificial Neural Networks and K-Nearest Neighbours method can be used in industrial buildings [1] and in electricity buildings [14] to improve the energy efficiency. Forecasting techniques are being used due to the increased availability and power of computation systems [15] and Artificial Neural networks are one of the most used techniques for this purpose [16]. Hybrid approaches are adopted on several forecasting domains including sustainable office buildings [17] and building electrical energy consumption [18] to achieve optimal solutions that minimize energy consumption. Fuzzy techniques are used for information retrieval and clustering in different domain problems [19].

The performance associated to the use and supply of electricity in buildings can be improved through forecasting studies that use deep learning methods to forecast the electric energy consumption in buildings [20]. The use of deep learning methods for forecasting may result on more accurate prediction when considering hyperparameter tuning through trial-and-error scenarios to find the combination of parameters associated to a deep learning method version that result in higher performance [21]. The electricity power load demand forecasting is essential for the energy management [22]. An improved method of Recurrent Neural Networks is considered on forecasting tasks gifted with the ability to remember previously computed information. A deep learning model proposed in [23] forecasts energy consumption and peak power hours in the electricity sector using a Python application and a Keras library for deep learning. A hybrid deep learning model is proposed in [24] to obtain more accurate forecasts for energy management and scheduling operations. Demand response strategies are essential in the electricity sector and smart grids as explained in [25], which highlights the challenge to propose deep learning predictive models that accurately predict the hourly load consumption. Reliability open questions regarding the effectiveness of deep learning for prediction tasks lead to a study where the accuracy of this approach is compared to other machine learning models. Results presented in [26] prove that deep learning models are the most effective considering a dataset of students' performance and the prediction error metrics MAE and RMSE. A survey of machine learning algorithms including decision trees, Bayesian networks, support vector machines, clustering, association rules, artificial neural networks, deep learning and ensemble is presented in [27]. A survey of machine learning techniques and smart grid applications covering over 200 publications is presented in [28].

2.3 Multiagent Systems and Reinforcement Learning

The influence of distributed generation in the electricity sector has motivated the implementation of Multiagent Systems to study the market operations with different players and market mechanisms. Simulations studies based on Multiagent Systems allow the analysis of players' behaviour and interactions to understand these players' outcome in the market according to different scenarios [29]. Moreover, a distributed decision making approach considering several agents that interact in a common environment allows the system to readapt better for environment changes when compared to systems with centralized decision making. The change of behaviour and the cooperation of the agents are aspects that should improve the agents' performance [30]. These two aspects are also highlighted in [31] that stresses the importance of reinforcement learning in a Multiagent System which provides allows agents to learn from past actions thus providing to each agent the change of behaviour capability while also the switching between cooperative and adversarial behaviour in order to check in each scenario how it is best suitable to achieve a final goal. The reinforcement learning in a Multiagent System has been used in many applications including in strategic games as referred in [32]. Reinforcement learning is evidenced in [33] as a potential approach to analyze the best configuration possible on airline alliance applications. Reinforcement learning approaches have relevant role on energy management applications as in [34] that presents a framework for home energy management that uses reinforcement learning to overcome demand response issues caused by induced dissatisfaction and to minimize the electricity bill. A similar household problem is addressed in [35] adding the consumption profile as essential to reduce the electricity bill and power grid during peak time. In [36] reinforcement learning is used for supporting demand response focusing on how to maximize consumption of photovoltaic energy and how to minimize the electricity cost in residential levels. Accordingly, in [10] a reinforcement learning application with a bandit algorithm integrated in a neural network that learning consumption patterns in different contexts is used as an alternate decision to dynamic pricing. A deep Q network responsible for dealing with demand response problems to find variable consumption patterns in the electricity sector is proposed in [37]. Additionally, this learning is formulated in a Markov Decision Process that considers three components: state, action and reward. The multiagent model is researched in [38] featuring the suppliers and consumers of electricity as autonomous agents capable of making local decisions to maximize their own profit. The difficulty to balance the supply with the demand is an issue on a residential energy management level [39]. The home energy appliance proposed in [40] studies a double deep Q-learning integrated in reinforcement approaches to perform schedule task optimizations with impact on the energy management which shows to have increasing complexities and uncertainties in the end user [40]. While reinforcement learning has already been demonstrated as an effective solution to obtain reliable and accurate building energy consumption predictions as seen in [33-36] a study on the specific techniques of reinforcement learning which are the most suitable and the advantages and disadvantages of each one is presented in [41]. Accordingly, to [42] the integration of reinforcement learning in energy applications presents the benefit of preventing user discomfort and adding human feedback to the control loop. Analysis of several publication concerning the use or the abstention of reinforcement learning on the energy area has been researched in [43] highlighting the improvement from 10% to 20% with reinforcement learning integration and the fact that half of publication with reinforcement learning usage are about q-learning algorithm. Additionally, [44] recognizes the value of reinforcement learning for control problems, namely for energy building management. The training and evaluation of reinforcement learning is performed in [45] according to different techniques. A multiagent based decentralized energy management approach is integrated in a microgrid in [46] where all distributed energy resources and customers are modelled as interested agents who optimize their behavior and operation costs.

Several problem domains can be structured considering agents with reinforcement learning approaches including demand response just as electricity price agents that send price signals to customers in the environment to decrease the demand on certain periods [47]. The high relevance of electricity markets models and the complex dynamics of electricity prices lead to a very complex environment that required the construction of market simulators for analysis studies and for supporting the involved players in their decisions [48].

2.4 Evaluation of forecasting algorithms

The evaluation of forecasting algorithms is addressed in [49] considering different sources of data for supervised and unsupervised problems. Therefore, evaluation strategies are employed to deal with the different sources of data. The decision models according to [50] are rather challenging when considering how these evolve continuously over time due to detections of changes that happen in the environment generating data. These are dynamic and non-stationary environments as evidenced in [51] where data changes over time. The type of learning to deal with these changes consists in incremental learning [52] where the models are updated considering a continuous influx of data. Incremental learning was used for online prediction in large sensor networks as in [53]. The application consists in aggregating sensors into clusters to predict the value of different sensors for different horizons. The clustering system aggregates sensors with high correlation. Incremental learning plays a relevant role when integrated with artificial neural networks to deal with the cluster's diameters [53]. Incremental learning has been successfully used in other areas. For instance, in [54] it used to address the adequate care of COVID-19 patients considering the constraints of doctor planning, maximizing the effectiveness of a task execution as well as reducing the time needed for each task.

3. Proposed solution

In this Chapter we describe the problem, the data and the proposed solution. We aim at performing and obtaining forecasting data based on algorithm's precision in each five minutes, and simultaneously evaluating which forecasting algorithm is the most appropriate in different five minutes periods.

The access to real time data is crucial to address the problem targeted in this dissertation, namely the electric energy consumption forecasting in a building owned by GECAD. The research center has been monitoring not only energy consumption but also photovoltaic generation, different sensors and several types of events, including people's behavior, having a large historic database. This dissertation uses five minutes periodic consumption data and different sensors data.

The aim is to perform several tasks based on two types of problems. The first consists in performing and obtaining forecasting data to obtain algorithm's precision in each five minutes. The second consists in applying methodologies capable of evaluating and selecting the best algorithm in each context. Sub-section 3.1 presents the final goal of the multiagent system, the agents tasks and the environment. Sub-section 3.2 presents the forecasting method. Sub-section 3.3 presents a decision tree capable of selecting the best forecasting algorithm in different contexts. Sub-section 3.4 presents reinforcement learning applications that select the most suitable forecasting algorithm in different contexts. Sub-section 3.5 addresses the forecasting error calculation metrics.

3.1 Multiagents system

This sub-section details the MARLEC (Multi-Agent system with Reinforcement Learning for forecasting electricity consumption) multi-agent system. The multi-agent system determines the most appropriate algorithm to be used in each context to forecasting a building electric energy consumption for each five minute period. Figure 1 presents the four agents responsible for data, forecasting, schedule, and learning activities in the methodology diagram.

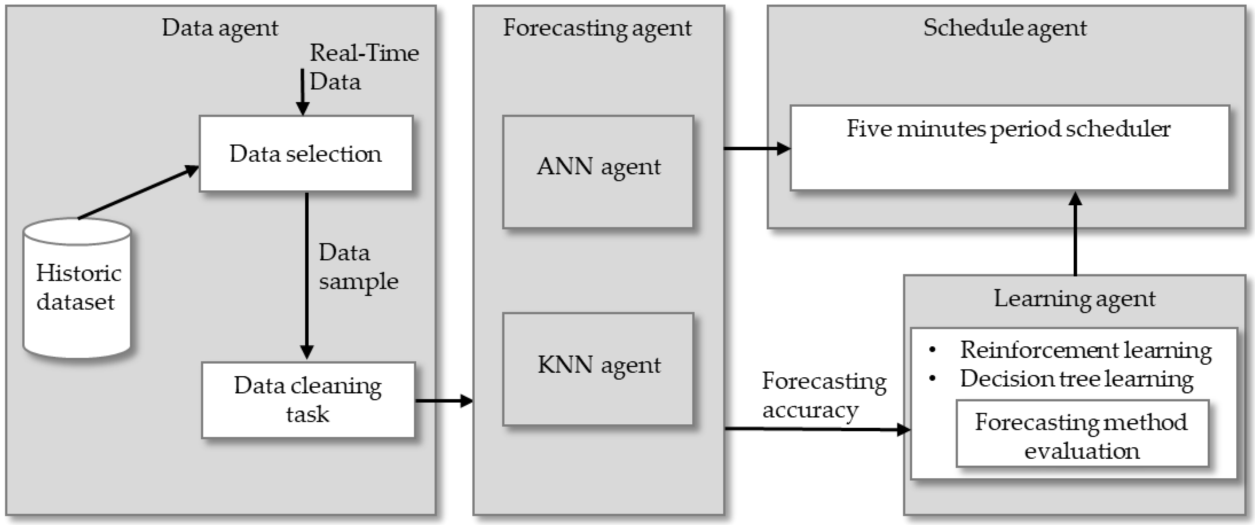

Figure 1. Methodological diagram of the problem

The MARLEC multi-agent system has four different agents that deal with four different aspects of the problem: data, forecasting, schedule, and learning. The data related activities include the selection from the historic data a sample for training and testing the models used on later forecasting tasks. The same rules applied for the selection of the historic of data are consistently used with real-time data. The historic of data associated with forecasting tasks considers five minutes contexts fed by energy consumption and sensors data showing a high correlation with consumption patterns. The sensors planning present the different sensors considered for the prediction's enhancement including the temperature and outside lighting, presence sensors, energy meters, CO2 sensors, and temperature and humidity sensors. The sensors planning is illustrated in Figure 2. The sensors with potential for the prediction's activities enhancement correspond to CO2 and light intensity. The data sample goes through a cleaning process that makes data more cohesive and consistent for later forecasting tasks. More concretely, this cleaning process considers time adjustments to five minutes periods, average calculations for data duplicates and copy of previous records for missing data for particular five minutes periods. An outlier's treatment is also applied for excessive values using an average criterion.

The forecasting agent is responsible to perform predictions of consumptions in five minutes contexts according to two algorithms, Artificial Neural Networks and K-Nearest Neighbours. These predictions are integrated in a schedule agent that performs five minutes predictions. A learning agent evaluates according to the available methodologies which forecasting algorithm is better in five minutes contexts. The reinforcement learning is used to decide which forecasting algorithm is the most appropriate in each five minutes context, according to a forecasting method evaluation. The reward criterion consists in comparing the forecasting errors and assigning a reward of 1 if the selected algorithm corresponds to the one with lower forecasting error; otherwise, the assigned reward is 0.

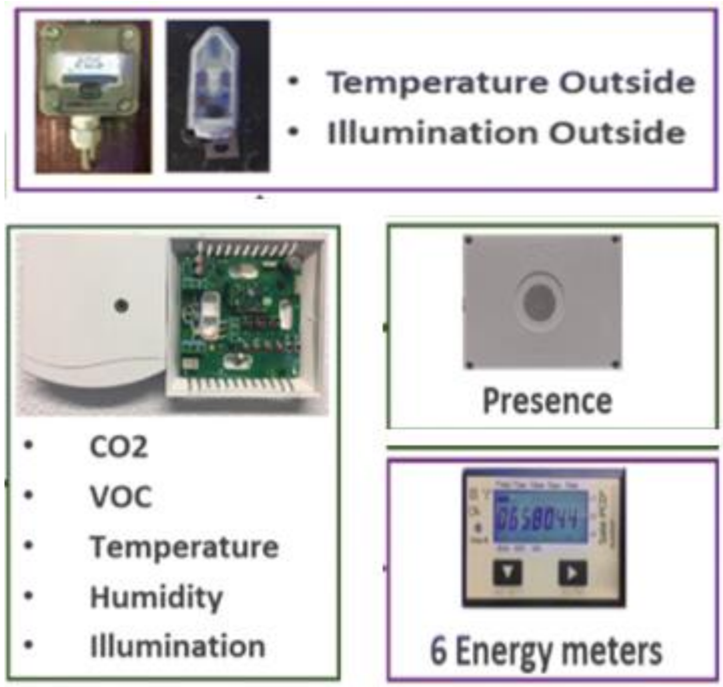

Figure 2. Diagram with sensors planning

3.2 Load forecast module

The load forecast module includes all the required steps for forecasting tasks. These include the data collection, the data set reducer, the training service, and the forecasting service. These involve a series of steps that reduce the dataset to a simpler version and restructure it in order to make it cohesive for the respective forecasting technique. Figure 3 illustrates the methodology process which was published in [55].

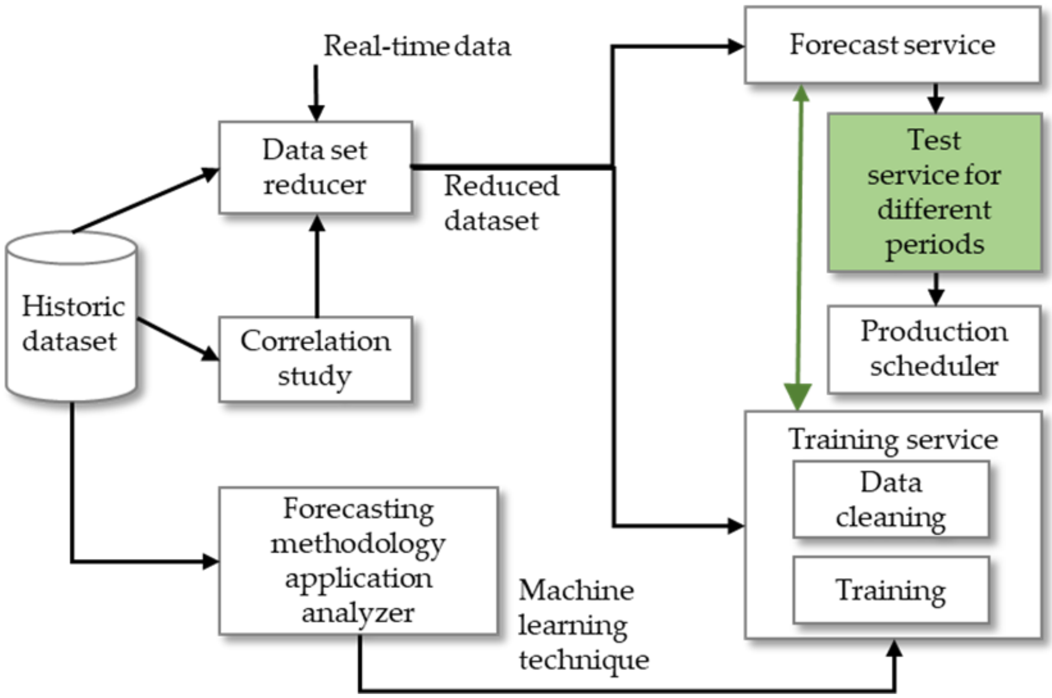

Figure 3. Methodology diagram of the problem

The real time data is collected and sent to a data set reducer component that simplifies the data to a version capable of providing better forecasts for the selected machine learning technique. The simplification considers the exclusion of data found to be pointless or too excessive for the prediction of the target data. The targets are contextualized according to consumption integrated in short time periods. The correlation study finds patterns associating sensors data fields that are more associated to the consumption data. Therefore, the correlation study finds the relevant sensors data that should improve the consumption predictions. The same rules applied to the data set reducer are used in the same way for processing the selected historic dataset. The forecasting methodology application analyser performs a decision making of the forecasting technique that should provide more accurate forecast according to the features present in the historic dataset. The reduced version of the data and the forecasting technique are sent to the training service which cleans the data, finding and correcting outliers and removing unreliable weeks from the samples of data. The result of the training service supports the forecasting service which forecasts consumption for different time periods according to a production scheduler.

3.3 Decision tree module

A decision tree process has been programmed to select the best forecasting in different contexts (see full process in Figure 4) which involves the decision tree training, the obtaining of rules for the decision criterion and the selection of the best forecasting algorithm according to the rules chosen.

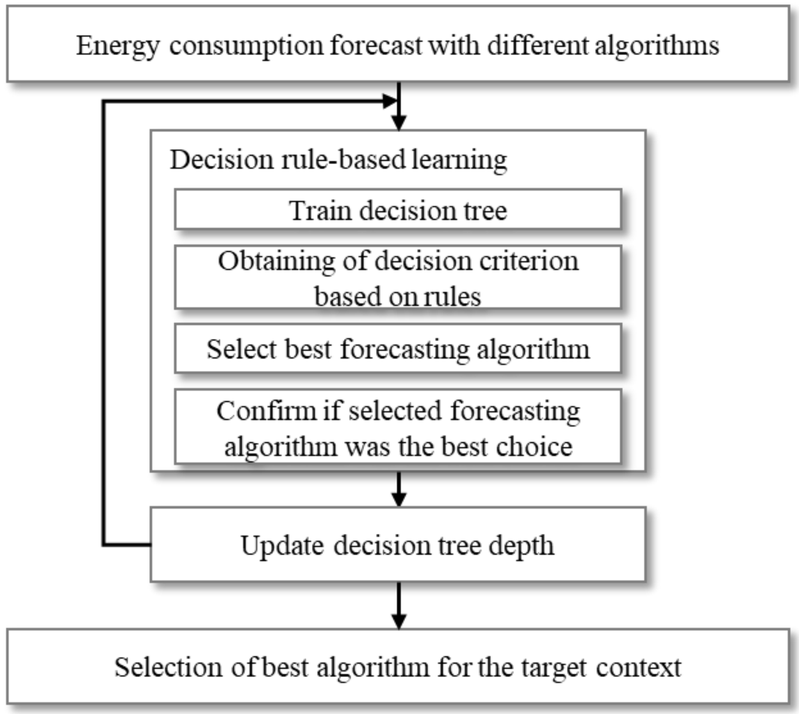

Figure 4. Methodology diagram of the problem (Decision tree)

The decision tree is trained through an historic of data that selects the forecasting algorithm that looks more suitable in each five minutes context according to two alternatives: Artificial Neural Networks and K-Nearest Neighbours. The training selects one of the two algorithms, and it associates to a logical value that makes clear if the selection option was the most pragmatic. This training is followed by decision rules construction that support the decision of associating which one of the two alternatives should be the most suitable in different five minutes contexts. A decision confirmation is applied to verify if the forecasting algorithm selection was the most convenient in each five minutes period. The decision tree depth is updated to control the decision tree split for the rules' construction as the most convenient way possible.

3.4 Reinforcement learning

A reinforcement learning-based procedure selects, according to a sequence of experiments, which of the forecasting algorithms is the most convenient choice in each five minutes context. The full process is explained in Figure 5.

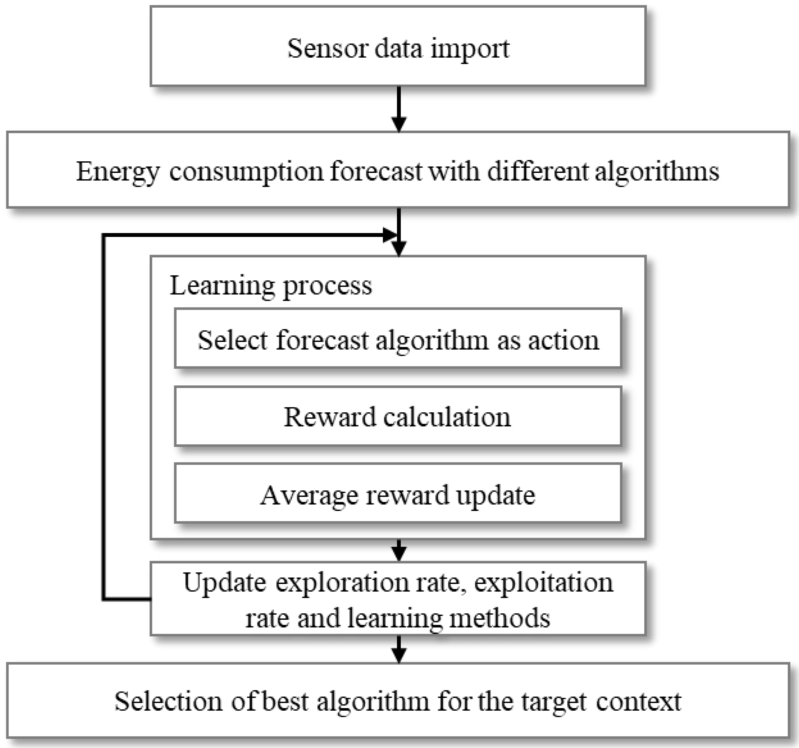

Figure 5. Methodology diagram of the problem (Reinforcement learning)

The sensor data is imported to the program to support the observation of the multi-agent system. This multi-agent system takes the reinforcement learning application consisting in choosing the forecasting algorithm that looks the most suitable between two alternatives: Artificial Neural Networks and K-Nearest Neighbours. The learning process starts to select one of the two algorithms in each five minutes followed by a reinforcement learning calculation dependant on the forecasting error. The reward criterion consists of assigning 1 if the selected forecasting algorithm was the most pragmatic alternative or by other words with lower forecasting error. The value 0 is assigned to the reinforcement learning if the forecasting algorithm selection was not the most pragmatic. This reward is added to an average of rewards that considers an historic of rewards with the performance for a sequence of five minutes. The exploration and exploitation rates are updated as well as the learning methods greedy and upper confidence bound to adjust to more optimized results. The process to select the action is different for the exploration and exploitation rates. While the exploration rate motivates to choose randomly alternate decisions, the exploitation instead follows the decision criterion seen in equation 5. The current estimation is updated for the undertaken action in equation 6. The current estimation corresponds to the trust level of a particular action between k-nearest neighbours and artificial neural networks based on the reward feedback.

$$A = argmax(Q(t) + c * \sqrt{\frac{\ln{(t)}}{Nt(a)}}) \tag{5}$$

$$Qt(a) = lr * (R - Qt(a)) \tag{6}$$

- A – selected action
- Q(t) – current estimation
- Nt(a) – number of times that action has been selected
- c – degree of exploration
- R – reward
- lr – exploitation rate

3.5 Forecasting accuracy

The error analysis consists in obtaining and studying the forecasting accuracy of the various forecasting techniques according to different error metrics. These consist in calculations that measure the deviation of actual observations to forecast counterparts according to different calculation processes. The error metrics are represented in Equations 1 to 4. The Symmetric Mean Absolute Percentage Error (SMAPE) [56], in Equation 1, is an accuracy measure that performs in each time period the ratio between the absolute difference of the actual and forecasting counterparts and half of the sum of the absolute values of the forecasting and actual counterparts. The Mean Absolute Percentage Error (MAPE) [56, 57, 58], in Equation 2, is an alternative accuracy measure that calculates in each time period the absolute value consisting in the ratio of the absolute difference of the actual and forecasting observations and the actual value. The Mean Absolute Error (MAE) [55, 56, 58], in Equation 3, performs the average of the absolute difference of each actual observation and the forecasting counterpart. The root mean square error (RMSE) [56,58,59], in Equation 4, calculates a square root associated to an average factor and a sum of sequences featuring the squared difference between the actual and forecasting observations.

$$SMAPE = \frac{1}{F} * \sum_{t=n-F}^{n} \frac{|F(t) - A(t)|}{0.5 * (A(t) + F(t))} \tag{1}$$

$$MAPE = \frac{1}{F} * \sum_{t=n-F}^{n} \left| \frac{A(t) - F(t)}{A(t)} \right| \tag{2}$$

$$MAE = \frac{1}{F} * \sum_{t=n-F}^{n} |A(t) - F(t)| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{F} * \sum_{t=n-F}^{n} (A(t) - F(t))^2} \tag{4}$$

- A – actual observation
- F – forecast observation
- n – number of observations
- F – frame used for observations
- t - period

MAPE and MAE represented respectively in Equations 2 and 3 are used as the error metrics in electric load forecasting tasks [56]. Accordingly, to [57] the wind energy forecasting involves two error metrics including SMAPE and MAE featured respectively in Equations 1 and 3. The power demand application suggested in [58] within the electricity sector uses similar metrics using comparations between SMAPE and MAPE featured respectively in Equations 2 and 3. Several error metrics are suggested in [59] for a recovering missing time series application including SMAPE, MAPE, MAE and RMSE presented in Equations 1 to 4.

4. Infrastructure and software description

The data used for this dissertation is composed by data regarding electric energy consumption, photovoltaic power production and sensors, which include CO2, air quality, temperature, humidity, light, movement, door status and intensity of each lamp. The data is obtained from three different building zones with three rooms each and from the corridor. Going to concrete details zone 1 is composed by rooms N101, N102 and N103 while zone 2 is composed by rooms N104, N105 and N106 ending in zone 3 with rooms N107, N108 and N109. Figure 2 illustrates the structure of the building highlighting the three zones to different colours respectively zone 1, zone 2 and zone 3 with blue, green and orange.

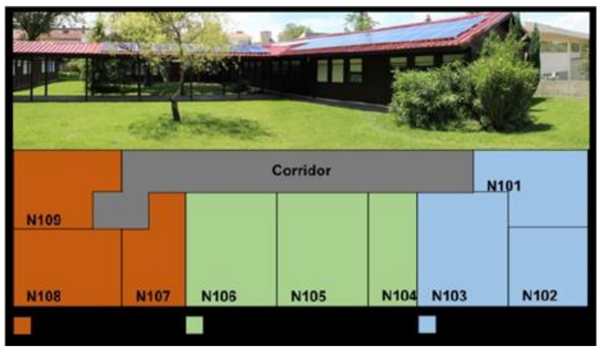

Figure 6. Building structure with zones and rooms evidence

The rooms are equipped with sensors devices including air conditioners, thermometers and lamps as evidenced in zone 1 illustration in figure 7.

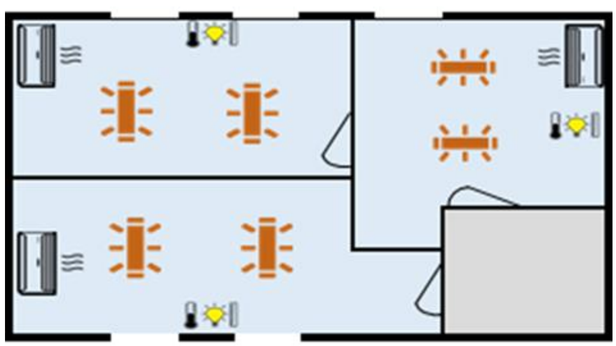

Figure 7. Building plan of zone 1 evidencing the installed sensors equipment

The sensors’ equipment of zone 1 is composed by the following devices:

- Four movement sensors;
- Three door status indicators;
- One air quality sensor;
- One temperature sensor;
- One humidity sensor;
- One CO_2 sensor ;
- Seven light power indicators.

The CO2 concentration and lights intensity present with daily patterns for the last week as illustrated in Figures 8 and 9.

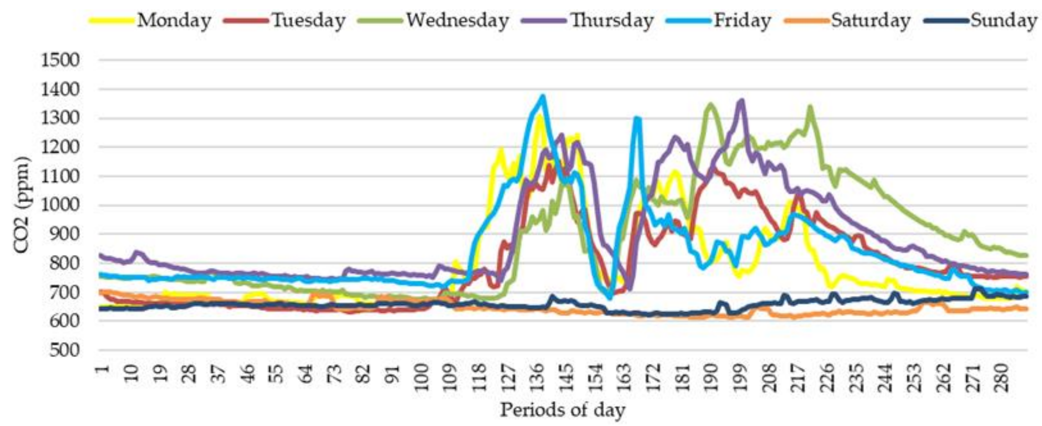

Figure 8. CO2 concentration data of 7 days of the week with 5 min time intervals

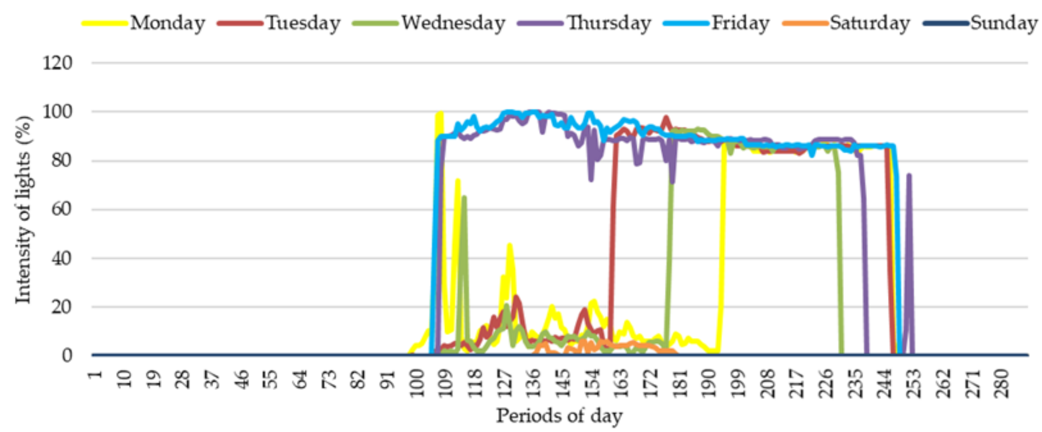

Figure 9. Light intensity data of 7 days of the week with 5 min time intervals

The CO2 concentration reflects the higher or lower activity in the building during the pst hours. In the early morning the CO2 concentration lays in a range between 600 and 800 ppm. CO2 presents higher values before the afternoon with values above 800 and below 1300 ppm. During the late evening, the CO2 decreases again to values between 600 and 800 ppm until the next morning. Saturday and Sunday present low CO2 concentration for all the forty-eight hours with values between 600 and 700 ppm. The light intensity presents values between 80 and 100 % during activity times which starts daily before the afternoon and end before the late evening. The early morning and the night present no light intensity, corresponding to 0%. This is also seen for all the forty-eight hours of Saturday and Sunday.

The considered historic of data for the electric power regarding the energy consumption in the building corresponds to nearly two and half years. The consumption week profile is presented in figure 10 containing for each week 2016 points regarding the data for each five minutes.

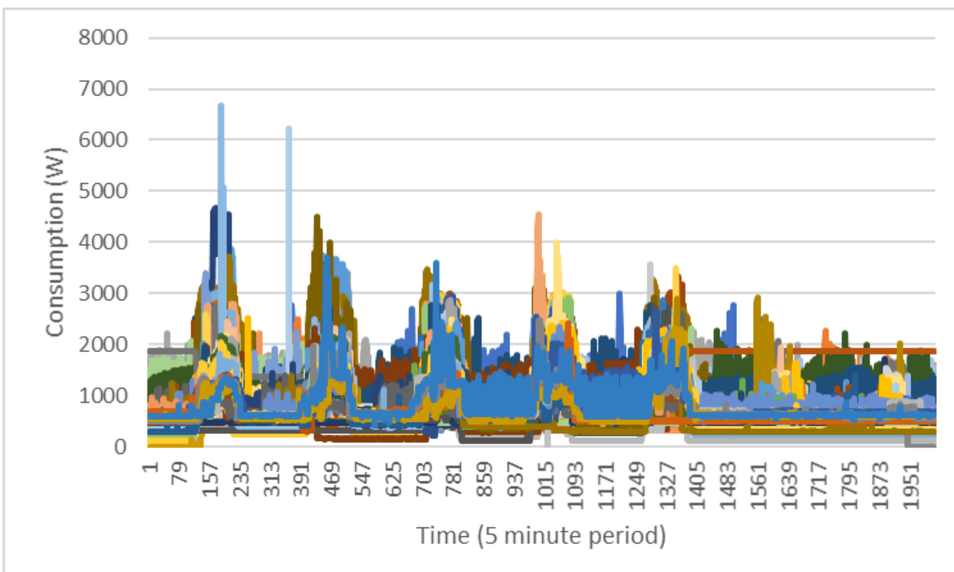

Figure 10. Weekly consumption profiles from 22 May 2017 to 24 November 2019

Several tools are considered in the implementation work underneath the dissertation. The python software has been used for the development of programs where most of them are developed to implement the functionalities with the support of python libraries needed for data analysis and machine learning tasks. This includes data cleaning operations, performance of data forecasts, and implementation of multiagent systems with reinforcement learning.

Excel has been used as an auxiliary tool where data obtained from cleaning operations, from forecasting tasks and from reinforcement learning results is analysed. This analysis studies were done in order to study the information obtained including the influence between the forecasting learning algorithm decision on each five minutes period and the penalization dependent on the forecasting error. Excel is also used to save all cleaned data obtained from a python program to persistent storage described by an unique csv file. Additional calculations concerning forecast errors are also calculated with the support of excel as a more productive and effective practice as it is possible to reuse the same calculation methods manipulations to easily calculate the forecasting errors for each five minutes.

The Pandas library supports excel tasks as the first performs data manipulations that allow the saving or reading of data to an excel file. The NumPy library is useful on calculations required in python language. The TensorFlow and scikit-learn libraries contain the algorithms implementation allowing the user only to insert the algorithms parametrization.

5. Tests and results

This section presents the obtained results according to different tests which are structured in different modules. Sub-section 5.1 presents the forecasted targets. Sub-section 5.2 addresses the decision tree studies as well as the observations. Sub-section 5.3 presents the reinforcement learning study. Sub-section 5.4 addresses the error analysis. Table 1 shows the historic and target considered for the different studies. Table 1 also presents the time periods considered for the input and target for each sub-section from 5.1 to 5.4.

Table 1. Historic and target of each sub-section / topic

Section / topic	**Historic / Input**	**Target / Output**
Section 5.1 / Forecasting	22 May 2017 to 17 November 2019	18 to 24 November 2019
Section 5.2 / Decision tree	18 to 24 November 2019 (except the first five minutes of each hour)	18 to 24 November 2019 (with only the first five minutes of each hour)
Section 5.3 / Learning	18 to 24 November 2019	18 to 24 November 2019
Section 5.4 / Forecasting accuracy	-	18 to 24 November 2019

The forecasting tasks are integrated in sub-section 5.1 considering a large historic featuring 22 May 2017 to 17 November 2019 and a single test week featuring 18 to 24 November 2019 with five minutes contexts. The decision tree module featured in sub-section 5.2 uses an input with all periods of five minutes for the week except the first five minutes of each hour presented from 18 to 24 November 2019. This input supports the decision making for a target with the first five minutes of each hour present from 18 to 24 November 2019. The learning module featured in sub-section 5.3 has access to the observations of the period 18 to 24 November to support the reward learning criterion for this period. The error analysis featured in sub-section 5.4 calculates the forecasting errors for the same period of the forecasting module describing 18 to 24

November 2019 according to different metrics. The identified target period is common for all sub-sections to provide comparison and interdependency of different developed methods.

5.1 Forecasting

The forecasting considers the consumption predictions with five minutes contexts for a single week considering 18 to 24 November 2019 with the support of an annual historic featuring 22 May 2017 to 17 November 2019. The forecasting algorithms supporting these predictions consider Artificial Neural Networks and K-Nearest Neighbour. The Symmetric Mean Absolute Percentage Error (SMAPE) is calculated in Table 2 for different Artificial Neural Network configurations and input structures for train and test data. The Artificial Neural Network present different configurations including the number of neurons for 32, 64 or 128, the clipping ratio for 5 or 6, quantity of epochs for 200 or 500, early stopping for 10 or 20 and the validation split for 0.2 and 0.3. Additional parameterizations consider the input structure of the train and test data considering the adding or absence of the day of the week and the number of inputs. The learning rate defines how accurate to search for possible minimization losses between the actual and forecasting values between 0.001 and 0.005. All possible presented parametrizations combinations account for a total of 60 scenarios for the following reasons:

- The combination of parameters featuring the learning rate, number of neurons, clipping ratio, number of epochs, early stopping, validation split and day of the week account for a total of 20 scenarios
- Each of the 20 alternatives is cross tabulated for three different configurations featuring the number of entries presented for train and test data presented in the different columns accounting a total of 60 scenarios
- These scenarios are independently of the selected forecasting algorithm, Artificial Neural Networks and K-Nearest Neighbours

The orders of magnitude of the parameters correspond to the most convenient choices after a series of trial and test studies that lead to more accurate forecasts. Thus, it has been observed the following:

- Despite the possibility of the learning rate to stay in a range between 0 and 1 it has been observed that low ranges with precise analysis within 0.001 and 0.005 lead to best scenarios

- The number of neurons with values lower than 32 do not acquire knowledge enough to serve as basis while values higher than 128 lead to overfitting of data
- The number of epochs has a minimum of training iterations in order to obtain accurate data with 200 iterations; 500 is also used in order to explore more possible accurate data however with the overfitting risk
- The validation split follows good practices with small percentages of data between 30 and 30%

Table 2. SMAPE errors for ANN and KNN according to 60 scenarios

Learning rate	Nr. neurons	Clipping ratio	Epochs	Early stopping	Validation Split	Days of the week	SMAPE_ANN (entries)			SMAPE_KNN (entries)		
							10	50	100	10	50	100
0.001	32	5	500	20	0.2	-	2.78 *	2.75	4.14	3.60 ***	5.27	7.57
0.001	32	5	500	20	0.2	x	3.37	2.73	5.83	3.61	5.27	7.57
0.001	32	6	200	10	0.3	-	2.75	5.75	3.29	3.60	5.27	7.57
0.001	32	6	200	10	0.3	x	2.53 **	3.63	5.24	3.61	5.27	7.57
0.001	128	5	500	20	0.2	-	3.63	3.52	5.97	3.60	5.27	7.57
0.001	128	5	500	20	0.2	x	2.56	2.72	3.72	3.61	5.27	7.57
0.001	128	6	200	10	0.3	-	4.17	3.07	3.98	3.60	5.27	7.57
0.001	128	6	200	10	0.3	x	3.38	3.10	3.44	3.61	5.27	7.57
0.005	32	5	500	20	0.2	-	6.26	3.97	5.41	3.60	5.27	7.57
0.005	32	5	500	20	0.2	x	2.78	8.64	5.29	3.61	5.27	7.57
0.005	32	6	200	10	0.3	-	5.31	6.42	7.76	3.60	5.27	7.57
0.005	32	6	200	10	0.3	x	3.66	2.74	6.94	3.61	5.27	7.57
0.005	128	5	500	20	0.2	-	4.31	4.66	3.99	3.60	5.27	7.57
0.005	128	5	500	20	0.2	x	4.04	4.21	6.74	3.61	5.27	7.57
0.005	128	6	200	10	0.3	-	4.26	4.24	8.11	3.60	5.27	7.57
0.005	128	6	200	10	0.3	x	6.36	5.06	7.91	3.61	5.27	7.57
0.005	64	5	500	20	0.2	-	5.10	4.52	5.64	3.60	5.27	7.57
0.005	64	5	500	20	0.2	x	3.03	3.44	5.94	3.61	5.27	7.57
0.005	64	6	200	10	0.3	-	5.40	7.00	6.48	3.60	5.27	7.57
0.005	64	6	200	10	0.3	x	3.49	4.79	11.38	3.61	5.27	7.57

The tables indicate three different scenarios signed with asterisks classified in A, B and C. These involve scenarios featuring lower forecasting errors, thus with higher accuracy. While the scenarios A and C correspond to an identical configuration, the forecasting technique was different respectively ANN and KNN. These three scenarios have in common the use 32 neurons for Artificial Neural Networks and the use of the inputs for the train and test data structure. Additional metrics contextualized for forecasting errors are presented later on section 5.4.

The consumption profile is presented for the week from 18 to 24 November 2019 in Figure 11 evidencing the five activity days from Monday to Friday and the weekend with low activity.

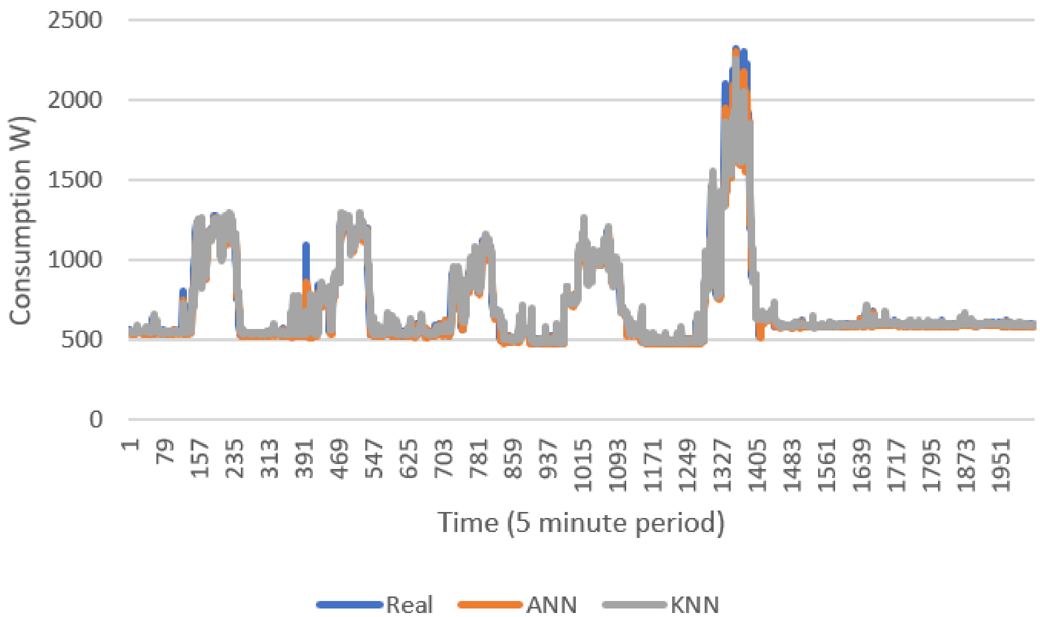

Figure 11. Real and forecasted consumptions for the week 18 to 24 November 2019 in five minutes contexts

The consumption presents five similar daily patterns starting with low consumption nearly the 500 W changing this in the late morning to behaviours above 700 and below 2500 W. While it is usual to reach behaviours not higher than 1300 W as seen from Monday to Thursday, Friday presents behaviours until 2500 W showing a lot more productivity. During the late evening, the consumption profile changes to low activity resuming behaviours of nearly 500 W until the next morning. These daily patterns correspond to each day of the week from Monday to Friday. Saturday and Sunday present low activity displaying behaviours nearly 500 W during all the forty-eight hours.

The SMAPE metrics is presented showing scenarios from 12 AM to 8AM and from 8 AM to 5 PM respectively in Figures 12 and 13.

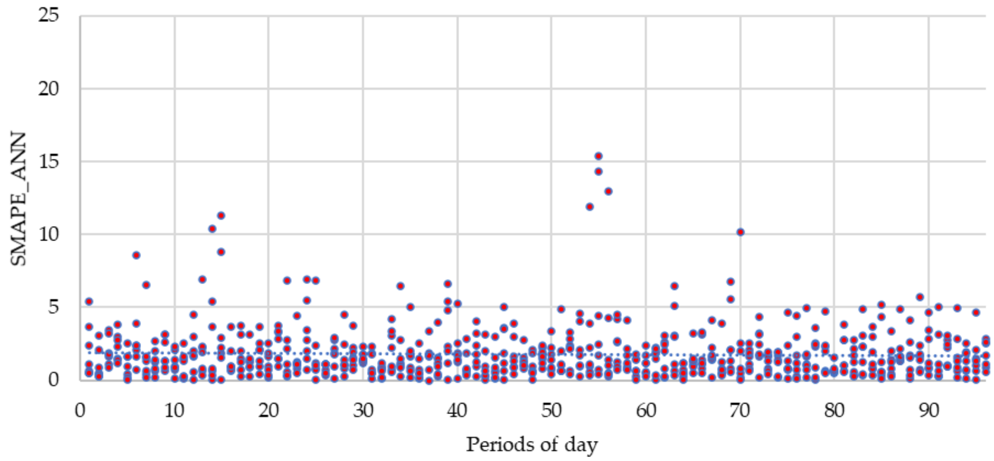

Figure 12. Forecast errors based on ANN approach in scenario A from 00:00 to 08:00

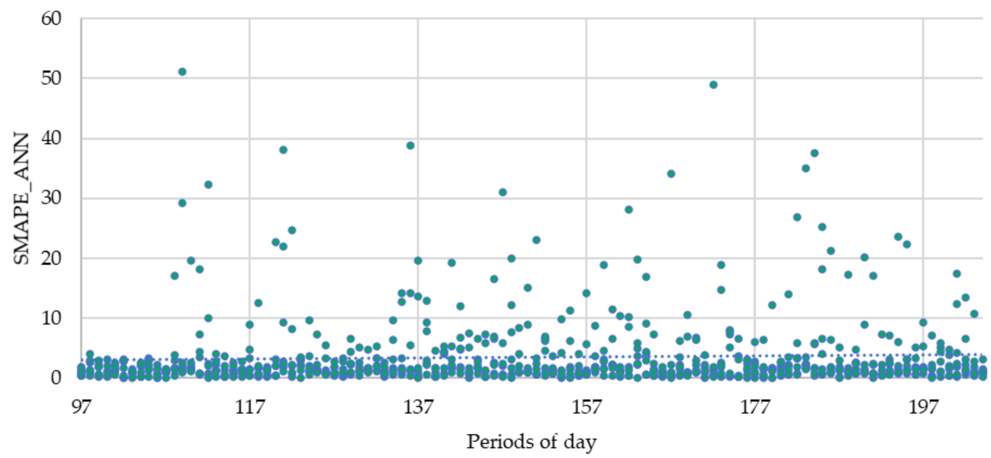

Figure 13. Forecast errors based on ANN approach in scenario A from 08:00 to 17:00

The forecasting consumptions for the period from 12 AM to 8 AM present usual forecasting errors between 0 and 5 % with some within the range between 5 and 15 %. During the period from 8 AM to 5 PM most forecasted consumptions present SMAPE errors between 0 and 10%. Some exceptions however present forecasting errors between 10 and 50 %.

5.2 Decision tree

The train data features measures collected from different electronic devices that take place in all five minutes periods scheduled in a particular week from 18 to 24 November 2019. These measures are monitored in electronic devices corresponding to different input parameterizations including consumption, light intensity and CO_2. These three factors are presented in the train data as illustrated in Fig. 14.

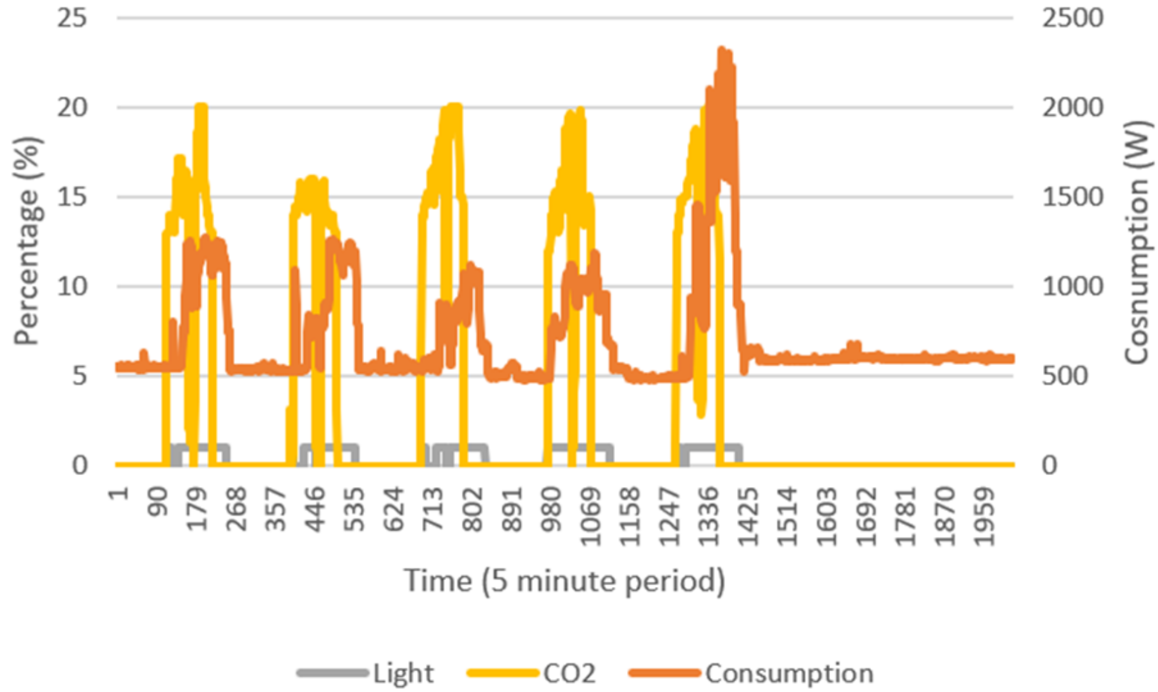

Figure 14. Input parameters for train data with all five minutes periods from 18 to 24 November 2019

The different input parameterizations taken from consumption, light intensity and CO_2 are represented in a weekly pattern featuring periods of five minutes. This presents five similar patterns featuring the productive behaviour of the five working days more specifically Monday to Sunday. This is followed by two similar patterns featuring the low activity present in the weekend more specifically Saturday and Sunday. The consumption features initial low activities between 500 and 600 W presented in the morning changing to behaviors between 700 and 1300 W happening between 10 AM and 12 PM. This productive behavior is again switched to low activity in the late evening that occurs nearly at 7 PM. This low activity featuring behaviors between 500 and 600 W maintains until the morning of the next day. While Monday to Thursday represents usual behaviors between 700 and 1300 W, Friday tends to reach ranges until 2320 W which is still acceptable but out of the usual. The low activity of Saturday and Sunday represent behaviors between 500 and 600 W. The light intensity sensors progress during the week represents switches between 0 and 1 which shows respectively no light presence and at least some light intensity activity. The week progress shows the sensor inactivity until 8 AM. Afterwards, the sensor presents possible activity starting at 8 AM until 7 PM where the sensor remains inactive until the next morning. The sensor shows to be inactive mode during Saturday and Sunday due to there being no activity in the weekends. The CO2 gains daily activity shortly after 8 AM presenting behaviors between 12.5% and 20%. There is an unusual behavior between 12 PM and 2PM where the CO2 changes to 0% before resuming the daily activity shortly after 4 PM resuming the inactivity mode until the next morning. Logically, the CO2 percentage remains 0% on Saturday and Sunday due to the inactivity status during the weekend.

The target featuring a weekly profile from 18 to 24 November 2019 is studied according to different input parametrizations. This weekly profile takes in consideration only the first five minutes of each hour keeping a reduced dimension of data for the test set representing the variation for a sequence of hours. Additionally, periods from 12 AM to 7 AM are discarded as well. Similarly, to what happened in the train, the features considered in the parameterization are the CO2, light intensity and the consumption. These parameters are represented for a whole week as evidenced in Figure 15.

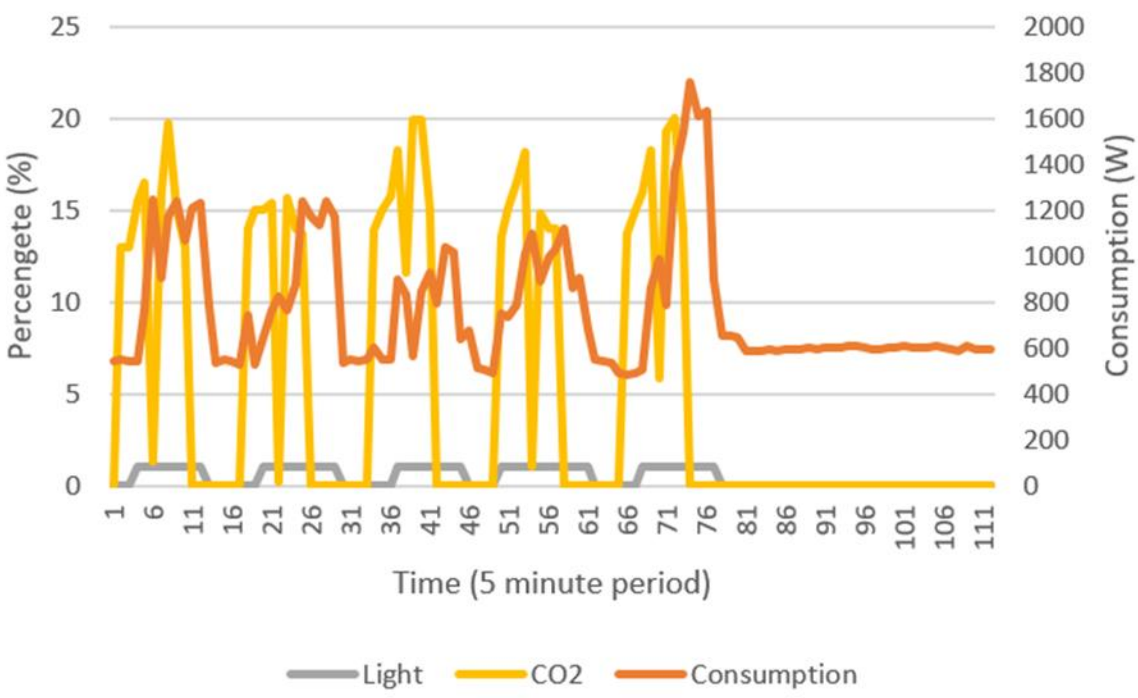

Figure 15. Input parameters for test data

The presence of the first five minutes of each hour for the sequence of data present in the test set provides an overview of the factor variations from hour to hour. The test set presents five similar patterns associated to the daily activities from Monday to Friday followed by two similar patterns with the inactivity of the weekend. Each daily activity shows low activity in the morning with consumptions between 500 and 600 W as presented between 8 AM and 11 AM. The consumption starts to gain more activity in the period between 11 AM and 12 PM reaching ranges above 700 and below 1300 W. Higher daily activities are present between 4 PM and 7 PM. During the late evening, after 7PM the consumption resumes the low activity until the next morning. The weekends present the same low activity featuring in the inactivity times between 500 and 600 W. The light intensity gains activity between 8 AM and 12 PM switching to no activity between 7 PM and 9 PM. During Saturday and Sunday this sensor shows signs of inactivity due to the low activity status during the weekend. The CO2 present behaviours between 12.5 and 20% during the activity times which start between 8 AM and 9 AM. During the weekend, the CO2 presents no production.

The decision tree creates rules according to factors obtained from electronic devices to support the decision making of verifying if the selected forecasting algorithm was the most convenient choice in different contexts (see results in table 8). The decision tree accuracies for different scenarios are presented in table 8. The factors involved in these rules' creations are the allocated period, and values allocated in the previous period including the consumption, the CO_2 and the light intensity sensors. This decision tree targets decisions to the first five minutes of all hours between 8 AM and 11 PM. Additionally four different scenarios are considered with depth variations as a decision tree parameter. This parameter specifies the decision tree rules split complexity. The decision tree corresponding to the scenario with a depth parameterization assigned to 3 is studied in order to understand the rules creation according to the factors provided from electronic devices. These rules depend on several factors including the allocated period and data obtained from the previous allocated period including consumption, CO_2 and light intensity. The decision presents the rules applied to the indicated factors as seen in Figure 16.

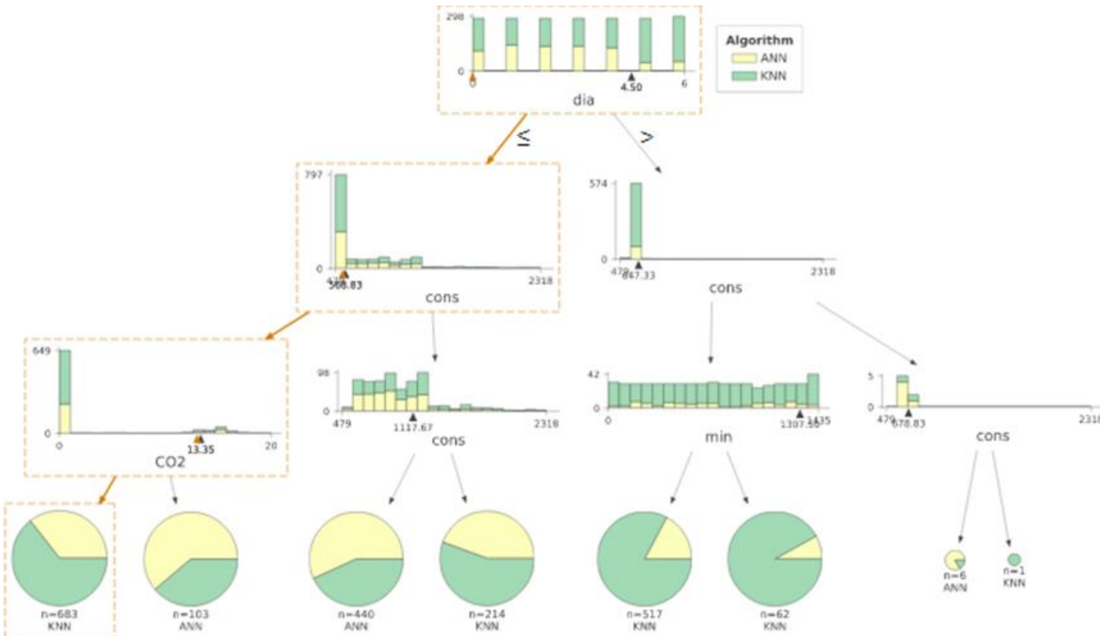

Figure 16. Decision tree featuring a depth parameterization of 3

The first rule of the decision tree considers the split of the days in two possible sets: Monday to Friday and the weekends representing the Saturday and Sunday days. This is an understandable rule as the weekend represent days with inactivity while Monday to Friday represent activity times. Activity days may use enhance sensors data if the consumption is below 479 W while equal or greater than this value will on no enhanced information. The presence of enhanced sensors corresponds to more reliable predictions for KNN algorithm while using data with consumption below 479 W, by other words out of activity times will result on relying more on ANN. Data integrated in the weekends present 2 alternatives associating most targets to data below 479 W as Saturday and Sunday represent days of low activity. The alternative case shows most cases being assigned to KNN than ANN. To highlight that light intensity data is not included for the weekend as the depth 3 does not make the rules complex enough to include this information. The sensor CO_2 is excluded for the weekend as this information is not relevant for the rules due to the low activity time.

5.3 Learning

The real and forecasted consumptions obtained in sub-section 5.1 contextualized for one week from 18 to 24 November are presented in Figure 7. This evidences data integrated for an entire week contextualized in five to five minutes periods according to three different scenarios: morning, afternoon and night. The classification of data in these three categories make possible to study data from independent periods featuring different aspects. Morning features periods from 9AM to 12PM, afternoon describes time placed between 1 PM and 6 PM, and night provides a sequence of periods from 8 PM to 9 AM. Recalling the five minutes contexts and the quantity of observations for each scenario in Figure 17, morning has a total of 312 observations, afternoon presents 360 observations and night finally presents a total of 984 observations.

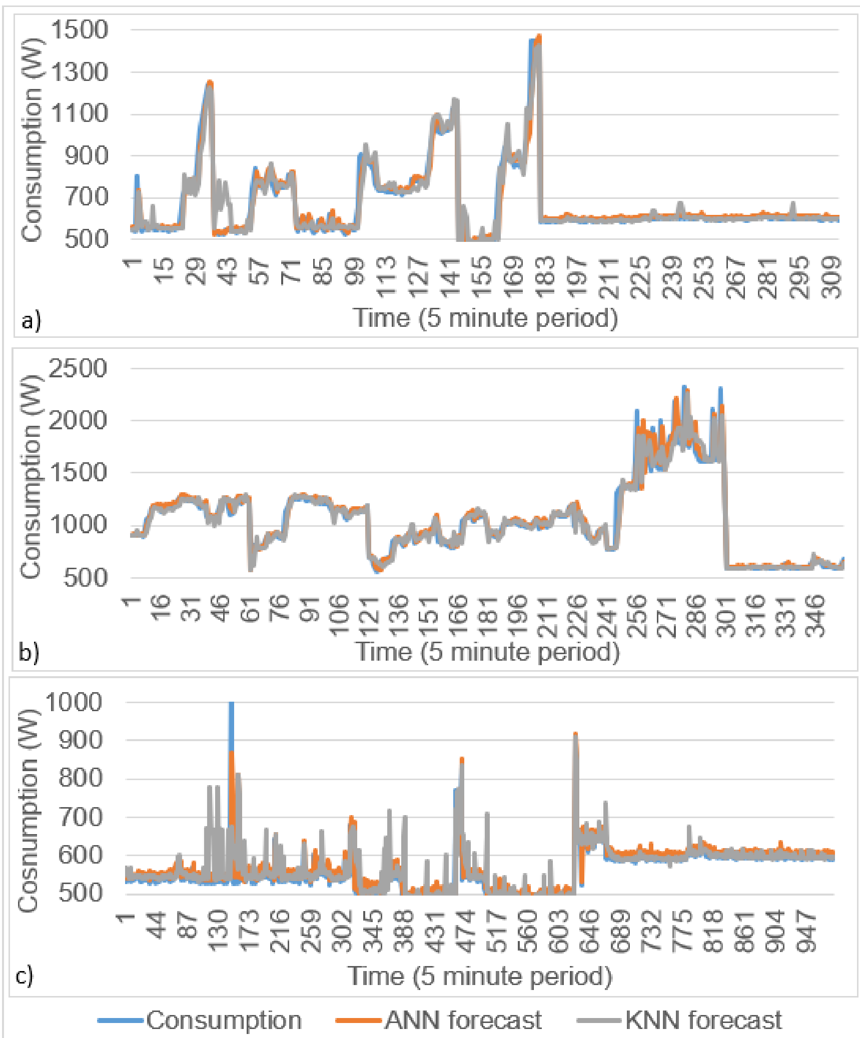

Figure 17. Consumption profiles in scenarios a) morning; b) afternoon; c) night

The three scenarios present different consumption profiles and describe activity consumptions with behaviours above 500 W and below 2500 W. Morning presents consumption sequences with a tendency to remain in a range between 500 and 650 W with low activity presenting however some productive behaviour including the increase of 510 to 1290 W, the increase of 510 to 1490 W and the productive time between 700 and 1100 W on particular periods. Afternoon presents an initial productive behaviour between 500 and 1500 W changing this after 241 sequences of five minutes to behaviours between 1500 and 2500 W. After 301 sequences of five minutes the afternoon reaches low activities representing consumption profiles nearly 500 W. Night has a consumption profile tendency between 500 and 600 W. However, this profile is mixed with some peaks reaching consumptions until 1000 W on particular five minutes periods before resuming the usual behaviour describing consumption patterns between 500 and 600 W. Nearly after 646 sequences of five minutes the night changes the consumption pattern to stay nearly the 600 W.

The reinforcement learning is applied to perform decisions concerning the most convenient forecasting application in different five minutes contexts. This decision making is elaborated for all five minutes periods of a particular week from 18 to 24 November 2019 studying this for the morning scenario corresponding to the consumption profile illustrated in Figure 17 for scenario a). Each decision integrated in five minutes contexts considers a forecasting algorithm selection between KNN and ANN supposed to be the most appropriate in each context. Figure 18 presents the historic of decisions respectively for KNN and ANN in five minutes contexts for all the five minutes integrated in the mornings placed in the week from 18 to 24 November 2019. This historic adds the exploration rate parameterization which studies different parameterizations concerning the focus on attending unexplored territory.

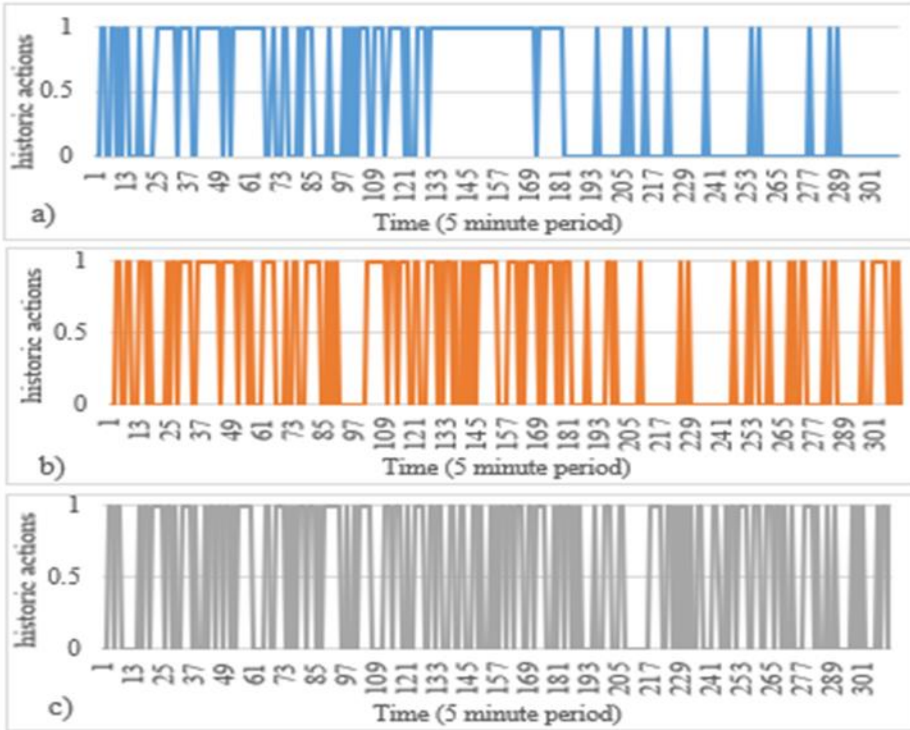

Figure 18. Historic actions classified in 0 and 1 respectively KNN and ANN in morning scenario: a) exploration rate =0.2; b) exploration rate =0.5; c) exploration rate =0.8

The historic of decision shows many switches between the KNN and ANN decisions as the forecasting algorithm in each five minutes context. It is noticed that the increase of the exploration rate increases the switching between decisions having a higher tendency to explore more often new territory belonging to the alternative forecasting method.

The decision-making respects that the selected forecasting algorithm should present a lower forecasting error. Therefore, the reward criterion consists in assigning the value 1 if the selected forecasting algorithm corresponds to the one with lower forecasting error. An accumulated reward sums the rewards in different five minutes contexts adding this information in each five minutes to an average reward that keeps a performance measure for every five minutes period. Figure 19 presents the average reward integrated in five minutes context for the week from 18 to 24 November with the upper confidence bound and exploration rate variations for different scenarios: morning, afternoon and night.

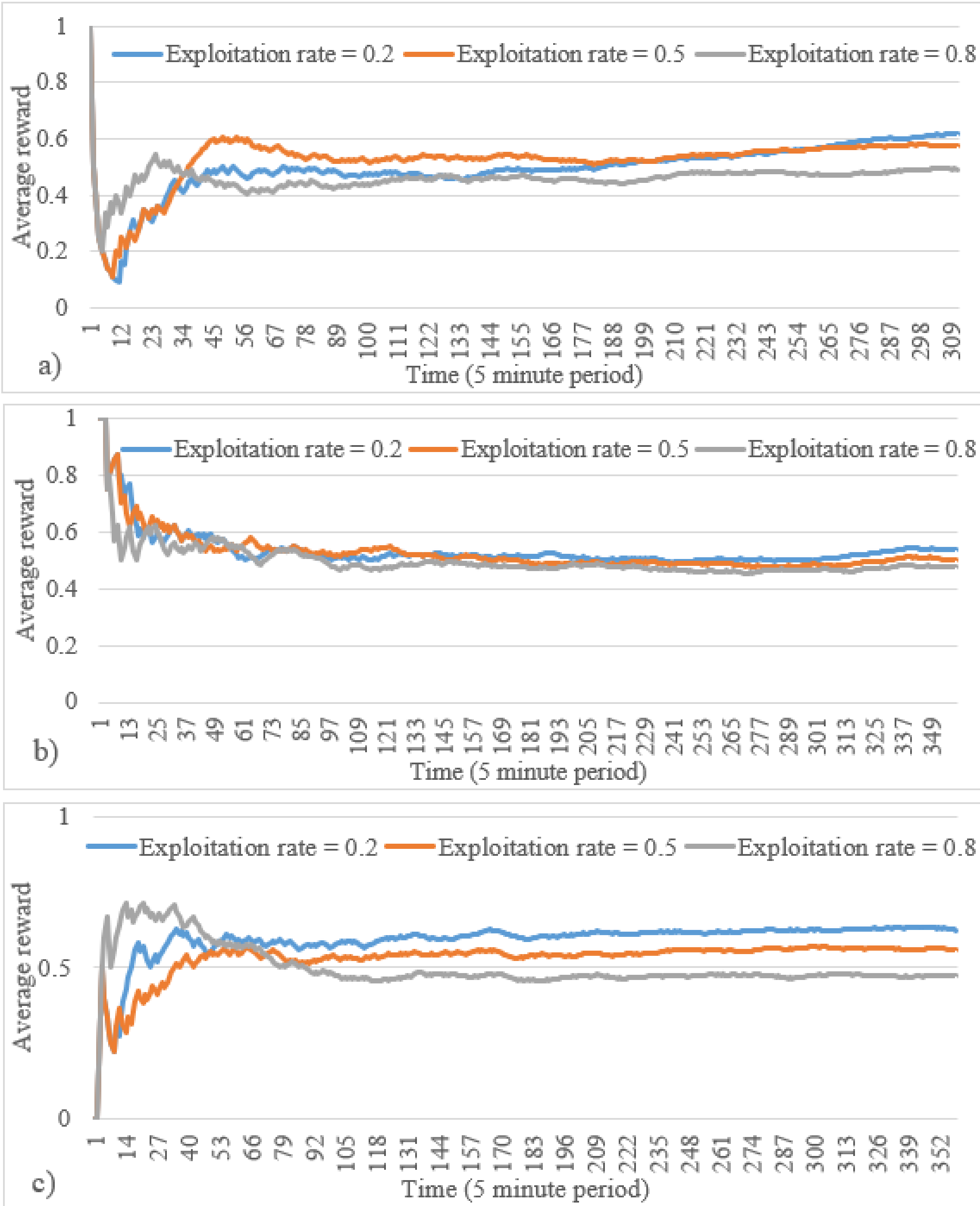

Figure 19. Average reward for confidence bound in scenario

The average reward is initially higher for a higher exploration rate as it has an higher chance of switching the knowledge of a decision between the forecasting algorithms known as ANN and KNN. However, as the exploration increases during the five minutes analysis, this starts to lose sense of knowledge for a particular decision ending to be outperformed by lower exploration rates. Despite this, the average reward difference is not very significative. Morning and afternoon scenarios make an initial right forecasting selection for the first five minutes followed by at least one wrong forecasting algorithm selection. In morning, this makes more forecasting algorithm wrong selections than afternoon as the average reward loses from 1 to 0.2 before converging to a range between 0.4 and 0.6. Night scenarios makes an initial wrong forecasting algorithm selection followed by at least one right forecasting algorithm selection. In a range of exploration rate between 0.2 and 0.8 it is possible to say that the average reward converges on all scenarios to a range between 0.4 and 0.6.

The confidence rate evidencing the forecasting algorithm's reliability is presented for different exploration rates and different scenarios as seen in Table 3.

Table 3. Confidence rate for each scenario

Scenario	Exploration rate					
	0.2		0.5		0.8	
	KNN	ANN	KNN	ANN	KNN	ANN
Morning	1.27362846	0.64103993	1.28437704	0.51420728	1.26276409	0.47323593
Afternoon	0.95506168	0.77442147	0.91544816	0.6591162	1.07098973	0.59035046
Night	0.925389	0.91983783	0.88298552	0.83060459	0.92708423	0.69229677

The confidence rate shows that the KNN tends to be the more reliable forecasting algorithm with a confidence rate higher than 0.9. While ANN is in disadvantage, the confidence rate presents a value higher than 0.45 showing that ANN is still a forecasting alternative more reliable on particular five minutes contexts. KNN shows higher reliability on morning periods while ANN tends to be the right choice more at night. It is further observed that increasing the exploration rate decreases the reliability in ANN forecasting algorithm.

The reinforcement learning method considers two possible alternatives: upper confidence bound and greedy. The exploration and exploitation rates are considered in reinforcement learning parameterizations as potentials respectively to search alternate forecasting algorithm or focus more on the current decision. Figures 20 and 21 show the average reward for all five minutes periods belonging to the morning for the week from 18 to 24 November 2019. Moreover, these are associated respectively to the upper confidence bound and greedy algorithm with different exploration and exploitation rate parameterizations from 0.1 to 0.9.

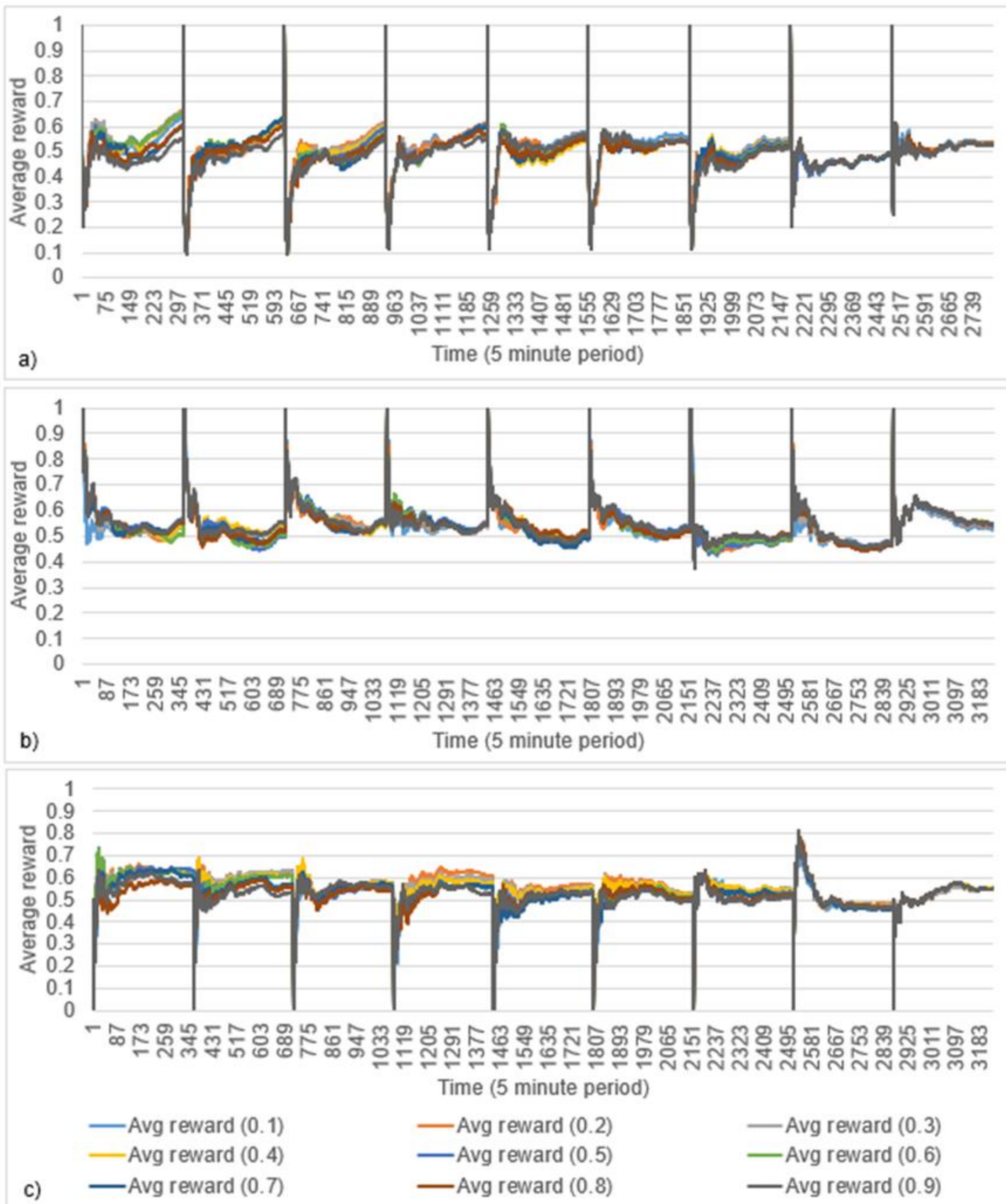

Figure 20. Average reward in scenario for upper confidence bound: a) morning; b) afternoon; c) night

The upper confidence bound method shows many average reward differences on five minutes contexts for the various exploitation rates considering the data belonging to smaller exploration rates. The increase of exploration rate results in the average reward pattern being more similar for the different exploitation rates. The morning and afternoon scenarios present an initial right forecasting algorithm selection followed at least by one wrong forecasting algorithm selection in a short sequence of five minutes converging then to an average reward between 0.4 and 0.7. Morning presents more wrong forecasting algorithm selections in a short period in the beginning since it shows to decrease the average reward almost afterwards from 1 to 0.2 before converging to a behaviour between 0.4 and 0.7 while afternoon tends to converge directly to this behaviour. Night presents an initial wrong forecasting algorithm selection followed by at least one right forecasting algorithm selection staying in an average reward range between 0.4 and 0.8.

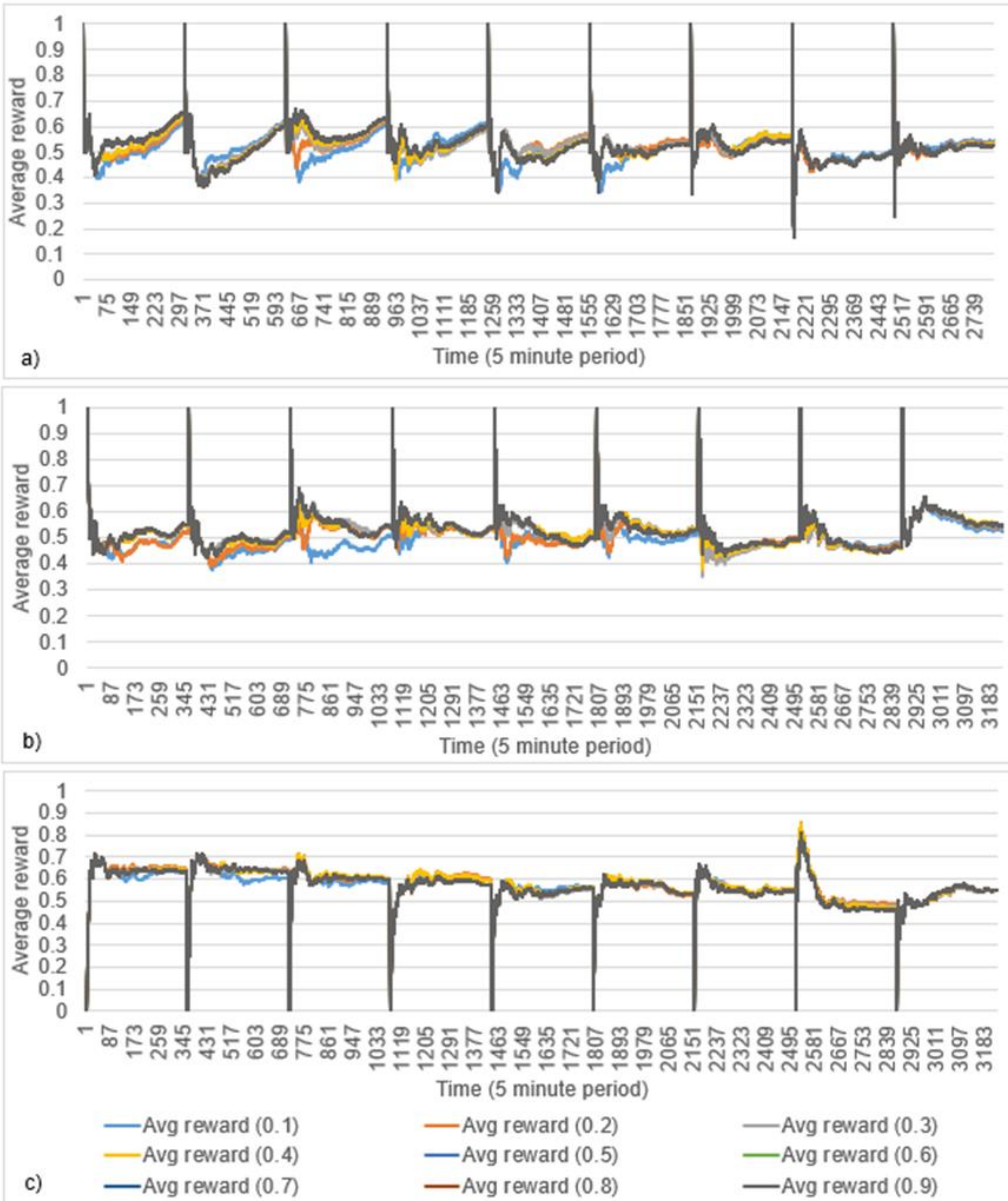

Figure 21. Average reward in scenario for upper confidence bound: a) morning; b) afternoon; c) night

The greedy method has similar average rate behaviours in five minutes contexts for the different exploitation rates being this more notorious as the exploration rate increases. Morning and afternoon scenarios present initial right forecasting algorithm selections followed by at least one wrong selection that converges almost afterwards to an average reward behaviour between

0.4 and 0.7. The night on the other hand starts a wrong forecasting algorithm selection for the first five minutes followed by at least one forecasting algorithm selection converging almost afterwards to an average reward behaviour between 0.5 and 0.8.

The confidence bound is studied for different scenarios considering combinations with the allocated period of five minutes, the exploration and exploitation rates. This confidence measures the trust of the forecasting algorithms KNN and ANN in five minutes contexts. Figure 22 presents the confidence bound for each forecasting algorithm according to different configuration scenarios.

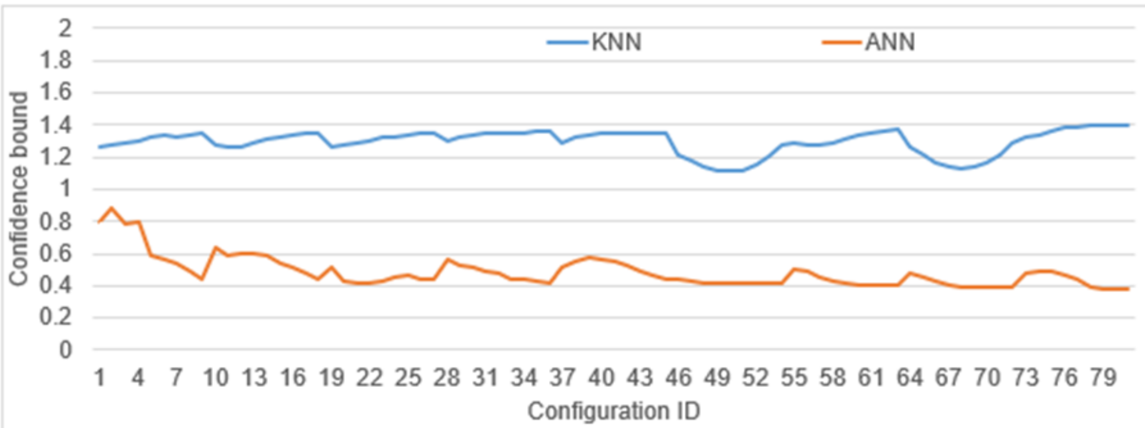

Figure 22. Confidence bound concerning KNN and ANN decisions for morning scenario

The confidence bound shows that KNN is the most reliable forecasting algorithm in five minutes contexts as seen in the two-forecasting algorithm confidence bound comparation for all possible configuration scenarios in Figure 22. Going to more detailed levels, KNN presents a trust with a behaviour between 1 and 1.4. Despite this ANN reliability shows that on some five minutes contexts ANN is still a best choice than KNN with a confidence bound range between 0.4 and 0.8.

5.4 Evaluation

The evaluation of reinforcement learning consists on comparing the forecasting errors according to different metrics with and without reinforcement learning for the two forecasting algorithms. Four error metrics are calculated for a target week from 18 to 24 November 2019 based on artificial neural networks and K-nearest neighbours approaches for a total of 60 scenarios considering parameter alterations for the different scenarios. The parameterization considers variations the day of the week, the number of entries for the input for train and test data and variations in ANN parameters including the learning rate, the number of neurons, the clipping ratio, the number of epochs, the early stopping and validation split. The error metrics considered consist in SMAPE, MAPE, MAE and RMSE respectively presented in Table 2 and from Tables 4 to 6.

The SMAPE forecasting errors show ranges between 2.5 and 11.4 considering the 60 presented scenarios. The ANN configuration shows many differences as this takes ranges from 2.5 to 11.4 while KNN takes ranges only from 3.5 to 7.6. The mentioning of the day of the week usually provides more accurate forecasts for a small learning rate about 0.001 and for a number of entries between 10 and 50. To highlight that the increase of number of entries for the input of the train and test structure may lead to higher forecasting errors especially for the KNN algorithm. ANN tends to provide more accurate predictions for a lower learning rate within rages between 2.53 and 5.97 considering more accurate analysis while dealing with local minimum searches. The best scenario that contributes for higher forecasts for ANN are a low learning rate of about 0.001, the use of a small number of neurons for the hidden layers of about 32, a higher validation split and the mentioning to the day of the week presenting an error of about 2.53. A scenario featuring a similar accuracy is to maintain the low learning rate, while increasing the number of neurons to 128 and to decrease the validation split but keeping a higher number of epochs with an higher early stopping. The best scenarios for KNN consider configurations with 10 entries and with no mention with the day of the week.

Table 4. MAPE calculation based on artificial neural networks (ANN) and K-nearest neighbors approaches for 60 scenarios

sLearning rate	Nr. neurons	Clipping ratio	Epochs	Early stopping	Validation Split	Days of the	MAPE_ANN (entries)			MAPE_KNN (entries)		
							10	50	100	10	50	100
0.001	32	5	500	20	0.2	-	2.79 *	2.73	4.21	3.69 ***	5.44	7.93
0.001	32	5	500	20	0.2	x	3.42	2.70	6.01	3.71	5.44	7.93
0.001	32	6	200	10	0.3	-	2.72	5.93	3.23	3.69	5.44	7.93
0.001	32	6	200	10	0.3	x	2.51 **	3.69	5.09	3.71	5.44	7.93
0.001	128	5	500	20	0.2	-	3.55	3.44	5.76	3.69	5.44	7.93
0.001	128	5	500	20	0.2	x	2.54	2.73	3.78	3.71	5.44	7.93
0.001	128	6	200	10	0.3	-	4.24	3.03	4.04	3.69	5.44	7.93
0.001	128	6	200	10	0.3	x	3.31	3.14	3.48	3.71	5.44	7.93
0.005	32	5	500	20	0.2	-	6.05	3.87	5.22	3.69	5.44	7.93
0.005	32	5	500	20	0.2	x	2.76	9.06	5.11	3.71	5.44	7.93
0.005	32	6	200	10	0.3	-	5.15	6.64	8.09	3.69	5.44	7.93
0.005	32	6	200	10	0.3	x	3.72	2.70	7.23	3.71	5.44	7.93
0.005	128	5	500	20	0.2	-	4.19	4.77	3.88	3.69	5.44	7.93
0.005	128	5	500	20	0.2	x	3.93	4.30	6.47	3.71	5.44	7.93
0.005	128	6	200	10	0.3	-	4.34	4.32	7.74	3.69	5.44	7.93
0.005	128	6	200	10	0.3	x	6.11	5.19	7.56	3.71	5.44	7.93
0.005	64	5	500	20	0.2	-	5.24	4.41	5.46	3.69	5.44	7.93
0.005	64	5	500	20	0.2	x	2.98	3.37	5.72	3.71	5.44	7.93
0.005	64	6	200	10	0.3	-	5.22	6.72	6.71	3.69	5.44	7.93
0.005	64	6	200	10	0.3	x	3.53	4.91	10.69	3.71	5.44	7.93

The MAPE forecasting errors present ranges between 2.5 and 10.7. While ANN presents this extensive range for all the 60 scenarios, KNN presents ranges between 3.69 and 7.93. The mentioning of the day of the week usually provides more accurate forecasts for a small learning rate about 0.001 and for a number of entries between 10 and 50. To highlight that the increase of number of entries for the input of the train and test structure may lead to higher forecasting errors especially for the KNN algorithm. ANN tends to provide more accurate predictions for a lower learning rate with ranges between 2.5 and 6.01 considering more accurate analysis while dealing with local minimum searches. The best scenario that contributes for higher forecasts for ANN are a low learning rate of about 0.001, the use of a small number of neurons for the hidden layers of about 32, a higher validation split and the mentioning to the day of the week presenting an error of about 2.51. A scenario featuring a similar accuracy is to maintain the low learning rate, while increasing the number of neurons to 128 and to decrease the validation split but keeping a higher number of epochs with an higher early stopping. The best scenarios for KNN consider configurations with 10 entries and with no mention with the day of the week.

Table 5. MAE calculation based on artificial neural networks (ANN) and K-nearest neighbors approaches for 60 scenarios

Learning rate	Nr. neurons	Clipping ratio	Epochs	Early stopping	Validation Split	Days of the	MAE_ANN (entries)			MAE_KNN (entries)		
							10	50	100	10	50	100
0.001	32	5	500	20	0.2	-	23.93 *	23.82	32.79	29.82 ***	43.00	59.93
0.001	32	5	500	20	0.2	x	28.01	23.56	43.78	29.90	42.99	59.93
0.001	32	6	200	10	0.3	-	23.77	44.39	27.19	29.82	43.00	59.93
0.001	32	6	200	10	0.3	x	22.37 **	29.81	39.23	29.90	42.99	59.93
0.001	128	5	500	20	0.2	-	29.07	28.42	43.15	29.82	43.00	59.93
0.001	128	5	500	20	0.2	x	22.40	23.70	30.27	29.90	42.99	59.93
0.001	128	6	200	10	0.3	-	33.50	25.78	31.55	29.82	43.00	59.93
0.001	128	6	200	10	0.3	x	27.62	26.49	28.20	29.90	42.99	59.93
0.005	32	5	500	20	0.2	-	45.90	31.72	41.75	29.82	43.00	59.93
0.005	32	5	500	20	0.2	x	24.03	65.20	40.63	29.90	42.99	59.93
0.005	32	6	200	10	0.3	-	40.14	49.16	57.04	29.82	43.00	59.93
0.005	32	6	200	10	0.3	x	30.12	23.86	53.81	29.90	42.99	59.93
0.005	128	5	500	20	0.2	-	33.02	36.42	32.08	29.82	43.00	59.93
0.005	128	5	500	20	0.2	x	31.66	34.27	47.66	29.90	42.99	59.93
0.005	128	6	200	10	0.3	-	33.93	34.09	55.87	29.82	43.00	59.93
0.005	128	6	200	10	0.3	x	46.46	39.45	55.46	29.90	42.99	59.93
0.005	64	5	500	20	0.2	-	39.98	34.83	41.26	29.82	43.00	59.93
0.005	64	5	500	20	0.2	x	25.53	28.39	43.58	29.90	42.99	59.93
0.005	64	6	200	10	0.3	-	40.54	50.67	49.05	29.82	43.00	59.93
0.005	64	6	200	10	0.3	x	28.71	37.71	77.29	29.90	42.99	59.93

The MAE forecasting errors present ranges between 22.37 and 77.29. While ANN presents this extensive range for all the 60 scenarios, KNN presents ranges between 29.82 and 59.93. The mentioning of the day of the week usually provides more accurate forecasts for a small learning rate about 0.001 and for several entries between 10 and 50. To highlight that the increase of number of entries for the input of the train and test structure may lead to higher forecasting errors especially for the KNN algorithm. ANN tends to provide more accurate predictions for a lower learning rate with ranges between 22.37 and 44.39 considering more accurate analysis while dealing with local minimum searches. The best scenario that contributes for higher forecasts for ANN are a low learning rate of about 0.001, the use of a small number of neurons for the hidden layers of about 32, a higher validation split and the mentioning to the day of the week presenting an error of about 22.37. A scenario featuring a similar accuracy is to maintain the low learning rate, while increasing the number of neurons to 128 and to decrease the validation split but keeping a higher number of epochs with an higher early stopping. The best scenarios for KNN consider configurations with 10 entries and with no mention with the day of the week.

Table 6. RMSE calculation based on artificial neural networks (ANN) and K-nearest neighbors approaches for 60 scenarios

Learning rate	Nr. neurons	Clipping ratio	Epochs	Early stopping	Validation Split	Days of the week	RMSE_ANN (entries)			RMSE_KNN (entries)		
							10	50	100	10	50	100
0.001	32	5	500	20	0.2	-	62.99 *	63.43	66.28	66.96 ***	83.41	105.58
0.001	32	5	500	20	0.2	x	63.57	62.93	70.12	67.06	83.41	105.58
0.001	32	6	200	10	0.3	-	64.58	72.44	64.35	66.96	83.41	105.58
0.001	32	6	200	10	0.3	x	63.71 **	65.44	69.24	67.06	83.41	105.58
0.001	128	5	500	20	0.2	-	63.66	64.75	72.11	66.96	83.41	105.58
0.001	128	5	500	20	0.2	x	63.11	61.99	64.89	67.06	83.41	105.58
0.001	128	6	200	10	0.3	-	66.01	63.56	66.04	66.96	83.41	105.58
0.001	128	6	200	10	0.3	x	65.21	63.90	64.16	67.06	83.41	105.58
0.005	32	5	500	20	0.2	-	73.46	66.26	73.50	66.96	83.41	105.58
0.005	32	5	500	20	0.2	x	66.32	88.58	72.30	67.06	83.41	105.58
0.005	32	6	200	10	0.3	-	71.33	75.35	79.29	66.96	83.41	105.58
0.005	32	6	200	10	0.3	x	65.82	62.79	79.94	67.06	83.41	105.58
0.005	128	5	500	20	0.2	-	63.72	66.56	66.93	66.96	83.41	105.58
0.005	128	5	500	20	0.2	x	65.12	65.84	75.27	67.06	83.41	105.58
0.005	128	6	200	10	0.3	-	64.62	65.84	79.91	66.96	83.41	105.58
0.005	128	6	200	10	0.3	x	74.71	69.28	79.85	67.06	83.41	105.58
0.005	64	5	500	20	0.2	-	69.28	67.50	70.11	66.96	83.41	105.58

0.005	64	5	500	20	0.2	x	64.24	64.03	73.40	67.06	83.41	105.58
0.005	64	6	200	10	0.3	-	70.93	77.36	75.37	66.96	83.41	105.58
0.005	64	6	200	10	0.3	x	64.28	67.77	99.25	67.06	83.41	105.58

The RMSE forecasting errors present ranges between 61.99 and 105.58. While ANN presents an extensive range from 61.99 to 99.26 for all the 60 scenarios, KNN presents ranges between 66.96 and 105.58. The mentioning of the day of the week usually provides more accurate forecasts for a small learning rate about 0.001 and for several entries between 10 and 50. To highlight that the increase of number of entries for the input of the train and test structure may lead to higher forecasting errors especially for the KNN algorithm. ANN tends to provide more accurate predictions for a lower learning rate with ranges between 61.99 and 72.44 considering more accurate analysis while dealing with local minimum searches. The scenario with a low learning rate of about 0.001, the use of a small number of neurons for the hidden layers of about 32, an higher validation split and the mentioning to the day of the week presents an error of about 63.71 which is one of the lowest within ranges between 61.99 and 105.58. The best scenarios for KNN consider configurations with 10 entries and with no mention with the day of the week.

As ANN is very dependent on the algorithm configurations this forecasting technique is more accurate than KNN for a lot of scenarios. It is observed that SMAPE is the error metrics for forecasting tasks that tends to present lower forecasting error. While MAPE is almost equal to SMAPE for ANN forecasting performance the KNN forecasting results show that SMAPE is much more convenient providing lower forecasting errors. Despite the metric differences for the forecasting accuracy performance, some common points are highlighted. The day of the week looks to provide lower forecasting results on most scenarios featuring 10 and 50 inputs for train and test data. KNN is observed to result in lower forecasting errors as the number of inputs increases first from 10 to 50 and then from 50 to 100. A lower forecasting rate of 0.001 results on increased accurate forecasts as it performs more careful analysis for the search of local minimum.

The four-error metrics are presented for each day of the week from 18 to 24 November 2019 and for all the week as presented in Table 7.

Table 7. Daily error metrics

Error metrics	SMAPE	SMAPE	MAPE	MAPE	MAE	MAE	RMSE	RMSE
Method	ANN	KNN	ANN	KNN	ANN	KNN	ANN	KNN
Full period	2.53	3.61	2.51	3.71	22.37	29.9	63.71	67.06
Monday	2.45	3.01	2.44	3.03	19.98	24.78	40.22	45.55
Tuesday	2.79	5.72	2.77	6.04	21	40	48.25	70.34
Wednesday	3.26	4.52	3.25	4.62	22.35	31.5	38.11	50.1
Thrusday	2.44	4.18	2.42	4.34	18.28	30.25	33.89	50.1
Friday	5.06	5.72	4.98	5.78	65.02	70.08	147.91	138.77
Saturday	1.06	1.24	1.06	1.25	6.41	7.61	9.97	14.88
Sunday	0.72	1.02	0.72	1.03	4.33	6.16	5.77	10.57

The table shows that SMAPE and MAPE result in lowest errors respectively between 0.72 and 5.72 and between 0.72 and 6.04. SMAPE provides almost the same performance in ANN predictions as MAPE however the first provides lower forecasting errors for KNN. The forecasting errors are higher for Friday possibly due to the high productivity present in that day of the week. On the other hand, Monday and Thursday are the days of the week with activity that result in more accurate forecasts.

Table 8 presents four different scenarios with four possible depth parameterizations variations from 3 to 6 with the forecasting accuracy results provided for each one of the four scenarios.

Table 8. Accuracy of each depth scenario

Depth	3	4	5	6
Accuracy	66.96%	66.96%	67.86%	71.43%

The more sighted observations present in table 8 are that the larger depths for the decision tree result in higher accuracy forecasts. This is present for a variation of the depth from 4 to 5 which increases the accuracy from 66.96 to 67.86% and then again for a variation of the depth from 5 to 6 which increases the accuracy from 67.86 to 71.43%. To highlight that the depth needs to be large enough for the rules creation to be complex enough to result in higher forecasts. As it is seen depth increases from 3 to 4 do not show any improvement presenting an accuracy of 66.96%. Depth increases of 4 to 5 show small accuracy improvements from 66.96 to 67.86%

presenting an increase of 0.9%. Depth increases of 5 to 6 present a large accuracy improvement from 67.86 to 71.43% presenting an increase of 3.57%. This means that improvements of the depth to 6 make the decision rules complex enough in order to provide better forecasts.

Table presented in annex A1 evidences the forecasting accuracy associated to different exploration and learning rates in the morning context. The results are provided by both the upper confidence bound and greedy applications. The forecasting accuracy interprets the average of forecasting algorithm selections that were more convenient on all five minutes periods. Therefore, each five minutes period corresponds to a forecasting accuracy of value between 0 and 1 meaning respectively that the forecasting algorithm corresponds to the less or more convenient on a particular context. The exploration and the learning rates take ranges from 0.1 to 0.9 being all the possible combinations associated to a forecasting accuracy. There is an alternative that associates the average of all the exploration rates to each learning rate. Tables from annexes A2 and A3 present similar contests respectively in the afternoon and night contexts.

The exploration rate increase is responsible for the decrease of the forecast accuracy. This is explained by a higher exhaustive search for previously unseen decisions thus being less trapped in a particular decision. Moreover, the greedy application shows difference accuracy outcomes according to the different learning rate parameterizations. To elaborate on this, the morning period shows that a more intense learning leads to more accurate predictions while during the night these predictions are more accurate for a lower learning rate.

Table from annex A4 presents the Symmetric Mean Absolute Percentage Error (SMAPE) associated to different exploration and exploitation rates in the morning context. The results are provided by both the upper confidence bound and greedy applications. The forecasting errors correspond to reinforcement learning applications associated to learning and exploration rates. Additionally, a KNN and an ANN without reinforcement learning applications are visible in the table. Tables from annexes A5 and A6 present the same contents for afternoon and night context.

The learning forecasting errors show to be generally lower than the forecasting errors of ANN and KNN without reinforcement learning applications. A few exceptions present errors with reinforcement learning higher than the basic ANN however this is overcome by increasing the learning rate high enough. The learning rate increase results in more accurate forecasts for both the upper confidence method and greedy applications. While the exploration increase has a nonlinear accuracy variation from 0.1 to 0.9, it is clear that the exploration rate increase motivates the different learning scenarios to converge more towards a particular scenario. The upper confidence bound shows this convergence for small exploration rate meaning that upper confidence bound readapts more than greedy to this convergence. The SMAPE errors show ranges between 3 and 4% and between 4% and 5% respectively for the morning or night and for the afternoon.

Annexes B1 to B9 present the forecasting errors according in the morning, afternoon and night contexts with the metrics MAE, RMSE and MAPE. MAE takes errors between 25 and 28 during the morning, between 53 and 58 during the afternoon and between 19 and 22 during the night. It is noted that improving the exploration to 0.2 or 0.3 results in more accurate forecasts however increasing it more will decrease the accuracy due to much switching between alternate decisions. Although the reinforcement learning application shows lower errors always compared to KNN and in many situations compared to ANN, there are some scenarios where the learning rate is not high enough or where the exploration is too large that influence negatively the reinforcement learning application. RMSE follows similar assumptions taking ranges between 45 and 51 in the morning, between 108 and 114 in the afternoon and between 36 and 44 in the night. From this, the ranges of the different periods of the day are larger for RMSE as this takes squared errors. In RMSE particular case the reinforcement learning application tends to result in higher errors when compared to ANN with no learning methodology in the morning and night contexts. Although MAPE shares that the learning rate increase improves the forecasting accuracy, all exploration rate increases lead to forecasting accuracy decreases on this particular metric. MAPE takes ranges between 3 and 4% in the morning, between 4 and 5% during the afternoon and between 2.9 and 5% during the night.

6. Conclusions and future work

The research work that regards this dissertation covers different activities, from models conception, to experimental work for test and validation of the proposed solution. The main goal of the undertaken research was to contribute with adequate forecasting methodologies for five minutes periods electric energy consumption. The research should contribute to enhance electric energy consumption forecasting for buildings, selecting the best forecasting methodology to the particular context of the period for which the consumption is forecasted. This focuses on two directions, the first one consisting in prediction tasks for five minutes contexts with Artificial Neural Networks and K-Nearest Neighbours. The second direction regards the use of decision making strategies to study which of the two forecasting methods is the most appropriate choice for each particular five minutes context. The latter considers two possible evaluation strategies, the first one consisting of decision rules that establish logical decisions and the second one consisting of reinforcement learning to teach agents based on experience.

The decision model implemented has four modules, namely forecasting, decision tree, learning, and error analysis. In the forecast module, prediction tasks are scheduled for a single week with the support of a large historic of data and the forecasting algorithms Artificial Neural Networks and K-Nearest Neighbours. The prediction activities established under these conditions are very accurate as the consumption profile of the target week shows small deviations to the forecasted consumptions for periods of five minutes. A total of 60 forecasting models have been proposed and implemented by means of computational algorithms. These have been tested with real data. The experimental results show that the forecasting models' accuracy is significantly dependent from the different configurations associated to the train and test structure and to the forecasting algorithm parameters.

In the decision tree module, the decisions regarding the choice of the forecasting model to use for each particular five minutes period are based on decision rules. These rules determine if the selected forecasting algorithm for different five minutes periods are the best ones. The decision tree construction shows that the rules construct pragmatic logic at least for a depth assigned to three. These imply logics of possible scenarios if the day of the week corresponds to work day or to a weekend, if the consumption profile has higher or lower consumption values and the use of CO_2 data for power values lower than 479 W. It is observed that forecasting low consumption does not benefit from using CO_2 sensor data. Additionally, it is inferred that the datasets used for forecasting consumption during weekends should also discard CO2 data. The obtained accuracy shows that increasing the decision tree depth high enough makes the rules complex enough to result in more accurate forecasts. The lack of CO2 data on particular decision rules and the absence of other sensors data on a scenario with a decision tree of depth three shows that the decision tree construction is not complex enough to elaborate some particular logic rules.

In the reinforcement learning module, decisions concerning the selection of the forecasting models based on Artificial Neural Network or on K-Nearest Neighbours are applied to all five minutes periods. The confidence rate associated to a reinforcement methodology clarify that KNN is usually the more suitable choice despite the confidence rates of ANN showing that the respective forecasting algorithm is still the best option in particular five minutes contexts. The average of rewards show that five minutes contexts are assigned correctly with an outcome above reasonable. Increasing the exploration rate has an initial better performance. However, it ends being outmatched by lower exploration rates. The upper confidence bound method presents the different exploitation rates with a similar pattern while greedy present very different average reward patterns. Additionally, the exploration rate increase motivates the different exploitation rates to converge the average reward towards a particular pattern.

In the error analysis module, the forecasting errors are calculated for both Artificial Neural Networks and K-Nearest Neighbors algorithms using MAPE, SMAPE, MAE and RMSE. The more adequate forecast accuracies involve SMAPE and MAPE metrics. Three forecasting models using ANN configurations with 32 neurons and the use of 10 inputs for the train and test structure evidence more accurate predictions. Different configurations show that including the day of the week with a low learning rate and a total of 10 or 50 inputs of the train and test structure may improve the forecasts. Additionally, increases in the input for the train and test structure may decrease the forecasting accuracy being K-Nearest Neighbor the more evidenced case. The model that results in the highest accuracy forecasting consists in an Artificial Neural Network parameterization with a small number of neurons, a low learning rate, the use of the day of the week and a high validation split. The accuracy for the different depth parameterizations shows that the decision tree rules result in high accurate forecasts and that increasing the depth value enough may make the rules complex enough to result in increases for the forecasting accuracy.

This thesis has contributed with accurate predictions and a decision model that selects the best forecasting algorithm for different periods contexts. The decision tree and the reinforcement learning modules show outcomes concerning the decision regarding the choice of the algorithms based on Artificial Neural Networks or the algorithm based on K-Nearest Neighbors. The error analysis module shows low errors both on the whole period and on different contexts presenting higher accurate forecasts. The case study consists of simplified data integrated in an historic with consumption enhanced with sensors data.

As future work, it is expected to research and to use more forecasting techniques for the prediction tasks and to evolve the decision criterion to make the most adequate choice according to the new set of available forecasting models. Improved work should consider additional deep learning methods involved in the decision criterion responsible for the forecasting algorithms selection in different five minutes contexts. There is also room for improvement on the context definition namely considering other parameters than the time. Additional approaches for the agents should be considered as well.

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Annexes

Annex A1. Accuracy in the morning context

		learning								
	exp	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
ucb	All	0.64	0.64	0.65	0.65	0.65	0.66	0.65	0.65	0.65
	0.1	0.76	0.75	0.75	0.75	0.77	0.76	0.72	0.76	0.75
	0.2	0.69	0.70	0.71	0.71	0.72	0.73	0.73	0.71	0.72
	0.3	0.69	0.68	0.69	0.70	0.70	0.68	0.69	0.67	0.69
	0.4	0.67	0.67	0.68	0.68	0.69	0.70	0.68	0.68	0.66
	0.5	0.67	0.67	0.67	0.68	0.68	0.67	0.67	0.68	0.68
	0.6	0.66	0.66	0.67	0.67	0.67	0.67	0.66	0.66	0.65
	0.7	0.54	0.56	0.56	0.57	0.56	0.57	0.58	0.58	0.59
	0.8	0.58	0.59	0.59	0.59	0.59	0.60	0.60	0.59	0.59
	0.9	0.51	0.52	0.51	0.51	0.51	0.52	0.52	0.52	0.53
greedy	All	0.59	0.62	0.62	0.63	0.64	0.64	0.64	0.64	0.64
	0.1	0.62	0.67	0.68	0.69	0.70	0.70	0.70	0.70	0.70
	0.2	0.62	0.65	0.65	0.65	0.66	0.66	0.66	0.66	0.66
	0.3	0.63	0.66	0.67	0.68	0.69	0.69	0.69	0.69	0.69
	0.4	0.62	0.66	0.66	0.68	0.68	0.68	0.68	0.68	0.68
	0.5	0.59	0.64	0.64	0.64	0.65	0.65	0.65	0.65	0.65
	0.6	0.59	0.64	0.65	0.65	0.66	0.66	0.66	0.66	0.66
	0.7	0.55	0.56	0.56	0.56	0.58	0.58	0.58	0.58	0.58
	0.8	0.57	0.57	0.59	0.59	0.59	0.59	0.59	0.59	0.59
	0.9	0.51	0.51	0.51	0.51	0.52	0.52	0.52	0.52	0.52

Table A2. Accuracy in the afternoon context

		learning								
	exp	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
ucb	All	0.53	0.52	0.52	0.52	0.52	0.51	0.51	0.51	0.51
	0.1	0.61	0.59	0.60	0.58	0.60	0.54	0.55	0.53	0.55
	0.2	0.52	0.51	0.51	0.53	0.53	0.50	0.50	0.53	0.51
	0.3	0.58	0.50	0.52	0.51	0.51	0.52	0.52	0.51	0.52
	0.4	0.53	0.52	0.52	0.51	0.51	0.52	0.52	0.50	0.53
	0.5	0.55	0.53	0.53	0.53	0.53	0.53	0.51	0.51	0.51
	0.6	0.52	0.52	0.52	0.51	0.51	0.51	0.51	0.52	0.51
	0.7	0.49	0.51	0.50	0.50	0.50	0.50	0.51	0.51	0.52
	0.8	0.47	0.49	0.50	0.51	0.51	0.51	0.51	0.51	0.51

	0.9	0.46	0.47	0.47	0.46	0.46	0.46	0.46	0.46	0.47
greedy	All	0.53	0.52	0.51	0.49	0.50	0.50	0.50	0.50	0.50
	0.1	0.60	0.59	0.67	0.58	0.59	0.59	0.59	0.59	0.59
	0.2	0.54	0.48	0.47	0.48	0.45	0.45	0.45	0.45	0.45
	0.3	0.59	0.58	0.49	0.46	0.47	0.47	0.47	0.47	0.47
	0.4	0.53	0.49	0.48	0.46	0.47	0.47	0.47	0.47	0.47
	0.5	0.55	0.55	0.53	0.52	0.53	0.53	0.53	0.53	0.53
	0.6	0.56	0.52	0.50	0.50	0.51	0.51	0.51	0.51	0.51
	0.7	0.46	0.49	0.49	0.48	0.47	0.47	0.47	0.47	0.47
	0.8	0.48	0.50	0.50	0.52	0.52	0.52	0.52	0.52	0.52
	0.9	0.46	0.47	0.46	0.46	0.46	0.46	0.46	0.46	0.46

Table A3. Accuracy in the night context

		learning								
	exp	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
ucb	All	0.60	0.59	0.58	0.58	0.57	0.56	0.55	0.52	0.51
	0.1	0.65	0.65	0.65	0.65	0.64	0.60	0.56	0.51	0.52
	0.2	0.64	0.63	0.62	0.61	0.60	0.59	0.57	0.55	0.53
	0.3	0.63	0.62	0.62	0.60	0.60	0.61	0.60	0.52	0.52
	0.4	0.63	0.62	0.62	0.60	0.59	0.59	0.58	0.53	0.52
	0.5	0.62	0.61	0.61	0.60	0.58	0.58	0.56	0.53	0.54
	0.6	0.58	0.57	0.57	0.57	0.56	0.55	0.55	0.52	0.52
	0.7	0.57	0.57	0.57	0.55	0.55	0.53	0.52	0.52	0.51
	0.8	0.53	0.52	0.51	0.51	0.50	0.50	0.50	0.51	0.50
	0.9	0.50	0.50	0.49	0.48	0.48	0.48	0.48	0.48	0.48
greedy	All	0.64	0.63	0.63	0.62	0.61	0.61	0.61	0.61	0.61
	0.1	0.77	0.75	0.74	0.74	0.72	0.72	0.72	0.72	0.72
	0.2	0.70	0.69	0.70	0.68	0.67	0.67	0.67	0.67	0.67
	0.3	0.73	0.71	0.71	0.71	0.69	0.69	0.69	0.69	0.69
	0.4	0.70	0.68	0.67	0.67	0.66	0.66	0.66	0.66	0.66
	0.5	0.66	0.66	0.65	0.64	0.64	0.64	0.64	0.64	0.64
	0.6	0.63	0.61	0.61	0.60	0.60	0.60	0.60	0.60	0.60
	0.7	0.58	0.58	0.58	0.57	0.56	0.56	0.56	0.56	0.56
	0.8	0.53	0.52	0.51	0.51	0.51	0.51	0.51	0.51	0.51
	0.9	0.50	0.50	0.49	0.48	0.48	0.48	0.48	0.48	0.48

Table A4. SMAPE forecast error in morning context

		learning								
	exp	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
ucb	All	3.51	3.49	3.48	3.46	3.45	3.44	3.46	3.46	3.43
	0.1	3.08	3.16	3.13	3.13	3.05	3.08	3.20	3.12	3.06
	0.2	3.44	3.38	3.42	3.41	3.37	3.34	3.36	3.36	3.33
	0.3	3.35	3.35	3.32	3.28	3.26	3.32	3.27	3.40	3.27
	0.4	3.44	3.42	3.37	3.36	3.35	3.28	3.30	3.28	3.30
	0.5	3.39	3.39	3.42	3.33	3.33	3.33	3.37	3.41	3.39
	0.6	3.54	3.54	3.47	3.47	3.47	3.48	3.48	3.48	3.50
	0.7	3.71	3.67	3.67	3.65	3.67	3.62	3.62	3.61	3.56
	0.8	3.70	3.63	3.62	3.63	3.63	3.62	3.62	3.62	3.62
	0.9	3.92	3.91	3.92	3.92	3.92	3.88	3.88	3.88	3.85
greedy	All	3.80	3.65	3.64	3.62	3.60	3.60	3.60	3.60	3.60
	0.1	3.86	3.52	3.51	3.50	3.46	3.46	3.46	3.46	3.46
	0.2	3.95	3.90	3.91	3.92	3.91	3.91	3.91	3.91	3.91
	0.3	3.88	3.47	3.45	3.42	3.37	3.37	3.37	3.37	3.37
	0.4	3.62	3.51	3.49	3.42	3.43	3.43	3.43	3.43	3.43
	0.5	3.74	3.51	3.51	3.50	3.48	3.48	3.48	3.48	3.48
	0.6	3.81	3.65	3.60	3.60	3.58	3.58	3.58	3.58	3.58
	0.7	3.70	3.67	3.68	3.67	3.64	3.64	3.64	3.64	3.64
	0.8	3.72	3.71	3.66	3.66	3.66	3.66	3.66	3.66	3.66
	0.9	3.90	3.92	3.92	3.92	3.89	3.89	3.89	3.89	3.89
KNN	4.09									
ANN	3.68									

Table A5. SMAPE forecast error in afternoon context

		learning								
	exp	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
ucb	All	4.51	4.47	4.45	4.42	4.42	4.44	4.41	4.40	4.38
	0.1	4.40	4.39	4.32	4.35	4.37	4.47	4.31	4.31	4.17
	0.2	4.28	4.21	4.18	4.12	4.20	4.34	4.31	4.27	4.17
	0.3	4.56	4.43	4.40	4.33	4.30	4.29	4.24	4.29	4.29
	0.4	4.46	4.41	4.47	4.39	4.37	4.37	4.39	4.36	4.33
	0.5	4.48	4.50	4.45	4.48	4.45	4.45	4.46	4.39	4.44
	0.6	4.50	4.43	4.44	4.40	4.37	4.34	4.34	4.33	4.33
	0.7	4.69	4.67	4.61	4.61	4.61	4.58	4.56	4.57	4.55
	0.8	4.58	4.58	4.57	4.53	4.53	4.53	4.54	4.55	4.54

	0.9	4.60	4.61	4.60	4.58	4.58	4.57	4.57	4.57	4.57
greedy	All	4.63	4.54	4.50	4.45	4.44	4.44	4.44	4.44	4.44
	0.1	4.61	4.59	4.55	4.39	4.42	4.42	4.42	4.42	4.42
	0.2	4.65	4.48	4.43	4.40	4.39	4.39	4.39	4.39	4.39
	0.3	4.80	4.58	4.42	4.34	4.30	4.30	4.30	4.30	4.30
	0.4	4.53	4.44	4.42	4.37	4.38	4.38	4.38	4.38	4.38
	0.5	4.58	4.45	4.44	4.41	4.41	4.41	4.41	4.41	4.41
	0.6	4.64	4.44	4.42	4.37	4.34	4.34	4.34	4.34	4.34
	0.7	4.67	4.70	4.65	4.61	4.60	4.60	4.60	4.60	4.60
	0.8	4.59	4.60	4.56	4.55	4.55	4.55	4.55	4.55	4.55
	0.9	4.60	4.61	4.60	4.58	4.57	4.57	4.57	4.57	4.57
KNN	5.01									
ANN	4.45									

Table A6. SMAPE forecast error in night context

		learning								
	exp	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
ucb	All	3.30	3.25	3.19	3.17	3.14	3.15	3.13	3.16	3.17
	0.1	2.88	2.92	2.82	2.83	2.79	2.75	2.75	2.82	2.86
	0.2	2.74	2.76	2.67	2.67	2.71	2.71	2.64	2.70	2.83
	0.3	3.15	3.10	3.09	3.04	2.96	3.01	2.99	3.10	3.02
	0.4	3.36	3.31	3.18	3.14	3.13	3.14	3.09	3.18	3.12
	0.5	3.32	3.26	3.20	3.19	3.17	3.16	3.16	3.12	3.11
	0.6	3.58	3.39	3.33	3.24	3.28	3.27	3.27	3.22	3.23
	0.7	3.38	3.31	3.27	3.24	3.15	3.17	3.16	3.15	3.17
	0.8	3.60	3.50	3.48	3.48	3.42	3.43	3.42	3.46	3.47
	0.9	3.70	3.70	3.69	3.68	3.68	3.68	3.68	3.68	3.68
greedy	All	3.52	3.29	3.22	3.17	3.17	3.17	3.17	3.17	3.17
	0.1	3.63	2.90	2.88	2.81	2.83	2.83	2.83	2.83	2.83
	0.2	3.36	2.85	2.77	2.63	2.71	2.71	2.71	2.71	2.71
	0.3	3.36	3.16	3.08	3.07	3.06	3.06	3.06	3.06	3.06
	0.4	3.53	3.38	3.24	3.22	3.21	3.21	3.21	3.21	3.21
	0.5	3.45	3.35	3.22	3.17	3.15	3.15	3.15	3.15	3.15
	0.6	3.57	3.39	3.33	3.26	3.29	3.29	3.29	3.29	3.29
	0.7	3.46	3.36	3.29	3.20	3.14	3.14	3.14	3.14	3.14
	0.8	3.59	3.54	3.49	3.49	3.43	3.43	3.43	3.43	3.43
	0.9	3.70	3.70	3.69	3.68	3.68	3.68	3.68	3.68	3.68
KNN	4.32									

ANN	3.07

Annex B1. MAE forecast error in morning context

		learning								
	exp	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
ucb	All	25.18	25.06	25.01	24.92	24.79	24.71	24.80	24.82	24.65
	0.1	22.28	22.91	22.71	23.00	22.21	22.30	23.15	22.49	22.14
	0.2	24.93	24.41	24.84	24.77	24.49	24.12	24.23	24.20	23.96
	0.3	24.10	24.12	23.87	23.65	23.43	24.06	23.61	24.46	23.64
	0.4	24.50	24.29	24.02	23.91	23.92	23.43	23.59	23.43	23.54
	0.5	24.36	24.27	24.62	23.92	23.89	23.92	24.17	24.41	24.36
	0.6	25.43	25.47	24.94	24.91	24.96	24.99	24.99	24.98	25.13
	0.7	26.68	26.32	26.36	26.29	26.43	26.06	26.01	25.96	25.70
	0.8	26.35	25.83	25.79	25.83	25.83	25.77	25.77	25.80	25.80
	0.9	27.98	27.88	27.95	27.95	27.95	27.69	27.69	27.69	27.57
greedy	All	27.13	26.15	26.02	25.94	25.81	25.81	25.81	25.81	25.81
	0.1	27.59	25.37	25.30	25.28	24.97	24.97	24.97	24.97	24.97
	0.2	28.21	27.83	27.96	27.98	27.90	27.90	27.90	27.90	27.90
	0.3	27.64	24.96	24.73	24.53	24.22	24.22	24.22	24.22	24.22
	0.4	25.77	25.02	24.80	24.32	24.41	24.41	24.41	24.41	24.41
	0.5	26.67	25.07	25.09	25.05	24.92	24.92	24.92	24.92	24.92
	0.6	27.38	26.30	25.83	25.84	25.74	25.74	25.74	25.74	25.74
	0.7	26.56	26.39	26.45	26.39	26.24	26.24	26.24	26.24	26.24
	0.8	26.49	26.43	26.10	26.10	26.10	26.10	26.10	26.10	26.10
	0.9	27.85	27.98	27.95	27.95	27.75	27.75	27.75	27.75	27.75
KNN	29.34									
ANN	26.00									

Annex B2. MAE forecast error in afternoon context

		learning								
	exp	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
ucb	All	55.51	55.00	54.76	54.59	54.55	54.72	54.47	54.50	54.17
	0.1	54.56	54.69	53.84	54.11	54.42	55.43	53.62	53.62	52.07
	0.2	53.74	52.89	52.47	51.86	52.45	53.30	53.29	53.22	52.30
	0.3	56.38	54.34	54.16	53.52	53.06	53.10	52.44	53.39	53.30
	0.4	55.22	54.67	54.98	54.64	54.50	54.52	54.72	54.48	54.22
	0.5	55.17	55.10	54.68	54.95	54.57	54.61	54.75	54.31	54.51
	0.6	55.64	54.64	54.68	54.46	54.27	54.09	54.13	54.05	54.19

	0.7	56.92	56.60	56.18	56.28	56.15	55.95	55.70	55.81	55.42
	0.8	55.83	55.84	55.68	55.45	55.45	55.45	55.54	55.60	55.50
	0.9	56.15	56.25	56.20	56.04	56.10	56.02	56.02	56.02	56.03
greedy	All	56.85	55.94	55.43	54.96	54.88	54.88	54.88	54.88	54.88
	0.1	56.75	57.07	56.52	55.12	55.37	55.37	55.37	55.37	55.37
	0.2	57.20	55.63	55.14	54.72	54.43	54.43	54.43	54.43	54.43
	0.3	59.07	56.73	54.35	53.48	53.19	53.19	53.19	53.19	53.19
	0.4	56.19	54.95	54.78	54.43	54.58	54.58	54.58	54.58	54.58
	0.5	56.20	54.84	54.76	54.54	54.53	54.53	54.53	54.53	54.53
	0.6	57.03	54.81	54.74	54.34	54.16	54.16	54.16	54.16	54.16
	0.7	57.00	57.08	56.62	56.24	56.06	56.06	56.06	56.06	56.06
	0.8	56.03	56.11	55.72	55.69	55.68	55.68	55.68	55.68	55.68
	0.9	56.19	56.25	56.21	56.04	55.94	55.94	55.94	55.94	55.94
KNN	60.22									
ANN	55.23									

Annex B3. MAE forecast error in night context

		learning								
	exp	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
ucb	All	19.31	19.02	18.67	18.55	18.40	18.40	18.29	18.46	18.51
	0.1	16.91	17.12	16.50	16.61	16.33	16.10	16.10	16.45	16.79
	0.2	16.04	16.12	15.64	15.63	15.86	15.89	15.40	15.70	16.49
	0.3	18.38	18.06	18.05	17.74	17.22	17.46	17.37	17.96	17.51
	0.4	19.72	19.46	18.63	18.42	18.38	18.43	18.14	18.63	18.30
	0.5	19.51	19.20	18.85	18.80	18.68	18.59	18.61	18.40	18.31
	0.6	20.76	19.68	19.26	18.77	19.02	18.94	18.94	18.64	18.70
	0.7	19.76	19.35	19.13	18.98	18.47	18.58	18.50	18.49	18.57
	0.8	21.04	20.49	20.37	20.37	20.03	20.04	19.99	20.28	20.32
	0.9	21.71	21.71	21.63	21.60	21.56	21.56	21.56	21.56	21.56
greedy	All	20.63	19.24	18.82	18.53	18.50	18.50	18.50	18.50	18.50
	0.1	21.37	16.89	16.77	16.35	16.38	16.38	16.38	16.38	16.38
	0.2	19.67	16.69	16.20	15.33	15.85	15.85	15.85	15.85	15.85
	0.3	19.72	18.42	17.98	17.93	17.82	17.82	17.82	17.82	17.82
	0.4	20.84	19.83	18.97	18.87	18.82	18.82	18.82	18.82	18.82
	0.5	20.23	19.68	18.87	18.58	18.47	18.47	18.47	18.47	18.47
	0.6	20.74	19.63	19.27	18.90	19.06	19.06	19.06	19.06	19.06
	0.7	20.35	19.66	19.24	18.77	18.42	18.42	18.42	18.42	18.42
	0.8	21.03	20.70	20.44	20.43	20.09	20.09	20.09	20.09	20.09
	0.9	21.71	21.71	21.63	21.60	21.56	21.56	21.56	21.56	21.56
KNN	25.50									
ANN	17.81									

Annex B4. RMSE forecast error in morning context

		learning								
	exp	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
ucb	All	48.39	48.36	48.32	48.18	48.01	47.99	48.07	48.37	48.03
	0.1	44.95	46.29	46.10	46.79	45.14	45.28	46.19	45.57	45.04
	0.2	49.85	49.00	49.90	49.88	49.60	49.18	49.26	49.14	48.95
	0.3	47.07	47.09	46.64	46.22	45.70	46.97	46.14	48.71	46.51
	0.4	46.60	46.56	46.40	45.83	46.52	45.72	45.83	45.41	45.43
	0.5	45.95	46.05	46.50	45.54	45.52	45.52	46.00	47.66	47.50
	0.6	49.11	49.45	48.41	48.40	48.51	48.69	48.69	48.43	48.54
	0.7	50.45	49.79	49.89	49.87	49.96	49.61	49.60	49.56	49.41
	0.8	50.65	50.34	50.33	50.35	50.35	50.34	50.34	50.34	50.34
	0.9	50.45	50.37	50.42	50.42	50.42	50.23	50.23	50.23	50.21
greedy	All	51.40	49.74	49.59	49.53	49.42	49.42	49.42	49.42	49.42
	0.1	54.23	49.99	49.95	49.91	49.69	49.69	49.69	49.69	49.69
	0.2	54.78	54.17	54.47	54.45	54.41	54.41	54.41	54.41	54.41
	0.3	53.58	47.99	47.50	47.31	46.76	46.76	46.76	46.76	46.76
	0.4	47.92	47.62	47.34	46.88	46.98	46.98	46.98	46.98	46.98
	0.5	49.56	46.51	46.52	46.65	46.62	46.62	46.62	46.62	46.62
	0.6	51.13	50.00	49.30	49.32	49.28	49.28	49.28	49.28	49.28
	0.7	49.90	49.82	49.86	49.84	49.80	49.80	49.80	49.80	49.80
	0.8	50.71	50.69	50.51	50.51	50.51	50.51	50.51	50.51	50.51
	0.9	50.37	50.45	50.42	50.42	50.26	50.26	50.26	50.26	50.26
KNN	56.90									
ANN	45.46									

Annex B5. RMSE forecast error in afternoon context

		learning								
	exp	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
ucb	All	111.38	111.03	110.99	111.07	110.89	111.10	111.12	111.42	110.82
	0.1	108.44	109.05	108.28	108.36	108.32	110.60	109.32	109.30	107.36
	0.2	110.59	109.68	109.26	108.90	109.89	108.59	109.37	109.85	109.09
	0.3	110.89	109.52	109.63	109.27	108.87	109.07	108.50	110.64	109.77
	0.4	111.18	110.58	111.17	111.98	111.27	111.28	111.40	111.46	111.35
	0.5	110.91	110.92	110.78	111.68	111.13	111.13	112.29	112.02	111.12
	0.6	111.49	110.98	111.33	111.25	111.20	111.95	111.95	111.93	111.86
	0.7	112.92	112.81	112.79	112.66	111.79	111.70	111.61	111.70	110.94
	0.8	113.27	112.93	112.90	112.80	112.80	112.80	112.89	113.15	113.11

	0.9	112.64	112.67	112.66	112.60	112.68	112.67	112.67	112.67	112.67
greedy	All	112.49	111.67	111.41	111.33	111.22	111.22	111.22	111.22	111.22
	0.1	109.20	111.08	110.82	110.62	110.69	110.69	110.69	110.69	110.69
	0.2	115.46	111.53	110.48	110.04	110.85	110.85	110.85	110.85	110.85
	0.3	112.64	110.89	109.81	109.06	108.93	108.93	108.93	108.93	108.93
	0.4	111.70	110.86	111.37	111.72	111.44	111.44	111.44	111.44	111.44
	0.5	111.92	110.47	110.56	111.32	110.87	110.87	110.87	110.87	110.87
	0.6	112.44	111.13	111.11	110.98	110.91	110.91	110.91	110.91	110.91
	0.7	112.95	112.98	112.92	112.57	111.65	111.65	111.65	111.65	111.65
	0.8	113.32	113.35	112.90	113.01	113.01	113.01	113.01	113.01	113.01
	0.9	112.67	112.67	112.66	112.60	112.57	112.57	112.57	112.57	112.57
KNN	112.04									
ANN	113.79									

Annex B6. RMSE forecast error in night context

		learning								
	exp	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
ucb	All	41.25	40.88	40.17	40.14	39.71	39.67	39.40	39.47	39.52
	0.1	38.77	39.03	37.24	38.48	36.92	36.24	36.13	36.45	36.99
	0.2	36.29	36.34	35.67	35.63	35.83	35.85	33.83	34.11	35.16
	0.3	39.51	39.22	39.14	38.65	37.02	37.27	37.30	37.54	36.70
	0.4	42.43	42.23	40.46	40.29	40.28	40.29	39.84	40.11	39.73
	0.5	42.32	42.01	41.63	41.56	41.47	41.45	41.45	40.81	40.79
	0.6	41.79	40.37	38.84	38.25	38.41	38.39	38.38	38.09	38.10
	0.7	41.61	40.96	40.73	40.66	40.04	40.07	39.94	40.08	40.11
	0.8	43.64	42.92	42.83	42.83	42.45	42.45	42.44	42.88	43.00
	0.9	44.31	44.31	44.25	44.24	44.17	44.17	44.17	44.17	44.17
greedy	All	43.64	40.88	40.21	39.78	39.66	39.66	39.66	39.66	39.66
	0.1	46.50	37.44	37.40	36.97	35.70	35.70	35.70	35.70	35.70
	0.2	42.22	37.09	36.36	34.06	35.81	35.81	35.81	35.81	35.81
	0.3	42.52	39.51	39.06	39.05	38.65	38.65	38.65	38.65	38.65
	0.4	45.10	42.54	40.77	40.72	40.67	40.67	40.67	40.67	40.67
	0.5	43.11	42.48	40.78	40.33	40.25	40.25	40.25	40.25	40.25
	0.6	41.76	39.14	38.83	38.30	38.42	38.42	38.42	38.42	38.42
	0.7	43.43	41.58	40.94	40.54	40.03	40.03	40.03	40.03	40.03
	0.8	43.64	43.14	42.86	42.86	42.48	42.48	42.48	42.48	42.48
	0.9	44.31	44.31	44.25	44.23	44.17	44.17	44.17	44.17	44.17
KNN	52.20									
ANN	35.72									

Annex B7. MAPE forecast error in morning context

		learning								
	exp	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
ucb	All	3.48	3.47	3.46	3.44	3.43	3.41	3.43	3.45	3.41
	0.1	3.03	3.11	3.08	3.08	3.00	3.02	3.16	3.07	3.00
	0.2	3.41	3.37	3.40	3.39	3.35	3.32	3.34	3.34	3.30
	0.3	3.28	3.28	3.25	3.22	3.19	3.27	3.22	3.38	3.22
	0.4	3.40	3.38	3.33	3.33	3.31	3.24	3.26	3.24	3.26
	0.5	3.36	3.35	3.38	3.30	3.29	3.30	3.34	3.40	3.39
	0.6	3.53	3.53	3.48	3.47	3.48	3.48	3.48	3.48	3.51
	0.7	3.69	3.65	3.65	3.64	3.65	3.61	3.60	3.59	3.54
	0.8	3.72	3.65	3.64	3.65	3.65	3.64	3.64	3.64	3.64
	0.9	3.90	3.89	3.90	3.90	3.90	3.86	3.86	3.86	3.84
greedy	All	3.80	3.63	3.62	3.60	3.58	3.58	3.58	3.58	3.58
	0.1	3.87	3.48	3.47	3.47	3.43	3.43	3.43	3.43	3.43
	0.2	3.98	3.93	3.94	3.95	3.94	3.94	3.94	3.94	3.94
	0.3	3.89	3.40	3.38	3.35	3.31	3.31	3.31	3.31	3.31
	0.4	3.59	3.47	3.45	3.38	3.39	3.39	3.39	3.39	3.39
	0.5	3.73	3.47	3.48	3.46	3.44	3.44	3.44	3.44	3.44
	0.6	3.81	3.64	3.60	3.59	3.58	3.58	3.58	3.58	3.58
	0.7	3.68	3.65	3.66	3.65	3.63	3.63	3.63	3.63	3.63
	0.8	3.74	3.73	3.68	3.68	3.68	3.68	3.68	3.68	3.68
	0.9	3.89	3.90	3.90	3.90	3.87	3.87	3.87	3.87	3.87
KNN	4.14									
ANN	3.62									

Annex B8. MAPE forecast error in afternoon context

		learning								
	exp	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
ucb	All	4.47	4.43	4.41	4.38	4.38	4.40	4.37	4.37	4.34
	0.1	4.36	4.36	4.28	4.31	4.33	4.43	4.27	4.28	4.14
	0.2	4.24	4.17	4.14	4.07	4.17	4.29	4.26	4.23	4.13
	0.3	4.52	4.39	4.37	4.30	4.27	4.26	4.20	4.27	4.26
	0.4	4.43	4.38	4.44	4.37	4.34	4.34	4.36	4.34	4.32
	0.5	4.46	4.47	4.42	4.45	4.42	4.42	4.43	4.37	4.41
	0.6	4.45	4.38	4.38	4.35	4.32	4.28	4.29	4.28	4.29
	0.7	4.63	4.61	4.56	4.56	4.55	4.52	4.50	4.52	4.49
	0.8	4.52	4.53	4.51	4.47	4.47	4.47	4.49	4.49	4.48

	0.9	4.57	4.58	4.58	4.55	4.55	4.55	4.55	4.55	4.55
greedy	All	4.59	4.50	4.46	4.41	4.40	4.40	4.40	4.40	4.40
	0.1	4.57	4.54	4.51	4.34	4.36	4.36	4.36	4.36	4.36
	0.2	4.61	4.44	4.38	4.36	4.35	4.35	4.35	4.35	4.35
	0.3	4.75	4.54	4.39	4.31	4.27	4.27	4.27	4.27	4.27
	0.4	4.50	4.40	4.39	4.34	4.35	4.35	4.35	4.35	4.35
	0.5	4.54	4.42	4.41	4.39	4.39	4.39	4.39	4.39	4.39
	0.6	4.58	4.39	4.37	4.32	4.29	4.29	4.29	4.29	4.29
	0.7	4.62	4.65	4.60	4.56	4.54	4.54	4.54	4.54	4.54
	0.8	4.54	4.55	4.50	4.49	4.49	4.49	4.49	4.49	4.49
	0.9	4.57	4.58	4.58	4.55	4.54	4.54	4.54	4.54	4.54
KNN	4.93									
ANN	4.44									

Annex B9. MAPE forecast error in night context

		learning								
	exp	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
ucb	All	3.41	3.35	3.29	3.26	3.23	3.24	3.21	3.25	3.25
	0.1	2.94	2.98	2.86	2.88	2.83	2.78	2.78	2.85	2.90
	0.2	2.80	2.82	2.72	2.72	2.76	2.77	2.68	2.73	2.88
	0.3	3.25	3.19	3.19	3.13	3.03	3.09	3.07	3.18	3.09
	0.4	3.47	3.42	3.26	3.23	3.22	3.23	3.17	3.26	3.20
	0.5	3.45	3.39	3.32	3.32	3.30	3.28	3.28	3.24	3.22
	0.6	3.71	3.50	3.42	3.32	3.37	3.36	3.36	3.30	3.31
	0.7	3.47	3.40	3.35	3.33	3.23	3.25	3.24	3.23	3.25
	0.8	3.75	3.64	3.62	3.62	3.56	3.56	3.55	3.61	3.61
	0.9	3.84	3.84	3.82	3.82	3.81	3.81	3.81	3.81	3.81
greedy	All	3.66	3.40	3.32	3.26	3.26	3.26	3.26	3.26	3.26
	0.1	3.81	2.97	2.95	2.87	2.88	2.88	2.88	2.88	2.88
	0.2	3.49	2.92	2.83	2.66	2.76	2.76	2.76	2.76	2.76
	0.3	3.50	3.26	3.18	3.16	3.14	3.14	3.14	3.14	3.14
	0.4	3.68	3.49	3.33	3.31	3.30	3.30	3.30	3.30	3.30
	0.5	3.59	3.48	3.33	3.27	3.25	3.25	3.25	3.25	3.25
	0.6	3.70	3.49	3.42	3.35	3.38	3.38	3.38	3.38	3.38
	0.7	3.58	3.45	3.38	3.29	3.22	3.22	3.22	3.22	3.22
	0.8	3.75	3.68	3.64	3.63	3.57	3.57	3.57	3.57	3.57
	0.9	3.84	3.84	3.82	3.82	3.81	3.81	3.81	3.81	3.81
KNN	4.56									
ANN	3.13									