Machine Learning Application to Priority Scheduling in Smart Microgrids

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***Abstract*—The need to integrate flexible and intelligent mechanisms for energy management becomes a necessity. In this paper, we are considering a microgrid with infrastructures having production capacities and consumption needs. Several data and constraints related to the microgrid consumption have been collected, in addition to data concerning the production of renewable energy from Photovoltaic panels (PV). Data history is used as input to a neural network to predict one day ahead of consumption and production. Then, a prioritized scheduling family of algorithms is presented. First, we introduce a mathematical formulation to our problem. Then, we propose various scenarios that go from an exact solution to heuristic-based use cases, including scheduling of several energy classes with a maximum scheduling time lapse. Results show that prioritized scheduling, including time lapse based on predictions, can give more reliable results than scheduling based on bin packing.**

***Index Terms*—Artificial Intelligence (AI), Deep Learning (DL), Long Short-Term Memory (LSTM), Bin Packing (BP), Smart Microgrid, Optimization**

I. Introduction

Resource management dilemmas are omnipresent in different fields, especially in smart grids, computer networks, and transport supervision. In this paper, we investigate a microgrid case: we predict building energy consumption and renewable energy production so that we could do the best energy management. The studied microgrid is composed of a set of buildings that integrate renewable energy production and short-long term energy storage. We aim to avoid costly upgrades to the microgrid system while increasing the penetration of renewable energy sources: solar, wind, and other micro-sources. The interest of this paper in our opinion is that the proposed algorithm could be not only applied to the microgrid problem but also the resource management problems in different other fields. It is worth mentioning here that the microgrid needs online optimization methods that make predictions of both consumption and production to plan and manage the smart grid. These online techniques provide real-time recommendations and automatic actions for consumers and prosumers to encourage more efficient use of electricity while assuring their satisfaction.

The rest of the paper is structured as follows: in Section II, we discuss the energy management scheduling state-of-the-art. In Section III, we formulate the studied problems using different use cases. In Section IV, we describe the proposed management algorithms. In Section V, we evaluate our work in terms of various key performance metrics. Finally, we conclude and discuss our work in Section VI.

II. State of the art

In this work, we investigate 1) the prediction of consumption and of renewable energy production and 2) the response to the need to serve the demands of end-users. We start by investigating the relevant work in the forecasting of the consumption and production in a microgrid. The literature presents some statistical methods (linear regression, principal component analysis, and fuzzy modeling) that utilize historical data to estimate future energy consumption. Several works focus on learning models to predict energy consumption in residential and commercial buildings, using features such as weather and energy bills. A. Bogomolov et al. [1], aim to solve in their work the problem of modeling and predicting energy consumption. They present an innovative approach to predict energy consumption using people mobility patterns extracted from Call Detail Records (CDRs). They applied diverse techniques to decrease the computational complexity of the enormous amount of data. Moreover, results (accuracy, Mean Square Error (MSE), etc.) justify the quality of feature selection procedures and the use of learning techniques. Chengdong et al. [2] propose advanced techniques to solve the problem of energy forecasting. Authors adapted a deep learning-based method to the context of building energy management. Complex systems such as stacked auto-encoders have been introduced in the same model parameter tuning. Riccardo et al. [3] consider the problem of energy consumption forecasting in residential microgrids. The authors propose several approaches: Support Vector Machine (SVM), Auto-Regressive Moving Average (ARMA), Nonlinear Auto-Regressive (NAR), and recurrent neural networks (RNN). Then, they evaluate the efficiency of each technique in power demand forecasting. Results show that the proposed RNN configuration led to minimal error variance related to the other techniques. In [4], The authors propose a dual deep neural network architecture. The main issue in this paper deals with forecasting and classifying time series. They compared various algorithms Support Vector

Regression (SVR), Gated Reccurent Unit (GRU), and LSTM for prediction and SVM, Convolutional neural network(CNN), and Multi Layer Perceptron (MLP) for classification. The authors showed that the proposed approach works on different domains (cellular, energy management, and transportation systems). Nonetheless, they focussed mainly on applying the proposed method to the microgrid context. In [5] the authors used a CNN-LSTM to extract features of energy consumption. The proposed method was compared to decision tree, random forest, and linear regression models.

Considering the necessity to serve the demands of end-users, we need to study the management mechanisms for microgrids in the literature. In [6], the authors focus on the influence of human presence and environmental sensors in the building for both efficient energy use and more reliable control of indoor environmental quality. They present a review of several recent publications detailing the application of agent-based involvement in the building's domain. In [7] and [8] authors proposed a wide range of methods: linear and dynamic programming, heuristic, game theory, fuzzy methods and so on to solve the problem of optimizing the building's energy and cost. Some works [9] focus on using dynamic programming (DP) algorithms to extract relevant rules from the optimization results, since DP could not be applied in real-time. In other works [10], authors used Reinforcement learning (RL) methods such as Q-learning [11] to schedule the energy of a smart home. But these solutions have limitations as they fail for large-scale problems. Since indoor environmental quality is crucial to ensure occupant health, comfort, well-being, and productivity the author in [12] investigates the use of sensors to do the best energy saving, thermal comfort, and indoor air quality. In [13] the authors present a comprehensive and critical review of the several methods used to deal with the energy management problem. They start with the classification of optimization techniques developed for microgrid energy management and approaches. The principal purposes of the energy management system are to optimize the energy use and system safety. In [14], the authors presented a Reinforcement learning approach to deal with the energy management problem in smart buildings. They started by modeling the system with a Markov decision process then by using a reinforcement-learning-based energy management algorithm to reduce the operational energy costs.

III. Context and Problem Formulation

In this paper, we are considering a microgrid example. One definition for microgrid is a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that act as a single controllable entity concerning the grid. It can be composed, as shown in figure 1, of factories, universities, houses, hospitals, different renewable energy resources like photovoltaic panels, wind turbines, and storage capacities.

The main objective of this work is to make all these actors collaborate to achieve the best management of the microgrid and to minimize the use of the electric utility network.

Figure 1: A Micro Grid example

A. Studied environment: Energy consumption differentiation

For energy consumption, we use data collected from real buildings. Diverse photovoltaic panels are installed on the same site, their output power is used as energy production in this work. We used an artificial intelligence method based on a recurrent neural network (RNN), to predict both energy consumption and energy production. This method is going to be explained in the next section.
These predicted values are used to obtain the optimized management knowing the predicted production, consumption and storage capacities.

In our work, we decided to distinguish between two classes of energy consumption to do the most reliable scheduling. Some consumption will be prioritized on others.

- The first identified type is critical (non flexible) energy demand,
- The second one corresponds to the energy demand that can be somehow flexible. It corresponds to devices that can be delayed for some time such as heaters, air conditioning or domestic appliances.
- Note that we restrict the work on two classes. It can easily be generalized to more classes as in computer networks. Some contributions include a third ”confort” class equivalent to best effort in the networking domain...

The table I summarize the used variables and their definitions.

B. Machine learning for predictions

Different machine learning algorithms have been compared in former contributions to choose the best algorithm to apply to our data. After thorough experiments, and previous work [4], we decided to use LSTM (long short term memory) family to make our predictions. LSTM is a variant of RNN. It has been proposed to overcome the problem of vanishing gradient caused by backpropagation over time in RNN. The LSTM learns to keep only the appropriate information to make predictions. It is built on three layers: an input layer, a hidden layer, and an output layer. Each layer is formed of memory blocks, and each memory block is constructed of special multiplicative units called gates. The most relevant gates are Input, Output and Forgot gates. Fig.2 shows results of one day ahead prediction for PV production and for the consumption

Table I: Variables and definition

Variable	Definition
E_t^T	Total predicted energy that needs service in time slot [t-1,t)
E_t^C	Critical predicted energy that needs service in time slot [t-1,t)
E_t^D	Delayed predicted energy that needs service in time slot [t-1,t)
P_t	Predicted produced energy at time slot [t-1,t)
B_t	Estimated Energy in the Battery at time slot [t-1,t)
G_t	Estimated energy drawn from the grid at time slot [t-1,t)
D_t	Total estimated demand of delayed traffic in slot t
R_t	Delayed traffic that has reached its time limit.
M_t	Total delayed trac traffic generated in (t-τt],
a_{Tot}	Total interaction between the systems actors
τ	How many instant that delayed predicted energy consumption can be shifted

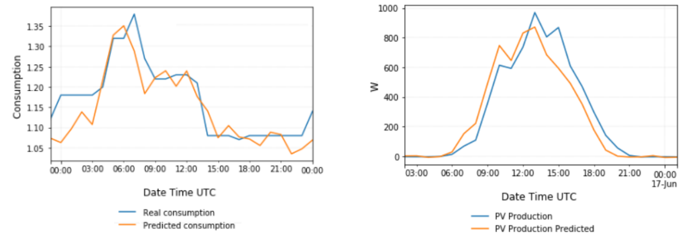
(we predict 24-time slots in the future based on learning input parameters such as panel type, humidity, temperature...).

The proposed model is as follows: $y = f(x)$, where y is the target variable which could indicate the total energy consumption or the PV produced energy and x corresponds to the features represented by weather data, such as temperature, historical consumption... The main objective of this model is to construct a machine-learning algorithm that can predict the building (residential or commercial) energy consumption given historical data for the target variable and the corresponding features.

LSTMs have been applied on advanced difficult problems, including Energy Management For electric vehicles in smart cities. In [15] the authors compared the use of Long Short Term Memory and Gated Recurrent Unit and in general on all-natural processing language problems. Since LSTM provided the best results while applied to different problems, we decided to implement it to make predictions of our building consumption and production [4]. The first step was to determine the best meta parameters, during the learning phase. We trained our model using different inputs to choose the most accurate ones related to our predictions. We also trained our model using different layers and the number of neurons. We used a real data set for both consumption and production data. The data used were collected over almost four years at several time steps in the tertiary building Drahi-X Novation Center of Ecole polytechnique, Palaiseau, France. The results were evaluated using metrics such as Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE). More details could be found in [4].

C. Energy management scenarios definition

In the first place, we defined three cases for our energy management problem. These cases could be extended in future



(a) Energy consumption prediction (b) Energy production prediction

Figure 2: One day ahead prediction

work since they do not take into account all the possibilities.

1) Case I: No delay, One class : Here, we are considering all the energy demands of consumers without categorizing them. We try to serve the energy demand using the renewable energy produced at each time slot. We store the produced energy in the battery. We intend to minimize a_{Tot} that represents the total action executed on the system(storing in the battery, consuming from the battery, and buying from the grid). If the state of charge of the battery is enough we use it to serve the energy demand, else the electrical grid is used to serve the service of all traffic in a time slot. The objective function could be of this form:

$$Minimize : a_{Tot}{=}\sum_{t=1}^{T} \alpha_t B_t{+}\beta_t G_t$$

subject to:

$$\alpha_t B_t{+}\beta_t G_t{>=}E_t^T \tag{1}$$

$$\alpha_t{+}\beta_t{<=}1 \tag{2}$$

$$\alpha_t{*}\beta_t{=}0 \tag{3}$$

2) Case II: Different energy classes: In this case, we are categorizing our energy consumption demands. To start, we identify two kinds of energy demands. The first is called critical energy (CE), it's the energy demand that we need to serve without any delay (in analogy with realtime applications in the data network QoS). Here, in our dataset, this corresponds to appliances such as ventilation and data centers. The second is the delayed energy consumption demand (like variable bit rate in computer networks), that could be served later (in the dataset it corresponds to heating, air conditioning...). We target to minimize the energy consumed from the grid. Note that if there is insufficient battery energy, the delayed class is not served at all. The objective function is written as follows:

$$Minimize : G_T{=}\sum_{t=1}^{T} G_t$$

subject to:

$$G_t{+}B_t{+}P_t{-}E_t^C{-}\gamma_t D_t^D{>=}0 \tag{4}$$

$$G_t{>=}0 \tag{5}$$

$$(B_t{+}P_t{-}E_t^C){*}\gamma_t{>=}0 \tag{6}$$

$$0{<=}\gamma_t{<=}1 \tag{7}$$

$$D_t^D{=}(1{-}\gamma_{t-1}){*}D_{t-1}^D{+}E_t^D \tag{8}$$

3) Case III: Delay and different energy classes with deadline: As in the previous case, we consider two categories of energy consumption demands: critical and delayed. However, the delayed energy demand needs to be served at a maximum after τ time slots (timelapse).

$$Minimize : G_T = \sum_{t=1}^{T} G_t$$

subject to:

$$G_t + B_t + P_t - E_t^C - R_t^D - \gamma_t (D_t^D - -R_t^D) >= 0 \tag{9}$$

$$G_t >= 0 \tag{10}$$

$$(B_t + P_t - E_t^C - R_t^D) * \gamma_t >= 0 \tag{11}$$

$$D_t^D = (1 - \gamma_{t-1})(D_{t-1}^D R_{t-1}^D) + E_t^D \tag{12}$$

$$0 <= \gamma_t <= 1 \tag{13}$$

$$R_t^D >= 0 \tag{14}$$

$$R_t^D <= E_{t-\tau}^D \tag{15}$$

$$R_t^D >= D_t^D - (M_t - E_{t-\tau}^D) \tag{16}$$

$$M_t = \sum_{i=t-\tau}^{t} E_i^D \tag{17}$$

IV. Management Algorithms

In this section we are going to detail different used algorithm on the different cases described in the previous sections. Two principal strategies are introduced the first is based on scheduling the second aims to apply bin packing. The first algortithm EMAWC is based on the first approach, and the second algorithm EMAWCFF is based on the second approach. The different algorithms proposed are variations of the proposed approaches. The different inputs for our algorithms are the results of our machine learning predictions.

Table II summarizes the used algorithm on each scenarios

Table II: Used approach upon scenarios

Algorithm / Scenarios	Approach 1	Approach 2
Scenario 1	X	X
Scenario 2	X	X
Scenario 3	X	

Algorithm 1. is applied to the first scenario, where we are serving the energy consumption demand of users using the PV production or buying it from the Grid. We need to serve every consumption when it happens. For each instant, we store the produced energy in the battery. For each demand, if there is enough energy in the battery then it would be used for this demand else the needed energy will be bought. Algorithm 2 is based on Bin Packing (BP) problem and particularly the heuristic First-Fit. In a bin packing problem, we are considering the bins that will contain the elements that require placement. We chose it only because it gives an optimal solution. In our case, the bins will be the predicted produced energy and the elements to place are the predicted energy consumption demand. The policy of the First-Fit is to browse elements and bins one by one and place the first element in the first suitable bin. Since the production is variable the size of our bins will vary as a function of time so that we will be using a Variable Size Bin Packing VSBP. The major limitation of the BP family is that it does not meet time constraints.

Algorithm 1 Energy Management Algorithm without classification : EMAWC

Input: E_t^T, P_t, B_t, a_{tot}
Output: G_t,B_t, a_{tot}
Store harvesting energy in the Battery
Increment a_{tot}

if $B_t \geq E_t^T$ **then**
  Raise action consume
  Increment a_{tot}
  return 0,B_t , a_{tot}

else
  Raise action Buy
  $G_t = E_t^T$
  Increment a_{tot}
  return G_t,B_t , a_{tot}
end if

Algorithm 2 Energy Management Algorithm without classification using FirstFit heuristic for BinPacking : EMAWCFF

Input:E_t^T, P_t, B_t length(E_t^T), length(P_t)
Output: G_t,B_t, a_{tot}
Store harvesting energy in the Battery
Increment a_{tot}

while length(E_t^T,) **do**

  if $E_t^T \leq B_t$ **then**
    Raise Place Object
    Update B_t
    Increment a_{tot}

  else
    check next bin
    Increment a_{tot} (penalty)
  end if

end while

For algorithms 3 and 4, we introduced in our equations, the notion of classification or categorization of the energy demand so that we could serve the critical energy demand and if it's satisfied, we serve the delayed one.

Algorithm 3 Energy Management Algorithm with classification

Input: E_t^C, E_t^D, P_t, B_t, a_{tot}
Output: G_t,B_t, a_{tot}

while Critic Energy Demand **do**
  EMAWC(E_t^C, P_t, B_t, a_{tot})

end while

while Delayed Energy Demand **do**
  EMAWC(E_t^D, P_t, B_t, a_{tot})

end while

For algorithm 5, we are adding the concept of the deadline for the delayed energy consumption demand, that could be retarded but only for a certain time called *timelaps*.

Algorithm 4 Energy Management Algorithm with classification using FirstFit heuristic for BinPacking

Input: E_t^C, E_t^D, P_t, B_t length(E_t^T), length(P_t)
Output: G_t, B_t, a_{tot}

while Critic Energy Demand **do**
  EMAWCFF(E_t^c, P_t, B_t length(E_t^T), length(P_t)

end while

while Delayed Energy Demand **do**
  EMAWCFF(E_t^D, P_t, B_t length(E_t^T), length(P_t)

end while

Algorithm 5 Energy Management Algorithm with classification and deadline

Input: E_t^C, E_t^D, P_t, B_t, a_{tot}, τ
Output: G_t, B_t, a_{tot}

while Critic Energy Demand **do**
  EMAWC(E_t^C, P_t, B_t, a_{tot})

  if $t \geq \tau$ **then**
    EMAWC($E_{t-\tau}^D$, P_t, B_t, a_{tot})
  end if
end while

V. Performance Evaluation

In this section, we are evaluating the results obtained with the presented models. For each scenario, we compared the use of the algorithms based on three metrics, the number of total actions, the State Of Charge (SOC) of the battery and the amount of energy pulled from the grid.

As it can be seen in Fig. 3, we have compared the results of the first and second algorithms for the first case, on the basis of the three metrics. We claim that including the number of actions taken corresponds to the fact that charging and discharging a battery is a very costly function that affects its life cycle and other power electronic devices.

We can see that the first algorithm is better. In fact, the amount of energy consumed from the grid is lower than with the algorithm based on Bin Packing. The first algorithm needs fewer actions than the second one to serve the total energy. As it can be seen in Fig. 4, we have compared the results of the third and fourth algorithms on the basis of three metrics: The amount of energy drawn from the grid, the number of total actions made for one day and the state of charge of the battery. We can see that the third algorithm outperforms the other algorithms. In fact, the amount of energy consumed from the grid is again lower than with the algorithm based on Bin Packing. The first algorithm needs fewer actions than the second one to serve the total energy.

In Fig 5 we are comparing the first and third scenarios. In general, the Deadline based algorithm consumes less energy from the grid so it is better. But, they have an equal number of actions and the Deadline based algorithm uses more battery storage than the other.

A. A real load emulator

The algorithms developed in this paper will be integrated in a real load emulator shown in the figure 6. This emulator is connected to a solar panel and a wind turbine. It takes also the predicted and actual consumption and is equipped with Li-ion batteries. The management algorithm will be integrated so as to monitor state of charge for batteries and actual load bought from the grid. The loads are downscaled from a real building to correspond to the emulator size (300 W).

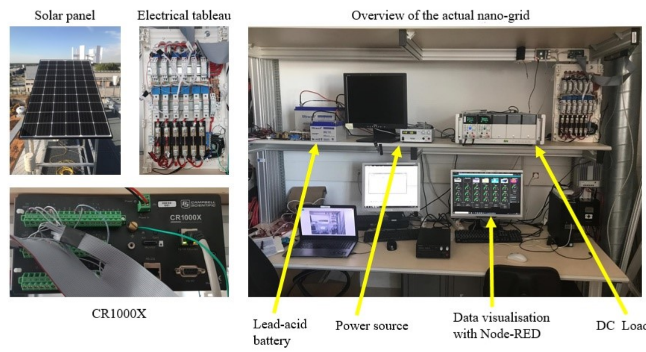


Figure 6: Ecole Polytechnique real load emulator

VI. Conclusion and future work

This paper presents a machine learning approach to make optimized scheduling in a smart microgrid. We made one day ahead prediction for the energy consumption of a building and energy produced by photovoltaic panels. We designed several management algorithms including maximum time-laps scheduling. We used a real dataset to train and predict future consumption and production. We then compared scheduling performance depending on different predefined scenarios. We compared our algorithm with a heuristic of bin packing. Results show that our scheduling algorithm with time-laps outperforms bin packing because it uses the battery as a temporary storage tool to program non-urgent consumption classes. As perspectives, first, the presented algorithms will be integrated with the NRLab emulator to benefit from a real battery behavior and they will be used in a different context: for QoS planning in an edge cloud RAN resource management system.

VII. Acknowledgements

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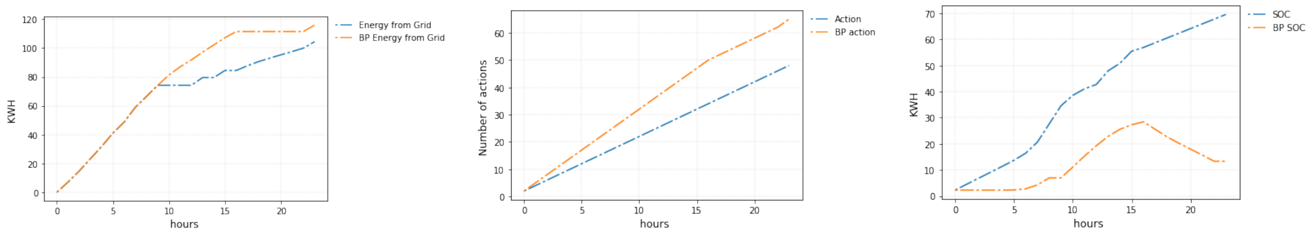
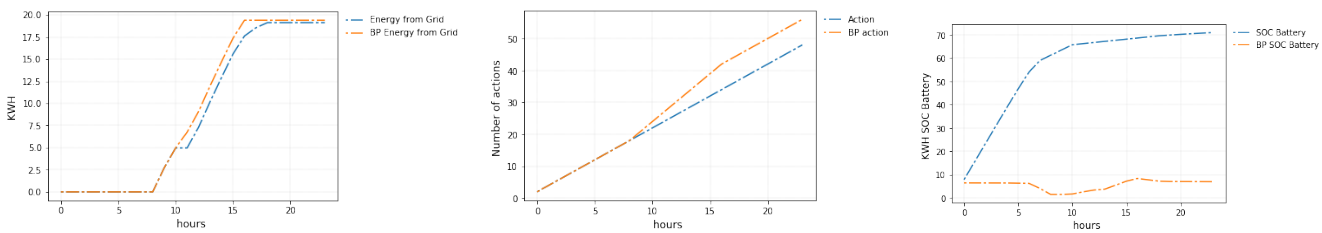


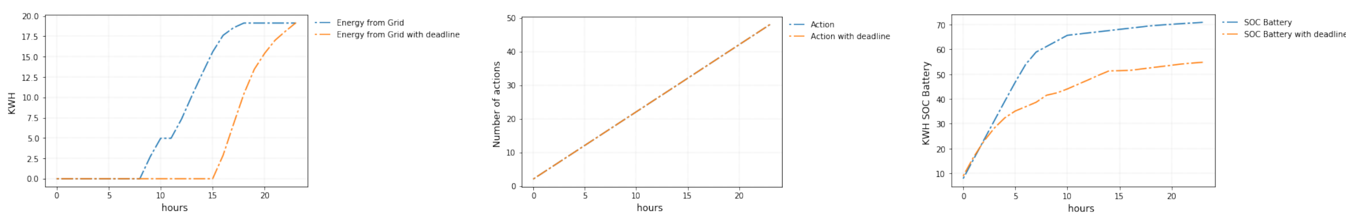
(a) Energy Consumption from the Grid
(b) Total actions for one day
(c) State of charge

Figure 3: Comparison between AMAWC and AMAWCFF for the first scenario one day scheduling



(a) Energy Consumption from the Grid
(b) Total actions for one day
(c) State of charge

Figure 4: Comparison between AMAWC and AMAWCFF for the second scenario one day scheduling



(a) Energy Consumption from the Grid
(b) Total actions for one day
(c) State of charge

Figure 5: Comparison between the first and the third scenario one day scheduling

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