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A Study on Forecasting Electricity Production and Consumption in Smart Cities and Factories

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Abstract

The electrical power sector must undergo a thorough metamorphosis to achieve the ambitious targets in greenhouse gas reduction set forth in the Paris Agreement of 2015. Reducing uncertainty about demand and, in case of renewable electricity generation, supply is important for the determination of spot electricity prices. In this work we propose and evaluate a context-based technique to anticipate the electricity production and consumption in buildings. We focus on a household with photovoltaics and energy storage system. We analyse the efficiency of Markov chains, stride predictors and also their combination into a hybrid predictor in modelling the evolution of electricity production and consumption. All these methods anticipate electric power based on previous values. The main goal is to determine the best method and its optimal configuration which can be integrated into a (possibly hardware-based) intelligent energy management system. The role of such a system is to adjust and synchronize through prediction the electricity consumption and production in order to increase self-consumption, reducing thus the pressure over the power grid. The experiments performed on datasets collected from a real system show that the best evaluated predictor is the Markov chain configured with an electric power history of 100 values, a context of one electric power value and the interval size of 1.

***Keywords*: Electricity prediction, Markov chains, photovoltaics, energy storage, energy management system.**

Declarations of interest: none.

1 Introduction

One of the major societal concerns is the energy consumption and the environmental footprint of consumers (like buildings, city street lighting, IT servers of data centers, etc.). Some statistics show that cities are consuming globally about 75% of the energy (Oliveira-Lima et al., 2016). The Environment Protection Agency of USA highlighted that computing systems, in particular data storage centers, consume the same amount of energy as civil aviation (about 2% of the world's total energy in 2010) (Duranton et al., 2010). Without a considerable energy efficiency improvement, high-end parallel computers will be of questionable economical viability and most of mobile computing, wearables and IoT (Internet of Things) devices will suffer from a lack of autonomy. Energy-saving solutions have to follow two directions. On the one hand, the total energy consumption must decrease. Electronic devices must be made more efficient from the energetic viewpoint by using less energy-hungry applications on smartphones and in other embedded systems or by diminishing the energy per floating-point operation. On the other hand, it is necessary to research safe alternative energy sources to replace current energy sources: wind power, renewable sources obtained through passive solar techniques, photovoltaic panels, biomass and hydropower. The current economic approach that basically amounts to a linear industrial model where materials are taken, transformed into products, and then disposed with, is evolving into a circular economy which encourages reduction, reuse, and recycling. The value of resources is thus maintained for as long as possible, resulting in energy savings and in lower greenhouse gas emissions.

The transition from linear to circular economy has received support from the European Commission that adopted a package in 2015. In the same year, the Paris Agreement was signed under the United Nations Framework Convention on Climate Change. The electrical power sector must undergo a thorough metamorphosis to achieve the ambitious targets in greenhouse gas reduction set out in the Agreement. Given the growth in trade volumes and diversity of products exhibited by the market of electricity derivatives, electrical energy plays an increasingly important role on the market. Electricity spot prices are driven largely by demand. Reducing the uncertainty relative to non-elasticity of demand (and, in case of renewable electricity, supply) and non-storability of electricity is essential when one is confronted with the arduous task of modelling spot prices (Weron, 2014).

Energy systems tend to become increasingly distributed due to the resilience and sustainability needs and the advanced researches in the field of distributed energy resources (Howell et al., 2017). The penetration of distributed energy resources is determined by governmental policies, economic incentives and the social pressure on companies and individuals to perceive them green and progressive. The use of distributed energy resources results less transmission losses with respect to the centralized power systems and allows an intelligent management, being thus more efficient and in trend with the smart city concept.

Nowadays, photovoltaics allow decentralized electricity production at a cost lower than that of the power grid. Costs are even lower if energy storage systems are included. Self-consumption, *i.e.*, the consumption of self-produced electricity, can be significantly increased with an intelligent energy management system which is able to streamline electricity production and consumption. The software architecture of one such system was proposed in (Feilmeier, 2015), applying Artificial Neural Networks (ANN) to anticipate the future electricity consumption and production. Based on these predictions, the energy management system can make decisions in order to increase self-consumption, thus reducing the electricity intake from the power grid, finally decreasing the total annual operating cost (Sembroiz et al., 2018). The energy management system can decide to activate some electrical appliances when cheap electricity is available and delay their activation when only high-cost electricity is available. Self-consumption will also reduce losses in distribution networks, improving efficiency.

In smart grids, households must react accordingly when the electricity grid requires an adjustment, for example when a reduction of intake is desired and achieved through the signaling of instant price increments (Nyberg, 2018). Data analysis is a key factor in data-based value creation (Lim et al., 2018). Through the interconnection of sensing and actuating devices, data collected from the smart grid can support decision making with respect to the adjustment of the electricity supply level. Additionally, smart grid data analytics can support the prediction of future demand, helping in planning expansions (Hashem et al., 2018).

In this work, we compare different prediction techniques on the data recorded by the FENECON Energy Management System (FEMS) (Feilmeier, 2015). We evaluate the performance of Markov chains as electricity consumption and production predictors. Markov chains are widely-used context-based methods which can provide predictions. Electrical power data cannot be applied directly as input in Markov chains, since that would imply a huge number of states and, thus, the predictor would be inefficient. Therefore, we preprocessed input data in order to enable usage of Markov chains with a reasonable number of states for an efficient prediction process. We also analyze the possibility to use stride predictors which are using the last strides from a sequence of values in order to predict future values. The previously mentioned preprocessing of the input data is necessary for the stride predictor, too. We will also study the combination of Markov chains and stride predictors for hybrid electricity forecasting. Such an adaptive hybrid prediction would take the advantage of each of its components based on their dynamic behavior. We analyze the accuracy of the proposed predictors on real data with the goal of minimizing the mean absolute error. We will determine the most appropriate configuration for electricity forecasting. We will also compare our optimal prediction method with the already existing neural network approach. Accurately predicting energy consumption could help improve energy management, grid performance, and reduce maintenance costs by pre-planning inspections and replacing equipment susceptible to damage. Moreover, it could improve the social and economic benefits by alerting the population if certain consumption thresholds are overtaken.

The remainder of this paper is organized as follows. Section 2 reviews related work in electricity prediction. Section 3 presents the proposed forecasting techniques. Section 4 reports and discusses experimental results, while Section 5 studies the impacts and applications. Finally, Section 6 presents conclusions and some possible directions for further work.

2 Related Work

Traditional energy resources (fossil fuels) tend to be exhausted. Without rethinking energy management, critical situations will be reached (researchers estimate in 2040) when energy demand will exceed the world's estimated energy production. To further exacerbate the problem, electrical energy is not uniformly distributed on the planet and does not cover the minimum required for everyone. In 2016 there were over 1 billion people with limited or no access to electricity (Watson & Pek, 2017). Renewable energy solutions like wind power or photovoltaic energy generation represent the key in the fight against climate change. However, the unpredictability of meteorological and climatic parameters (the wind does not constantly beat, the lack of sunny days, rare rain and drought) contrasts with the need for a continuous and stable energy supply, and this represents a drawback of renewable energy systems. Smart solutions are required regarding the locations of wind farms and solar panels, or the introduction of energy storage stations.

Solar energy is one of the most important renewable energy sources in support of decarbonization efforts. Over the past twenty years, technology for power generation and storage associated to photovoltaics (PV) has known an impressive development. Due to environmental conditions, fossil fuel depletion, governmental support or just plainly looking for a cleaner energy source, PV were widely adopted. As solar energy depends on many factors and is not constant, prediction is indispensable. There are many studies, some using only solar irradiation while others also considering air temperature, humidity or wind speed. The predictions of energy production contribute to the identification of the right time for plant maintenance and to the establishment of adequate prices for electricity on the day-ahead market.

Moreover, predictions can be made for energy production, but also for energy consumption. Predictions can also be categorized based on their time range: short-term predictions (covering usually a time slot of a few hours), average predictions (ranging from several weeks to one year) and long-term predictions (more than one year). In this paper we will review only related works (both on production and on consumption) that are focused on short-term analysis, emphasizing the differences between our research and the state-of-the-art methods. Prediction models have been developed for consumers of different size: individual households, buildings, grids and plants. Most prediction methods aim at determining the minimum and average levels of energy consumption and the economic costs involved. The ultimate goal is to raise awareness, apply corrections to actions already performed, and stimulate customers to increase efficiency, reduce energy consumption, or choose alternative (renewable) resources.

Energy prediction and reduction solutions in Smart Buildings are based on automation of lighting, heating, ventilation and air conditioning (HVAC), security and surveillance, garden irrigation systems (Florea & Băncioiu, 2015; Sembroiz et al., 2018), on the basis of information inferred from past data or provided by data sources such as environmental sensors, laser beams, weather forecasts, building occupancy profiles, or number of parked cars. In (Oliveira-Lima et al., 2016) the authors implemented an embedded system for recording the number of people inside a university building using laser beams and microcontrollers. With the help of ANNs and using as supplemental information the count of cars parked in the lot, the amount of energy required by the building is estimated. The information regarding the degree of occupancy of the university building and the number of cars is kept for a period of 2 weeks, computing the correlation between data and then maintaining for a longer period (1 year) only the information about parked cars. Such data are fed into the prediction model to estimate the occupancy degree that, in conjunction with weather forecasts and day type (labor/holiday) information, is used to predict the energy consumption in the building.

Accurate measurement (using Smart Meter instruments) of energy consumption has become a commonly used practice, given the increase in energy prices. However, predicting the electricity load is difficult because demand patterns generally differ among consumers, increasing the uncertainty of prediction. In (Gajowniczek & Ząbkowski, 2014), the authors propose, in a short-term approach, two types of predictors – based on ANNs and Support Vector Machines (SVM) – to forecast the electricity demand of individual households for 24 hours ahead. The benefit to customers is that they will be able to better understand their energy consumption and the afferent costs.

Numerous factors influence and even limit the energy performance of buildings (Zhao & Magoulès, 2012). Among these factors we recall the environmental conditions, the buildings architecture, features and occupancy degree, behavior of inhabitants, and the operating regime of lighting and HVAC subsystems. The large number of input parameters involves a high algorithmic complexity in the prediction of energy consumption. The previously mentioned paper highlights some existing solutions for solving the energy prediction problem using statistical and ANN-based methods, and also further prospects are proposed.

The authors in (Escrivá-Escrivá et al., 2011) proposed a short-term approach to forecast the total power consumption of buildings using ANNs. The specificity of their approach consists in the prediction mechanism and its target. The multilayer perceptron neural network uses in the training process the type of day (labor activity parameter). Thus, for the prediction of consumption in a certain day the ANN will be trained only using days of the same type and weather characteristics as well. The goal of prediction is to accurately determine the load curve of energy consumption by identifying the energy process of each individual consumer, that will be aggregated later. The advantage is that each end user is independently related to network input parameters (schedule, weather, etc.). The solution has been tested at the University of Valencia, a complex institution with more than 60 buildings and whose energy consumption is about 11.5 MW, similar to the one of a big commercial consumer.

Optimization of energy consumption can also be achieved by adapting production to consumer demand. An important drawback of microgrids is represented by the dynamicity and irregularity of load curves in contrast to larger environments like national or regional power grids, more stationary from this point of view. In this sense, for microgrids a smart prediction mechanism is required to model the relation between consumption and demand of energy, taking into account all the parameters that influence this process, and it must be able to quickly adapt to any changes. In (Hernández et al., 2014) the authors describe a three-tier architecture for load prediction in microgrids. The first layer includes a self-organizing map (SOM) dedicated to classifying patterns of electricity consumptions based on historical data. On the second layer, the K-means clustering algorithm is applied to the SOM-generated partitions. The last layer consists in the multilayer perceptron which predicts the load curve for each cluster. Weather characteristics, day and month type are used as ANN inputs for predicting the electricity demand. The model was validated with data from microgrids situated in Castile and León, Spain, facilitated by the Iberdrola company. SOM-based prediction is applied also in (Chen at al., 2011). There, a complex model is described that forecasts PV power using a radial basis neural network which is trained through a system composed of the K-means clustering, nearest-neighbor and least squares methods. The SOM is used to classify the inputs of the weather predictions. The average daily values of parameters like solar irradiance, wind speed, humidity, and temperature represent the neural network inputs, while the predicted daily power of PV plant is the output.

In (Izgi et al., 2012), the power values produced by a small-scale solar PV panel are used as inputs for a multilayer perceptron using the Levenberg-Marquardt learning algorithm, aiming to find the time horizon with the best prediction accuracy of the generated electricity. As far as April is concerned, the best time horizons were 5 and 35 minutes for medium term predictions while the best time horizons relative to August were 3 and 40 minutes. Due to small variations of the climatic parameters in August, the prediction of electricity with ANNs is facilitated. In this case, the prediction could be determined by averaging the power of PV panels on wider time horizons.

In (Almonacid et al., 2014), the authors predict the power one hour ahead using ANNs. The inputs of the ANN consist in the solar irradiance and the temperature, each value being predicted by a distinct nonlinear autoregressive neural network. Such dynamic ANNs have the great advantage that they can correlate the output not only with the current input, but with previous inputs, too. The proposed method was validated on the data of a PV generator from the University of Jaen, Spain.

Two experiments regarding a grid-connected photovoltaic (GCPV) plant of 20 kWp are presented in (Mellit & Pavan, 2010; Bouzerdoum et al., 2013). In the first one, the power generated by the GCPV plant is predicted with the help of two complex neural predictors. The system was installed and tested on the roof top of the Italian city Trieste. Two ANNs are tested – a multivariate and a univariate one – aiming to determine the influence of climate conditions on the functional regime of the GCPV. The main difference between them is that the univariate model receives as an input parameter just the solar irradiance while the multivariate model also considers air temperature. In (Bouzerdoum et al., 2013), two forecasting methods are combined: a time series method based on Seasonal Auto-Regressive Integrated Moving Average (SARIMA) and the SVM method. The hybrid model performs better than each method separately.

Another system which anticipates the energy provided by a GCPV plant is presented in (Fernandez-Jimenez et al., 2012). The predictive mechanism consists in a chain of three modules. The first two make predictions of meteorological parameters starting from coarse-grained coverage of environmental data (global forecasting information provided by Spanish national center) and continuing with more accurate information (fine-grained weather prediction for points situated in the neighborhood of the location). The final module of the system that performs energy prediction over a 39-hour interval (15 hours from first day and the whole next day) consists in different types of predictors like *k*-nearest neighbors (*k*-NN), multilayer perceptron, or time series models.

The main difference between the works referred above and our solution is that the most of the state of the art solutions are using ANNs, SVMs or time series models, whereas our proposed approach applies context-based methods like Markov predictors, computational (stride) predictors, and the hybridization of these two techniques.

3 Electricity Prediction

We present Markov chains, stride prediction and their hybridization as forecasting methods for electricity consumption and production. Our goal is to adapt them to be functional in energy management systems with photovoltaics and energy storage. In particular, techniques amenable to efficient implementation in hardware devices are studied. The reason for this decision is that energy management is foreseen to be integrated in lightweight devices such as those used in IoT.

The scheme of the electrical installation used in the experiments is depicted in Figure 1.

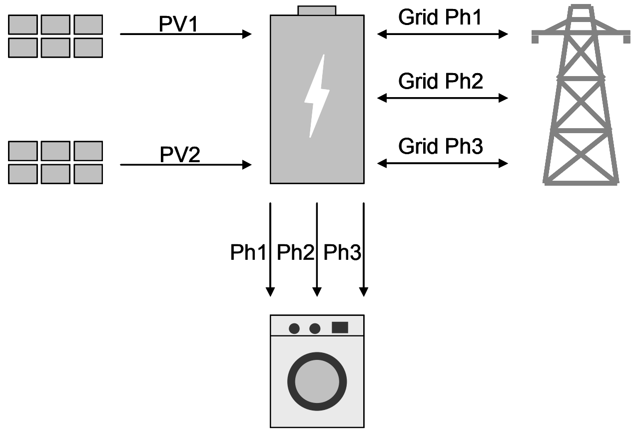

Figure 1. The energy production and storage system.

As Figure 1 illustrates, the energy storage system is connected with two photovoltaics of 12.24 kWp (PV1 and PV2) and also with three grid phases (Ph1, Ph2 and Ph3). The energy produced by PV1 and PV2 is kept in the storage system with a capacity of 8.5 kWh. Consumers can take electricity from the storage system or from the grid.

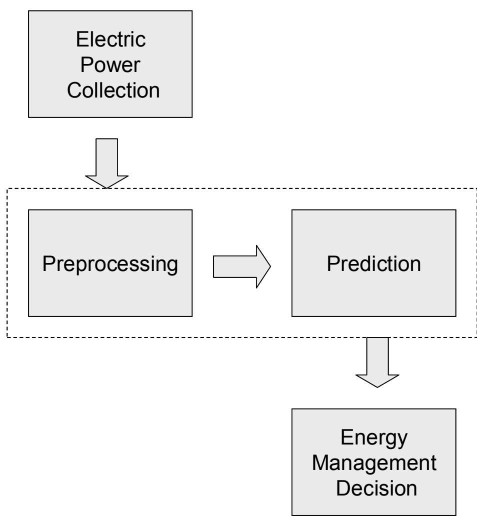

Figure 2. The prediction process in an energy management system.

Figure 2 depicts how the prediction process is integrated into an energy management system. In the first stage, data about produced and consumed electricity must be collected. In the next stage, the recorded data must be checked for erroneous values, which must be corrected. Such problems (especially huge values) can occur during data collection. We corrected such identified erroneous data by replacing the wrong value with the previous recorded value. We also encode all the data. After the preprocessing step, the predictor computes the electric power for the next period, based on the data relative to previous periods. These predicted electricity production and consumption values are then used to make decisions by the energy management system to increase self-consumption. Next, we present the prediction methods evaluated in this work. All these methods are returning the next forecasted electric power, or a special value (here, -1) whenever they are unable to deliver a prediction.

In such unpredictability cases, we will forecast the next electric power value as being equal to the previous one.

3.1 Markov Predictors

Observed levels of energy (production or consumption) constitute a sequence where subsequent samples are not independent. Such sequences can be described as being generated by a parametric random process, whose parameters can be learned from a training sample of sequences.

Since the high number of possible distinct electric power values would highly increase the state complexity of the Markov chain, a classical implementation could be inefficient for prediction. Therefore, we implement the Markov chain based prediction algorithm in an efficient way, as we did in (Gellert & Florea, 2016) for web access prediction. Instead of predicting the next electric power through trees, graphs or transition tables, we generate the prediction by performing simple searches in the electric power sequence. This way of implementation will make possible to use Markov chains with significantly lower number of states. We will further decrease the state complexity of the Markov chain by preprocessing the input data. All the input electric powers will be encoded to intervals, each interval being represented by an integer value. The output will be determined by decoding the predicted interval (scaling to an approximated electric power value).

In the Markov chains used in this work, states are represented by electric power values. In a Markov chain of order 1, the current state depends on the history only through the previous value:

$$P[e_t \mid e_{t-1},\ \ldots,\ e_1] = P[e_t \mid e_{t-1}] \qquad (1)$$

where e_t is the electric power at time *t*. In a famous sentence, P. Lévy stated this property as "the past influences the future only through the present". If we generalize, in a Markov chain of order *R*, the current electric power is deduced based on *R* previous electric powers (Gellert & Florea, 2016):

$$P[e_t \mid e_{t-1},\ \ldots,\ e_1] = P[e_t \mid e_{t-1},\ \ldots,\ e_{t-R}] \qquad (2)$$

Markov chains can be used to anticipate the electric power by searching for the current electric power context in the stored electric power history. The predicted power level is the state for which the estimated transition probability from the current state is the highest. Figure 3 presents an example of electricity forecasting with a Markov chain of order 1, using intervals of 10, on a real sequence of nine electric power values extracted from the PV1 dataset.

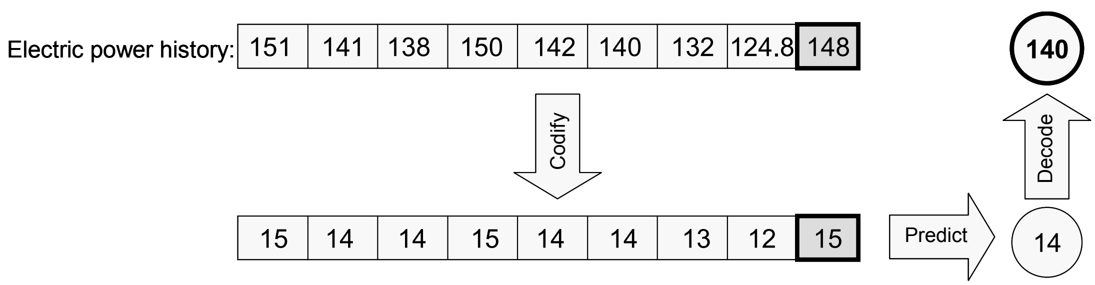

Figure 3. An example of electricity prediction with a Markov chain of order 1.

As Figure 3 illustrates, the electric power history (composed of nine values) is codified by division to the interval value (which in this certain case is 10). The codified context is 15. The Markov chain predicts 14, since it occurred with the highest frequency after the context 15. The predicted value 14 is decoded (by multiplying with 10) to the electric power value 140, which is the final prediction.

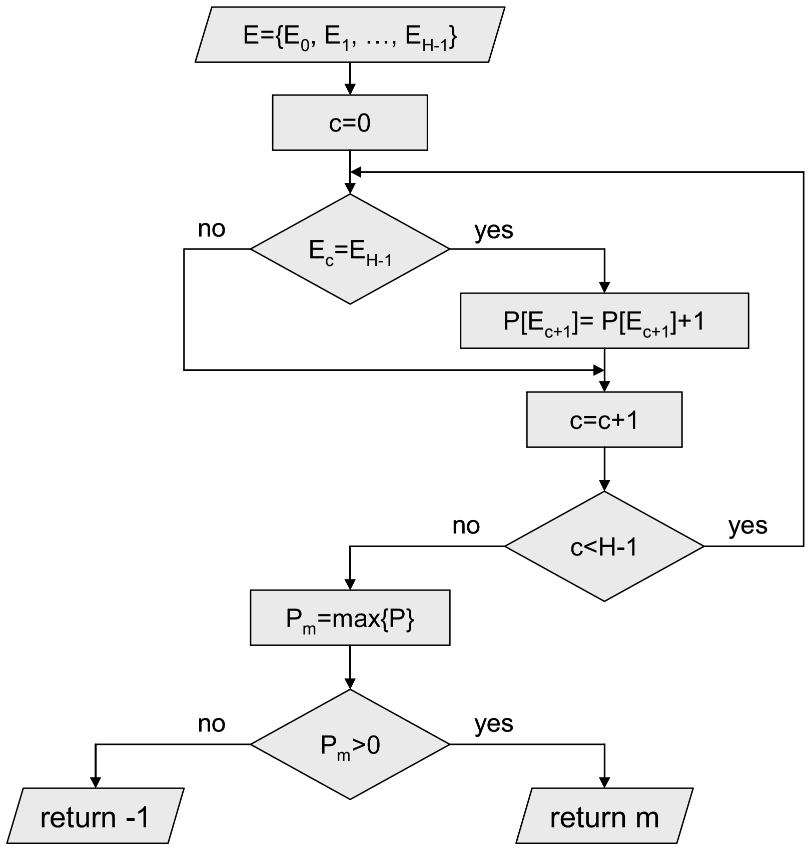

Figure 4. Flowchart of the prediction process with a Markov chain of order 1.

The pseudocode of the general R^{th} order Markov prediction algorithm, used for electricity forecasting, is presented below:

```
MARKOV (E, R)
   for c := 0 to R-1 do
      C[c] := E[H-R+c]
   endfor
   for h := R to H-1 do
      IS_CONTEXT := TRUE
      for c := 0 to R-1 do
         if E[h-R+c] != C[c] then
            IS_CONTEXT := false
            break
         endif
      endfor
      if IS_CONTEXT then
         P[E[h]] := P[E[h]] + 1
      endif
   endfor
   PREDICTION := 0
```

```
18.     MAX := P[0]
19.     for i := 1 to N-1 do
20.        if P[i] > MAX then
21.           MAX := P[i]
22.           PREDICTION := i
23.        endif
24.     endfor
25.     if MAX > 0 then
26.        return PREDICTION
27.     endif
28.     return -1
29.  end
```

where *R* is the order of the Markov chain, *E* is the electric power sequence, the context *C* is containing the last *R* values from the electric power sequence, *H* is the length of the electric power sequence, *P* is the probability distribution for *N* distinct electric power values, *PREDICTION* is the predicted electric power value, and *MAX* is the frequency of the predicted electric power value occurring after the context. If the current context is not found in the electric power sequence, which is expressed by returning -1, the Markov chain is unable to deliver a prediction. The Java implementation of such a Markov predictor is presented in (Gellert & Florea, 2013).

On the lines 2-4 the context *C* is extracted from the electric power sequence *E*. After that, on lines 5-16 the context *C* is searched within the electric power sequence *E* and each time the context is found, we increase the probability of the electric power value that follows the context. In this way, we compute the probability of some possible electric power values to be the next one in the sequence. On the lines 17-24, we determine the highest probability. On the lines 25-27, if the highest probability is not 0, we return the electric power value corresponding to that probability. Otherwise, if all the probabilities are 0, we return -1 on the line 28, meaning that the algorithm is unable to predict.

In this algorithm, we limit the value of *H* and thus we use a limited history of recorded electric powers. We will vary the parameter *H* in the experimental setup.

3.2 Stride Prediction

The stride predictor is a trend-based computational prediction method which determines the next value as the sum of the immediate previous value and a stride (Gellert, 2008). The stride is the difference between the two most recent values. In our algorithm we chose as condition the equality between the last two strides. Thus, we generate a prediction only if the stride between the last three values was constant. Figure 5 presents an example of prediction with the stride predictor, using intervals of 10, on a real electric power sequence extracted from the PV1 dataset.

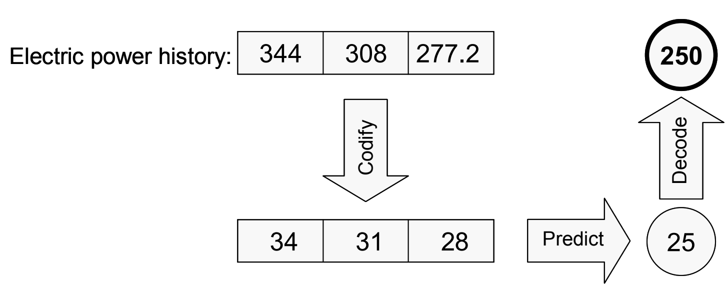

Figure 5. An example of prediction with the stride predictor.

As Figure 5 depicts, the electric power history (composed of three values) is codified by division to the interval value (which in this case is 10). After a constant stride of -3 is detected, the prediction is generated by adding the stride -3 to the last value 28. Then, the predicted value 25 is decoded (by multiplying with 10) to the electric power value 250, which is the final prediction in this case. Figure 6 presents the general stride prediction mechanism.

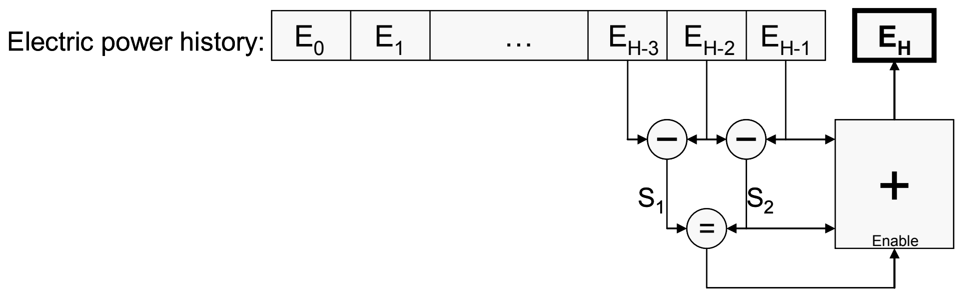

Figure 6. The stride prediction mechanism.

As Figure 6 shows, we compute the stride S_1 as the difference between E_{H-3} and E_{H-2} and also the stride S_2 between E_{H-2} and E_{H-1}. Only if S_1 and S_2 are equal, we predict the next electric power value E_H as the sum between the last electric power value E_{H-1} and the stride S_1. Next, we present the pseudocode of the stride prediction algorithm.

1. STRIDE (E_{H-1}, E_{H-2}, E_{H-3})
2. PREDICTION := -1
3. $S_1 := E_{H-1} - E_{H-2}$
4. $S_2 := E_{H-2} - E_{H-3}$
5. if $S_1 = S_2$ then
6. PREDICTION := $E_{H-1} + S_2$
7. endif
8. return PREDICTION
9. end

where *PREDICTION* is the predicted electric power value, which is -1 whenever the stride predictor is unable to predict. On the lines 3-4 the last two strides are computed. On the lines 5-7 the predicted electric power value is determined. This computational predictor should be able to identify and exploit constantly increasing or decreasing electric power sequences.

3.3 Hybrid Prediction

Since our previous experiments on different problems (branch and value prediction in the microarchitecture domain or webpage prediction) pointed out that a single predictor usually strives in capturing all the various types of predictability patterns that occur in real scenarios, we implemented a hybrid scheme for enabling high prediction accuracy. The hybrid prediction mechanism includes as components the above presented Markov and stride predictors. The hybrid predictor maintains a 4-state saturating counter for each component: C_M for the Markov predictor and C_S for the stride predictor.

When a component produces correct predictions, its associated confidence counter is incremented. On the other hand, when a predictor is mispredicting, its counter is decremented. We consider the prediction generated by the component predictor with the largest confidence counter. Thus, the hybrid predictor is dynamically adapting based on the behavior of its components and each time will select the most confident predictor. A low number of states in the saturating counters, assures fast adaptation to possible behavior changes in the electricity consumption or production. The hybrid prediction mechanism is presented in Figure 7.

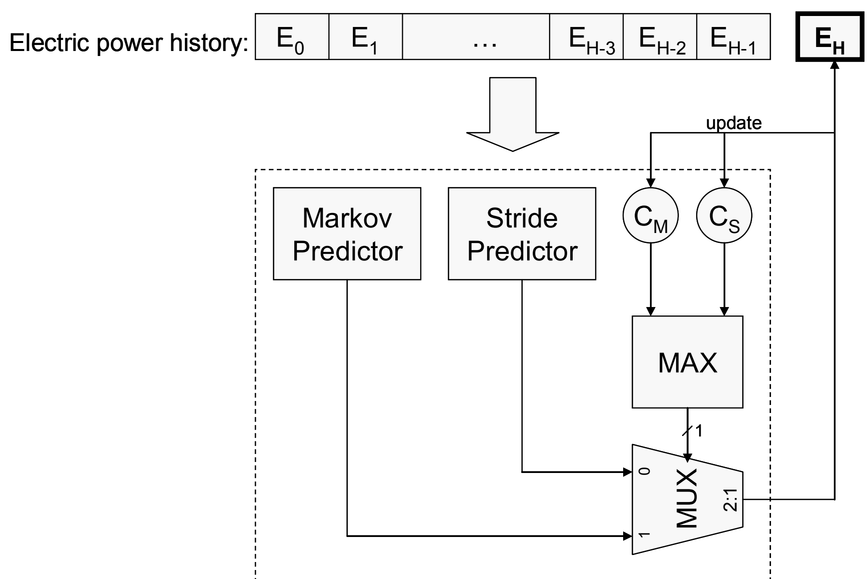

Figure 7. The hybrid prediction mechanism.

The MAX unit returns 1 if C_M is greater than C_S and 0 otherwise. Such a hybrid predictor can take the advantage of its components. It can be obviously extended to include more than two predictors.

4 Experimental Results

The performance of the proposed algorithms will be evaluated from the Mean Absolute Error (MAE) viewpoint, which is computed as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|R_i - F_i\right| \tag{3}$$

where R_i is the observed electric power at time i, F_i is the forecasted electric power at time i and N is the number of recorded electric power values. MAE has been preferred over the Mean Squared Error because the latter tends to exaggerate the influence of outliers. A manual exploration of the space of hyperparameters has been carried out to determine the best-performing models. Such analysis also provides insights into the dynamics of the data-generating process. We have evaluated the proposed methods on the datasets recorded by FEMS: two datasets with produced electricity (PV1 and PV2) and three datasets with consumed electricity (Ph1, Ph2 and Ph3). The electric power values, expressed in Watts, were collected in 2015 between 1st January and 31st May, with one record per 5 minutes (Feilmeier, 2015).

We started the evaluation with the Markov predictor. Figure 8 shows the MAE for different context sizes (Markov chain orders). We varied *R* between 1 and 5 and we used an electric power history size of 300 and an interval of 10.

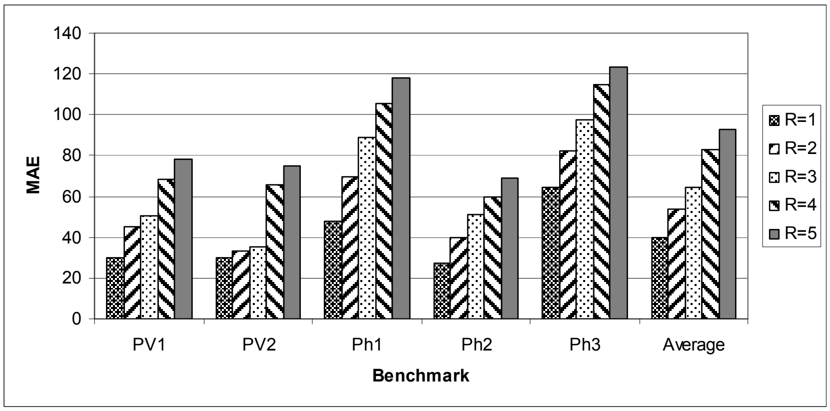

Figure 8. Varying the Markov chain's order.

Figure 8 shows that as the higher is the Markov chain's order, the higher is the MAE. Thus, for this type of data, lower order Markov predictors (with shorter context information) are more appropriate.

We continue the evaluations by fixing the order *R* to 1 and we will now vary the history size. We still keep the (electric power) interval size on 10.

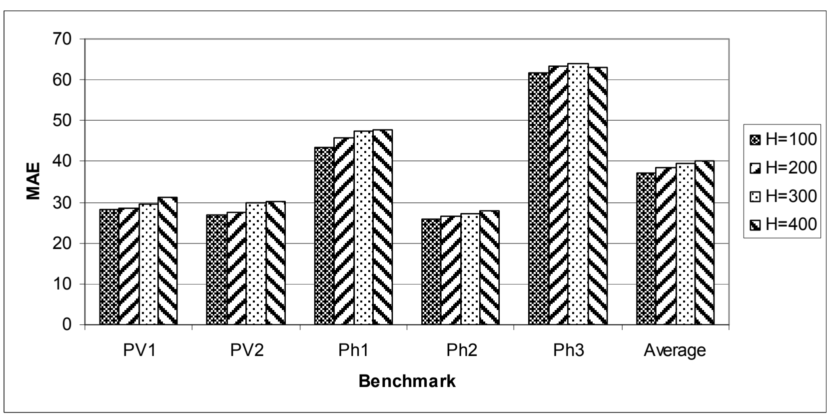

Figure 9. Varying the history size.

As Figure 9 illustrates, the lowest MAE was obtained with a history size of 100. With longer histories the MAE is slightly higher. Therefore, we fixed the history size *H* to 100. Lower values were not evaluated because of the bias-variance trade off.

Next, we have evaluated the interval size *I*, considering the previously optimized order of 1 and history length of 100.

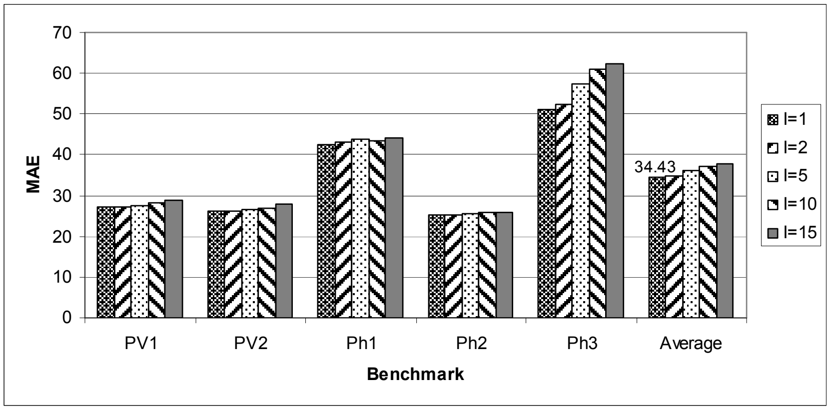

Figure 10. Varying the interval size.

As Figure 10 depicts, a lower interval size provides better results. The lowest MAE has been obtained with an interval size of 1. That means that we consider the integer part of the electric power values in the codification process. With the interval size set to 1, the decoding step becomes unnecessary. The history length of 100 seems to be sufficiently long to allow an interval size of 1, since the electric power values are mostly found in the electric power sequence. Consequently, the best Markov predictor is of order 1 and it is using a history length of 100 and an interval size of 1.

Finally, we have evaluated the stride predictor in conjunction with the Markov chain. We have also integrated the stride predictor and the best Markov predictor configuration (*R*=1, *H*=100, *I*=1) to a hybrid predictor which will dynamically select its most confident component.

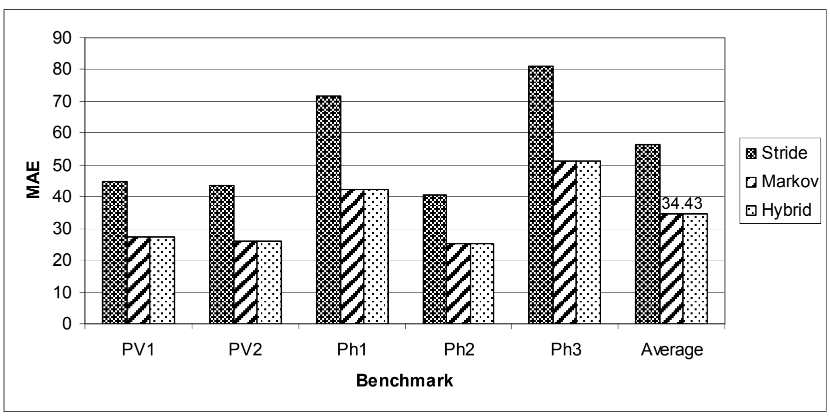

Figure 11. Comparing the Markov, stride and hybrid predictors.

As we can observe in Figure 11, the stride predictor has a considerably higher MAE than the Markov predictor. Due to the weakness of the stride predictor, the more complex hybrid predictor is not better than its Markov predictor component. Moreover, a hybrid predictor would induce higher costs than a single Markov predictor. Therefore, we can conclude that the Markov predictor is the most appropriate for electricity forecasting among the techniques analyzed in this work. In Figure 12 we compare our best method with the neural forecasting technique proposed in (Feilmeier, 2015).

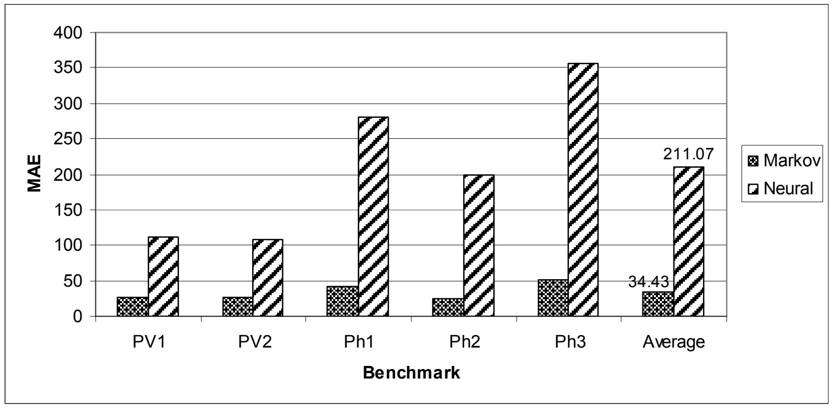

Figure 12. Comparing the Markov and neural predictors.

As Figure 12 illustrates, the Markov predictor provided significantly better results than the neural forecasting technique presented in (Feilmeier, 2015). Next, we will further analyse the Markov predictor by comparing the real electric power values with the Markov chain based predictions, on three days from the PV1 dataset.

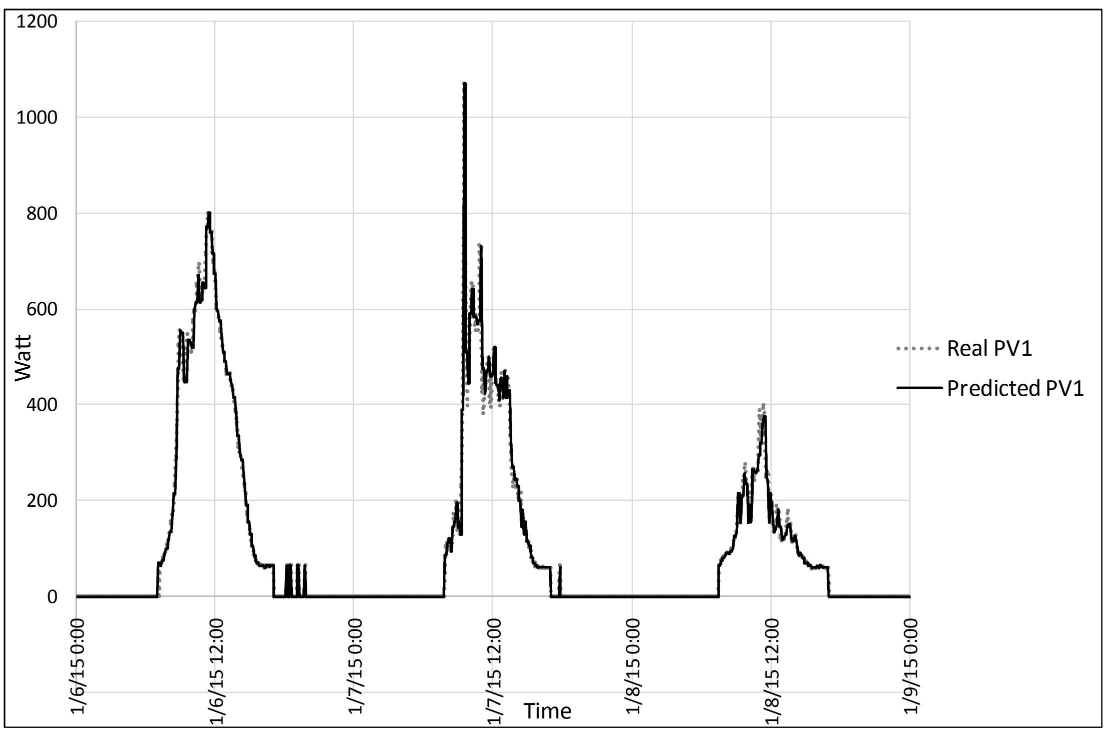

Figure 13. Comparing the real PV1 with the Markov predictions.

As Figure 13 shows, the Markov chain is able to accurately forecast electric power, since the two curves – the real one and the predicted one – are almost completely overlapped. The above presented results validate the Markov predictor as a powerful electricity modelling technique, which can be used for decision making in intelligent energy management systems like FEMS.

5 Discussion

Among economic sectors, infrastructure is somewhat special, in that it is normally invisible – unless it breaks down. Transfer of information has traditionally played a marginal role in the electricity grid, most often with the information flow in the form of a monthly bill and usage report. Bringing information to an infrastructure and observing the effects on processes and on the behavior of actors is an opportunity to focus attention on the impact of information in the reorganization of a sector (Nyberg, 2018). Data collection, both at the supply side and the demand side, facilitates the balancing of the grid, a critical requirement for an appropriate supply of energy to be maintained. In a smart grid, households could be expected to react accordingly when the electricity grid requires an adjustment, for example when a reduction of intake is desired and achieved through the signaling of instant price increments (Nyberg, 2018). The effects of a technology-induced reorganization of the smart grid when users no longer are passive participants in the relationship between them and the infrastructure, but they become active and the information flow becomes bidirectional, can be profound and should be studied with great attention.

Data analysis is one of the nine key factors that characterize data-based value creation (Lim et al., 2018). Through the interconnection of sensing and actuating devices, data collected from the smart grid can support decision makers in devising appropriate decisions with respect to the adjustment of the supply level of electricity. In addition, smart grid data analytics can help predict future demand, helping in planning expansions (Hashem et al., 2018). Such prediction is, though, centralized. If the electricity grid infrastructure is viewed from a socio-political perspective, a reflection on issues regarding power and control comes forward, because infrastructures are essential systems for living and a complete control over them implies potential expedients for enhanced power (Nyberg, 2018). The availability of autonomous, independent predictive systems might represent a valid protection mechanism.

Production and distribution of hardware devices is not the sole business model enabled by the mechanism proposed here. The complexity of smart homes and smart grid suggests that it may not be viable for a single actor to build a comprehensive management solution alone. Companies operating in the area will have to establish partnerships among them and such data analysis partnerships are foreseen to be among the most important building blocks in shaping new business models (Dijkman et al., 2015). For example, the analysis of readings from the device proposed in this paper could be integrated and augmented with the corresponding information coming from a smart thermostat used to monitor their pattern of use of heating.

5.1 Contributions to existing knowledge

We have implemented a Markov chain to efficiently forecast electricity consumption, avoiding complex data structures, facilitating thus the use in hardware. Moreover, we have shown that our context-based predictor outperforms the artificial neural network based prediction method. The last is one of the main methods used for prediction of electricity consumption in buildings even if it has disadvantages like slow convergence, fluctuations, and oscillation during training (Ye & Kim, 2018).

Big data and cloud computing favour studying the electricity consumption on long term. Keeping of large data sets for analysis leads to more accurate results. In our approach, even we made a short-term prediction we used for our datasets a longer period (from beginning of January to the end of May) than other studies, which included different seasons (with different weather characteristics) that might influence the electricity consumption.

5.2 Implications for Practice

In the following, we briefly present a few practical applications of our solution. Perhaps one of the most obvious advantages of predicting electricity consumption and production is the spreading of awareness of the negative environmental impact of a high consumption, the importance of balancing between production and consumption, and the benefits from intelligent energy management in buildings. Prediction of electricity patterns with different time granularities (day/week/month/year), isolation of ascending and descending trends, depending on geographic region and the lifestyle of consumers, will help consumers become more aware of their electricity consumption and enable them to develop intervention strategies according to their pattern of consumption. Furthermore, consumers who have direct and frequent access to consumption and production measurements and patterns specific to them, will likely become more ecologically aware about environmental issues.

In a renovated electrical grid, data are collected and used as a basis for decisions, with the aim of improving the efficiency, reliability, and sustainability of electricity production and distribution. The degree to which this process is automated plays an important role, as well as the self-monitoring and feedback capabilities offered to customers. In order to have accurate measurements of the operating conditions of the electricity grid, sensors need to be placed throughout it, in particular on production, transmission, and distribution systems, in addition to consumer access points (Yin et al., 2013). Processing the collected data, which falls into the realm of big data analytics, helps decision makers measure the level of energy supply they should guarantee, and estimate reasonable safety margins. In addition, predictions of energy demand can be used to determine innovative, flexible, and dynamic pricing plans that are closely tailored to usage patterns (Ahmed et al. 2017). In this context, the availability of individual predictions complements and completes centralized analysis systems.

The prediction of electricity consumption could be used as a monitoring and diagnostic solution embedded in the self-healing feature of modern smart grid technologies (Shafiq et al., 2015). If some piece of equipment would require an unusual amount of electricity or if there is a defective component inside the network (buildings, factories or city street lighting), our application could send a notification to the maintenance team that will then perform an on-site diagnosis on the identified component, deciding about the appropriate action: further close monitoring, repair, or replacement. Such an approach can reduce costs by preventing component loss, while avoiding unexpected electrical interruptions. Another implication in practice of our developed tool refers to predict electricity demand in order to know in advance when to start ventilation and cooling of electrical systems in data centers, to efficiently manage the networks and target interventions designed to reduce or time-shift peak loads. In general, the usefulness of predictions will be amplified whenever actuators with some latency are present.

In increasingly crowded cities, a detailed and current knowledge of the number of inhabitants becomes useful and necessary for city authorities in planning public transportation and traffic, and accurately managing public transport fleets. Prediction of electricity consumption could provide considerable opportunities to find out household characteristics. Our solution can be used to generate household consumption profiles and link these data to the number of people in buildings in order to implement a smart census process. In an experiment in UK, (Anderson et al., 2017) the authors analyze the feasibility of using household energy consumption for a specified period to infer their characteristics as a first step in aggregating them with other population and geographic location metrics. These area level population statistics could represent new insights for enhancing the census taking process with digital trace data.

Another implication in practice could be the inclusion of our Markovian predictor into a toolset developed to discover the typical load profiles of customers. In (Guo et al., 2018) are emphasized the advantages of big data and cloud computing technology for store and analyze massive electricity data, and to explore the pattern of electricity consumption. Several algorithms are analysed such as Deep Learning, Fuzzy C-Means (FCM) clustering method, including social network based predictors, suggesting a new perspective for describing the energy consumption behaviour of consumers: in the time dimension, user dimension and spatial dimension.

Last but not least, we believe that this work could impact at educational level as a Green Information Technology solution, by explaining specific Computer Architecture concepts and tools – such as the Markov prediction schemes, from the perspective of environmental impact, the requirement of cutting down the energy consumption and also the CO2 emissions. In (Florea, 2017), the teaching process of cache replacement algorithms as content of Microprocessors Systems curricula is presented focusing on main societal challenges, namely energy efficiency practices applied to data centres. The author's solution reflects the energy saved by the data centres of search engines by including algorithms for accelerating the search process of videos in YouTube, taking into account the prediction of ICT specialists that in 2020 video streaming and displaying will represent around 55% of all global mobile data traffic, requiring huge demands of capacity and electricity on future's networks.

6 Conclusions and Further Work

In this work, we propose a method for intelligent energy management in buildings, aimed at reducing uncertainty about the demand of electricity and its production from renewable sources. Within the framework of a decentralized energy production infrastructure, a network of networks where components are influencing each other, technology must support coordination, communication, and control. Predictions contribute to balance and smoothen the electricity intake from the power grid, with desirable consequences on both the operation of distribution grids and the stability of prices.

6.1 Conclusions Regarding the Implemented Methods

Systems that can be deployed as lightweight hardware devices reduce costs and facilitate diffusion and integration with existing infrastructure. We have applied Markov chains, stride prediction and also hybrid prediction to forecast electric power values based on previous values. We have implemented the Markov chains in an efficient manner, avoiding trees, graphs and transition tables so that an adaptation of the mechanism into miniaturized hardware will be not only possible, but very easy. We have further decreased the state complexity of the Markov chain by preprocessing the input data. We evaluated our methods on both produced and consumed electricity recorded by a real energy management system. The mean absolute error measured on the above mentioned datasets was 34 W. Thus, Markov chains proved their ability to anticipate electricity production and consumption and can be integrated into energy management systems and immediate integration with IoT is contemplated.

6.2 Limitations and Future Research Directions

Since Markov predictors are context-based, their main drawback is that predictions are solely based on the history accessed during the last time period. If a pattern appears for the first time, the context-based predictor cannot generate a prediction. Thus, complete prediction by partial matching (PPM) predictor which contains simple Markov predictors, from 0^{th} order to R^{th} order, or hybrid predictors could be used.

Another limitation of the proposed methods is that they cannot capture some possible hidden, not immediately accessible nor measurable, information. Therefore, a direction for future work is to analyze also other statistical modelling techniques such as ARIMA models or Hidden Markov Models, attempting to characterize power values as the observable result of a random process acting on unobservable state variables. In addition, further study will be dedicated to recurrent neural networks.

Yet another possible limitation of our prediction algorithm, that will be treated in a future approach, is the lack of environmental-specific input parameters. Knowing some information about the building's surface, temperature inside and outside of it, humidity, day of the week (workday or not), holiday or not, and weather characteristics like wind speed, may influence the prediction algorithm to increase its accuracy. These data will be fetched from weather stations or from environmental protection agencies. Measurements from locally installed sensors can also be used, extending the approach presented in (Florea & Băncioiu, 2015), where an embedded system was implemented in which some activities from smart home, like opening windows or using the thermal system for heating, are automatized and triggered taking into account some outside meteorological conditions like temperature or wind intensity.

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