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Autonomous Cycle of Data Analysis Tasks for Scheduling the Use of Controllable Load Appliances using Renewable Energy

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***Abstract*– With the arrival of smart edifications with renewable energy generation capacities, new possibilities for optimizing the use of the energy network appear. In particular, this work defines a system that automatically generates hours of use of the controllable load appliances (washing machine, dishwasher, etc.) within these edifications, in such a way that the use of renewable energy is maximized. To achieve this, we are based on the hypothesis that depending on the climate, a prediction can be made of how much energy will be generated and, according to the behavior of the users, the energy demand required by these appliances. Following this hypothesis, we build an autonomous cycle of data analysis tasks composed of three tasks, two tasks for estimating the required load (demand) and the renewable energy produced (supply), coupled with a scheduling task to generate the plans of use of appliances. The results indicate that it is possible to carry out optimal scheduling of the use of appliances, but that they depend on the quality of the predictions of supply and demand**.

***Keywords*– energy consumption scheduling, smart edifications, Smart Grids, artificial intelligence, data analysis.**

INTRODUCTION

Approximately 30% of total energy consumption comes from the residential sector, and this amount of consumption is expected to increase in the coming years [17, 21]. Much of this demand comes from the use of household appliances, and in particular, some of them whose load can be controllable. On the other hand, "Smart Grids" are a recent trend in electrical networks that try to respond to the current and projected high demand. Smart grids involve two-way communication between the consumer and the energy producer, among other things. Among its main objectives is the increase in the efficiency of the energy network.

Additionally, seeking to be more environmentally friendly, clean energy sources have grown and will continue to grow as energy technology advances [21]. Thus, buildings and homes are turning into small power plants, where the inhabitants are "active energy prosumers" of clean energy. However, many of the technologies used to acquire clean energy (mainly photovoltaic cells and wind turbines) depend on the weather, are intermittent, and are often available at times when residents are not at home or are not using electricity.

Derived from the above, as mentioned by the authors [23], the electrical network will have to accommodate bidirectional energy flows; from the network to the users and from the users to the network, taking into account multiple factors, such as occupational patterns and environmental conditions. Therefore, smart grids are expected to facilitate better integration of fluctuating renewable energy with energy from stable sources, considering distributed local demands.

A particularly attractive way of doing this integration is through planning the schedules for the use of the controllable load appliances, so that they better align with the productivity peaks of the renewable energy sources present in the building/home. The objective of this work is to propose a solution to the problem of scheduling controllable load appliances through artificial intelligence techniques to maximize the use of renewable energy and reduce the use and dependence on energy from the traditional grid (energy network of the city), complying with the energy needs demanded by controllable load appliances.

For that, this work proposes to use the concept of autonomous cycles of data analysis tasks, also called ACODAT. ACODAT uses the interaction of different successive analysis tasks to extract the necessary knowledge to recommend improvements in a given process [2, 3, 4], in our case, the optimal scheduling of controllable load appliances. ACODAT has been used in different domains such as education [20], telecommunications [15], industry 4.0 [22], Smart cities [3], among others.

In particular, an ACODAT is proposed for scheduling the hours of use of controllable load appliances, composed of three tasks, two that predict the required load (demand) and the renewable energy that can be produced (offer), and a third scheduling task that generates the plan for the use of appliances for a given period of time. The three data analysis tasks use artificial intelligence techniques for the development of their knowledge models, the first two machine learning techniques (random forest (RF) and a multi-layer perceptron (backpropagation neural network, BNN)) for the construction of predictive models, and the last one a meta-heuristic (genetic algorithms) for the definition of the optimization model.

DESIGN OF THE AUTONOMOUS CYCLE

The design process that has been followed is based on the MIDANO methodology [18]. MIDANO allows building an ACODAT, in our case, to plan the use of controllable load appliances in order to optimize the use of renewable energy. In this way, the cycle is made up of three tasks:

A. *Estimation of energy needs (demand)*

This task has the function of estimating, based on the behavior pattern of users, the energy required by each controllable load appliance (see table 1). The input information on the behavior of the users allows establishing the times and how the appliances should be used (frequency of use and how long they should be used). For example, if sports activities routinely appear in the behavior pattern of users (which could indicate a high frequency of very dirty clothes), this task should estimate a continued use of the washing machine. Whereas if in this pattern it appears that every Friday there is a family reunion at home and the rest of the week the habitants eat a few times in it, this task should estimate an intense punctual use of the dishwasher. Finally, with this information on the use of appliances, this task produces an estimation of how much energy will be required to satisfy the needs of users (energy demanded by each appliance). In particular, this task makes a predictor for each controllable load appliance.

Table 1. Energy demand estimation task

Data source	User behavior pattern (can be weekly/biweekly, etc.)
Data Analytics Task Type	Prediction
Data analytics techniques	RF and BNN
Result	Energy load demanded by each appliance

B. *Estimation of energy production (supply)*

This task estimates the energy contribution (production) of renewable energy sources based on environmental factors (see table 2). Thus, depending on the environmental conditions (sunny, rainy day, with strong winds, high humidity, etc.), it is estimated how much energy each renewable source can be expected to produce (solar, wind, etc.).

Table 2. Energy Production Estimation Task

Data source	Environmental data
Data Analytics Task Type	Prediction
Data analytics techniques	RF and BNN
Result	Produced energy

C. *Generation of hours of use of appliances*

This task is responsible for preparing the scheduling for the use of controllable load appliances for a given period of time (see table 3). This scheduling is carried out periodically according to the estimation range of the predictive models elaborated by the previous tasks. If those predictions can be made daily, every three days or weekly, that will be the scheduling range. The objective is to plan the use of household appliances, such that the entire load demanded is covered, maximizing the use of renewable energy. Here, we start from the assumption that renewable energy cannot be stored in batteries nor can it be sold.

Table 3. Task for scheduling the use of controllable load appliances.

Data source	Estimation of energy needs and energy production
Data Analytics Task Type	Optimization
Data analytics techniques	Genetic algorithms
Result	Appliance use plan

The required multidimensional data model is made up of three-dimension tables:

- Environmental Data Dimension: this dimension contains all the information to predict the renewable energy that can be produced.
- User Profile Dimension: this dimension contains the information that allows describing the behavior of users, useful for estimating the use of controllable load appliances.
- Appliances dimension: this dimension contains the information that describes the appliances (characteristics, required energy load, etc.).

EXPERIMENTATION

A. *Experimental Protocol*

For the experimentation, several conditions will be assumed at the environmental level, the behavior of the users, and on the controllable load appliances. At the renewable energy level, only wind and solar energy will be considered. With regard to the environment, only environmental variables that allow estimating the production of these renewable energy sources will be considered. Finally, with respect to the behavior of users, the activities that they carry out at home will be estimated, in order to deduce the possible controllable load appliances that should be used.

On the other hand, to evaluate the predictive models, the following quality metrics will be used: Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE), and R2, also called the coefficient of determination.

Regarding the scheduling model, it will be evaluated based on the amount of renewable energy used of the possible produced.

B. *Instantiation of our ACODAT*

Estimation of energy production

Regarding the environmental variables that will serve to predict the amount of renewable energy that can be produced, it is important to note that there are different sources of renewable energy: bioenergy, solar energy, geothermal energy, hydropower, wind and ocean energy (tide and wave) . In this work, we will only consider wind and solar as renewable energy sources.

The production estimation task receives information from the environmental variables for the period of time under study. In practice, this can come from weather or environmental predictors, or historical data. Then, the production estimator produces a "power Schedule" for each renewable energy source, an array of 24 positions per day, where each position represents one hour and the amount of energy generated at that hour.

The production estimator for each renewable energy source is implemented by two techniques, using RF and BNN. Specifically, the BNN was implemented using 3, 4 and 5 layers. Let's now describe how each prediction model for each renewable energy source was defined.

Solar energy:

Solar power is one of the major renewable energy, constituting an increasingly important component of the global future—low carbon—energy portfolio. Solar photovoltaic (PV) systems have largely penetrated the global energy market. According to [12], the performance of PV systems is influenced by internal and external factors such as structural features, visual loss, aging, radiation, shading, temperature, wind, pollution, among others. We have considered the following environmental variables for the definition of the prediction model of PV (power-generated), which is in the dataset [16]: distance-to-solar-noon (in radians), temperature (daily average temperature, in degrees Celsius), wind-direction (daily average wind direction, in degrees, 0-360), wind-speed (daily average wind speed, in meters per second), sky-cover (in a five-step scale, from 0 to 4, being 0 totally clear and 4 completely covered, visibility (in kilometers), humidity (in percentage), average-wind-speed-(period, average wind speed during the 3-hour period de measure was taken in, in meters per second), average-pressure-(period, average barometric pressure during the 3-hour period de measure was taken in, in mercury inches), power-generated (in kW), and irradiance.

These variables have undergone a feature engineering process to select those correlations to PV, avoiding collinearities between them. Below we comment on the quality of the predictive models of the amount of solar energy produced generated with RF and different BNN configurations used (only the results of the best configurations are shown).

Table 4. Results of the prediction of the solar energy produced

Technique	Number of layers	Number of epoch	SME	MAPE	R^2
RF			0.07	0.07	0.90
BNN	3	50	0.09	0.10	0.74
	4	50	0.08	0.06	0.88
	5	100	0.08	0.04	0.89

. Of all the models, the one with the highest errors, both for MSE and MAPE, is the first for BNN, with values of 0.09 and 0.10, respectively. In addition, the value of R^2 indicates that only 74% of the predicted results match the actual results. This behavior can be explained by the low number of layers and training cycles.

Wind Power:

A wind power forecast corresponds to an estimate of the expected production of one or more wind turbines referred to as a wind farm. By production is often meant available power for wind farm considered (with units kW or MW depending on the wind farm nominal capacity). In our case, forecasts be expressed in terms of energy, by integrating power production over each hour.

For wind power, the next environmental variables are considered: wind speed (V), wind direction (D), temperature (T), air pressure (P), and humidity (H). Based on the wind speed measurements, it is also calculated turbulence intensity (I, equal to the standard deviation of short-duration wind speeds divided by the average wind speed of the same duration) and wind shear (S, using wind speeds measured at different heights).

For the construction of the predictive model, we are used the ERA-Interim data, which is a global atmospheric reanalysis data from 1979, continuously updated in real-time [9], which contains the previous variables. These variables have undergone a feature engineering process to select those correlations to wind power, avoiding collinearities between them.

Table 5. Results of the prediction of the wind energy produced

Technique	Number of layers	Number of epoch	SME	MAPE	R^2
RF			2.05	0.10	0.88
[10]			2.56		0.71
BNN	3	50	2.07	0.12	0.85
	4	50	2.08	0.16	0.78
	5	100	2.08	0.21	0.74

Comparing the results of this group of models with those of the work [10, 19], we can see that our models have lower errors and higher precision. However, by increasing the number of neurons and the number of training epochs for BNN, no improvement is achieved. A different behavior is observed from the previous case, that is, a low number of training epochs and layers does not reduce the precision of the model.

Estimation of energy demand

There are different electrical appliances whose load can be controlled (washing machine, dishwasher, tumble dryer, electric pressure cooker, microwave, vacuum cleaner, but there are also other sources of controllable load that in the future it will be interesting to analyze (phone charger, car charge). In our case, we will estimate the charges for some appliances based on the behavior of the users in the home. For each case, a predictive model will be built with said behavior.

For this experiment, we have used the CASAS smart home dataset [6, 7]. This dataset describes the activity data collected from 24 CASAS smart homes for different residents and time-span. In addition, we are going to associate an activity with a requirement to use an appliance (see Table 6). Table 6 gives a list of appliances associated with each activity, where some appliances are associated with several activities, and an activity can have associated several appliances.

Table 6. Appliances associated with each activity [6, 7]

Activity	Associated Appliances
Cook	Dishwasher, electric pressure cooker
Eat	Dishwasher
Party	Vacuum cleaner
Enter home, Personal hygiene	Washing machine, tumble dryer,

Now, we are going to use this dataset to predict the appliances required to use. The way we organize the data is as follows. User activities at home in the dataset are grouped by hour. Thus, in each hour, we will know what demand for appliances has been generated. This implies that the need to use appliances several times accumulates over the hours. In order to determine the frequency demanded to use each appliance in a day, we use the condition defined in Table 7.

Table 7. Power Consumption of Typical Household Appliances [8]

Appliance	Power Consumption	Frequency
Dishwasher	1200W -1500W	for every 3 times a cooking-Eating activity then one washed
Electric pressure cooker	1000W -1000W	for every 3 times of a cooking activity then one cooked
Vacuum cleaner	450W -900W	for every 6 times of a party activity then one cleaned
Washing machine	500W - 500W	for every 2 times of an enter home-personal hygiene activity then one washed
Tumble dryer	1000W - 4000W	for every 2 times of an enter home-personal hygiene activity then one dried

On the other hand, each hour that each appliance is used will be multiplied by the load defined in Table 7. This value will be used to determine the energy demand that it requires in that period of time.

Once a new dataset has been generated using the CASAS dataset, the required times of use of each appliance organized by days, with the respective energy load demanded, we proceed to build the prediction models for each appliance daily.

Washing machine: Next, we comment on the quality of the predictive model of energy demand for the washing machine for RF and the best configurations of the BNN.

Table 8. Washing machine power demand prediction results

Technique	Number of layers	Number of epoch	SME	MAPE	R^2
RF			1.7	0.25	0.79
BNN	3	50	2.1	0.31	0.73
	4	50	2.1	0.36	0.70
	5	100	2.8	0.44	0.69

Of all the models, the one with the lowest errors, both for MSE and MAPE, is RF. The value of R^2 indicates that only 79% of the predicted results match the actual results. We see that more number of layers and epochs does not improve the results.

Dishwasher: Below, we comment on the quality of the predictive model of power demand for the Dishwasher using RF and the best BNN configurations.

Table 9. Dishwasher Power Demand Prediction Results

Technique	Number of layers	Number of epoch	SME	MAPE	R^2
RF			0.04	0.03	0.92
BNN	3	50	0.1	0.13	0.83
	4	50	0.1	0.06	0.90
	5	100	0.08	0.04	0.91

Again, RF gives the best results. On the other hand, these predictive models are of better quality because there is more data to train this model (more activities generate the use of this appliance). On the other hand, the use of BNN with more layers and epochs is important in this case, to improve the quality of the model.

Electric pressure cooker: Next, we comment on the quality of the predictive model for the electric pressure cooker.

Table 10. Electric pressure cooker Power Demand Prediction Results

Technique	Number of layers	Number of epoch	SME	MAPE	R^2
RF			0.08	0.06	0.86
BNN	3	50	0.13	0.13	0.80
	4	50	0.11	0.08	0.83
	5	100	0.07	0.06	0.84

The models are not as good as those of Dishwasher but it follows a very similar behavior. This is because there is less data.

Vacuum cleaner: Below, we comment on the quality of the predictive model for the Vacuum cleaner.

Table 11. Vacuum cleaner energy demand prediction results

Technique	Number of layers	Number of epoch	SME	MAPE	R^2
RF			3.01	0.33	0.76
BNN	3	50	3.11	0.41	0.75
	4	50	3.10	0.36	0.73
	5	100	3.03	0.33	0.69

The worst models are obtained in this case, and the reason is that this is the appliance with which there is less data for training.

Scheduling the use of controllable load appliances

The scheduler is implemented using a genetic algorithm. In its evaluation function, the algorithm uses the needs (demand) and production load generated (supply) estimated by the previous tasks.

Representation of the individuals of the genetic algorithm:

For its implementation, and to easily use the "crossover" operator, the individual was represented by a binary array of N * I * 24. N is the maximum number of appliances, N in our case is 5 and I is the planning period used (3., 7, 15 days). This chromosome can be extended or reduced according to I and N. A 1 means that the appliance will be used in that hour and 0 otherwise.

Fitness function: The optimization process for this case study uses as state variables A_{ij}, which means the appliance i will be used during the hour j. Once an appliance is activated, it will run until one hour and it will consume the nominal load required (see Table 7). Also, we suppose that during this hour it has finished its task (washing, cooking, etc.).

We suppose the next constraint: an appliance must be assigned the required load in the period of time of planning (described by Eq. 1).

$$\sum_{j=1}^{I} A_{ij} = A_i^* \tag{1}$$

Where, A_i^* is the predicted energy demanded by appliance i in I, which is determined using the prediction models for each appliance daily defined by the previous task.

And the fitness function is defined by Eq. 2:

$$\min(R + \alpha F) \tag{2}$$

Where, R defines the quality of the solution (see Eq. 3), α is a factor of penalization for a bad solution, and F is the penalization function. In our case, α is very large.

$$R = \begin{cases} \gamma \sum_{j=1}^{I}\left(\left|\sum_{i=1}^{N} A_{ij} - \sum_{k=1}^{D} P_{kj}\right|\right)\Big/_{I} & if \ \sum_{i=1}^{N} A_{ij} \geq \sum_{k=1}^{D} P_{kj} \ \forall j \\ \delta \sum_{j=1}^{I}\left(\left|\sum_{i=1}^{N} A_{ij} - \sum_{k=1}^{D} P_{kj}\right|\right)\Big/_{I} & if \ \sum_{i=1}^{N} A_{ij} < \sum_{k=1}^{D} P_{kj} \ \forall j \\ \beta \sum_{j=1}^{I}\left(\left|\sum_{i=1}^{N} A_{ij} - \sum_{k=1}^{D} P_{kj}\right|\right)\Big/_{I} & otherwise \end{cases} \tag{3}$$

Where, P_{kj} is the renewable energy of type k predicted in the hour j, γ, δ, and β are penalty factors for the use or not of renewable energy, and D is the number of renewable energy sources. On the other hand, F is defined according to Eq. 4:

$$F = \begin{cases} \left(\left|\sum_{j=1}^{I} A_{ij} - A_i^*\right|\right) & if \ \sum_{j=1}^{I} A_{ij} \neq A_i^* \\ 0 & otherwise \end{cases} \tag{4}$$

According to our fitness function, if the demand is not satisfied with renewable energy, it is penalized with a factor γ, if there is more renewable energy than is used according to a factor δ, or intermittency, sometimes being satisfied or not through the hours it is penalized by a factor β. In the case of a non-valid solution (F), if it is assigned more than what is demanded, it is penalized with a factor α (waste of assignments), the same as if it assigns less than what is required (its demand is not satisfied). α guarantees valid solutions with the assignment required by each appliance.

Normally, less should be penalized when renewable energy does not meet demand (γ is small). Next, if there is more renewable energy than is used ($\delta > \gamma$) because it is simply energy that is lost (it cannot be stored). It is penalized more when there is intermittence ($\beta \gg \delta$), and finally when bad solutions ($\alpha \gg \beta$) are generated. A value of the fitness function closer to 0 guarantees a correct solution.

We also assume that some appliances have to be operated several times, the next run can start after the completion of the previous if this helps maximize renewable energy usage.

Selection: For the selection, a simple roulette selection was used, see [1, 5] for more details of its implementation.

Crossover and mutation operators: For the crossover operator, a random point M is selected for two-parent individuals, then a new individual is produced that takes its first M-1 elements from parent individual 1 and the rest from parent individual 2.

The mutation operator randomly changes some of the values in the array (it schedules or unplanned the use of an appliance).

C. Experiments and Analysis of Results

In this work, we will assume that we have the following controllable load cases.

Table 12. Controlled load cases studied

Case	Appliances
1	Washing machine, Dishwasher
2	Washing machine, Dishwasher, Vacuum cleaner, Electric pressure cooker

Also, we will assume several runs for different days for different values of γ, δ, and β. α was always a very large value to eliminate invalid solutions (in our case, 1000). Tables 13-14 show the results obtained in kW. In Table 14, we see a low quality when the number of appliances to be planned is large and for several days (always above 3K in case 3) with the number of generations to converge larger, but it improves a lot for planning for short periods (periods equal to 3 to 7 days), and when there are few appliances, converging very quickly.

Table 13. Results for γ = 1, δ = 1, and β = 10

Days vs Case	3		7		15	
	Value	**Gener.**	**value**	**Gener.**	**Value**	**Gener.**
1	0	26	0	31	0.2	41
2	0	28	0.4	41	0.5	53

In Table 14, the intermittency and the surplus of renewable energy are penalized quite a bit. We see that there are even more demanding solutions, so it is difficult to obtain good solutions. More generations are required, but the quality of the solutions is still better for planning with few appliances and periods of less than 7 days

Table 14. Results for $\gamma = 1, \delta$=10, and $\beta = 100$

Days vs Case	3		7		15	
	Value	**Gener.**	**value**	**Gener.**	**value**	**Gener.**
1	0.4	41	0.8	52	1.2	81

2	1.2	44	1.2	57	2.5	86

In general, we see that γ, δ, and β influence the search process, since they determine what will be given relevance in the final solution to be obtained. This leads us to future studies where these values depend on the demand and supply in the market (γ, δ, and β adaptive), such that the optimization process is adapted according to this relationship. For example, a large γ when the external cost of energy is too high to avoid having to buy it.

Conclusion

It is possible to plan the use of household appliances in such a way as to reduce dependence on the city's energy network. The autonomous cycle performs the expected task. The objective function of the scheduling task tries to guarantee that all the available renewable energy load is used and penalizes certain situations, for example when this does not happen. It also penalizes if the real need for each appliance is not met

On the other hand, a feature engineering process was carried out to analyze the variables and their correlations in the prediction models, but other approaches could be studied to determine the behavior of users (for example, to predict activities in the building), or the utilization of environmental variables to predict energy demand, among other things, to improve the quality metrics of these models

Finally, future works should test with more appliances, more renewable energy sources, consider the costs of traditional energy (from the city's energy network), incorporate the capacity to store or sell the surplus renewable energy produced, define a mechanism adaptive in real-time for γ, δ, and β, and improve the prediction models considering other machine learning techniques and a more exhaustive analysis of feature engineering on the descriptor variables.

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Disclaimer

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Autonomous Cycle of Data Analysis Tasks for Scheduling the Use of Controllable Load Appliances using Renewable Energy

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***Abstract*– With the arrival of smart edifications with renewable energy generation capacities, new possibilities for optimizing the use of the energy network appear. In particular, this work defines a system that automatically generates hours of use of the controllable load appliances (washing machine, dishwasher, etc.) within these edifications, in such a way that the use of renewable energy is maximized. To achieve this, we are based on the hypothesis that depending on the climate, a prediction can be made of how much energy will be generated and, according to the behavior of the users, the energy demand required by these appliances. Following this hypothesis, we build an autonomous cycle of data analysis tasks composed of three tasks, two tasks for estimating the required load (demand) and the renewable energy produced (supply), coupled with a scheduling task to generate the plans of use of appliances. The results indicate that it is possible to carry out optimal scheduling of the use of appliances, but that they depend on the quality of the predictions of supply and demand**.

Keywords*– *energy consumption scheduling, smart edifications, Smart Grids, artificial intelligence, data analysis.

INTRODUCTION

Approximately 30% of total energy consumption comes from the residential sector, and this amount of consumption is expected to increase in the coming years [17, 21]. Much of this demand comes from the use of household appliances, and in particular, some of them whose load can be controllable. On the other hand, “Smart Grids” are a recent trend in electrical networks that try to respond to the current and projected high demand. Smart grids involve two-way communication between the consumer and the energy producer, among other things. Among its main objectives is the increase in the efficiency of the energy network.

Additionally, seeking to be more environmentally friendly, clean energy sources have grown and will continue to grow as energy technology advances [21]. Thus, buildings and homes are turning into small power plants, where the inhabitants are "active energy prosumers" of clean energy. However, many of the technologies used to acquire clean energy (mainly photovoltaic cells and wind turbines) depend on the weather, are intermittent, and are often available at times when residents are not at home or are not using electricity.

Derived from the above, as mentioned by the authors [23], the electrical network will have to accommodate bidirectional energy flows; from the network to the users and from the users to the network, taking into account multiple factors, such as occupational patterns and environmental conditions. Therefore, smart grids are expected to facilitate better integration of fluctuating renewable energy with energy from stable sources, considering distributed local demands.

A particularly attractive way of doing this integration is through planning the schedules for the use of the controllable load appliances, so that they better align with the productivity peaks of the renewable energy sources present in the building/home. The objective of this work is to propose a solution to the problem of scheduling controllable load appliances through artificial intelligence techniques to maximize the use of renewable energy and reduce the use and dependence on energy from the traditional grid (energy network of the city), complying with the energy needs demanded by controllable load appliances.

For that, this work proposes to use the concept of autonomous cycles of data analysis tasks, also called ACODAT. ACODAT uses the interaction of different successive analysis tasks to extract the necessary knowledge to recommend improvements in a given process [2, 3, 4], in our case, the optimal scheduling of controllable load appliances. ACODAT has been used in different domains such as education [20], telecommunications [15], industry 4.0 [22], Smart cities [3], among others.

In particular, an ACODAT is proposed for scheduling the hours of use of controllable load appliances, composed of three tasks, two that predict the required load (demand) and the renewable energy that can be produced (offer), and a third scheduling task that generates the plan for the use of appliances for a given period of time. The three data analysis tasks use artificial intelligence techniques for the development of their knowledge models, the first two machine learning techniques (random forest (RF) and a multi-layer perceptron (backpropagation neural network, BNN)) for the construction of predictive models, and the last one a meta-heuristic (genetic algorithms) for the definition of the optimization model.

DESIGN OF THE AUTONOMOUS CYCLE

The design process that has been followed is based on the MIDANO methodology [18]. MIDANO allows building an ACODAT, in our case, to plan the use of controllable load appliances in order to optimize the use of renewable energy. In this way, the cycle is made up of three tasks:

A. *Estimation of energy needs (demand)*

This task has the function of estimating, based on the behavior pattern of users, the energy required by each controllable load appliance (see table 1). The input information on the behavior of the users allows establishing the times and how the appliances should be used (frequency of use and how long they should be used). For example, if sports activities routinely appear in the behavior pattern of users (which could indicate a high frequency of very dirty clothes), this task should estimate a continued use of the washing machine. Whereas if in this pattern it appears that every Friday there is a family reunion at home and the rest of the week the habitants eat a few times in it, this task should estimate an intense punctual use of the dishwasher. Finally, with this information on the use of appliances, this task produces an estimation of how much energy will be required to satisfy the needs of users (energy demanded by each appliance). In particular, this task makes a predictor for each controllable load appliance.

Table 1. Energy demand estimation task

Data source	User behavior pattern (can be weekly/biweekly, etc.)
Data Analytics Task Type	Prediction
Data analytics techniques	RF and BNN
Result	Energy load demanded by each appliance

B. *Estimation of energy production (supply)*

This task estimates the energy contribution (production) of renewable energy sources based on environmental factors (see table 2). Thus, depending on the environmental conditions (sunny, rainy day, with strong winds, high humidity, etc.), it is estimated how much energy each renewable source can be expected to produce (solar, wind, etc.).

Table 2. Energy Production Estimation Task

Data source	Environmental data
Data Analytics Task Type	Prediction
Data analytics techniques	RF and BNN
Result	Produced energy

C. *Generation of hours of use of appliances*

This task is responsible for preparing the scheduling for the use of controllable load appliances for a given period of time (see table 3). This scheduling is carried out periodically according to the estimation range of the predictive models elaborated by the previous tasks. If those predictions can be made daily, every three days or weekly, that will be the scheduling range. The objective is to plan the use of household appliances, such that the entire load demanded is covered, maximizing the use of renewable energy. Here, we start from the assumption that renewable energy cannot be stored in batteries nor can it be sold.

Table 3. Task for scheduling the use of controllable load appliances.

Data source	Estimation of energy needs and energy production
Data Analytics Task Type	Optimization
Data analytics techniques	Genetic algorithms
Result	Appliance use plan

The required multidimensional data model is made up of three-dimension tables:

- Environmental Data Dimension: this dimension contains all the information to predict the renewable energy that can be produced.
- User Profile Dimension: this dimension contains the information that allows describing the behavior of users, useful for estimating the use of controllable load appliances.
- Appliances dimension: this dimension contains the information that describes the appliances (characteristics, required energy load, etc.).

EXPERIMENTATION

A. *Experimental Protocol*

For the experimentation, several conditions will be assumed at the environmental level, the behavior of the users, and on the controllable load appliances. At the renewable energy level, only wind and solar energy will be considered. With regard to the environment, only environmental variables that allow estimating the production of these renewable energy sources will be considered. Finally, with respect to the behavior of users, the activities that they carry out at home will be estimated, in order to deduce the possible controllable load appliances that should be used.

On the other hand, to evaluate the predictive models, the following quality metrics will be used: Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE), and R2, also called the coefficient of determination.

Regarding the scheduling model, it will be evaluated based on the amount of renewable energy used of the possible produced.

B. *Instantiation of our ACODAT*

Estimation of energy production

Regarding the environmental variables that will serve to predict the amount of renewable energy that can be produced, it is important to note that there are different sources of renewable energy: bioenergy, solar energy, geothermal energy, hydropower, wind and ocean energy (tide and wave) . In this work, we will only consider wind and solar as renewable energy sources.

The production estimation task receives information from the environmental variables for the period of time under study. In practice, this can come from weather or environmental predictors, or historical data. Then, the production estimator produces a “power Schedule” for each renewable energy source, an array of 24 positions per day, where each position represents one hour and the amount of energy generated at that hour.

The production estimator for each renewable energy source is implemented by two techniques, using RF and BNN. Specifically, the BNN was implemented using 3, 4 and 5 layers. Let's now describe how each prediction model for each renewable energy source was defined.

Solar energy:

Solar power is one of the major renewable energy, constituting an increasingly important component of the global future—low carbon—energy portfolio. Solar photovoltaic (PV) systems have largely penetrated the global energy market. According to [12], the performance of PV systems is influenced by internal and external factors such as structural features, visual loss, aging, radiation, shading, temperature, wind, pollution, among others. We have considered the following environmental variables for the definition of the prediction model of PV (power-generated), which is in the dataset [16]: distance-to-solar-noon (in radians), temperature (daily average temperature, in degrees Celsius), wind-direction (daily average wind direction, in degrees, 0-360), wind-speed (daily average wind speed, in meters per second), sky-cover (in a five-step scale, from 0 to 4, being 0 totally clear and 4 completely covered, visibility (in kilometers), humidity (in percentage), average-wind-speed-(period, average wind speed during the 3-hour period de measure was taken in, in meters per second), average-pressure-(period, average barometric pressure during the 3-hour period de measure was taken in, in mercury inches), power-generated (in kW), and irradiance.

These variables have undergone a feature engineering process to select those correlations to PV, avoiding collinearities between them. Below we comment on the quality of the predictive models of the amount of solar energy produced generated with RF and different BNN configurations used (only the results of the best configurations are shown).

Table 4. Results of the prediction of the solar energy produced

Technique	Number of layers	Number of epoch	SME	MAPE	R^2
RF			0.07	0.07	0.90
BNN	3	50	0.09	0.10	0.74
	4	50	0.08	0.06	0.88
	5	100	0.08	0.04	0.89

. Of all the models, the one with the highest errors, both for MSE and MAPE, is the first for BNN, with values of 0.09 and 0.10, respectively. In addition, the value of R^2 indicates that only 74% of the predicted results match the actual results. This behavior can be explained by the low number of layers and training cycles.

Wind Power:

A wind power forecast corresponds to an estimate of the expected production of one or more wind turbines referred to as a wind farm. By production is often meant available power for wind farm considered (with units kW or MW depending on the wind farm nominal capacity). In our case, forecasts be expressed in terms of energy, by integrating power production over each hour.

For wind power, the next environmental variables are considered: wind speed (V), wind direction (D), temperature (T), air pressure (P), and humidity (H). Based on the wind speed measurements, it is also calculated turbulence intensity (I, equal to the standard deviation of short-duration wind speeds divided by the average wind speed of the same duration) and wind shear (S, using wind speeds measured at different heights).

For the construction of the predictive model, we are used the ERA-Interim data, which is a global atmospheric reanalysis data from 1979, continuously updated in real-time [9], which contains the previous variables. These variables have undergone a feature engineering process to select those correlations to wind power, avoiding collinearities between them.

Table 5. Results of the prediction of the wind energy produced

Technique	Number of layers	Number of epoch	SME	MAPE	R^2
RF			2.05	0.10	0.88
[10]			2.56		0.71
BNN	3	50	2.07	0.12	0.85
	4	50	2.08	0.16	0.78
	5	100	2.08	0.21	0.74

Comparing the results of this group of models with those of the work [10, 19], we can see that our models have lower errors and higher precision. However, by increasing the number of neurons and the number of training epochs for BNN, no improvement is achieved. A different behavior is observed from the previous case, that is, a low number of training epochs and layers does not reduce the precision of the model.

Estimation of energy demand

There are different electrical appliances whose load can be controlled (washing machine, dishwasher, tumble dryer, electric pressure cooker, microwave, vacuum cleaner, but there are also other sources of controllable load that in the future it will be interesting to analyze (phone charger, car charge). In our case, we will estimate the charges for some appliances based on the behavior of the users in the home. For each case, a predictive model will be built with said behavior.

For this experiment, we have used the CASAS smart home dataset [6, 7]. This dataset describes the activity data collected from 24 CASAS smart homes for different residents and time-span. In addition, we are going to associate an activity with a requirement to use an appliance (see Table 6). Table 6 gives a list of appliances associated with each activity, where some appliances are associated with several activities, and an activity can have associated several appliances.

Table 6. Appliances associated with each activity [6, 7]

Activity	Associated Appliances
Cook	Dishwasher, electric pressure cooker
Eat	Dishwasher
Party	Vacuum cleaner
Enter home, Personal hygiene	Washing machine, tumble dryer,

Now, we are going to use this dataset to predict the appliances required to use. The way we organize the data is as follows. User activities at home in the dataset are grouped by hour. Thus, in each hour, we will know what demand for appliances has been generated. This implies that the need to use appliances several times accumulates over the hours. In order to determine the frequency demanded to use each appliance in a day, we use the condition defined in Table 7.

Table 7. Power Consumption of Typical Household Appliances [8]

Appliance	Power Consumption	Frequency
Dishwasher	1200W -1500W	for every 3 times a cooking-Eating activity then one washed
Electric pressure cooker	1000W -1000W	for every 3 times of a cooking activity then one cooked
Vacuum cleaner	450W -900W	for every 6 times of a party activity then one cleaned
Washing machine	500W - 500W	for every 2 times of an enter home-personal hygiene activity then one washed
Tumble dryer	1000W - 4000W	for every 2 times of an enter home-personal hygiene activity then one dried

On the other hand, each hour that each appliance is used will be multiplied by the load defined in Table 7. This value will be used to determine the energy demand that it requires in that period of time.

Once a new dataset has been generated using the CASAS dataset, the required times of use of each appliance organized by days, with the respective energy load demanded, we proceed to build the prediction models for each appliance daily.

Washing machine: Next, we comment on the quality of the predictive model of energy demand for the washing machine for RF and the best configurations of the BNN.

Table 8. Washing machine power demand prediction results

Technique	Number of layers	Number of epoch	SME	MAPE	R^2
RF			1.7	0.25	0.79
BNN	3	50	2.1	0.31	0.73
	4	50	2.1	0.36	0.70
	5	100	2.8	0.44	0.69

Of all the models, the one with the lowest errors, both for MSE and MAPE, is RF. The value of R^2 indicates that only 79% of the predicted results match the actual results. We see that more number of layers and epochs does not improve the results.

Dishwasher: Below, we comment on the quality of the predictive model of power demand for the Dishwasher using RF and the best BNN configurations.

Table 9. Dishwasher Power Demand Prediction Results

Technique	Number of layers	Number of epoch	SME	MAPE	R^2
RF			0.04	0.03	0.92
BNN	3	50	0.1	0.13	0.83
	4	50	0.1	0.06	0.90
	5	100	0.08	0.04	0.91

Again, RF gives the best results. On the other hand, these predictive models are of better quality because there is more data to train this model (more activities generate the use of this appliance). On the other hand, the use of BNN with more layers and epochs is important in this case, to improve the quality of the model.

Electric pressure cooker: Next, we comment on the quality of the predictive model for the electric pressure cooker.

Table 10. Electric pressure cooker Power Demand Prediction Results

Technique	Number of layers	Number of epoch	SME	MAPE	R^2
RF			0.08	0.06	0.86
BNN	3	50	0.13	0.13	0.80
	4	50	0.11	0.08	0.83
	5	100	0.07	0.06	0.84

The models are not as good as those of Dishwasher but it follows a very similar behavior. This is because there is less data.

Vacuum cleaner: Below, we comment on the quality of the predictive model for the Vacuum cleaner.

Table 11. Vacuum cleaner energy demand prediction results

Technique	Number of layers	Number of epoch	SME	MAPE	R^2
RF			3.01	0.33	0.76
BNN	3	50	3.11	0.41	0.75
	4	50	3.10	0.36	0.73
	5	100	3.03	0.33	0.69

The worst models are obtained in this case, and the reason is that this is the appliance with which there is less data for training.

Scheduling the use of controllable load appliances

The scheduler is implemented using a genetic algorithm. In its evaluation function, the algorithm uses the needs (demand) and production load generated (supply) estimated by the previous tasks.

Representation of the individuals of the genetic algorithm:

For its implementation, and to easily use the "crossover" operator, the individual was represented by a binary array of N * I * 24. N is the maximum number of appliances, N in our case is 5 and I is the planning period used (3., 7, 15 days). This chromosome can be extended or reduced according to I and N. A 1 means that the appliance will be used in that hour and 0 otherwise.

Fitness function: The optimization process for this case study uses as state variables A_{ij}, which means the appliance i will be used during the hour j. Once an appliance is activated, it will run until one hour and it will consume the nominal load required (see Table 7). Also, we suppose that during this hour it has finished its task (washing, cooking, etc.).

We suppose the next constraint: an appliance must be assigned the required load in the period of time of planning (described by Eq. 1).

$$\sum_{j=1}^{I} A_{ij} = A_i^* \qquad (1)$$

Where, A_i^* is the predicted energy demanded by appliance i in I, which is determined using the prediction models for each appliance daily defined by the previous task.

And the fitness function is defined by Eq. 2:

$$\min(R + \alpha F) \qquad (2)$$

Where, R defines the quality of the solution (see Eq. 3), α is a factor of penalization for a bad solution, and F is the penalization function. In our case, α is very large.

$$R = \begin{cases} \gamma \sum_{j=1}^{I}\left(\left|\sum_{i=1}^{N} A_{ij} - \sum_{k=1}^{D} P_{kj}\right|\right) \Big/ I & if \ \sum_{i=1}^{N} A_{ij} \geq \sum_{k=1}^{D} P_{kj} \ \forall j \\ \delta \sum_{j=1}^{I}\left(\left|\sum_{i=1}^{N} A_{ij} - \sum_{k=1}^{D} P_{kj}\right|\right) \Big/ I & if \ \sum_{i=1}^{N} A_{ij} < \sum_{k=1}^{D} P_{kj} \ \forall j \\ \beta \sum_{j=1}^{I}\left(\left|\sum_{i=1}^{N} A_{ij} - \sum_{k=1}^{D} P_{kj}\right|\right) \Big/ I & otherwise \end{cases} \qquad (3)$$

Where, P_{kj} is the renewable energy of type k predicted in the hour j, γ, δ, and β are penalty factors for the use or not of renewable energy, and D is the number of renewable energy sources. On the other hand, F is defined according to Eq. 4:

$$F = \begin{cases} \left(\left|\sum_{j=1}^{I} A_{ij} - A_i^*\right|\right) & if \ \sum_{j=1}^{I} A_{ij} \neq A_i^* \\ 0 & otherwise \end{cases} \qquad (4)$$

According to our fitness function, if the demand is not satisfied with renewable energy, it is penalized with a factor γ, if there is more renewable energy than is used according to a factor δ, or intermittency, sometimes being satisfied or not through the hours it is penalized by a factor β. In the case of a non-valid solution (F), if it is assigned more than what is demanded, it is penalized with a factor α (waste of assignments), the same as if it assigns less than what is required (its demand is not satisfied). α guarantees valid solutions with the assignment required by each appliance.

Normally, less should be penalized when renewable energy does not meet demand (γ is small). Next, if there is more renewable energy than is used (δ> γ) because it is simply energy that is lost (it cannot be stored). It is penalized more when there is intermittence (β≫δ), and finally when bad solutions (α≫β) are generated. A value of the fitness function closer to 0 guarantees a correct solution.

We also assume that some appliances have to be operated several times, the next run can start after the completion of the previous if this helps maximize renewable energy usage.

Selection: For the selection, a simple roulette selection was used, see [1, 5] for more details of its implementation.

Crossover and mutation operators: For the crossover operator, a random point M is selected for two-parent individuals, then a new individual is produced that takes its first M-1 elements from parent individual 1 and the rest from parent individual 2.

The mutation operator randomly changes some of the values in the array (it schedules or unplanned the use of an appliance).

C. Experiments and Analysis of Results

In this work, we will assume that we have the following controllable load cases.

Table 12. Controlled load cases studied

Case	Appliances
1	Washing machine, Dishwasher
2	Washing machine, Dishwasher, Vacuum cleaner, Electric pressure cooker

Also, we will assume several runs for different days for different values of γ, δ, and β. α was always a very large value to eliminate invalid solutions (in our case, 1000). Tables 13-14 show the results obtained in kW. In Table 14, we see a low quality when the number of appliances to be planned is large and for several days (always above 3K in case 3) with the number of generations to converge larger, but it improves a lot for planning for short periods (periods equal to 3 to 7 days), and when there are few appliances, converging very quickly.

Table 13. Results for γ = 1, δ = 1, and β = 10

Days vs Case	3		7		15	
	Value	**Gener.**	**value**	**Gener.**	**Value**	**Gener.**
1	0	26	0	31	0.2	41
2	0	28	0.4	41	0.5	53

In Table 14, the intermittency and the surplus of renewable energy are penalized quite a bit. We see that there are even more demanding solutions, so it is difficult to obtain good solutions. More generations are required, but the quality of the solutions is still better for planning with few appliances and periods of less than 7 days

Table 14. Results for $\gamma = 1$, δ=10, and $\beta = 100$

Days vs Case	3		7		15	
	Value	**Gener.**	**value**	**Gener.**	**value**	**Gener.**
1	0.4	41	0.8	52	1.2	81

2	1.2	44	1.2	57	2.5	86

In general, we see that γ, δ, and β influence the search process, since they determine what will be given relevance in the final solution to be obtained. This leads us to future studies where these values depend on the demand and supply in the market (γ, δ, and β adaptive), such that the optimization process is adapted according to this relationship. For example, a large γ when the external cost of energy is too high to avoid having to buy it.

CONCLUSION

It is possible to plan the use of household appliances in such a way as to reduce dependence on the city's energy network. The autonomous cycle performs the expected task. The objective function of the scheduling task tries to guarantee that all the available renewable energy load is used and penalizes certain situations, for example when this does not happen. It also penalizes if the real need for each appliance is not met

On the other hand, a feature engineering process was carried out to analyze the variables and their correlations in the prediction models, but other approaches could be studied to determine the behavior of users (for example, to predict activities in the building), or the utilization of environmental variables to predict energy demand, among other things, to improve the quality metrics of these models

Finally, future works should test with more appliances, more renewable energy sources, consider the costs of traditional energy (from the city's energy network), incorporate the capacity to store or sell the surplus renewable energy produced, define a mechanism adaptive in real-time for γ, δ, and β, and improve the prediction models considering other machine learning techniques and a more exhaustive analysis of feature engineering on the descriptor variables.

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