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Chapter

Energy Infrastructure of the Factory as a Virtual Power Plant: Smart Energy Management

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Abstract

Smart energy factories are crucial for the development of upcoming energy markets in which emissions, energy use and network congestions are to be decreased. The virtual power plant (VPP) can be implemented in an industrial site with the aim of minimizing costs, emissions and total energy usage. A VPP considers the future situation forecasting and the situation of all energy assets, including renewable energy generation units and energy storage systems, to optimize the total cost of the plant, considering the possibility to trade with the energy market. For a VPP to be constructed, a proper communication system is essential. The energy management system (EMS) enables the monitoring, management and control of the different energy devices and permits the transference of the decisions made by the VPP to the different energy assets. VPP concept is explained together with the methods used for forecasting the future situation and the energy flow inside the facility. To reach its benefits, the optimization of the VPP is assessed. After that, the communication technologies that enable the VPP implementation are also introduced, and the advantages/disadvantages regarding their deployment are stated. With the tools introduced, the VPP can face the challenges of energy markets efficiently.

Keywords: virtual power plant, smart grid, energy hub, ANFIS, communication technologies, energy management system

1. Introduction

Industry 4.0 is normally understood as smart factories where automation, digitalization, Internet of Things (IoT), cognitive computing and others are used. However, this does not stand without the use of energy. There is a settled relationship between energy consumption, energy prices and economic growth in different countries. For industries, the access to reliable and affordable energy is crucial to create greater economic and social prosperity. In the industry that is emerging nowadays, the physical processes are studied, modeled and monitored, and physical systems communicate and cooperate in a real-time scenario in order to optimize the behavior of the plant. The same can be done with energy. To reach the best efficiency of a manufacturing plant, the energy consumption processes have to be studied, modeled and monitored; the communication of the energy flows between equipment has to be known, and future situation prediction and real-time decisions have to be taken regarding energy purchasing, energy trading, generation and consumption.

There are several reasons for why the development of energy-smart factories is interesting. Policy is making an effort in order to achieve a reduction of greenhouse gas emissions, an increase in the share of renewable energy and an improvement in the energy efficiency. As an example, in Europe, the energy usage in the industrial sector accounts for more than 25% of total energy consumption, process heating having the most significant use with 66% followed by electricity with 26%. If energy efficiency measures are developed and incorporated in the industrial sector, the potential savings can be of more than 20% as shown in [1]. Regarding the increase in the share of renewable energies, it will be possible with the integration of smart energy systems. Some renewable energy sources such as solar and wind power generation are characterized by an intermittent nature. One of the fundamental properties of the electric grid is that the supply (generation) and the demand (consumption) must always be balanced. With the increase in the share of renewable power sources, the energy may not be generated in the best suited moment and with the exact amount of power dealing to grid instability and not assuring a security of supply. By defining, integrating and controlling the energy flow in order to optimize the consumption of energy hubs (EH) and, from there, exploit it in virtual power plants (VPP), the industrial sector the electricity usage can be optimized, allowing a greater efficiency and flexibility, improving the capacity factor of the installed renewable energy sources. Up to date, the EH concept has been presented by several studies in the industrial field, and its expansion into a VPP is a new research field in which the focus is the possibility of energy trading with the grid, as can be seen in [2, 3].

The constant monitoring of the energy flow combined with the integration of different energy generation sources will require management technologies capable of recognizing, predicting and acting in a way to guarantee quality, sustainability and efficiency, including costs, in energy consumption. Therefore, modern energy management systems should be able to monitor and exploit large volumes of data collected by various types of meters transmitted by digital channels mainly based on the IoT. The application of artificial intelligence techniques related with machine learning and big data will require thousands of meters collecting data at high resolution and high frequency (gigabytes per day), and, in order to assure the reliability and quality of this data, some aspects must be addressed such as the data model, the integration of information coming from several inputs or the data security.

The optimization of energy use will produce a direct reduction of costs and pollutants as the total energy consumption will be less. By increasing the share of renewable energy sources in the grid, the merit order will change. The merit order ranks the available energy sources from its operational cost, the cheaper ones being the first to meet the demand. Solar power generation and wind power generation are of the cheapest energy generation technologies, so if they are able to provide power, the operational cost of the last active power plant in order to meet demand will be less, allowing a more economic purchase of energy.

The path to reach a smart energy grid in the Industry 4.0 has already started. Development has been observed in the area of energy technologies, improving the efficiency of isolated systems. However, the overall energy efficiency can be greatly improved if multi-energy assets are analyzed and utilized in a more unified way. Energy assets can be interconnected physically in a plant, improving the energy usage in the plant and creating an EH. There is also the possibility to aggregate different plants physically or virtually, creating a digital entity of active prosumers that will be presented to the grid as a unique system that will be able to both consume and generate electricity.

This chapter is structured as follows. In Section 2, the VPP concept and tools are explained. First of all, its definition is exposed. This definition broadens the concept of EH and its functionality, creating a new entity able to perform an optimization considering internal and external factors. Secondly, the forecasting tools for predicting the situation at a stated horizon are presented. These tools include the forecast of renewable energy sources and demand and energy price from the grid. Third, the EH concept and method are developed for a general industry. Then, the optimization of the system is assessed, and resolution methods are proposed for obtaining high-quality results. In Section 3, some aspects related to the automation pyramid and the communication requirements of its levels are presented. Then some of the communication technologies and protocols are briefly introduced. Last of all, conclusions are drawn in Section 4.

2. Industry as a virtual power plant

One of the most important characteristics of the electrical grid is the constant balance between generation and consumption. With the rise of intermittent renewable energies, a degree of uncertainty is introduced. The discontinuity of this type of generation should not affect the fulfillment of the demand at every instant. With a proper management of energy assets and energy storage systems, renewable energy sources can be satisfactorily introduced without compromising the stability of the system. Once the balance between supply and demand is assured, there is leeway to generate an economic benefit from the energy transferred and stored inside a facility, such as a VPP. The VPP would be a power prosumer, meeting the local demand, and profit its own energy assets to trade energy with the external grid. Nowadays, the smart microgrid and prosumer concepts are being developed and tested in the tertiary sector, as can be seen in [4, 5]. Although the advancements are done, the presented ideas need further investigation. The prosumer smart grid approach can also be implemented in the industry, creating an energy-smart entity that will deal with the challenges and demands of the coming energy markets and will produce a profit from the exploitation of its own equipment against the external primary energy grids.

2.1 Virtual power plant concept

A VPP is a network of decentralized, medium-scale power-generating units as well as flexible power consumers and batteries. A VPP can be implemented in an industrial site, composed by all the controllable energy assets and the renewable energy generation units in the factory.

The VPP operates its energy assets efficiently taking into account the forecast of internal and external factors with the aim of maximizing the efficiency of the system in economic and environmental terms. As an example, internal factors can comprise coefficient of performance (COP) and efficiencies of energy equipment, energy storage capacity, energy generation at a given moment, cost of the different subsystems and reschedulable loads (both electrical and thermal). External factors may be constituted by electricity, natural gas and waste prices.

In **Figure 1** an example of a VPP is shown. It can be appreciated that the communication with the electrical grid is bidirectional, allowing to buy and sell electricity depending on the forecasted conditions. The working behavior lays in an energetic, economic and environmental evaluation that considers the forecasted input energy price, the forecast of available energy inside the VPP and the forecasted demand.

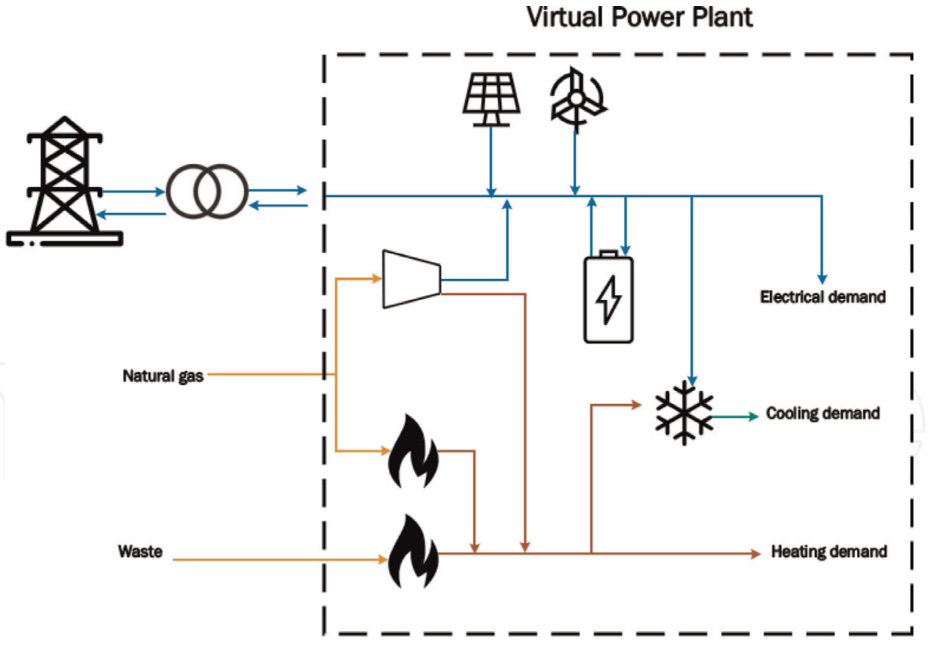

Figure 1.
Example schematic of a VPP where renewable energy sources (solar and wind) are present together with cogeneration system, boilers, absorption cooling and energy storage systems.

The benefits of implementing a VPP affect not only the industrial site itself but also the electrical grid through demand response (DR). The creation of a VPP out of an industrial facility will lead to:

- Integration of intermittent renewable energy, not only in the VPP but also in other points of the grid due to the electricity price response of the VPP. Also, expensive investments to expand the distribution network can be avoided if the generation is locally available.
- Integration of small electricity producers into the distribution network. The VPP itself is seen by the grid as a small electricity producer when the electricity cost is high, and thus there is a need to increase the generation at that moment.
- Optimization of energy use inside the VPP. The demand is analyzed, modeled and predicted using artificial intelligence method, and the optimal operation point of energy providers is computed.
- Optimization of the integration of electric vehicles (EV) for vehicle to grid (V2G) and grid to vehicle (G2V). The storage systems managing the surplus energy at the VPP can be combined with the EV batteries, which will work then as a part of the system. In this way not only the energy storage systems are improved, but also the EV-grid integration is made easier.
- Reduction of emissions. By integrating renewable energy sources and increasing the efficiency of the energy used, the emissions are directly reduced.
- Exploitation of energy assets. The systems present in a facility are nowadays not used in all its potential. With the implementation of a VPP, its working periods will be optimized according to internal and external factors and allowing an exploitation and efficient use of all energy carriers present in a system.
- Market opening. There are several facilities that will allow the creation of a VPP. However, their owners and operators are not aware of the possibilities

and benefits it will produce. The introduction of a VPP in an industrial site will lead to a market opening that will encourage other similar facilities to take the same role, and thus the previous benefits will be amplified to the whole electrical grid.

- Autonomy and strong position of the owner of the facility in front of the operators of the electricity market that will allow a greater competitiveness market.

To implement the VPP features, the future energy status of the system should be continuously computed, which includes demand, generation of renewable sources and energy prices. This information leads to VPP operation including energy conversion and storage, which drives the EH, a crucial part of the VPP as it optimizes the path from energy input to demand. Once the forecast of the future situation and the model of the EH is obtained, the VPP is formed. The objective of the VPP is to fulfill local demand while, at the same time, exploiting its own energy assets to be able to trade electricity with the grid. During the modeling and the optimization of the VPP, the electricity exchange with the grid, the energy transfer with the energy storage system, the dispatch factors between the present transformers and the destination of power from the PV system are computed to assure an optimal operation from the economical, energetic and environmental points of view.

2.2 Future situation forecasting

Forecasting is the process of making predictions of the future based on past and present data analyzing the trends that appear. Forecasting can be qualitative or quantitative. For the application to a VPP, quantitative methods are more suitable, as they are based on past data to estimate future states and do not lay on subjective opinions. This approach extracts patterns of the available data and assumes that these are expected to continue in the future and are applied usually to short- and medium-term forecasts. There are several models used for forecast, and its suitability depends on the nature of the problem that is being studied. Examples of them are time series, causal and econometric forecasting and artificial intelligence. The forecast of several variables is needed to optimize the VPP. The demand, generation from renewable energy sources and electricity price from the grid are used in order to compute the optimal operation point of the VPP.

2.2.1 Renewable energy

The prediction of the renewable energy that is generated depends directly on the climatic conditions and the characteristics of the equipment. The prediction of weather conditions, i.e. sun irradiation and wind speed, can be obtained from the meteorology databases. Two types of renewable energy systems will be shown in this section: photovoltaics (PV) and wind power (WP) generation.

On the one hand, for a PV system, the most important factor in estimating its performance is solar radiation. The uncertainty in solar radiation is the largest source of error in the computation of the energy provided, as shown in [6]. The solar radiation depends on the orientation and the inclination of the area studied. Once this value is obtained, the theoretical energy output can be computed. However, the result should be corrected by adding a performance ratio that is influenced by factors such as shadows, dust, dirt, frost, snow, reflectance of the module surface, conversion efficiency, sunlight spectrum and temperature. As an example, in **Figure 2**, extracted from [7], the performance of different chemistries along temperature is shown. The value of the performance ratio (η) can be obtained statistically, and then the output power of the PV system will be:

$$P = P_{nom} \frac{G}{1000} \eta \quad (1)$$

where G is the received solar irradiance in W/m^2 and P_{nom} the peak power in kW.

On the other hand, for the case of wind turbines, there is a direct relationship between wind speed and energy output [8]. The extra parameter that has to be considered is air density, which can be computed using temperature and pressure and obtained from a meteorological database as with the wind speed. The output power can be computed with the data specified by using the wind turbine power curves provided by the manufacturer. These curves are obtained by the manufacturer by means of theoretical and statistical analysis of the performance of the turbine.

The previous methods are useful for a first assessment of the energy generated by the renewable sources. However, after the renewable energy sources equipment are installed and working on an industrial environment, the generation forecast can be improved by modeling specifically its behavior. A correlation of meteorological data with PV and WP output should be performed to assure high model accuracy and obtain the real efficiency and performance of the equipment. According to [9, 10], artificial neural networks (ANN) and support vector machine (SVM)-based forecasting methods are suitable for the modeling and prediction of the behavior of PV generation systems, while ANN, adaptive neuro-fuzzy inference systems (ANFIS) and autoregressive moving average (ARMA) perform well for WP generation.

2.2.2 Demand

The demand is the amount of load that the system has and the energy that is required to be fulfilled. Inside a VPP, this demand can be divided into two types: manageable and non-manageable. Non-manageable loads are those which run continuously or that cannot be controlled. Inside a VPP, the owner or end user can

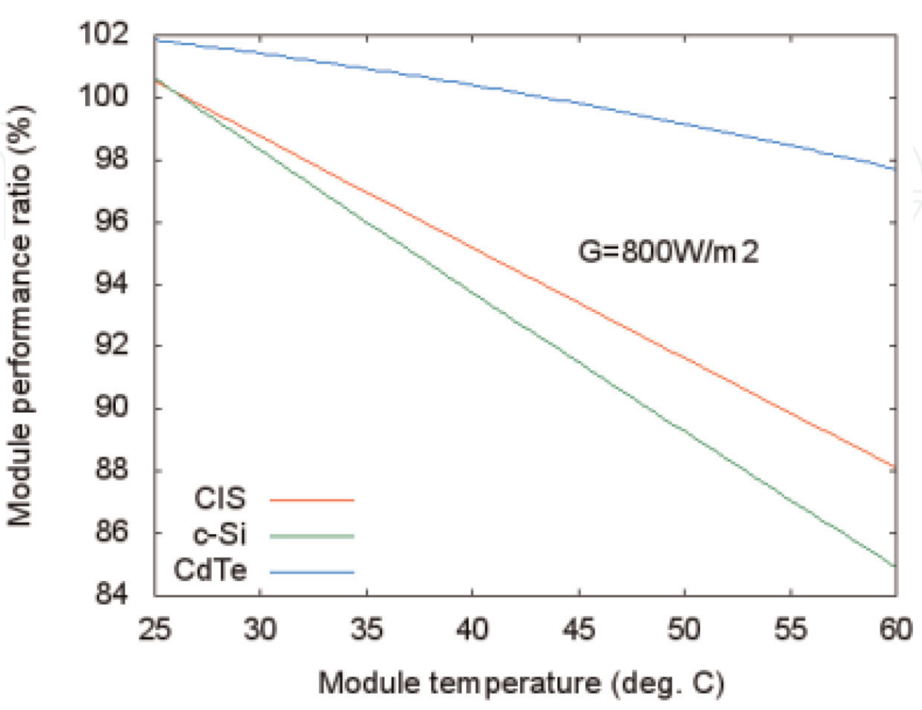

Figure 2.
Performance of PV modules with a solar radiation of 800 W/m².

decide which loads are manageable and which are not according to the business objective criteria. Manageable loads can be further divided into shiftable, interruptible and heating, ventilation and air conditioning (HVAC) loads. The forecasting of both types of demands follows a different way and will be now assessed.

2.2.2.1 Non-manageable loads

Classically, energy loads can be either electrical or thermal. The behavior of both types of demand lies in the same principles, so the prediction of them can be done using the same method. In recent times, the artificial intelligence methods that have been used for load forecasting (LF) include mainly neural networks, expert systems and support vector machines. Nowadays, the focus lays in the development of hybrid methods, combining different forecasting methodologies. For example, in [11] a LF method based on self-organized map and support vector machine is developed. The method is tested for prediction of the power consumption of a whole city. However, its suitability for an industrial site application has not been proven. In [12] an extreme learning machine with the Levenberg-Marquardt method is proposed, and in [13] the possibility to use artificial neural network to create a hybrid method with other techniques such as backpropagation, fuzzy logic, genetic algorithm and particle swarm optimization is shown. The industry is a sector where the demand can have an irregular and infrequent behavior depending on several conditions, and it is constantly under improvement processes. For this reason, a method that enables periodically auto-adjustment and high accuracy results is searched. ANFIS aim at mapping input to output for highly nonlinear processes such as energy management field. ANFIS was first introduced in [14] as a combination of two soft computing methods: artificial neural network and fuzzy logic. The ANFIS architecture is an adaptive network that uses supervised learning on learning algorithm, which has a function similar to the model of Takagi-Sugeno FIS [15]. This architecture is shown in **Figure 3**, extracted from [16].

In the first layer, the fuzzification of the inputs takes place. This is done by a membership function which can be a Gaussian membership function, a generalized bell membership function or other types of membership function. The parameters of this layer that define the membership function are called premise parameters. In the second layer, the fire strength of the rule is calculated. The output is the result of multiplying the signals coming into the node. In the third layer, a calculation of the ratio between the *i*th rule firing strength and the sum of all rules firing strength is

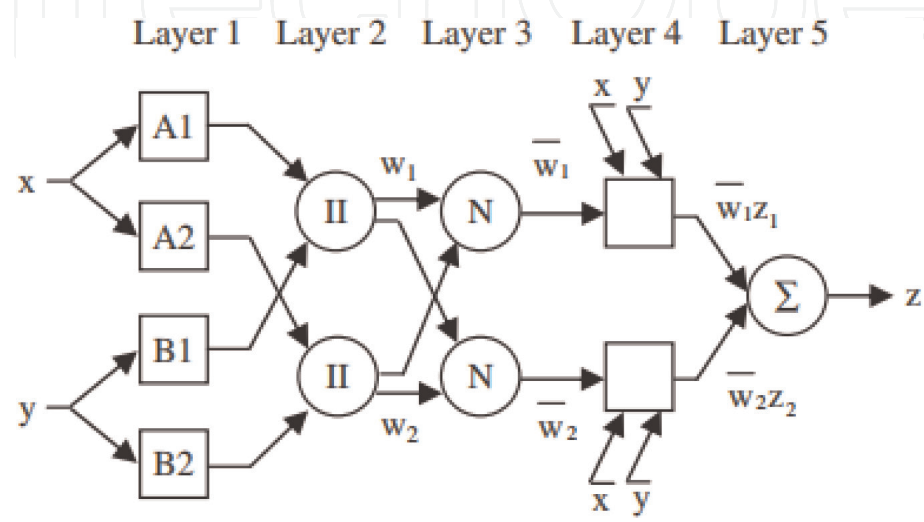

Figure 3.
ANFIS architecture.

done. The output is named the normalized firing strength. The fourth layer executes the Takagi-Sugeno fuzzy reasoning method. The parameters that appear here are the consequent parameters. Finally, in the last layer, the computation of the overall output as the summation of all incoming signals from previous nodes is done. It can be seen that the parameters that need to be trained are the premise and consequent parameters, present in layers 1 and 4. They can be obtained in the learning process by using the forward path and the backward path. During the forward path, the premise parameters are specified, while the consequent parameters change using a recursive least square estimation, and, during the backward path, the consequent parameters obtained remain fixed, while the error propagates to the first layer updating the premise parameter in a gradient descent way.

2.2.2.2 Manageable loads

According to [17], manageable loads can be divided into:

- Shiftable: Loads with predefined working cycles and load profiles. These loads appear between certain time limits which are specified by the end user. In an industry, these can be formed by noncritical processes with a variant energy consumption profile which can be rearranged on time depending on the production goals for the specific time interval.

- Interruptible: These loads are defined by its state, which can be either on or off. When its state is on the consumption remains constant. An example of a load of constant consumption is a water heater. The heating of water can be interrupted and restarted according to the time specification by the end user and the thermal inertia of the system.

- HVAC: Air conditioning and heating devices. Its consumption depends on parameters such as ambient conditions and comfort level specified by the end user.

The consumption of these loads depends on the situation on different factors regarding the state of the EH, the forecast of renewable energy input, the forecast of non-manageable demand and the price of energy from the distribution grids. The consumption of manageable loads is not forecasted but optimized inside a VPP according to restrictions specified by the end user with the objective of minimizing a utility function, which will be presented in the energy optimization section.

2.2.3 Energy price from the grid

In a future situation, demand side management (DSM) will be broadly implemented in the energy grids, specifically in the electrical grid. The price of the electricity is specified in the wholesale market with an anticipation of 24 h for each hour of consumption. In a situation where a VPP wants to interact with the market and obtain benefits from the exploitation of its energy assets, it is important to predict the price of the electricity in order to be able to optimize its energy carriers and offer or demand electricity from the grid.

In [18], two methods to predict next-day electricity demand and price daily curve are proposed given past curves: robust functional principal component analysis and nonparametric models with functional response and covariate. In [19], a hybrid methodology is proposed, combining autoregressive integrated moving average (ARIMA) with adaptive dynamic corrector lazy learning algorithm.

Although these methods were studied, due to the integration of renewable energies in the electricity market and the changes in the structure of the pricing that it supposes, during the last years, ANN have been the focus to forecast electricity prices. ANN models for short-term electricity modeling perform better than time series models such as ARIMA models, as shown in [20]. It is also verified that the performance of ANN depends on appropriate input parameters; clustering and data selection algorithms of k-nearest neighbor algorithm and mutual information methods were used. The problem of this model is the need to remove trend and seasonal components. In the electricity market, there are strong seasonal effects and other nonlinear patterns that harm ANN forecasting performance. In [21] a robust method to solve the seasonal problem with ANN is proposed and verified. The method is seasonal autoregressive neural network (SAR-NN) defined as a dynamic feedforward artificial neural network. In [16] a hybrid approach based on the combination of particle swarm optimization and ANFIS is proposed and demonstrated in a case study in Spain. The study shows that soft computing techniques such as neural networks can be much more efficient computationally and accurate if correct inputs are considered. To select the most suitable inputs, several methods can be used, and genetic algorithm (GA) is one of them. The combination of ANFIS with GA has been proved to solve market price prediction and other economic parameters, as shown in [22, 23].

2.3 Energy hub model

The energy conversion equipment of the VPP forms the EH. In order to develop the model and the optimization of the system to create a VPP, the EH should be modeled. An EH is a multi-carrier energy system consisting of multiple energy conversion, storage and/or network technologies and characterized by some degree of control. In **Figure 4** an example of a schematic of an EH can be seen. In the figure, it is possible to appreciate that the EH in this case is composed by the energy conversion equipment, excluding the storage system. The EH is nowadays understood as the set of energy drivers that allow energy management. However, with the implementation of the VPP concept, the energy management possibilities are expanded and can take place in a level above the EH. Thus, although in most cases energy storage is included inside the EH, when a VPP is implemented, the trading

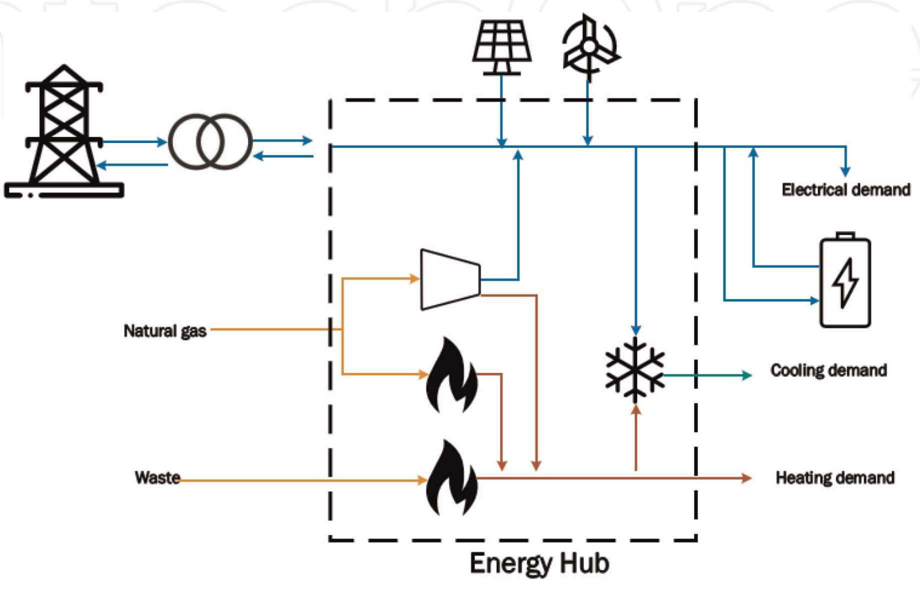

Figure 4.
Example schematic of an EH.

relationships are placed outside the EH, so it becomes coherent to also place the energy storage system outside the EH but inside the VPP.

In this section the formulation of an EH will be established from a generic perspective. According to [24], the relationship between input power and output power inside and EH is:

$$\begin{bmatrix} L_\alpha \\ L_\beta \\ \dots \\ L_\gamma \end{bmatrix} = \begin{bmatrix} \eta_{\alpha\alpha} & \eta_{\alpha\beta} & \dots & \eta_{\alpha\gamma} \\ \eta_{\beta\alpha} & \eta_{\beta\beta} & \dots & \eta_{\beta\gamma} \\ \dots & \dots & \dots & \dots \\ \eta_{\gamma\alpha} & \eta_{\gamma\beta} & \dots & \eta_{\gamma\gamma} \end{bmatrix} \begin{bmatrix} P_\alpha \\ P_\beta \\ \dots \\ P_\gamma \end{bmatrix} \tag{2}$$

where L represents the demand, P the power input and η the coupling matrix. It has to be observed that according to the example proposed, the energy coming from the electrical grid and the energy coming from the battery can be placed both in the demand and in the generation side.

The determination of the coupling matrix needs to be assessed taking into account the amount, characteristics and interconnections of the energy equipment. In the following paragraphs, an outline of relationships depending on different situations is carried out. These basic rules form the information needed to develop the model for more complex systems. With these, it will be possible to establish the coupling matrix that represents the EH and which relates the generation side with the demand side.

2.3.1 Energy converter with one input and one output

In this case an energy converter β with an input energy P_α has one only output: L_β. The power relationship between input and output is represented by:

$$L_\beta = P_\alpha \eta_{\beta\alpha} \tag{3}$$

where $\eta_{\beta\alpha}$ is the performance indicator of the converter, which can be the COP or the efficiency depending on the equipment considered. The COP can be constant or can be dependent on different parameters such as temperature or operating point.

2.3.2 Energy converter in series

This case represents the situation where all the output from one energy converter goes directly to another energy converter. This is called multistage energy conversion. The power output at the end of the last energy converted is computed by multiplying all the COPs in the chain. For the case with two energy converters:

$$L_\theta = P_\alpha \eta_{\beta\alpha} \eta_{\theta\beta} \tag{4}$$

2.3.3 Available energy in a converter

The power provided by an energy converter or energy source can be supplied to several energy converter or demand points. Power can be given to these systems simultaneously as long as there is energy available in the energy converter or generator. This can be represented mathematically as:

$$\sum_{i=1}^{n} P_{\alpha i} \leq P_{\alpha} \tag{5}$$

where:

$$P_{\alpha i} = P_{\alpha i} v_i \tag{6}$$

v_i being the dispatch factor to the different demands connected to the same source.

2.3.4 Upper and lower production limits

Every energy conversion equipment has a range within which it is possible to generate or convert electricity. It has to be assured that the energy that passes through the equipment falls between the specified thresholds. Mathematically it is expressed as:

$$lb_{\gamma} \leq P_{\alpha} \eta_{\gamma\alpha} \leq ub_{\gamma} \tag{7}$$

where lb_{γ} and ub_{γ} are the lower and upper limits, respectively.

The basic rules for the proper development of the coupling matrix have been explained. Their logic can be applied to any system composed by interconnected energy assets to develop the mathematical model of an EH.

2.4 Energy optimization

The optimization is an essential step for the successful implementation of a VPP. Once the model of the system has been developed, an evaluation of the state of the plant at a specified number of time instants has to be carried out to achieve all the benefits mentioned in this chapter. The optimization will allow to reach the best efficiency in the use of resources from an economical and environmental perspective as well as facilitate to the grid the integration of active prosumers, demand side management (DSM) and renewable energy sources.

An optimization is the selection of the best solution for a specified problem. The simplest optimization problems deal with the maximization or minimization of a variable. In mathematics, conventional optimization problems are usually stated in terms of minimization. A general manner to represent one of these is:

$$\text{Given}: f : A \rightarrow \mathfrak{R}$$
$$\text{Find}: x_0 \in A \text{ such that } f(x_0) \leq f(x) \text{ for all } x \in A$$

For the purpose here assessed, f can be considered as the energy of the system that is being considered, the operational and maintenance cost, the environmental impact or any other aspect related to the exploitation of energy assets. The function f is the *objective function* that wants to be minimized. A is a subset of the real space that is understood as a set of constraints that needs to be achieved or fulfilled. It is represented as group of equalities and inequalities that the solution should meet to be valid. In the energy frame, these equations deal with factors such as meeting the demand and comply with the operational bounds of the system. The domain A of f is called the *search space,* and the elements x in A are called *candidate solutions*. There are several types of optimization problems and possible solutions depending on the nature of the situation that is being studied. For a system where several energy assets are present and a time optimization has to be carried out, multi-period mixed-integer problems are the ones that represent the most of its operation, as can be seen in [25].

There are different purposes that lead to the decision of building a VPP, as, for example, total energy use, energy cost, production scheduling and emissions. All these factors have to be reflected in the objective function. The most used method to handle multi-criteria decisions is the weighted global criterion method. This method allows the interested party to adjust the preferences of the system. The objective function is obtained as:

$$f = \sum_{j=1}^{N} f_j^{trans} w_j \tag{8}$$

where f_j^{trans} is a normalized value of a single objective function and w_j the relative weight assigned to that objective function. f_j^{trans} is created in order to obtain the same range for the different objectives contemplated and has to be calculated as:

$$f_j^{trans} = \frac{f_j(x,y) - f_j^{\min}}{f_j^{max} - f_j^{\min}} \tag{9}$$

where f_j^{max} and $f_j^{\min}$ are maximum and minimum values of the objective function in question, respectively.

In order to obtain the optimal operation point of the VPP, the optimization process should be performed in two stages. The first stage deals with the decision of where to introduce or extract energy from the battery, decision of selling or buying energy from the electrical grid and the scheduling of manageable loads. The scheduling horizon of this optimization is normally one day, as this is the time interval at which the electricity price from the market is known. The scheduling horizon is divided into time slots; usually there are 96 time slots per day, one every 15 minutes. As shown in [17], the objective function in this optimization case is formed by three terms: energy cost, scheduling preferences and climatic comfort. For the case of the energy cost, it can be expressed as:

$$f_1^1 = B\sum_t P_{BE}C_{BE} + A\sum_t P_{CB}C_{CB} + (1-B)\sum_t P_{SE}C_{SE} + (1-A)\sum_t P_{DB}C_{DB} \tag{10}$$

where A and B are Booleans that designate if the VPP if selling/buying electricity from the grid and charging/discharging the battery. The other parameters refer to the following:

- P_{BE}: energy bought from the electrical grid
- C_{BE}: cost of the energy bought from the electrical grid
- P_{CB}: energy inserted in the battery
- C_{CB}: cost for inserting energy in the battery
- P_{SE}: energy sold to the electrical grid
- C_{SE}: cost of energy sold to the electrical grid. It has to be noted that this value is negative

- P_{DB}: energy extracted from the battery
- C_{DB}: cost of the energy extracted from the battery

The objective function related to the scheduling is expressed as:

$$f_2^1 = \frac{\sum_{SL} \sum_t \gamma}{N_{SL}} \tag{11}$$

where γ is a scheduling preference parameter and N_{SL} is the number of scheduling loads. Last of all, the objective function for the comfort is:

$$f_3^1 = g^{max} + \frac{\sum_{SL} \sum_t g_r}{RT} \tag{12}$$

where g^{max} is the maximum temperature gap allowable, g_r is the real temperature gap, R are the rooms considered and T are the time slots. For this first optimization stage, the restrictions should contain the fulfillment of non-manageable loads, the characteristics of manageable load (working cycles, minimum number of consecutive ON slots, maximum number of consecutive slots OFF, etc.) and power restriction on the energy input.

Once the energy input and output from the grid, batteries and loads are obtained, the second stage deals with the optimization of the energy flow inside the EH. In this case the objective functions are related to maximizing the efficiency and minimizing the energy cost and the total emissions. The function that represents the total energy use can be represented as:

$$f_1^2 = \sum_{\alpha} \sum_{t} P_t^{\alpha} \tag{13}$$

where P_t^{α} represents the energy generated or converted by α at the time instant t. It can also represent the energy input to the VPP such as the electricity from the grid and the natural gas. For the case of the cost of the system, the objective function is:

$$f_2^2 = \sum_{\alpha} \sum_{t} P_t^{\alpha} \lambda^{\alpha} \tag{14}$$

where λ^{α} represents the cost of the energy for a converter or energy input α. Last of all, for considering the emissions of the system:

$$f_3^2 = \sum_{\alpha} \sum_{t} P_t^{\alpha} e^{\alpha} \tag{15}$$

where parameter e^{α} represents the emission factor of the energy provided by α. For this stage, the restrictions should include the fulfillment of the demand and the power limitation of the different energy converters inside the EH.

3. Communication architecture and data management

As it has been mentioned in the previous section, forecasting techniques based on data-driven models are widely used when dealing with energy-related variables. This kind of models usually needs huge amounts of information to properly train or tune their inner structures, and once the models are generated, the central controller must be capable of sending the forecasted schedule decisions to each system's local controller. To do so, not only a sensor network has to be deployed in the facility, but also an efficient data communication system is needed.

Therefore, one of the key elements of the VPP concept is the communication systems. The existence of reliable, accurate, efficient and safe data exchange is crucial for a bidirectional, near real-time information flow. In addition, the current trend in the field is to make use of a service-oriented architecture (SOA), enabling an easy integration of the plant data in systems that can analyze and optimize not only the operation of the facility itself but also the global operation of the whole energy grid. To this extent, the cloud computing platforms such as Amazon Web Services, Microsoft Azure or Google Cloud.

The cost of implementing a communication system can be high, so it is vital to select a suitable data communication technology. There are several wired and wireless technologies available that can provide the required communication infrastructure. The selection of one (or more) of these communication technologies will depend on the quality of service (QoS), data range, reliability, latency, economic viability, etc. The capabilities offered by these technologies are also strongly related to the VPP grid structure. Looking it from the prosumer point of view, the main automation system is the energy management system (EMS) which is responsible for the management and optimization of the energy assets supervised in the VPP.

3.1 Energy management systems

The term energy management system (EMS) refers to an integrated system that enables the monitoring, management and control of several devices providing the necessary support for an effective operation of electrical generation and transmission facilities.

At a high level, the architecture of an EMS is divided into three layers which are management, automation and field levels [26] as depicted in **Figure 5**. The management (or supervisory) level comprises the human interface with the system by means of human machine interfaces (HMI) or SCADA-like software systems and contains most of the system logic and modules related with data analysis. The automation (or local) level provides the primary control devices connected via networked controllers and usually operating via BACnet, ZigBee, etc. protocols. The field (or plant) level represents the physical devices like energy meters, sensors and actuators installed to the plant equipment. These devices should be connected to local controllers by means of field-bus communications to allow control functionalities.

VPP supervision and control systems can be centralized or decentralized [27]. In the centralized control, all the knowledge about the devices in the VPP and the energy market is located in the central controller. Although this is a simple solution in most of the cases, when dealing with a large number of devices, the optimization of the control strategy can become computationally expensive for the central controller. In a distributed or decentralized control, the complexity is divided vertically within the VPP. Local controllers supervise and define the control strategy, and a higher-level controller coordinates their decisions in order to reach a global optimum state.

3.2 Communication requirements

The architecture defined above is organized in three hierarchical levels. Each of these communication layers has its requirements in terms of bandwidth, latency or cyber security. For example, at the field level, to have a large bandwidth is not a

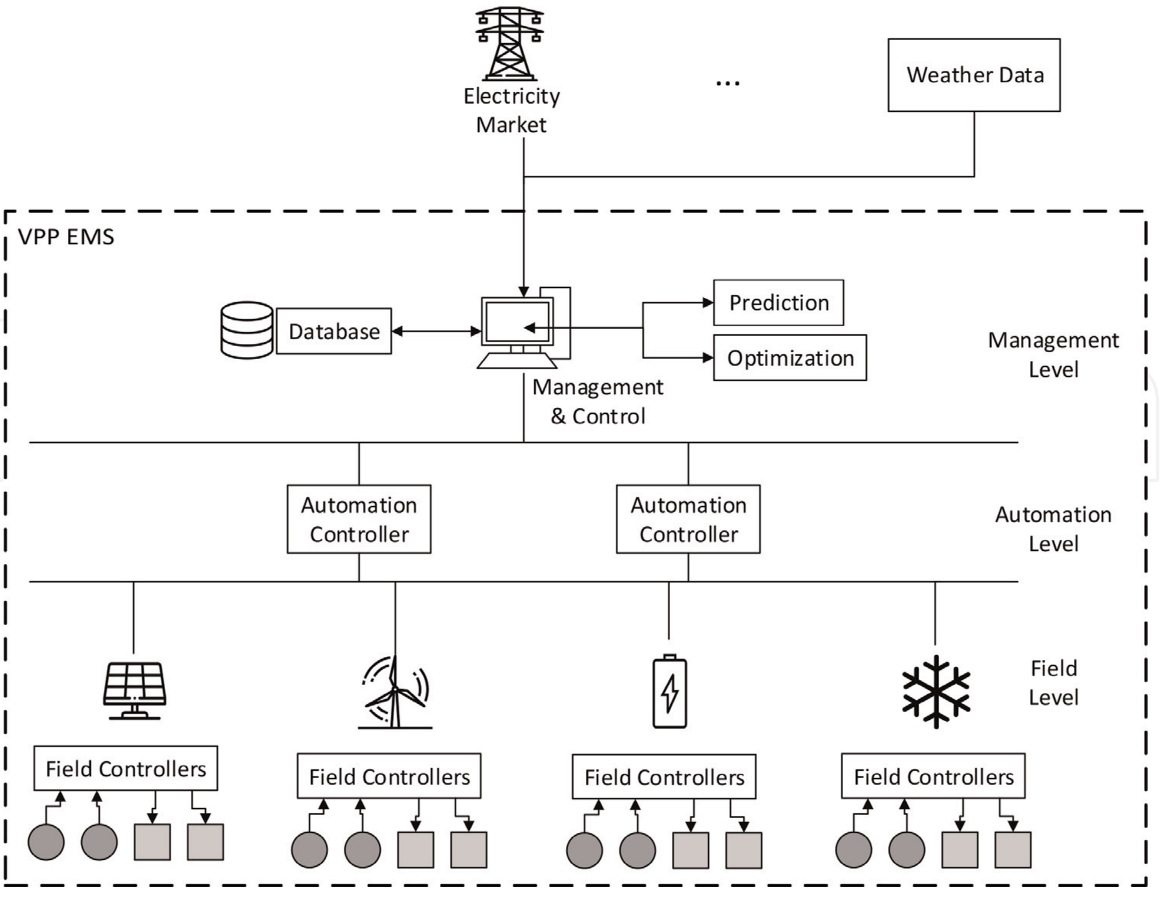

Figure 5.
EMS three-level architecture.

common requirement, but a short latency is mandatory given the near real-time control performed at this level.

3.2.1 Field level requirements

The total amount of data sent per node per transmission is typically less than a hundred bytes. That being the case, the communication bandwidth at this level is well within 100 kbps [28]. The sampling and transmission frequency are commonly between a range of 5 and 15 min. A simulation carried out in [29] showed that larger data collection frequencies fail at detecting short-term voltage anomalies. Besides, a time synchronization service is required to refer all the data gathered in the plant with respect to the UTC. A general-purpose time synchronization service like the network time protocol (NTP) is used given that the accuracy required does not exceed the order of seconds.

Typically, the sensors manage analogical data that is then is handled to an analog to digital converter (ADC) followed by an interface to a process control computer. The sensors can also have a digital communication module and contain embedded digital electronic processing systems. Actuators work in a reverse sense, converting electrical signals to the appropriate physical variable. However, as they have to amplify the energy level to produce the change in the real variables, actuators are high-power devices, while sensors are not.

3.2.2 Automation level requirements

At the automation level, the data from several local controllers is received; typically, the order of system it aggregates is in the order of tens. Hence, a bandwidth of more or less 1 Mbps is enough to fulfill its requirements [28]. The time synchronization and latency are also limited like in the field level.

The automation level is in charge of several tasks such as the monitoring of the variables to check the system or component failure, the management of the set points for the important process variables and the control reconfiguration and tuning of the control loops.

3.2.3 Management level requirements

The management level shares a large part of the requirements of the automation level. Typically, in this layer, the main limits for its requirements are represented by the capabilities of the already existing communication infrastructure.

Here, the information arrives as time series type of data; this data is characterized by having a timestamp associated with each value. In the management level, this data is collected and analyzed to perform some actions like process scheduling or maintenance management.

3.3 Communication technologies and protocols

When a message is transmitted onto a bus, it has to contain information like the identifier of the sending device, the message or data to transmit, the destination device address and some additional information (e.g. for error checking). After that, when the message reaches the destination device, this one has to know not only the message codification but also how to handle its reception using procedures to avoid collisions and prioritization.

These rules about connectivity and communication are defined by the communication system protocol. These protocols for VPP system must adhere to several criteria: efficient and reliable communication, interoperability with other systems and integration into the power system. For easier integration, it is usually desirable that the VPP system supports the communication protocols already in use by any other equipment. In addition to standardized protocols, there are many proprietary protocols like C-Bus or PROFIBUS.

Both wired and wireless technologies have been specified through standards. The advantages of wired technologies over wireless ones are the higher data transmission rate, security and reliability but at the expense of high installation cost. On the other hand, wireless technologies have fewer installation costs and can be easily deployed, but they exhibit low data transmission rates and signal interference problems. With the advent of ICT and IoT, more and more sensors and meters are needed to be integrated, monitored and controlled. In this situation, the lower deployment cost and better scalability of wireless technologies make them better candidates. In the below sections, some of the widely used communication technologies for metering and sensory purpose will be covered.

3.3.1 Power line carriers

In terms of wired technologies, PLC is the most widely used technology [30]. Power line carriers (PLCs) consist of introducing a modulated carrier signal over the existing electricity grid. No additional wiring is required; therefore, PCL can be considered as a cost-effective and straightforward solution. PLC can be classified into two major categories: narrowband PLC and broadband PLC.

The operating rate of the narrowband PLC is in a range of 3–500 kHz. It can be further classified as low data rate and high data rate narrowband PLC. The former is a single carrier technology with data rate up to 10 kbps and works on the recommendations of standards like LonWorks or KNX. The high data rate narrowband is a multi-carrier technology with a data rate below 1 Mbps. The broadband PLC technology has an operating range of 2–250 MHz with a data rate of hundreds of Mbps.

PLC technologies have been used since a long time ago for electric energy-related services in industrial automation like remote meter reading and remote load management. PCLs can be applied in any point of the VPP environment, and its main advantage is the low running costs, and that can be installed using current infrastructure. The security issues are solved like in the ZigBee technology, using the 128-bit AES encryption.

3.3.2 GSM and GPRS

Global System for Mobile Communications (GSM) is known as the world's most deployed cellular technology. It operates on the 1800 MHz and 900 MHz bands, and its data rate is up to 270 kbps. General Packet Radio Service (GPRS) data rate is much larger than GSM. Its main drawback is the reliability of Short Message Service (SMS) in case of network congestion.

The main application of GPRS and GSM is in smart metering solutions for remote billing and power consumption monitoring, usually applied in smart grids covering from the generation stage to the consumption one, including both the transmission and distribution.

3.3.3 WiFi

Wireless sensing technology has been gaining popularity in the last years given the fact that wireless sensors are easy to install and cheaper in price and, among all the wireless sensing technologies, WiFi is the most popular. Developed under the IEEE 802.11 standards family, it provides a robust performance even in noisy channels and supports a wide range of data rates. The local security issues are tackled by the WPA2 protocol based on the 128 bit AES encryption technique, and to ensure secure communication through public Internet access, virtual private networks (VPNs) are typically used [31].

WiFi is the most dominant wireless technology for the high speed it can offer but is more expensive than other technologies because of its higher consumption and device price. WiFi is mostly used for building automation, remote control, meter reading, etc. in the tertiary sector and has been used as a proxy for human occupancy in some HVAC actuation models.

3.3.4 Ethernet

Ethernet is a low-cost communication method and is widely used for communication between PLCs and SCADA systems. Ethernet is available like optical fiber, shielded twisted pairs or coaxial cables. Among these, optical fiber is more secure and popular due to the absence of electromagnetic interference and electrical current. Ethernet uses carrier-sense multiple access with collision detection (CSMA-CD) methods for sensing data. Ethernet is not suitable for real-time application because the a priori estimation of the data packet maximum transmission time is impossible.

The main disadvantage of Ethernet is its wired nature and the need of deploying a new cable network. However, it is robust and does not have running costs. The most common implementation of Ethernet in today's industrial automation field is to use an Ethernet/IP network, applying the capabilities of traditional Ethernet to connect different facilities in the same network via the Internet.

3.3.5 Modbus

Introduced by Modicon Corporation, it is widely used due to its simplicity and reliability. It includes a remote terminal unit (RTU), transmission control protocol (TCP) and ASCII mode of transmission and supports RS-232, R-422, RS-485 and Ethernet-based equipment. Because of its simplicity and open-source availability, it is popular for local communication building and also has become the standard for industrial SCADA systems.

The security issues are not addressed in Modbus. It does not support authentication nor encryption; thus, it is less secure and more vulnerable to cyberattacks.

3.3.6 OPC UA

The OPC UA is a machine-to-machine communication protocol for industrial automation developed by the OPC Foundation. It is the next generation of the original OPC which is applied in different technologies like building automation or process control. OPC UA was developed to tackle the emerging needs of industrial automation.

OPC UA was designed to be fully scalable and enable both the horizontal and vertical communications across all the layers. In addition, it uses a service-oriented architecture, and two transport protocols are defined: an optimized TCP for high performance and a HTTP/HTTPS web service with binary or XML-coded messages.

Table 1 shows a summary of the main characteristics of each of the communication technologies reviewed.

3.4 Selection of sensing solution

According to [32], the factors that influence the selection of sensing and metering solutions are the following:

- Accuracy: In Europe, the accuracy of meters is defined by directives such as the Measuring Instruments Directive (MID). A common feature in this kind of directives is to classify the meters by their percentage accuracy.

- Ease of deployment: The ease of deployment refers to the different installation and networking challenges that must be tackled. For example, wireless sensors have reduced installation costs and provide better flexibility than their wired counterpart. Other factors to consider are the interoperability, installation in an accessible location or safety regulations.

- Communication protocol: As it has been seen in the previous section, there is a wide range of communication technologies each with its advantages and disadvantages.

- Resolution: The resolution determines the possible level of analysis that can be performed. As aforementioned the typical data collection rate is within a range between 5 and 15 minutes.

- Cost: The cost of the equipment is always a driver when deciding the metering equipment. Both initial costs and operating costs must be considered. Usually,

Technology	Type of technology	Characteristics
PLC	Wired	• Low installation costs (no additional wiring is required) • Cost-effective, widely used solution • Narrowband PLC: up to 500 MHz with a data rate below 1 Mbps • Broadband PLC: up to 250 MHz with a data rate of hundreds of Mbps
GSM/GPRS	Wireless	• World's most deployed wireless technology • Operates on 900 and 1800 MHz bands • Rate up to 270 kbps • Low reliability in congested networks
WiFi	Wireless	• Most popular wireless technology • Robust even in noisy channels • Security issues tackled by the WPA2 protocol
Ethernet	Wired	• Low-cost solution • Not suitable for real-time sensing • Needs a new cable network
Modbus	Comm. protocol	• Simple and reliable • Open-source • Standard for SCADA systems • Vulnerable to cyberattacks
OPC UA	Comm. protocol	• Robustness • Scalable and platform independent • Standard transport and encoding protocols (TCP and HTTP)

Table 1.
Summary of characteristics of the technologies and protocols reviewed.

the number of sensors is limited to the minimum to provide adequate control and ensure compliance with regulations.

- Availability: The geographical availability of a particular manufacturer's sensing solution. It will affect to the delivery time and provisioning of technical support.

4. Conclusions

In this chapter the concept of VPP has been explained as the solution for the challenges of upcoming energy markets. The forecasting of future energy situation regarding demand, energy prices and renewable generation has been assessed, reaching the conclusion that artificial intelligence methods are best suited for the stated purpose. The internal energy assets have been modeled by means of an EH. By adding these factors, the VPP is constructed, and its optimization can be carried out. The optimal operation point is obtained by considering current and future energy prices from the market, renewable energy generation, manageable and non-manageable demands and costs and operation constraints of energy equipment. For it to be possible, the EMS and the communication technologies of the plant have to be studied and adapted. The high-level structure and requirements of the EMS have been explained together with the more common communication technologies and protocols. Its advantages and drawbacks have been presented and the important factors for the selection of the sensing technologies described. By incorporating all the exposed factors in an industrial plant, a VPP can be created which will satisfactorily help the energy grid to evolve and will also produce a benefit for the exploitation of its own energy equipment.

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References

[1] Chan Y, Kantamaneni R. Study on energy efficiency and energy saving potential in industry and on possible policy mechanisms. 2015; 1-461

[2] Davatgaran V, Saniei M, Mortazavi SS. Optimal bidding strategy for an energy hub in energy market. Energy. 2018;**148**:482-493

[3] Choi S, Min SW. Optimal scheduling and operation of the ESS for prosumer market environment in grid-connected industrial complex. In: 2017 IEEE Ind Appl Soc Annu Meet IAS 2017 2017. 2017. pp. 1-7

[4] Mengelkamp E, Gärttner J, Rock K, et al. Designing microgrid energy markets: A case study: The Brooklyn microgrid. Appl Energy. 2018;**210**: 870-880

[5] Barzegkar-ntovom GA, Kontis EO, Kryonidis GC, et al. Performance assessment of electrical storage on Prosumers via pilot case studies. In: 2019 1st Int Conf Energy Transit Mediterr Area (SyNERGY MED). 2019. pp. 1-6

[6] Huld T. Estimating solar radiation and photovoltaic system performance, the PVGIS approach. In: AFRETEP 1ST Reg Work; Kampala. 2011. pp. 1-84

[7] European Commission. Photovoltaic Geographical Information System (PVGIS). Available from: http://re.jrc.ec.europa.eu/pvgis.html [Accessed: 12 March 2019]

[8] Vestas Wind Systems A/S. General Specification V90–3.0 MW 60 Hz Variable Speed Turbine General Specification for V90–3.0 MW. 2004. pp. 1–31

[9] Chen Q, Folly KA. Wind power forecasting. IFAC-PapersOnLine. 2018; **51**:414-419

[10] Das UK, Tey KS, Seyedmahmoudian M, et al. Forecasting of photovoltaic power generation and model optimization: A review. Renewable and Sustainable Energy Reviews. 2018;**81**:912-928

[11] Shu F, Luonan C. Short-term load forecasting based on an adaptive hybrid method. IEEE Transactions on Power Apparatus and Systems. 2006;**21**: 392-401

[12] Li S, Wang P, Goel L. A novel wavelet-based ensemble method for short-term load forecasting with hybrid neural networks and feature selection. IEEE Transactions on Power Apparatus and Systems. 2016;**31**:1788-1798

[13] Baliyan A, Gaurav K, Kumar Mishra S. A review of short term load forecasting using artificial neural network models. Procedia Computer Science. 2015;**48**:121-125

[14] Jang JR. ANFIS: Adaptive-network-based fuzzy inference system. 1993;**23**. DOI: 10.1109/21.256541. [Epub ahead of print]

[15] Takagi T, Sugeno M. Derivation of fuzzy control rules from human operator's control actions. IFAC Proceedings. 1983;**16**:55-60

[16] Pousinho HMI, Mendes VMF, Catalão JPS. Short-term electricity prices forecasting in a competitive market by a hybrid PSO-ANFIS approach. International Journal of Electrical Power & Energy Systems. 2012;**39**:29-35

[17] Agnetis A, De Pascale G, Detti P, et al. Load scheduling for household energy consumption optimization. IEEE Transactions on Smart Grid. 2013;**4**: 2364-2373

[18] Aneiros G, Vilar J, Raña P. Short-term forecast of daily curves of electricity demand and price. International Journal of Electrical Power & Energy Systems. 2016;**80**:96-108

[19] Vaccaro A, El-Fouly THM, Canizares CA, et al. Local learning-ARIMA adaptive hybrid architecture for hourly electricity price forecasting. In: 2015 IEEE Eindhoven PowerTech, PowerTech 2015. 2015. DOI: 10.1109/PTC.2015.7232253. [Epub ahead of print]

[20] Keles D, Scelle J, Paraschiv F, et al. Extended forecast methods for day-ahead electricity spot prices applying artificial neural networks. Applied Energy. 2016;**162**:218-230

[21] Saâdaoui F. A seasonal feedforward neural network to forecast electricity prices. Neural Computing & Applications. 2017;**28**:835-847

[22] Svalina I, Galzina V, Lujić R, et al. An adaptive network-based fuzzy inference system (ANFIS) for the forecasting: The case of close price indices. Expert Systems with Applications. 2013;**40**:6055-6063

[23] Wei LY. A hybrid model based on ANFIS and adaptive expectation genetic algorithm to forecast TAIEX. Economic Modelling. 2013;**33**:893-899

[24] Kampouropoulos K, Andrade F, Sala E, et al. Multiobjective optimization of multi-carrier energy system using a combination of ANFIS and genetic algorithms. IEEE Transactions on Smart Grid. 2018;**9**:2276-2283

[25] Kampouropoulos K. Multi-Objective Optimization of an Energy Hub Using Artificial Intelligence. Universitat Politècnica de Catalunya; 2018

[26] Brooks DJ, Coole M, Haskell-Dowland P, et al. Building Automation & Control Systems: An Investigation into Vulnerabilities, Current Practice & Security Management Best Practice. Perth; 2017. Available from: https://goo.gl/RM7ukP

[27] Zia MF, Elbouchikhi E, Benbouzid M. Microgrids energy management systems: A critical review on methods, solutions, and prospects. Applied Energy. 2018;**222**:1033-1055

[28] Pasetti M, Rinaldi S, Manerba D. A virtual power plant architecture for the demand-side management of smart prosumers. Applied Sciences. 2018;**8**:432

[29] Wan Yen S, Morris S, Ezra MAG, et al. Effect of smart meter data collection frequency in an early detection of shorter-duration voltage anomalies in smart grids. International Journal of Electrical Power & Energy Systems. 2019;**109**:1-8

[30] Erlinghagen S, Lichtensteiger B, Markard J. Smart meter communication standards in Europe—A comparison. Renewable and Sustainable Energy Reviews. 2015;**43**:1249-1262

[31] Kolenc M, Nemček P, Gutschi C, et al. Performance evaluation of a virtual power plant communication system providing ancillary services. Electric Power Systems Research. 2017;**149**:46-54

[32] Ahmad MW, Mourshed M, Mundow D, et al. Building energy metering and environmental monitoring—A state-of-the-art review and directions for future research. Energy and Buildings. 2016;**120**:85-102