



Optimization of Energy Distribution with Demand Response Control in 6G Next Generation Smart Grids

Rola Naja^{1,2(✉)}, Asma Tannous³, Nadia Mouawad⁴, and Nazih Moubayed³

¹ LyRIDS, ECE Paris, 10 rue Sextius Michel, 75015 Paris, France
rnaja@ece.fr

² LiPARAD-Université de Versailles-Saint Quentin, Paris, France

³ EDST Laboratory, Lebanese University, Beirut, Lebanon
nazih.moubayed@ul.edu.lb

⁴ Orange Labs, Paris, France
nadia.mouawad@orange.com

Abstract. The transition to an intelligent electrical network that is more respectful to the environment and consumers' needs requires the adoption of renewable energies. However, and despite the progress made in this area, renewable energies present significant constraints, such as their intermittency. Therefore, the convergence between the worlds of energy and 5G/6G network techniques offers relevant solutions, including the use of Virtual Power Plants, SDN technology coupled with network slicing. As a way to achieve power balancing between power generation and demands, this study offers a unique architecture for a smart grid that makes full use of optimization techniques to rationalize the distribution of energy resources. Performance evaluation shows the optimization of resource consumption.

Keywords: Renewable Energy Sources · SDN · VPP · Demand Response

1 Introduction

This article focuses on the integration of 6G network technology for the management of renewable, environmentally friendly energy sources in smart grids. Indeed, the development of 6G networks relies heavily on energy efficiency. In order to improve resource management, network performance, and user experience, energy optimization algorithm is of paramount importance in this regard. Artificial Intelligence solutions have the potential to optimize energy consumption and enhance the overall efficiency of 6G networks. Moreover, the architecture of 6G networks will require the integration of wireless communication technologies that are anticipated to be a key technology.

Beyond the pollution and environmental challenges [1], the electrical system is facing new constraints, such as the growing energy demand, particularly during peak periods, the aging of network infrastructures and new electrical uses, i.e., electric vehicles.

Based on these findings, players in the energy sector are now orienting their efforts towards 1) the deployment of renewable resources and 2) the development of technologies that make electricity demand more flexible.

Deployment of Intermittent Renewable Resources (RES): The management of renewable resources, such as solar and wind farms, provides environmental problem solutions by allowing greener electricity production. Nevertheless, certain drawbacks related to these resources, such as their intermittent nature require the development of an effective energy management mechanism.

Flexible Electricity Demand: In current electrical networks, the energy demand is stochastic; thus, energy management is carried out at the supply level. On the other hand, in future networks, the intermittency of renewable energies implemented on a large scale will shift the random feature of the electrical demand from consumers to producers; demand must therefore be flexible and controlled via specific management programs, called Demand Response (DR) programs. These programs act on the electricity load curve shape by *shifting loads, clipping peaks or filling valleys* [2].

In order to adapt consumption needs to intermittent resources, we emphasize the need to set up innovative Next Generation Smart Grids, NGSG, that can convey information flows between producers and consumers in order to develop an efficient energy consumption control mechanism. The latter considers the constraints of intermittent sources, and the needs/preferences of the consumer and may provide an efficient solution to optimize the management of the electrical system.

With NGSG networks, all electrical devices should be connected and controlled to manage and monitor power consumption. These connected objects can generate, collect, save, and process massive amounts of data. The huge data opens new dimensions to explore electrical network's reliable and efficient design. Nevertheless, traditional strategies are unable to process and analyze this large portfolio of data. Therefore, it would be necessary to rethink the techniques for processing the rich data generated by electrical devices in NGSGs which are at the convergence of electrical system technologies and information and communication technologies. Based on this understanding, NGSGs include a set of technologies that provide real-time management of electricity consumption: prediction, load balancing, network reliability, detection and monitoring of faults and assistance in decision-making of adherence to DR programs.

More specifically, our paper raises four issues:

1. How to allocate energy to consumers, while taking into account the energy constraints of intermittent renewable sources and while meeting the energy needs and preferences of consumers?
2. How to implement an energy distribution mechanism in order to satisfy two types of profiles: Flexible Load Profile, FLP, (e.g. Elderly Home Care and electrical vehicle) and Strict Load Profile, SLP, (e.g. medical clinic)?
3. How to manage the energy allocation of a fleet of electric vehicles, knowing that these vehicles can restore energy during periods of inactivity, through Vehicle to Grid technology?

In this order to provide solutions to the highlighted problems, we implement an NGSG architecture that adopts the following technologies.

Technology 1: Implementation of a centralized SDN-based energy management architecture with network slicing

Our proposed NGS architecture incorporates the SDN technology. The SDN paradigm can be extensively employed as the foundation for supporting power grid communications due to its properties of separating the control plane from the data plane. In particular, SDN approach can be applied to manage the communication entities in the SG system given that the power grid primarily depends on communication networks for control. As a result, SDN will be able to offer load balancing, load displacement, dynamic routing path adjustment in response to SG control requests [3], rapid fault detection [4], security [5], self-healing [6], and tracking and scheduling of crucial SG traffic flows in electrical networks.

Based on this understanding, we implement a centralized SDN-based energy management architecture with network slicing [7]. In fact, slicing the network enables to efficiently manage resources [8–14]. Therefore, we recommend three slices for the envisioned use cases: elderly home care, electrical vehicles, and medical clinic. In the second step, we consider the implementation of a fair energy distribution mechanism at the level of a Virtual Power Plant (VPP) located within an SDN controller. This mechanism should optimize the energy consumption while considering the constraints of wind and solar sources and consumers' needs.

Technology 2: Demand Response Energy Program

DR programs aim to modulate the electricity load curve by shifting loads, clipping peaks, or filling in valleys as explained hereafter:

- Load-shifting consists of shifting the demand for an electrical device, i.e. postponing or advancing a demand from one-time slot of the day to another.
- The reduction in the peak of electricity demand, or peak clipping, can be done by reducing or very occasionally cutting off electricity use. This solution essentially makes it possible to reduce the electrical power required during peak periods and induce a consumption drop [15].
- While the last two action strategies of Demand Response seek to flatten the load curve by clipping demand peaks, valley filling makes it possible to increase the load during periods when it is less important.

As a part of our architecture, we advocate peak clipping as DR program applied on controlled thermal devices in elderly home care. In fact, EHC is considered a flexible load that should adapt to the energy fluctuation in order to satisfy strict requirements of home clinics.

Moreover, our architecture applies an optimization algorithm that distributes efficiently energy to consumers. In fact, NGS smart grids enable the collection of consumption data that calls for ongoing observation, evaluation, and interpretation. In return, owners of wind and solar farms gather data on the volume and energy composition of renewable energy sources exported to the grid [16]. This will guarantee that the demand for electricity is met by the supply. In this scenario, the application of an optimization algorithm will significantly affect energy output and help to optimize energy utilization.

Technology 3: Energy management of a fleet of vehicles

This technology aims to develop a bidirectional energy transition mechanism towards a fleet of intelligent vehicles, by adopting V2G technology [17, 18]. Indeed, the large-scale deployment of electric vehicles could have a considerable effect on the charging curve, particularly during peak periods, in case vehicle charging is not correctly distributed over time. Thus, V2G technologies consider the battery of an electric car as an extension of the distribution network, i.e., an energy pool from which the electricity supplier can draw from time to time.

Charging thus becomes bidirectional, which means that the network does not limit itself to loading electricity to the vehicle's battery, with Grid to Vehicle technology: it also considers it as a source of power that can be used to meet various energy consumption needs. Based on this understanding, we develop a flexible V2G energy management that enables battery charging the batteries during the renewable energy production phases; then the mechanism makes electricity available when the supply offered by solar, or wind sources is interrupted. We concentrate our efforts on developing a 6G-based architecture combined with an energy management algorithm specific to three use cases, driven by the aforementioned technologies. The following is a list of our contributions:

- Based on an optimization function, we suggest a comprehensive energy distribution algorithm that addresses various restrictions relating to suppliers and consumers.
- We shed light on V2G technology that aims at handling charging and discharging according to the RES fluctuation energy.
- We distinguish between two different load profiles: strict profile and flexible with induce service differentiation.
- By conducting analysis of the following performance metrics, we validate our platform: availability function, power sources, load sources, battery state of charge, temperature of thermal controlled loads.

The rest of this paper is organized as follows: Sect. 2.1 exhibits our proposed architecture of NGSG. In Sect. 2.2, we provide the loads and power sources modelling. Section 2.3 sheds the light on the energy optimization mechanism implemented at the VPP. In Sect. 3, we present the simulation findings that assess the effectiveness of the suggested method. Section 4 serves as the paper's conclusion.

2 Energy Based Management Architecture

2.1 Architecture Modules

We propose an innovative architecture for NGSG energy optimization architecture that consists of three modules (Fig. 1):

Module 1: Implementation of a centralized SDN-based energy management architecture with network slicing

This module consists of defining the architecture of NGSG networks coupled with the functional entities of 5G networks relying on a SDN controller and SDN switches. We recommend three slices for the three use cases: medical clinic, elderly home care and electrical vehicle. In a second step, we consider the implementation of an equitable energy distribution mechanism at the level of a VPP located within the SDN controller.

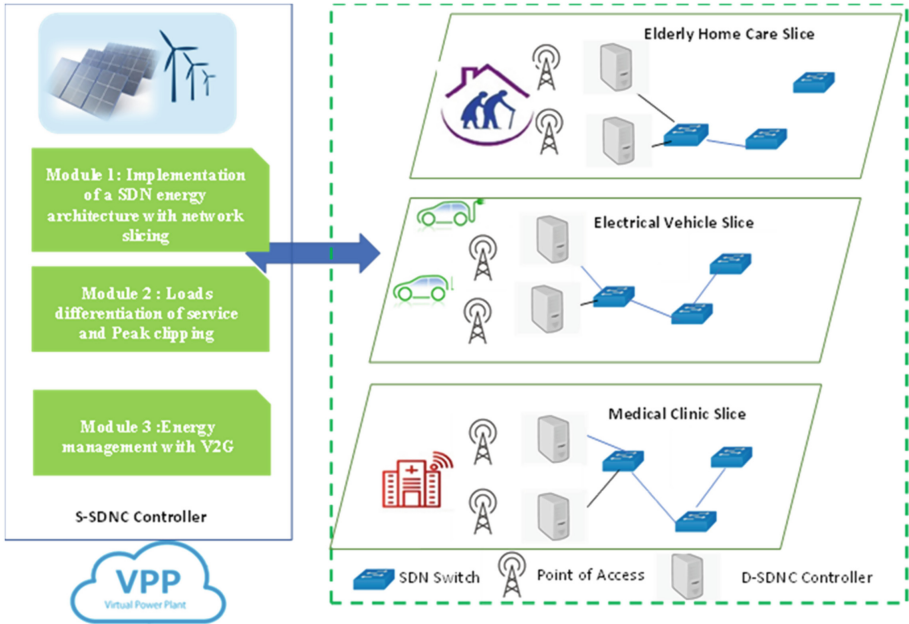


Fig. 1. NGSG Energy Optimization Architecture

This mechanism should optimize energy consumption while considering restrictions of wind and solar sources as well as the needs of consumers having two energy profiles consumers.

Module 2: Loads service differentiation and peak clipping

This module consists of an energy distribution algorithm deployed at the VPP, that is endorsed with fair energy dispatching. In fact, it adopts an optimization algorithm that manipulates weather information, such as wind speed and solar radiation parameters for WT and PV systems, load demand profile of EHC and medical clinic and EV state of charge. More specifically, we perform energy balancing to two energy profiles: flexible and strict. Since flexible energy profile loads are more adaptive to energy fluctuation, we devise to apply peak clipping during peak hours. It is noteworthy that VPP presents high computational capacities that enable it to handle massive data volumes within tight timeframes. Moreover, the SDN technology, due to the decoupling control planes, provides low latencies.

Module 3: Energy management of a fleet of vehicles

This module aims to develop a two-way energy transition mechanism towards a fleet of intelligent vehicles, by adopting vehicle-to-grid technology. This mechanism will also be able to efficiently manage the Grid-to-vehicle technology, which considers the vehicle as a consumer.

Indeed, the large-scale deployment of electric vehicles could considerably affect the charging curve, particularly during peak periods, if vehicle charging is not correctly distributed over time. Thus, V2G technologies consider an electric car's battery as an

extension of the distribution network, a reservoir from which the electricity supplier can draw from time to time. Charging thus becomes bidirectional, which means that the network does not limit itself to routing electricity to the vehicle’s battery: it also considers it as a source of power that can be used to meet various energy consumption needs. This module therefore consists in setting up a flexible V2G energy management mechanism, which will make it possible to recharge the batteries during the renewable energy production phases; then the mechanism will make electricity available when the supply offered by solar or wind sources has been interrupted.

2.2 Loads Sizing and Renewable Energy Sources Modeling

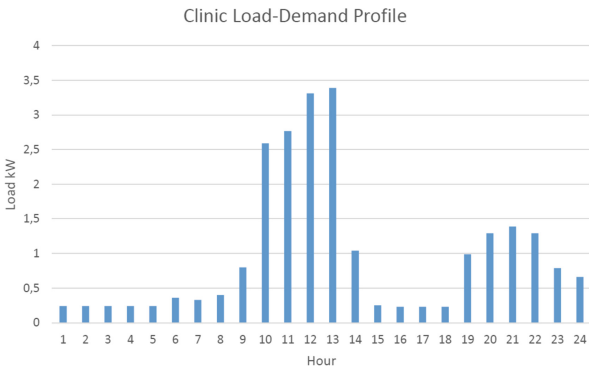


Fig. 2. Medical Load Sizing [19]

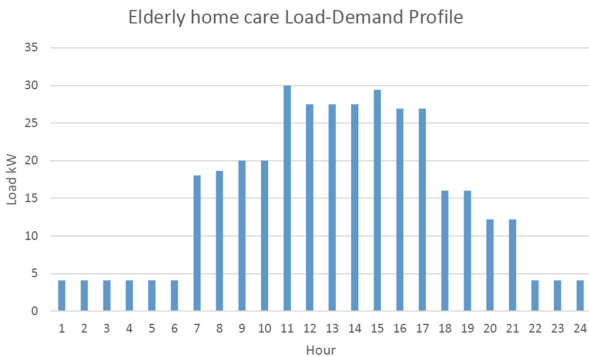


Fig. 3. Elderly home care sizing [19]

1) Loads Sizing

Accurate load sizing, required for authentic operations, is one of the substantial obstacles presented by energy optimization. Therefore, load modeling should accurately replicate real-world dynamics and reflect load’s behavior as much as possible.

Loads fall into two categories: strict load and flexible load. Strict loads must be supplied regardless of energy conditions and their load cannot be shifted. Flexible loads imply that their operation can be shifted, and their power consumption can be adapted according to the smart grid conditions. The medical clinic is considered as a strict while the Elderly home care (EHC) and the electrical vehicle (EV) charging process are considered as flexible loads. Consequently, we consider that strict loads have priority over flexible loads.

Medical clinic sizing

Figure 2 [19] depicts the load demand profile for the medical clinic. The busiest times of the day are from 9 am to 1 pm and from 7 pm to 10 pm. According to this profile, the peak load and average daily energy demand are calculated to be 3.39 kW and 23.784 kWh, respectively.

Elderly home care sizing

Figure 3 [19] depicts the load demand profile for elderly home care. The busiest period of day is from 9 am to 5 pm. This profile indicates that the peak load and average daily energy demand are roughly 372.061 kWh and 29.992 kW, respectively.

Electric vehicle sizing

The electricity in the EV battery at instant t after charging is derived as follows [19]:

$$\begin{aligned} & Nom_{EV}(j) \times SOC_{EV}(t, j) \\ &= Nom_{EV}^{int}(j) \times SOC_{EV}(t - 1, j) + \frac{P_{EV}^{Ch}(t, j) \times dt}{e_c} - e_d \times P_{EV}^{disch}(t, j) \times dt \end{aligned}$$

where

- $Nom_{EV}(j)$ (resp. $Nom_{EV}^{int}(j)$) is the nominal (resp. initial) capacity of electric vehicle battery j [kWh].
- $SOC_{EV}(t, j)$ is the state of charge of electric vehicle battery j at time t [%].
- $P_{EV}^{Ch}(t, j)$ (resp. $P_{EV}^{disch}(t, j)$) is the power charge (resp. discharge) by electric vehicle j at time t [kW].
- e_c (resp. e_d) is the charging (resp. discharging) coefficient factor [%].

2) Power sources sizing

This section elaborates the power sources sizing of the following renewable energy sources: wind turbine, photovoltaic system as well as electric vehicles.

Wind turbine (WT) sizing:

The wind speed at the hub height determines the availability of wind resources and the amount of electricity produced by WT in a given area. Based on the features of the WT's usual power curve, the output power, P_w , is described as follows in terms of wind speed:

$$P_w = \begin{cases} 0 & u < u_c \text{ or } u > u_f \\ P_r \frac{u^2 - u_c^2}{u_r^2 - u_c^2} & u_c \leq u \leq u_r \\ P_r & u_r \leq u \leq u_f \end{cases}$$

- P_r is the rated power of wind system [kW]
- u is the forecasted wind speed [m/s]
- u_r is the rated speed of the wind turbine [m/s]
- u_c is the cut-in speed of the wind turbine [m/s]
- u_f is the cut-off speed of the wind turbine [m/s]

Photovoltaic (PV) system sizing:

The area of the PV system and surface solar radiation both affect how much electricity is produced by the system. The following equation is used to calculate the output power of the PV system at time t :

$$P_{pv}(t) = SI(t) \times A_{pv} \times \rho$$

- ρ is the efficiency of photovoltaic system [%]
- A_{pv} is the area of photovoltaic system [m²]
- $SI(t)$ is the solar irradiation at time t [kW/m²]

Electric vehicle discharging mode:

The Electricity stored in the EV battery at time t after discharging is as follows [20]

$$\begin{aligned} & Nom_{EV}(j) \times SOC_{EV}(t, j) \\ &= Nom_{EV}^{int}(j) - \left(e_d \times P_{EV}^{Disch}(t, j) \times dt \right) \end{aligned}$$

- $P_{EV}^{Disch}(t, j)$ is the power discharge of electric vehicle battery j at time t [kW]

2.3 Energy Distribution Methodology at the Virtual Power Plant

The VPP is entitled to distribute energy to the various loads. To this purpose, we adopted the methodology illustrated in Fig. 4. In a first stage, we adopt an optimization algorithm that manipulates weather data, e.g. wind speed, solar radiation specifications of WT and PV energy sources, load demand profile of EHC and medical clinic and EV state of charge (refer to next subsection). In a second stage, we perform NGSG smart grid load balancing as expressed in the following sub-section.

At a third stage, the VPP will take the decision of electrical vehicles charging or discharging. More specifically, it computes the power output of WT and PV system. Then, it investigates the load demand profiles while comparing the power produced by renewable energy sources with the power needed to provide the load.

Consequently, the surplus power generated from the RES is either used to charge EVs or is stored. More specifically,

- Whenever the power generated from renewable energy sources cannot supply the various loads, we discharge the electrical vehicles.
- In case the power discharged from the electrical vehicles cannot fill the power deficiency in RES we use the power stored.

1) Smart grid load balance

Every time interval t , the equilibrium between consumption and production systems should be ensured. More specifically, the electricity demand is the sum of the EHC loads consumption, the medical clinic loads consumption, the charging power of the EV batteries and the unused power, $P_{Store}(t)$. This demand is supplied from RES sources, discharging power from EV batteries and the stored power, $P_{Store}(t)$. It is noteworthy that $P_{use}(t)$ and $P_{Store}(t)$ are two VPP variables that are not physically modeled in the smart grid. Therefore, load balancing is formulated as follows:

$$\begin{aligned}
 P_{pv}(t) + P_w(t) + \sum_j^{N_{EV}} P_{EV}^{Disch}(t, j) + B_{use} \times P_{use}(t) \\
 = P_{clinic}(t) + \sum_j^{N_{EV}} P_{EV}^{ch}(t, j) + P_{EHC}^{new}(t) + B_{store} \times P_{Store}(t)
 \end{aligned}$$

The following equations highlight the conditions at which there is storage of excess power or usage of stored power.

$$\begin{aligned}
 B_{store}(t) &= \begin{cases} 1 & \text{if } P_{res}(t) > P_{load}(t) + \sum_j^{N_{EV}} P_{EV}^{ch}(t, j) \\ 0 & \text{else} \end{cases} \\
 B_{use}(t) &= \begin{cases} 1 & \text{If } P_{res}(t) + \sum_j^{N_{EV}} P_{EV}^{Disch}(t, j) < P_{load}(t) \\ 0 & \text{else} \end{cases}
 \end{aligned}$$

2) Energy Optimization formulation

This section is dedicated to the mathematical modelling of the energy management problem. The resolution of the optimization problem is based on a technique that generates a local optimal solution every time slot (i.e. one hour).

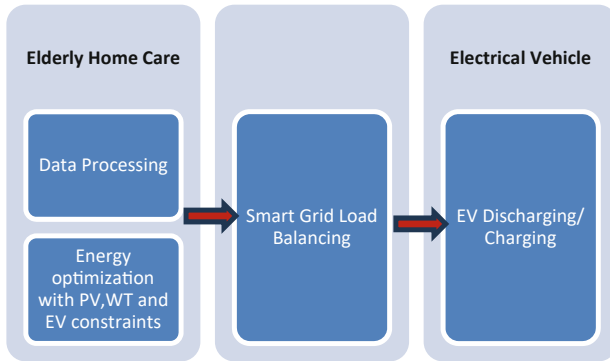


Fig. 4. Energy distribution methodology at VPP

Our algorithm objective consists of reducing the power consumed by the flexible EHC load in order to supply the medical clinic.

$$\text{Minimize } \sum_{t=1}^T (P_{EHC}^{new}(t) - P_{desired}(t))^2$$

where $P_{EHC}^{new}(t)$ and $P_{desired}(t)$ are the required and the desired power.

It is noteworthy that the power of the EHC is equal to the sum of the uncontrollable electric loads power and the thermal controllable loads (TCL) power (refrigerator, water heater and air conditioner AC) such that:

$$P_{EHC}^{new}(t) = P_{el}(t) + P_{tcl}(t)$$

$$P_{tcl}(t) = \begin{cases} N_{ac} * P_{ac}(t) & \text{if } B_{ac}(t) = 1 \\ N_{wh} * P_{wh}(t) & \text{if } B_{wh}(t) = 1 \\ N_{ref} * P_{ref}(t) & \text{else} \end{cases}$$

Whenever the AC is on, the AC power should be degraded. Moreover, in case the heater is on, its power should be reduced. Otherwise, the refrigerator temperature should be decreased.

Our goal consists to reduce EHC required power by lowering the power consumed by the thermal controllable loads used in EHC. More specifically, the TCL power can be reduced by peak clipping. It is noteworthy that the EHC is a FLP so that the electrical appliances can be controlled. Conversely, the medical clinic is a SLP with no control over its electrical load.

The optimization problem should be solved while fulfilling the following constraints.

a) *Photovoltaic system Constraints*

The limit of the produced power from the PV system, $P_{pv}(t)$, must be less than P_{pv}^{max} the maximum allowed PV power.

$$0 \leq P_{pv}(t) \leq P_{pv}^{max}$$

b) *Wind system Constraints*

$$0 \leq P_w(t) \leq P_w^{max}$$

The wind turbine power system produced power, $P_w(t)$, must be less than P_w^{max} , the maximum allowed WT power.

c) *Electric vehicles Constraints*

The permitted charging (resp. discharging) power is bounded by a maximum power. Moreover, the charging (resp. discharging) are prohibited when the vehicle is not available (i.e. time exceeds stay time T_{stay}):

$$P_{EV}^{Ch}(t, j) \leq P_{Ev}^{Cmax}(j) \times W(t, j) \forall t \in T_{Stay}$$

$$P_{EV}^{Ch}(t, j) = 0 \quad \forall t \notin T_{Stay}$$

$$P_{EV}^{Dish}(t, j) \leq P_{Ev}^{Dmax}(j) \times X(t, j) \forall t \in T_{Stay}$$

$$P_{EV}^{Dish}(t, j) = 0 \quad \forall t \notin T_{Stay}$$

The battery is disallowed from simultaneously charging and discharging. This is guaranteed by the following equation since $W(t, j)$ and $X(t, j)$ are binary values:

$$W(t, j) + X(t, j) \leq 1$$

The electric battery state of charge is limited between the minimum SOC of the EV battery and the maximum value 1, to preserve the battery life, as expressed in the following equation:

$$SOC_{EV}^{min}(j) \leq SOC_{EV}(t, j) \leq 1$$

The following equations aim at reducing the number of charge cycles (resp. discharge cycles) by restricting the charging (resp. discharging) process to EVs that have a state of charge lower (resp. higher) than the required SOC [20]. By limiting charging and discharging cycles the battery life is maintained [21].

$$SOC_{EV}(t_{charge}, j) < SOC_{EV}^{required}(j)$$

$$SOC_{EV}(t_{leave}, j) \geq SOC_{EV}^{required}(j)$$

The maximum EV battery charge limit should be lower than the EV battery's nominal capacity such that:

$$\frac{P_{EV}^{Ch}(t, j) \times dt}{e_c} + (Nom_{EV}(j) \times SOC_{EV}(t - 1, j)) \leq Nom_{EV}(j)$$

3 Evaluation of Architecture Performance

This section tackles the performance of our architecture.

We conducted simulation batches to evaluate the performance parameters. The smart grid includes 7 EVs considered as power sources and loads. The EHC and medical clinic load-demand profiles are provided in Sect. 2.

Power sources parameters are given in Table 1 [20, 23, 24].

Performance is assessed by computing the following parameters: availability function, power sources, load sources, battery state of charge, temperature of thermal controlled loads and availability function as detailed in the following paragraph.

3.1 Availability function

The availability function reflects the state when the demand is not satisfied. In fact, we rely on the function computation in order to detect if the optimization problem solution respect the load balancing. The availability function is computed as follows [22].

$$Av = 1 - \frac{\Delta D}{D}$$

Table 1. Power source parameters

Parameters	Values	Unit
Photovoltaic system		
P_{pv}^{max}	15	Kw
ρ	19	%
A_{pv}	73	m^2
Wind turbine system		
P_w^{max}	21	Kw
P_r	15	Kw
u_c	3	m/s
u_r	10	m/s
u_f	50	m/s
Electric vehicles		
P_{EV}^{Cmax}	3.3	Kw
P_{EV}^{Dmax}	3.3	Kw
Nom_{EV}	24	KWh
e_c	95	%
e_d	95	%

$$\Delta D = \sum_1^T (P_{pv}(t) + P_w(t) + P_{use}(t) + \sum_j^{N_{EV}} P_{EV}^{Disch}(t, j) - P_L(t) - P_{Store}(t))$$

where A_v , D , ΔD , $PL(t)$ represent respectively the availability index, the early power demand, the demand not met and the total demand in time t . The availability function will be equal to 1 if the power provided exceeds or is equal to the demand. In contrast, the function will be larger than one if the demand power is not met.

It is to be noted that the fluctuation of the meteorological data may be the major cause of RES's inability to produce enough electricity. As a result, we use more EVs to supply the entire load.

3.2 Performance Results

Figure 5 illustrates the power of EHC consumer. One can notice that the power consumed by the EHC is reduced to the desired power between 1 am and 9 am. Nevertheless, restrictions prevent the power consumed by the EHC is prevented to reach the desired power between 18 and 23 pm. This is since the peak clipping is adopted in order to prioritize the clinic loads.

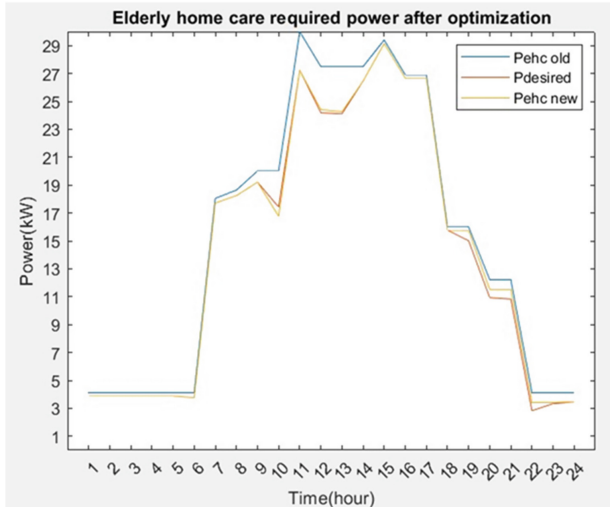


Fig. 5. EHC Power

Figure 6 illustrates the fluctuation of the power produced by the RES sources (WT and PV) system and the power consumed by the total load of the smart grid. The mentioned chart is of paramount importance since it sheds the light on the surplus (resp. lack) of produced power and on the balance between production and consumption; this will induce electrical vehicle charging/discharging.

Figure 7 exhibits the electrical vehicle charging. In case of power surplus, vehicles start to charge. The EV batteries stored power is the difference between the produced power and the loads powers. One can see that between 22 and 24 pm, vehicles are not charged due to the fact that the state of charge has reached the required SOC, therefore there is no need to charge EVs.

Figure 7 depicts the vehicle discharging. In case RES sources lack of power, vehicles batteries are discharged. It can be noticed that the charging and discharging processes do not take place simultaneously; this result corroborates the optimization limitations.

Figure 8 illustrates the variation of SOC of 4 EVs batteries. One can see that the SOC of batteries increases when the charging process begins and decreases when there is discharge. We may also notice that the EV battery starts charging when the state of charge of EV battery is lower than the required SOC.

Figure 9 exhibits the temperature fluctuation of the TCLs.

We observe that the water temperature rises when the heater is on and remains between the lowest and higher boundaries. At the instant the AC is on, the inside temperature drops and stabilizes between the lower and higher bound when the AC is on. The refrigerator temperature is constantly on. In fact, we managed to maintain its temperature between the lower and upper bounds.

After solving the optimization problem, we compute the availability function to assess the load balancing between the consumption and production. We obtain the availability function equal to 1. This confirms that our objective is reached; that is the power produced by energy sources compensates to the energy consumed by loads.

To conclude:

- Applying peak clipping to flexible low profile loads enables to restore energy to strict low profile loads.
- The energy service differentiation between strict load profile and flexible load profile helps proving strict energy requirements of medical loads.
- The main benefit of vehicle to grid is to provide collaboration with energy producers and consider vehicles battery as an extension to the smart grid. We devote a special concern to batteries life time.
- The virtual power plant VPP plays an important role dedicated to energy distribution. Since the VPP has a global view of the smart grid, it manipulates meteorological data, loads demand profile and EV state of charge: these data are essential for energy balancing to two energy profiles: flexible and strict.

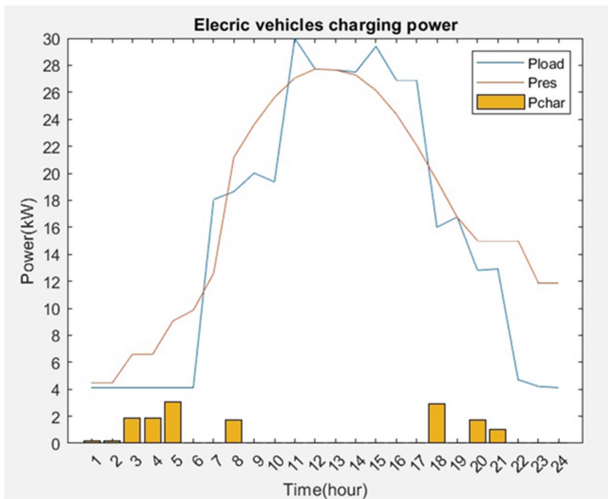


Fig. 6. Source, loads and vehicle charging power

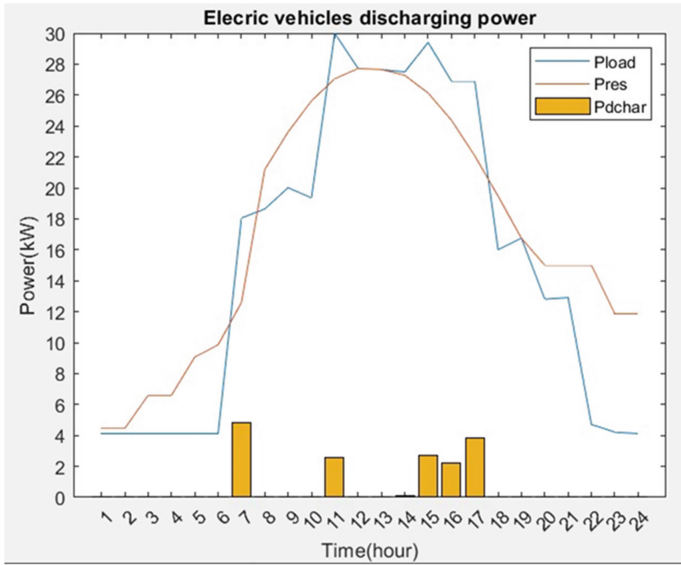


Fig. 7. Vehicle discharging power

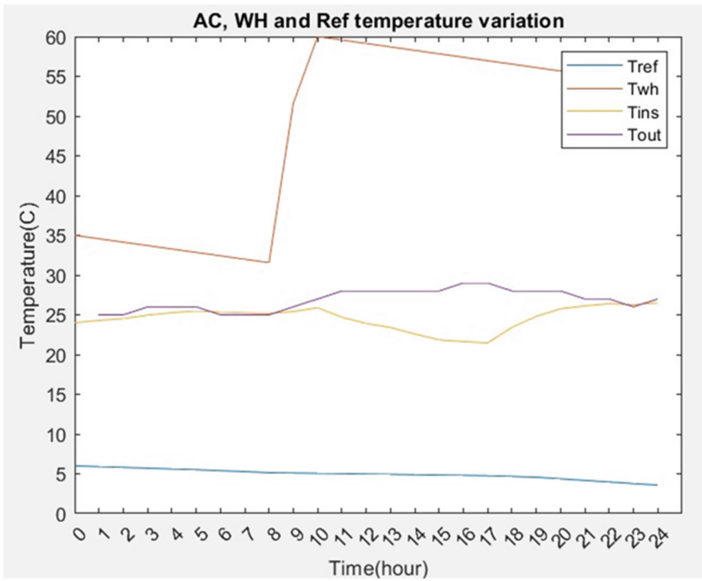


Fig. 8. Variation of Ac, Ref and Wh temperatures

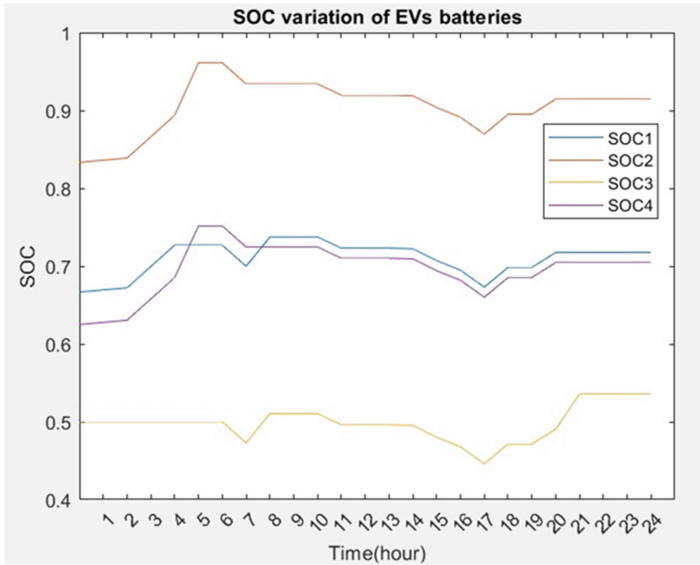


Fig. 9. Vehicle State of Charge

4 Conclusion

In the framework of a smart grid powered by SDN, the present research presents a contribution to the design of a feasible energy management architecture dedicated to different load profiles.

Our study provides important insights in the energy optimization and presents potential impact on the field, especially in the context of 6G's transformative role in energy management.

More specifically, we implemented an energy optimization algorithm at the level VPP. This algorithm performs energy differentiation among two loads profile: strict and flexible, while considering the energy constraints of intermittent RES and while meeting the loads energy demands. Moreover, we handled a fleet of vehicles that restore energy during inactivity periods. By solving energy optimization, we provided load balancing between power source and different types of loads.

Performance analysis show the result of the objective function, the charging-discharging processes of EVs, the variation of SOC of EVs batteries after charging or discharging and the variation of the temperature of TCLs after changing their consumed power. It is noteworthy that our approach lacks to predict energy consumption. Therefore, in our perspectives, we aim at implementing a machine learning algorithm that permits to predict power consumption and recommend flexible load profile consumer the most appropriate demand response program. Moreover, we envision to perform a thorough study on the data transmission energy consumption analysis and the computational expenses.

Statements and Declarations

Ethical Approval

No ethical approval is needed.

Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Authors' Contributions

All authors contributed to the study conception and design. Material preparation was performed by Asma Tannous. The manuscript was written by Rola Naja and all authors read and approved the final paper version.

Funding

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Availability of Data and Materials

The datasets generated during and/or analysed during the current study are not publicly available due to confidential reasons but are available from the corresponding author on reasonable request.

References

1. International Energy Agency IEA. World Energy Outlook, 2021. www.iea.org/weo
2. Patil, S., Deshmukh, S.R.: Development of control strategy to demonstrate load priority system for demand response program. In: 2019 IEEE International WIE Conference on Electrical and Computer Engineering (WIECON-ECE), pp. 1–6 (2019). <https://doi.org/10.1109/WIECON-ECE48653.2019.9019950>
3. Zhao, J., Hammad, E., Farraj, A., Kundur, D.: Network-aware QoS routing for smart grids using software defined networks. In: Leon-Garcia, A., et al. (eds.) Smart City 360°. SmartCity 360 SmartCity 360 2016 2015. LNICS, Social Informatics and Telecommunications Engineering, vol. 166, pp. 384–394. Springer, Cham (2016). https://doi.org/10.1007/978-3-319-33681-7_32
4. Dorsch, N., Kurtz, F., Girke, F., Wietfeld, C.: Enhanced fast failover for software-defined smart grid communication networks. In: IEEE Global Communications Conference (GLOBECOM), pp. 1–6, December 2016
5. Ghosh, U., Chatterjee, P., Shetty, S.: A security framework for SDN-enabled smart power grids. In: IEEE 37th International Conference on Distributed Computing Systems Workshops (ICDCSW), pp. 113–118, June 2017
6. Lin, H., et al.: Self-healing attack-resilient PMU network for power system operation. IEEE Trans. Smart Grid **9**(3), 1551–1565 (2018)
7. Mouawad, N., Naja, R., Tohmé, S.: Inter-slice handover management in a V2X slicing environment using bargaining games. Wirel. Netw. **26**(5), 3883–3903 (2020)
8. Bessem, S., Marco, G., Vasilis, F., Dirk von, H., Paul, A.: SDN for 5G mobile networks: norma perspective. In: Proceedings of the 11th International Conference on Cognitive Radio Oriented Wireless Networks, CROWNCOM, Grenoble, France (2016)

9. Ersue, M.: ETSI NFV management and orchestration-an overview. In: Proceedings of 88th IETF Meeting (2013)
10. Elayoubi, S., Maternia, M.: 5G-PPP use cases and performance evaluation modeling. 5G PPP white paper (2016)
11. Campolo, C., Molinaro, A., Iera, A., Menichella, F.: 5G network slicing for vehicle-to-everything services. *IEEE Wirel. Commun.* **24**(6), 38–45 (2017)
12. Campolo, C., Molinaro, A., Iera, A., Fontes, R.R., Rothenberg, C.E.: Towards 5G network slicing for the v2x ecosystem. In: Proceedings of the 4th IEEE Conference on Network Softwarization and Workshops (NetSoft), pp. 400–405 (2018)
13. Seremet, I., Causevic, S.: Benefits of using 5G network slicing to implement vehicle-to-everything (V2X) technology. In: Proceedings of the 18th International Symposium INFOTEHJAHORINA (INFOTEH), pp. 1–6 (2019)
14. Khan, H., Luoto, P., Bennis, M., Latva-aho, M.: On the application of network slicing for 5G-V2X. In: European Wireless 2018; 24th European Wireless Conference, VDE, pp. 1–6 (2018)
15. ADEME. Rapport sur L'effacement de consommation électrique en France. Evaluation du potentiel d'effacement par modulation de process dans l'industrie et le tertiaire en France métropolitaine, 2017
16. Strielkowski, W., Dvořák, M., Rovný, P., Tarkhanova, E.: 5G wireless networks in the future renewable energy systems. *Front. Energy Res.* **9** (2021). <https://doi.org/10.3389/fenrg.2021.714803>
17. Chekired, D.A., Khoukhi, L., Mouftah, H.T.: Decentralized cloud-SDN architecture in smart grid: a dynamic pricing model. *IEEE Trans. Ind. Inf.* **14**(3), 1220–1231 (2018)
18. Nafi, N.S., Ahmed, K., Datta, M., Gregory, M.A.: A novel software defined wireless sensor network based grid to vehicle load management system. In: 10th International Conference on Signal Processing and Communication Systems (ICSPCS), pp. 1–6, December 2016
19. Olatomiwa, L., Blanchard, R., Mekhilef, S., Akinyele, D.: Hybrid Renewable Energy Supply for Rural Healthcare Facilities: An Approach to Quality Healthcare Delivery, Loughborough University. Journal contribution (2018). <https://hdl.handle.net/2134/35194>
20. Melhem, F.: Optimization methods and energy management in smart grids, Thesis, Université Bourgogne Franche-Comté, 2018
21. Arango, J., Rajan Velayutha, H., Rohde, A., Denhof, D., Freitag, M.: Design and simulation of a control algorithm for peakload shaving using vehicle to grid technology, Controller design for vehicle to grid technology (2019). <https://doi.org/10.1007/s424520190999x>
22. Ullah, K., Hafeez, G., Khan, I., Jan, S., Javaid, N.: A multi-objective energy optimization in smart grid with high penetration of renewable energy sources
23. Wind turbine parameters. <https://www.windpowercn.com/new-15kw-wind-turbine.asp>
24. Solar systems parameters. <https://kenbrooksolar.com/system/25kw-solar-system-price#:~:text=About%2020kW%20Solar%20System,on%20average%20throughout%20the%20year>