

Article

On the Feasibility and Efficiency of Self-Powered Green Intelligent Highways

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Abstract: (1) Background: The present development of transport networks focusses on the better management of fuels and energy and the preservation of the environment. To fulfill these desiderates, some countries have already reconsidered the deployment plans of new highways. This research studies the feasibility of less polluting, quasi-self-powered, intelligent highway infrastructure functional blocks accommodating functions for the future introduction of smart wireless sensor grids and connected autonomous vehicles. Subject of investigation are the possibilities of energy harvesting, and the intelligent management of resources. (2) Methods: the research investigates the main technologies for energy harvesting and recommends an optimal solution. It also proposes a framework for the intelligent, AI-based management of energy and the use of an optimized backup solution relying on 5G beamforming for energy supply of the local wireless sensing network devices; (3) Results: recommendations are made for the best energy harvesting solution, an architecture of the energy management system, an algorithm for energy management and backup solution based on 5G beamforming; (4) Conclusions: the research emphasizes the advantages and drawbacks for different solutions regarding energy harvesting in an intelligent green highway scenario with a focus on the infrastructure developed to accommodate future connected and autonomous vehicles. The term “intelligent highway” must be understood in the automotive industry to describe a network of roads where cars communicate with the infrastructure and among themselves for the purpose of avoiding congestion and performing the seamless operation of services, and a space where cars and infrastructure cooperatively process information for obtaining better road safety, less pollution, and efficient energy management. With the recent recession of conventional fuel availability and the increase in prices, a solution to improving autonomy of both cars and infrastructure might be welcomed.

Keywords: energy harvesting; AI-based energy management; beamforming wireless charging; machine learning algorithm



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1. Introduction

Nowadays, road traffic is a major source of environmental pollution, both by infrastructure works and traffic-generated emissions. For example, in Canada, a very large main route for travelling in and out of Toronto is represented by Highway 401, a motorway that spreads to 12–14 lanes at its widest portions, accommodating more than 350,000 vehicles (mixed traffic) daily [1]. Most recent preoccupations concerning the impact of the transport infrastructure on the environment have been in focus worldwide and especially of decision factors in the main developed regions, such as Europe, North America, and Asia. Austria is a first example of a country that controversially revised its highway development projects to start a wider process of protecting the environment [2]. On the other hand, countries in Asia, such as India, started building the first stretch of a green highway under the Green National Highways Corridor Project (GNHCP) [3], which is expected to be completed by December 2021 in Rajasthan. Combined with an intelligent infrastructure, such a green

highway will be able to accommodate in the future mixed traffic of classic fuel powered and electrically powered vehicles, with a combination of non-autonomous and autonomous cars. Its future target is to interconnect these vehicles to obtain better traffic management, safer travel conditions, and a reduced amount of emissions and noise pollution. Combining all these with energy harvesting would profile a futuristic image of the best solution for the environmental protection via Intelligent Transport Systems (ITSs). Different researchers are engaged in a process of studying new possibilities for energy harvesting, to power-up smart grids of wireless sensors, and to improve the efficiency of the ITS infrastructure.

Green highways have also caught the attention of scientists and researchers, and scientific papers have also been written for this niche research. Jin Liu et al. presented in their work [4] the implementation of this concept in China. The work described developments and implementation of the first green highway concept in the province of Jiangxi. Along with the formulation of three standards in the field, the province also promoted the development of green/renewable energy using photovoltaic energy, ecological materials, and recycling of waste materials.

The present paper has the objective to assess the most employed technologies for energy harvesting in a highway scenario (with emphasis on interurban highways) and to determine whether they are suitable for designing a self-powered data collection and energy distribution system. The role of the system is to provide information regarding traffic and environmental conditions, and to provide signaling and powering IoT-enabled sensors, drastically reducing the impact of the highway on the environment. An AI-based solution is suggested for the management of the processes involved in the energy distribution between harvesters and consumers. The paper is organized as follows: The next section presents an extensive overview of several energy harvesting technologies, with emphasis on their efficiency and applicability in the highway scenario. Additionally, storage and balance are analyzed, and a specific architecture is designed to produce the best management of the harvested energy. The next section is dedicated to loads profiling, clustering, and intelligent management based on specific algorithms. As a backup solution in case of low harvesting results, a solution for beamforming is proposed for compensating in periods of high energy consumption. In the final part of the article, a discussion clarifies specific aspects of the research and experimental results, and the conclusion section also presents future possible developments.

2. Literature Review

In the following, a literature review is presented on the most significant and recent works regarding technologies for energy harvesting, experiments, and new procedures and initiatives for improving the energy efficiency and environmental protection for road transportation and associated domains.

James M. Bryce [5] proposed a classification of the research and development activities concerning green highways in the U.S., issuing a set of recommendations including a definition of a path for research in the field, identification of key areas, development of a rating system, and development of standards for use in a green highway rating system. In the same direction, the authors in [6] delivered a review of the green highway-related literature from Asia and North America, addressing issues such as definitions of the domain, terminologies that cover green highway aspects, and rating systems, and also presenting key findings. The practical development of a green highway was carried out in Xinjiang, China, and was presented in [7]. This research analyzes the requirements for a network of sensors for the monitoring of the environmental conditions of a green highway. The work in [8] explored the usage of a V2G (Vehicle to Grid) solution for collecting information regarding the usage of a fleet of vehicles, energy/fuel consumption (for both fuel and electrical energy propelled vehicles) and using deep neural network (DNN) training for the data analysis.

Shifting intelligence from vehicles to road infrastructure, an innovative C-ITS solution was introduced in [9]. The purpose was to improve road safety via the integration of

sensors in the road infrastructure and using vehicle data and processing power to improve the management of the sensors grid.

Energy harvesting in highway scenarios is a relatively recent topic of research. The research in [10] focused on analyzing all available energy harvesting technologies, such as piezoelectric systems, thermoelectric systems, solar panels, and electromagnetic modules. The authors concluded that the most effective technology is the one produced by electromagnetic-based systems, with an average value of 15 W.

Marufa Yeasmin Mukta et al. explored the efforts of boosting the efficiency of lighting in green and normal highways in an IoT environment. A taxonomy was presented specifying the most efficient approaches for generating light for the highway environment [11].

The research in [12] introduced the novel integration of amorphous silicon photovoltaic cells and profiles with glass fiber reinforcements for multiple scenario applications, including green highway energy harvesting. Additionally, different photovoltaic cells were investigated in terms of efficiency, temperature coefficient, and efficacy of the panel, such as c-Si, a-Si, CIGS, and CdTe.

The authors in [13] performed a review of energy harvesting in airport environments, employing different technologies such as electromagnetic, piezoelectric, electrostatic (capacitive), thermoelectric, and solar.

In [14], Van Can Nguyen et al. delivered a study on the availability of renewable energy on a highway network located in Taiwan. A model was proposed for solar and wind power energy harvesting, along a specific region, but the developed model had a very large number of variables and data collected, so the runtime exceeded 90 min. The authors also assessed the optimization of the whole process of energy harvesting employing these two technologies, also taking into consideration the non-operational periods for maintenance at the electro-kinetic generators and the decreases in performance of solar panels.

A theoretical and experimental study for investigating the technologies and related parameters for piezoelectric energy harvesting in an environment of highways and smart roads was given in [15]. The researchers concluded that PZT (lead zirconate titanate) is one of the most employed materials in this kind of energy harvesting.

Ruben Del-Rio-Ruiz et al. [16] focused on developing a solution for energy harvesting in road transportation based on a PGEH (piezoelectric generator for energy harvesting) that had its natural resonance frequency adjusted in order to obtain the highest power spectral density. The approach was oriented towards powering IoT devices for different scenarios, such as airplanes, truck transportation in urban areas, and intercity railways. As the authors concluded, the research demonstrates that piezoelectric technology is capable of increasing the autonomy of IoT devices in applications where mechanical aperiodic vibration sources occur, such as air and road transportation.

Other authors performed a study on different designs, nonlinear methods, optimization techniques, and harvesting materials in PGEH technology to obtain the best efficiency from these types of energy harvesters [17].

A study on methodology was also performed to define and calculate the energy conversion efficiency of piezoelectric generators [18]. Different types of PGEHs (linear and non-linear) were tested under different conditions, such as at resonance and at non-resonance, in a single degree of freedom (SDOF) assumption. Based on their findings, the authors suggested evaluating efficiency only at resonance conditions.

The results of research on input acceleration and output power for a piezoelectric harvester device, trying to determine the upper limits of key parameters, are given in [19]. The authors developed a formula for the maximum power of a given harvester design that enables the maximum power over a wide range of excitation frequencies to be found.

Wind power density was also analyzed in a wind farm located in Rajasthan, India. The authors of this research [20] determined that variations of wind gusts may reach 500 W/m^2 , and during a year, three months are the most productive for wind power generation.

Another study [21] used different methodologies for vehicle on-board energy harvesting from shock absorbers. A methodology was introduced for comparing performances between different energy-generating shock absorbers.

Tae Dong Kim and Jin Ho Kim employed simulations to study the efficiency of vehicle suspension energy harvesters via a blades system installed on the suspensions of the vehicles. A resulting 60 W were obtained from a system consisting of blades ensemble, a shock absorber with a rotor and piston, a snap ring, and a bearing [22].

Urvesh Kabariya and Sagil James conducted a study on an energy-harvesting magnetorheological damper system in a parallel configuration intended for use in lightweight battery-operated automobiles [23]. The research integrated different subsystems of a vehicle in a system for energy harvesting.

Lincoln Bowen et al. conducted a study, modeling and manufacturing two types of rotational energy harvesting shock absorbers, one employing a ball-screw transmission and the other a cable transmission [24].

A study concentrated on the design of a wind powered turbine including blade design and calculations of input (wind) power and output (electric) power [25]. The conclusion of the authors was that the highest efficiency is situated around 30 percent of the incoming power.

Mudhafar Al-Saadi et al. presented research where different techniques for the management of harvested energy based on decentralized, centralized, multiagent, and intelligent control strategies were analyzed. The review provided a clear categorization and description for the different control strategies, methodologies, applications, and the essential strengths and weaknesses [26].

Tifenn Rault et al. conducted a survey on the same topic. This study referred to a wireless sensor network analyzed from the point of view of energy consumption and power management, taking into consideration the specific requirements of different types of applications [27].

Michal Prauzek et al. conducted an investigation on the related scientific literature on subjects such as energy harvesting sources, energy storage devices, and corresponding topologies of energy harvesting systems, mainly oriented towards studies published in the past 10 years. It also provided a review of state-of-the-art technologies [28].

Modern green highways that are equipped with a certain level of intelligence may also be empowered to perform higher levels of maintenance, resulting in redundant resources for supplying energy. In this direction, researchers have been oriented towards the new technology of beamforming. One possibility would be to employ specific antennas to power low-energy smart sensors. Mohamed Hassanien and Dirk Plettemeier proposed a design for a two-layer Rotman lens in their work [29] that may be employed in short-range communications and power distribution over radio waves. In the same area of interest, Mohammad Ranjbar Nikkhah et al. proposed another design for a Rotman lens antenna. Dielectric resonator array antenna design was the subject of this research, with the authors providing a new methodology for designing a Rotman lens based on E and H wall symmetrical planes. Due to the complexity of the calculations in the normal Rotman lens process, the new approach proposed by the authors of the research has the advantage of significantly reducing the processing time, as shown in [30].

It can be observed that the research is still in development in this domain, as demonstrated by several and diverse research works [31–41], and that the interest of modern countries is to further develop technologies associated with intelligent and green highways. The present work analyzes the main technologies for energy harvesting with the purpose of finding the best solutions for powering a grid of wireless sensors attached to an intelligent highway infrastructure with the aim of supporting information-connected and smart vehicles.

The rest of the paper is organized as follows: Section 3 presents the state-of-the-art in the field of energy harvesting technologies; Section 4 presents the materials and methods used for profiling a small grid for energy management; Section 5 presents the results; and finally the conclusions are presented in Section 6.

3. Main Contributions and Objectives

3.1. Analysis of Sensing Technologies for Energy Harvesting in a Highway Scenario

In this section, the focus is set on comparing the most employed technologies in terms of energy harvesting, with the emphasis on a highway scenario. Conditions include average vehicle traffic, mixed vehicle traffic, and non-urban (or peri-urban) environments. Several types of energy harvesting solutions are investigated and compared in order to select the most appropriate for building a semi- or completely autonomous green highway able to support IoT sensors and communications systems from the harvested energy.

3.2. Concerns and Investigations

The actual concerns of specialists regard greenhouse gas (GHG) emissions and overall increases in environmental temperatures, leading to significant changes of climate, with violent storms, tornadoes, extreme temperatures, and so on. Natural disaster intensity is also connected with this aspect. To significantly reduce the contribution of GHGs due to road traffic, several directions of action are taking place: the transition towards non-polluting electric vehicles and autonomous and connected vehicles; the transformation of infrastructure, building green highways; and additional regulatory measures. In this context, finding the optimal solutions for collecting green energy for infrastructure is an important topic of research. Highways and expressways have potential in this context. The present research investigates several possibilities to ensure recovery of a part of the energy that is usually transformed into heat, mechanical work, and emissions along a highway in order to power up networks of sensors and signaling equipment for increasing traffic safety, comfort, and improved environmental friendliness. We start by investigating the most appropriate technologies that are adequate for this purpose, with an emphasis on the advantages and disadvantages of each considering the conditions that such an installation involve and which we decide are the most economically applicable in the field. Then we propose a novel solution for the management of harvested energy in an IoT network of sensors scenario for a green highway.

3.3. Energy Harvesting

Energy harvesting is the most promising feature of future green highways. Along with constructive measures to reduce impacts on the environment, introducing networks of cooperative sensors and communication with intelligent vehicles could help to improve the protection and safety and to reduce the pollution caused by road traffic. There is a set of technologies that may be appropriate for this purpose that will be briefly analyzed in this research. Additionally, for the harvested energy, another challenge is to find appropriate solutions for storing it. Batteries, as common energy supply sources, are usually associated with some disadvantages, such as limited lifespan involving increased maintenance operations, the increases in size of the associated equipment, the environmental pollution created by producing and storing them, and the higher maintenance costs involved. Therefore, a better solution would probably be to consider both the reduced consumption of the equipment on the one hand, and the employment of non-polluting energy storage solutions, such as capacitors, on the other.

Usually, when discussing about energy harvesting in a highway scenario, the following types of green, renewable energy technologies are taken into consideration:

- Solar (in the entire world there are around 16 million km of sun-exposed road surfaces)—that energy could be used in the winter to melt snow accumulated on the carriageway, and car parks could use roof-installed solar panels to supply energy to charge electrical vehicles during their stay;
- Thermoelectric generators (TEGs)—based on the Seebeck effect (differences between the temperature on the road surface, compared to the layers beneath);
- Piezoelectric effect—used for harvesting energy from mechanical vibrations—either produced in soil by the vehicles or by the air pressure (noise that the vehicles generate);

- Electro-kinetic energy ramps—at the entrances of highway sections, or exits; mobile mechanical pedals, with a connecting rod–crank system to produce rotational force that drives an electric generator or a dynamo;
- Wind energy—produced by natural wind or by air currents generated by the passage of vehicles.

The different forms that we identified for producing green energy are illustrated in Figure 1. There is also a need to have an intelligent system for the efficient management of the harvested energy to optimize the process of energy consumption and efficiently allocate energy to consumers, such as IoT sensors, communication devices, and so on.

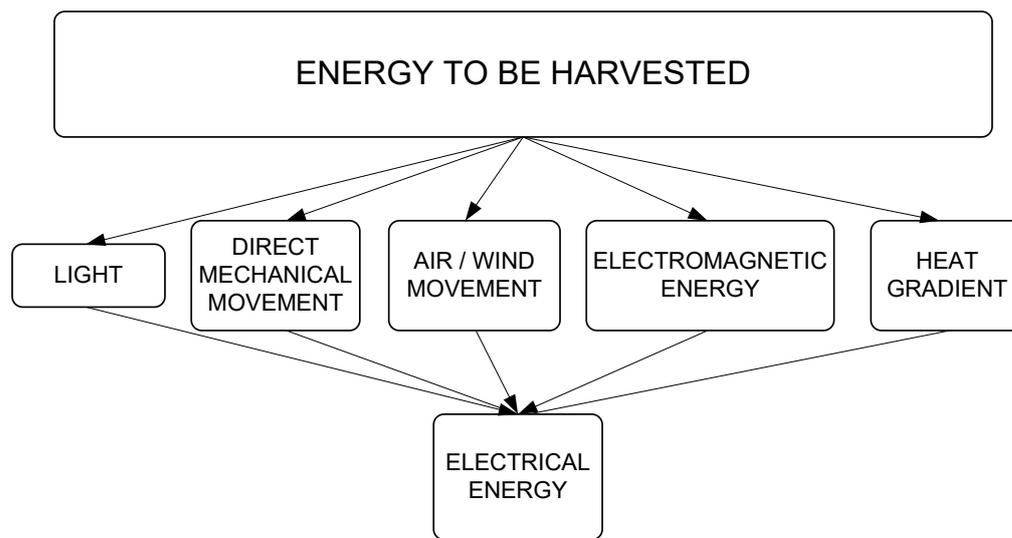


Figure 1. Forms of harvesting energy to be taken into consideration on a green highway.

3.4. Analysis of Solar Cell Energy Harvesting (SCEH)

Silicon-based solar cells or panels are easy to produce on a large industrial scale and to employ for SCEH. While quite unpredictable, solar energy can, however, be estimated via temporal patterns. Most common types of solar cells can be classified as follows:

- Si-based monocrystalline—around 20% efficiency: a drawback is that the fabrication process consumes a lot of energy (thick layer technology);
- Si-based polycrystalline—around 16% efficiency: it has a less energy consuming production process and a good cost/performance ratio (thick layer technology);
- Amorphous silicon—5 to 7% efficiency: largest market sector production (thin layer technology);
- (Micro) crystalline silicon technology—7 to 10% efficiency;
- GaAs (GaInP/GaAs, GaAs/Ge), solar cells made based on group III–IV elements—the greatest efficiency is around 29%: they are expensive in terms of production costs, and it is difficult to find raw materials for large-scale fabrication; they are used especially in space technology due to their robustness to extreme temperatures.

As stated in international regulations, the nominal operating cell temperature, or NOCT, represents a performance parameter that is to be taken into consideration when analyzing the efficiency of a solar panel for a certain application. However, there are many natural factors that should be taken into consideration when the solar panel is designated to be installed near a highway: latitude, angular variation of light source according to the position of the solar panel, average yearly solar radiation, average weather conditions including precipitation, wind direction, and gusts, etc. If the solar panel is to be produced from silicon, then temperature might play a significant role in its efficiency. Besides for NOCT, another parameter must be taken into consideration: the maximum power temperature coefficient, or the temperature coefficient of P_{max} . The NOCT represents a temperature that the panel reaches when exposed to 800 W/m^2 of irradiance (a normal

sunny day, with moderate solar radiation) at the ambient temperature of 20 °C. The temperature coefficient of P_{max} is the percentage of energy a solar panel loses for every degree Celsius that the panel exceeds the STC temperature of 25 °C.

Calculation of a solar panel's efficiency may be based on the following formula:

$$E_{sp} = \frac{100 P_{max}}{S_{AA} \cdot STC} \quad (1)$$

where:

- E_{sp} —efficiency of the solar panel (%);
- P_{max} —peak power of the solar panel (W);
- S_{AA} —active area of the solar panel surface (m^2); $S_{AA} = L_{AA}(m) \cdot W_{AA}(m)$, with L_{AA} meaning the length of the active area, and W_{AA} the width of it;
- STC —standard test conditions— $STC = 1000 \text{ W/m}^2$.

Another way to determine the more exact efficiency of the solar panel is to consider the real fraction of incident power that is converted to electricity, taking into account reflections, incident angle, and other factors such as ambient temperature. For a more efficient setup, additional reflectors to direct the sunlight towards the solar panels might be recommended for a highway scenario. A simplified version of the formula used in this case could be as follows:

$$P_{max} = V_{OC} I_{SC} \psi_F, \quad (2)$$

where:

- P_{max} —maximum delivered power in real exploitation conditions, (W);
- V_{OC} —open-circuit max voltage of the solar panel (V);
- I_{SC} —short-circuit max current intensity delivered by the solar panel (A);
- ψ_F —a form/fill factor that depends on the light incidence angle, $\psi_F = \frac{P_{max_{SP}}}{V_{OC} I_{SC}}$, with $P_{max_{SP}}$ being the maximum power that can be obtained from the solar panel in real conditions, and

$$E_{SP} = \frac{V_{OC} I_{SC} \psi_F}{P_i}, \quad (3)$$

where P_i represents the total incident (light) power. Usually, the most typical value of power density that must be considered in the design of energy harvesting for different functional components is around 15 mW/cm^2 . Later in this paper, an experiment with different light incidence angles is presented.

3.5. Analysis of Thermoelectric Generator Usage for Energy Harvesting (TGEH)

A thermoelectric generator (TEG) is a device able to convert a temperature gradient (flux) into electrical energy based on the Seebeck effect. The thermoelectric effect is produced by a temperature gradient in a conducting (solid) material, leading to the release of a charge carrier in the same way as it happens in semiconductors or in processes in electronic vacuum tube cathodes. Usually, materials used for TEG must experience good electrical and heat conductivity. Examples of the best industrial materials include bismuth telluride (Bi_2Te_3), lead telluride (PbTe), and silicon germanium (SiGe). Because the composition contains rare compounds, these products are rather expensive for mass production. Moreover, the efficiency of these types of electric energy generators is not very attractive, being lower than that of heat engines. Typical usage of these is in thermoelectric powerplants to reduce heat waste by recovering a part of it in electrical energy, or in cars engines, such as automotive thermoelectric generators (ATGs), to provide auxiliary energy for different loads and onboard equipment, recovering a part of the consumed fuel in usable electrical energy. Amongst the advantages we can mention, they have good durability and resistance to environmentally difficult conditions; therefore, some of their applications may also be found in space and aeronautics industries.

The Seebeck coefficient of a typical material is defined by the ratio between the voltage and the temperature gradients:

$$S = -\frac{\Delta V}{\Delta T} \quad (4)$$

or it can be defined by the density of the current in the Seebeck material:

$$J = -\sigma \nabla V - \sigma S \nabla T \quad (\text{A/mm}^2). \quad (5)$$

where $\sigma = \frac{1}{\rho}$ represents the electrical conductivity of the material [Ωm], and $\nabla V = \frac{dV}{dx}$ and $\nabla T = \frac{dT}{dx}$ the gradients of voltage and temperature, respectively. Materials with higher positive Seebeck coefficient values include selenium (900), tellurium (500), silicon (440), germanium (330), and more.

A practical formula for computing the generated voltage given by an N group of thermocouples is [28]:

$$V = N \cdot \Delta T (2 \cdot 10^{-4} \cdot 1.004^{\Delta T}), \quad (6)$$

where N represents the total number of thermoelectric elements, $\Delta T = T_{max} - T_{min}$, and T_{max} represents in fact the temperature of the hottest point where the thermocouples are connected, and T_{min} the corresponding coldest point. The maximum electrical power delivered by a TEG is obtained when the load resistance equals the equivalent internal resistance of the thermoelectric couples in series ($R_L = R$). Considering n thermocouples (thermoelectric generators) connected in series, the resulting maximum power will become:

$$P_{max} = n \cdot \frac{(S\Delta T)^2}{4R}. \quad (7)$$

The efficiency of a TEG is given by the ratio between the electric output power and the rate of heat $\frac{dQ_h}{dt}$ at the input, when the TEG is connected between a cold and a hot thermal source:

$$E_{TEG} = \frac{P_L}{\frac{dQ_h}{dt}} \quad (8)$$

For characterizing the thermoelectric materials, a figure of merit is employed, meaning a quantity to describe the performance of the finite device in relationship with alternatives:

$$Z\bar{T} = \frac{S^2\sigma}{\lambda}\bar{T}, \quad (9)$$

$$\lambda = \alpha \cdot C_p \cdot d \quad (10)$$

where:

- σ —electric conductivity (S/m);
- λ —thermal conductivity (W/mK);
- α —thermal diffusivity (mm^2/s);
- \bar{T} —mean temperature (K);
- C_p —specific heat of the material (J/kgK);
- d —density of the material (g/cm^3).

There is a quite smooth linearity of the TEG efficiency with respect to the rise of temperature. The maximum efficiency of such an energy harvester depends on the temperature difference between the hot and cold layers. Thus, in the case of using such a technology for recovering a small part of the heat difference between the upper (hotter) layer of a highway (considered on a sunny summer day) and the lower (colder) layers, in electric form, the requirements include the following for maximized efficiency:

- The material of the TEG should have a very low electric resistivity.
- The material of the TEG should have a Seebeck coefficient as high as possible.

- Thermal conductivity should be at the minimum possible.
- The difference between the hot and the cold layers should be the maximum possible.

Of course, for specific energy harvesting in highway scenarios [10], it is possible to design other forms of TEG solutions, such as special panels oriented to the predominant region of the sky where the sun lies (usually south), inserted in a mirror concentrated beam, in order to convert more heat into electric energy, similar to solar plants. Shown in Table 1 are the required values of power, by different types of applications, and in Table 2 the recorded temperatures in asphalt for lower latitude regions [31].

Table 1. Power requirements of different applications related to highway scenario energy harvesting.

Crt. No.	Type of Application	Average Power Requirements	Observations
1	Very low power applications	1 μ W to 10 μ W	Not applicable to highway harvesting for this solution
2	Biomedical sensing and related applications	10 μ W to 1 mW	Not applicable to highway harvesting for this solution
3	Wireless sensor networks, small signal applications	1 mW to 10 mW	For local energy supplying of low energy sensor system
4	Signaling, low energy local signal processing	100 mW to 100 W	For local energy supplying of small signaling systems
5	Signaling, communications, average energy signal processing and distribution	100 W to 1 kW	For larger systems involving networking of IoT equipment

Table 2. Recorded measurements for an application with TEG in the road surface (source: [31]).

Road Surface Temperature T_{\max} ($^{\circ}$ C)	Underground Soil Temperature T_{\min} ($^{\circ}$ C)	Electric Power Generated (mW)
40	29	4
45	30	5
50	31	11
55	32	13

Usually, the energetic efficiency of TEGs is between 8% and 15% [32,33], so their applications in the infrastructure might be limited for highway scenarios [31], except perhaps specific situations where there are dedicated structures to collect supplementary energy from heat-generating processes, or small solar plants containing both solar cells and TEGs. However, there is more to deal with in terms of these transducers on mobile platforms, as the vehicles have more heated parts that can be employed to recover a certain amount of the energy generated by the fuel, which would be otherwise lost by dissipation, with negative effects on the environment. Experiments and field tests [31] demonstrated that a 0.7×0.7 (approximately) mm thermal system can usually collect around 10 mW on a permanent basis over an eight-hour period.

3.6. Analysis of Piezoelectric Generators for Energy Harvesting (PGEH)

There is a possibility to recover a part of the lost mechanical work produced by the passage of vehicles on a highway in its mechanical form: vibration, kinetic energy, or deformation of a specific material. Of course, in cases in which such technology is to be installed on a highway for energy harvesting purposes, the loss of energy produced to vehicles must be taken into consideration by creating supplementary resistance to movement; therefore, we recommend installing these devices only where potential energy helps the vehicles, such as on descending slopes or in similar situations. These solutions are presently investigated

for industrial-scale production and applications in the transport sector. They are promising renewable energy sources, especially for wireless sensor networks, small communication devices, or similar applications. In this section, only the PGEH solution based on the direct piezoelectric effect is analyzed. Usually, PGEHs for highway energy harvesting are required to operate at a much lower frequency than their resonance frequency in the form of irregular mechanical pulses produced when axles of vehicles overpass the sensing portion of the carriageway. Considering the mechanical measures S_s for stress and S_t for strain, and the electrical measures for charge density D and electrical field E , the following relationship applies:

$$\begin{bmatrix} S_s \\ D \end{bmatrix} = \begin{bmatrix} s^E & d^t \\ d & \epsilon^T \end{bmatrix} \begin{bmatrix} S_t \\ E \end{bmatrix}, \quad (11)$$

where d and d^t are normal, and the transposed matrices are for direct and converse piezoelectric effects, ϵ^T represents the dielectric permittivity of the material, and s^E represents the dependence under an electrical field E . Then, the total converted energy, W , on a piezoelectric element of dimensions $A \times t$ (area and thickness) is given by:

$$W = \frac{QV}{2} = \frac{dg\sigma^2V}{2}, \quad (12)$$

where Q is the accumulated electric charge, V is the voltage on the piezoelectric element, and d and g are, respectively, the current and the voltage constants corresponding to the operational mode.

The PGEHs can be combined in different structures with other types of energy harvesters, mainly with those based on electromagnetic field and mechanical movements. However, it is very difficult to conduct a pertinent performance analysis on the efficiency of PGEHs, especially when combined structures as those described above are employed. Different materials, structures, working conditions, temperatures, loads, stresses, and other factors may increase the degree of difficulty in choosing the most appropriate solution for PGEH in a highway scenario. Still, one of the most used metric for energy harvesters is the power density, P_D , defined by:

$$P_D = \frac{P_o}{V} \left[\frac{W}{m^3} \right], \quad (13)$$

where P_o represents the useful obtained power at the output of the PGEH, and V represents the volume. Additionally, the efficiency of the PGEH process may be defined by:

$$\eta_{PGEH} = \frac{P_o}{P_M}, \quad (14)$$

with P_o meaning the useful electrical power and P_M the consumed (mechanical) power, which is triggered when the vehicle passes over the sensitive area. Consequently, in a highway scenario, the PGEH will work under a pulsatory regime, and the total accumulated energy W_A will be:

$$W_A = \sum_{i=1}^n P_o \cdot t_i, \quad (15)$$

with t_i representing the time periods where a vehicle wheel applies deformative force on the PGEH sensitive surface. Usually [34], for PGEHs, the power density ($\text{mW} \cdot \text{cm}^{-3}$) can take values comprised between 0.2 and over 5×10^3 , depending on the materials used for producing the PGEH, with instantaneous power between microwatts and milliwatts. Other automotive applications, mostly related to safety, include tire pressure monitoring, and an increasing number of sensors are currently included in vehicles with the transition to autonomous driving. A difficulty that arises with this is the cabling in the vehicle, as physical cabling involves more and more paths for electrical connections, surpassing currently more than 4 km. These also create additional weight, industrial effort, consumption of non-ecological materials, and so on. Thus, the request of mobile energy harvesting may appear also as an interesting option, especially for vehicles equipped with wireless sensor

networking. Tire pressure monitoring systems (TPMSs) may, in this case, also be used for mobile energy harvesting.

3.7. Analysis of Electrokinetic Generators for Energy Harvesting (EGEH)

Usage of a vehicle's displacement for producing harvested energy usually involves supplementary mechanicals and/or hydraulics for converting movement and/or weight into linear reciprocal, or rotary motions to drive electrical energy generators. This possibly complicates the infrastructure of roads, and probably this solution would not be applicable on long distances, but instead on access ramps, where limitations of speed (including road bumps) may be present, or as mentioned above, on descending slopes of the roads, where vehicles are helped by potential energy and do not lose supplementary fuel to overcome the effort of moving small devices in the road surface. In such a way, instead of a fixed bumper aimed at reducing the speed of vehicles in special road sections, these bumpers could be equipped with a connecting rod crank coupled with a generator and a solution for energy storage.

Another solution that may be applied on long highway sections could involve, furthermore, wind generators. These could be driven either by natural winds in the region or by the air currents that the vehicles produce by their normal displacement. In either case, there are involved electro-mechanical devices for which reliability and cost-efficiency are to be studied in the highway scenario. However, in order to improve the efficiency of such an energy harvester solution, it should be combined also with other technologies to realize efficient cooperative work. In theory, the maximum power a wind turbine can generate is restricted by the conservation of mass and Bet's law:

$$P_{max_{WG}} = \frac{16}{27} \frac{1}{2} \rho V^3 R_A, \quad (16)$$

where ρ is the air density, V the wind speed, and R_A the rotor area.

A practical wind turbine power is given by [22]:

$$P_{WG} = 0.5 \rho \cdot C_p \cdot R_A \cdot \eta_{Gn} \cdot \eta_{Gb} \cdot V^3, \quad (17)$$

where C_p represents the efficiency of the wind generator rotor, η_{Gn} the efficiency of the generator section, and η_{Gb} the efficiency of the gear box. The power output of a wind generator thus directly depends on the area swept by the rotor and the wind speed raised at the cube. The power density of a wind generator may be estimated by [32]:

$$PD_{EGEH} = \frac{\rho c^3 \Gamma \left(1 + \frac{3}{k}\right)}{2}, \quad (18)$$

where ρ —air density, c —scale parameter, k —form factor, $\Gamma = \int_0^\infty e^{-t} \cdot t^{x-1} dt$ depending on the wind intensity, t —duration of wind, and x —intensity.

Usually, wind generators have an efficiency comprised between 10% and 45%, depending on construction and design. However, harvesting energy from wind-powered equipment needs a thorough analysis on site.

3.8. Powering IoT highway Sensors via Purposeful Transmission of Energy Based on RF Sources

The energy management system of an intelligent road must manage the balance between generated and consumed energies. When the harvested energy is not sufficient for powering different functional components, another solution could be to remotely power small detection/communication devices via RFEHs (radio frequency energy harvesters). This solution may be used in a modern approach, as the development of 5G and next generations of mobile telecommunication networks comes with the possibility of purposely transmitting a beam of radio waves with the goal of remotely energizing small automation devices. Along with this feature, there is also the possibility of harvesting the locally available RF energy of radio waves between 3 kHz and 300 GHz, with an efficiency ranging

from 0.4 to 0.8 from the received energy. Compared to solar energy harvesters, RFEHs are able to produce energy even in darkness or indoor environments.

The Rotman lens has some advantages over other, similar RFEHs: [29] true-time delay, cost effectiveness, wide bandwidth characteristics, large integration possibilities, and simple mechanical structures (can be built in several layered structures). The reflection coefficients of the original Rotman lens are given by:

$$S(k, k) = \frac{S_m(k, k) + S_e(k, k)}{2}, \quad (19)$$

where S_m and S_e are the S-parameters in the case of using the half structure with a magnetic wall and electric wall, respectively [30]. S-parameters are usually defined for a given frequency and system impedance and vary as a function of frequency for any non-ideal network, so a specific antenna for RFEH will be best only around a central frequency band.

A structure is proposed that is composed of a dedicated RF harvesting antenna/antennae array able to use both EM energy from the environment and purposely directed RF energy from a 5G base station. In this way, the local data hub could be capable of total energetic autonomy, as presented in Figure 2.

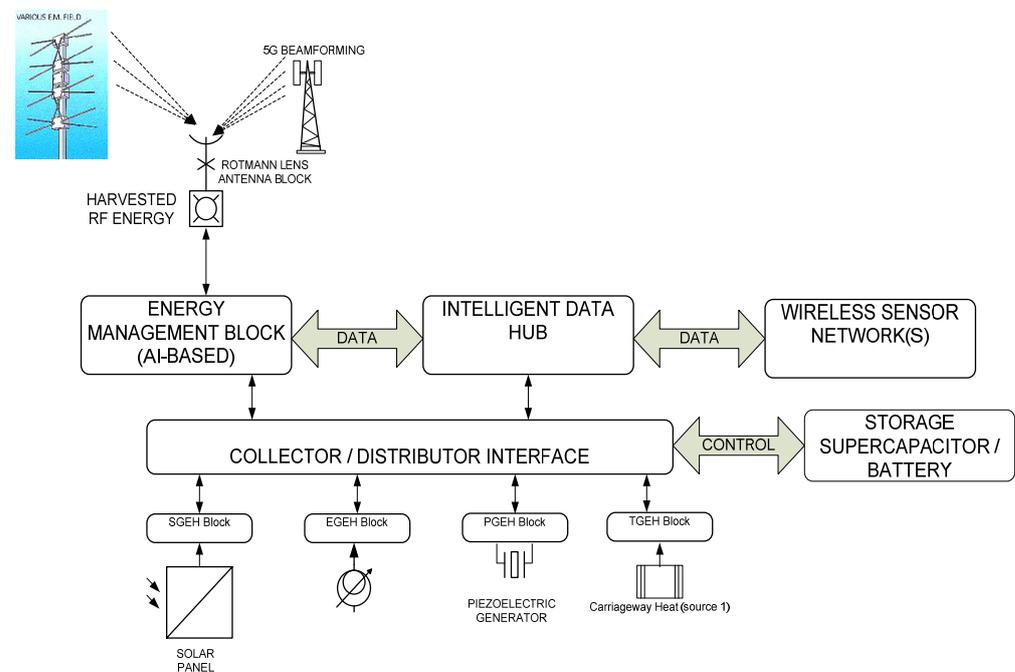


Figure 2. Possible usage of 5G-based RFEH with a dedicated Rotman lens antenna.

The core of the energy management is represented by the AI-based EMB (energy management block), which is able to take control of all energy flowing in this architecture:

- Management of stored energy in the storing solution (supercapacitor or battery bank).
- Responsible for maintaining an efficient harvested/consumed energy ratio.
- Control and switching of harvesting section—SGEH, EGEH, PGEH, and TGEH (not all of them need to be present).
- Able to communicate with a dedicated service to offer beamforming energy supply when the stored energy becomes insufficient to power all modules.
- Responsible for the selection of the best performing energy harvester based on an AI learning algorithm.

The IDH (intelligent data hub) is the core of information collection, processing, and distribution in a wireless sensor network (WSN) scenario. It may be used in a cooperative way with EMB. The storage solution must be efficient, with a very low self-discharging

process and able to support temperature variations according to location. These are difficult, and maybe contradictory requirements, so research in this area is still ongoing.

3.9. Energy Storage Architecture for Intelligent Green Highways

The problem of harvesting energy from different sources spread along a highway is not the only challenge for which the research in this field must find adequate solutions. There is also the need for a means for profitably and economically storing the harvested energy. Usually, the most common solutions for this activity include rechargeable batteries, but again, there is a conflict between the materials used for producing these batteries and the environment. A green highway should make use only of ecological materials, or at least reduce to the minimum possible the impact of dangerous or environmentally unfriendly materials for producing and installing energy storage devices along the highway. Nickel–metal rechargeable batteries have a capacity three times larger than that of the nickel–sodium ones. With a good energy/weight, the Li-ion and Li-ion polymer batteries are today's most common energy storage devices. They present a high specific working voltage, high energy storage capabilities, high specific power, sufficiently long life-cycle, and also an adequately low self-discharge rate (around 2% per month) and therefore are suitable in many mobile or remote-located applications for the supplying of energy. A smarter, autonomous, and decentralized system operating mostly on renewable energy is recommended for a green, intelligent highway. However, finding the optimal solution for storing the harvested energy is not a simple task. Additionally, controlling a distributed energy infrastructure requires a dedicated power management system, or an ESS (energy storage sub-system). Therefore, building an intelligent highway automation infrastructure involves the following:

- Wireless sensing sub-system (WSS)—Microgrids of different (wireless) sensors.
- Energy harvesting sub-system (EHS)—integrated, harmonized solution of different energy harvesting devices, contributing to optimal harvesting of green energy.
- Autonomous communication bus (ACS)—a means for self-energy supplying communication subsystem, transmitting data between different functional components of the intelligent green highway.
- Energy storage sub-system (ESS)—an energy decentralized-management sub-system designated to control the amount of collected energy, synchronization, reconfiguration, and optimal power consumption distribution. Usually, voltage drop control is an important feature of an ESS, and its main task is the provision of balanced load sharing between the available energy sources. Recently, AI-enhanced droop control, or state-of-charge (SOC) droop control, or virtual impedance (VImp) droop control have arisen as techniques aimed to improve the management of energy also for smart highways. The complete functional architecture of the highway intelligent power management system is presented in Figure 3.

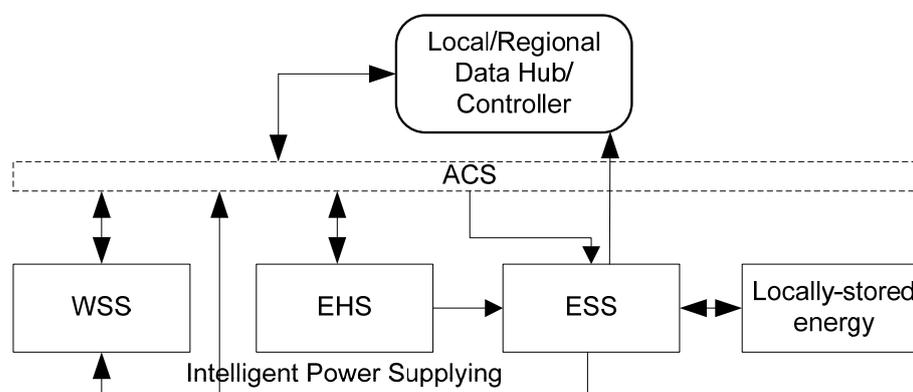


Figure 3. The functional architecture of the AI-based local management of harvested energy.

The EHS functional module is responsible for the integrated and harmonized collection of energy from the different technologies installed in the highway environment. The ESS then manages the charging process, continuously monitoring SOC, charging current and voltage. Additionally, ESS is responsible for the consumption monitoring in WSS and ACS, allowing for dynamic distribution of energy according to different power needs of these components. Solutions for locally stored energy may include but are not limited to:

- Classic rechargeable batteries—actually, an industrially-economical solution assumes usage of Li-ion, or Li-ion polymer solutions.
- Capacitive rechargeable devices—capacitors able to accumulate energy without compromising the environment due to usage of environment-friendly materials.
- Compressed air/rotative generators—compressed air may be produced by the wheels of vehicles, running on specific surfaces and creating mechanical forces to produce air compression via specific valves. Then, compressed air may be used for producing rotational force to a helix, mechanically coupled to an electric generator. While it still comprises numerous mechanical parts, the solution could be used at ramps for speed limitation, at the entrances/exits of highways, or in specific service areas.
- Inertial energy storage—similar as above, but the weight of a vehicle's wheel is used via a crank mechanism to store the energy in a kinetic format (a flywheel coupled to an energy rotative generator). Additionally, it can be used for wind-powered energy harvesting solutions.

In the same direction, the local/regional data hub/controller (DHC) could be made responsible for the connected management between different segments of a highway, allowing for harvested energy sharing, in situations where such a strategy might be imposed. The work regimes for DHC might be:

- Local (aggregated) management;
- Shared (distributed) regional management;
- Highway-level (global) management;
- Hybrid strategy—where a combination of the above solutions is chosen.

The adopted harvested energy storage solution is very important for the longevity and maintenance of the intelligent green highway. One principal objective of this is to ensure enough energy for the operating devices without excessive maintenance and for the long term. According to [34], the required harvested energy can be either obtained by converting physical forms of energy from the environment or by receiving purposely emitted energy with the goal of collecting it using a specific application (via RF beam forming, for example).

3.10. Energy Balance Analysis for the Green Highway Scenario

The present appliances in industry require a power density that ranges from 20 W/m² to 100 W/m², for intelligent homes, to 300 W/m² to 900 W/m² for energy-intensive industries. Different energy harvesters may provide variable energy amounts, ranging from μW/m² to W/m². According to [28] and other authors, the following values are typical for such sources:

- SCEH: 15–50 mW/cm² [28];
- TGEH: 15–80 μW/cm² [28];
- PGEH: 5–15 μW/cm³ [36];
- EGEH:
 - Wind: 500 mW/cm²–5 W/cm² [35] for large wind generators;
 - Pedal: N/A—depending on the mechanism employed, traffic flowing. An approximative formula could be:

$$PD_p = \frac{\Delta P}{S} = \frac{\eta c G v}{S}, \quad (20)$$

where η —efficiency of the mechanism employed at the pedal-crank system, c —form factor, G —weight of the vehicle per axle, v —the speed of the rotating generator scheme, S —surface of active area.

According to our research, current power consumption of different IoT solutions, present on today's market, may vary between the limits shown in Table 3.

Table 3. Usual power consumption values for IoT sensors.

Sensor Type	IoT Technology	Average Energy Consumption/Battery Life Span (If Supplied)
Temperature and humidity EM300TH	LoRa WAN	0.45 mWh 5/10 years 4000/8000 mAh Li-SOCl ₂
CO ₂ Monitoring EM 500CO ₂	LoRa WAN	1.08 mWh 10 years 19,000 mAh Li-SOCl ₂
Distance/snow level sensor EM500 UDL	LoRa WAN	1.08 mWh 10 years 19,000 mAh Li-SOCl ₂
Hall magnetic sensor (IC) QFN-O601	N/A	2.4 ÷ 5.5 V@ 8 μ A
NB-IoT system in package nRF9160	LTE M/NB-IoT	LTE-M: 2.7 ÷ 6 μ A NB-IoT: 2.7 ÷ 9 μ A @ 3.0 ÷ 5.5 V Avg 16 μ Wh
Temperature and humidity WSDCGQ11LM	ZigBee	Avg 0.8 mWh 2 years

Additionally, there are some IoT sensor manufacturers that already have introduced new solutions for power supply management during the transportation phase in order to preserve the energy for battery-powered IoT sensors based on a Li primary battery, 3.0 V, of manganese dioxide type/3.6 V/Thionyl chloride type.

Compared to traditional carbon-based fuel-obtained energy, the cost of the solar energy is significantly high. In fact, probably the main reason that harvesting solutions succeed so rarely in practice is because of the higher initial/exploitation costs, compared with using the national network power supply. According to scientific literature, on average, a ton of coal delivers approximately 6182 kWh of equivalent electric energy at a cost of about €27.1 per short ton (934 kg). The consumed coal expenses will rise only to less than €0.0075 per kWh. Similarly, a barrel of oil at €52.7/barrel gives 1700 kWh for a cost of around €0.038 per kWh. Initially, the equivalent solar energy would have cost around seven times more, but recent advances in technology and interest in benefiting from this source of energy have produced smaller costs, presently situated somewhere around €6500 per kW. These represent, still, high prices and therefore are making very attractive this type of energy for large applications. Most of the actual solutions for solar energy have an efficiency of around 15% without specific procedures of light concentration.

The thermal energy harvesters may produce electric energy with more efficiency when there is a greater gradient between the cold and the hot surface; e.g., for a gradient of 500 °C, a typical TGEH may reach around 1.8 W/cm². However, employing such solutions in road transportation seems to be inefficient, mainly because the difference between the hot (surface) and the cold one of the TGEH is never as high. Thus, from this point of view, other solutions are recommendable.

In what concerns the EGEHs, there is a remarkable efficiency of the dynamo part, but the contribution of the mechanical part that delivers the energy from the passage of a vehicle over the pedal should also be considered, as it also decreases, due to friction, the overall efficiency. Moreover, there is also the complicated maintenance of such a system, which makes it relatively unattractive for practical use. Therefore, the solution of harvesting

energy from the weight of vehicles is not efficient in practice. However, the EGEH solution based on wind generators may be.

Piezoelectric devices producing energy (PREGs) appear to be more efficient in terms of exploitation costs from this point of view. The usual efficiency of such a material (fabricated PEH) is about 6–12%, approaching it from that of the solar panels.

Taking into account the above figures, it can be concluded that the most suitable solutions for implementation in a highway environment would be solar panels, wind generators, and piezoelectric generators.

4. Materials and Methods

4.1. Building an Electric Load Profile

General assumptions: the loads in the nodes of the electrical Intelligent Data Hub vary depending on the time and place of consumption. Therefore, operators' distributions (ODs), or the highway energy management system needs information on the load of fed consumers in order to plan and operate the network optimally, adopt optimal power supply, operation solutions, and manage loads. The tasks required by consumers depend on several factors, including:

- Type of consumer: type of consumption, with/without temperature conditioning.
- Energy consumption profile according to date and time: time of day, day of the week, month of the year.
- Elements of interest that may depend on climatic and environment factors: temperature, humidity, cloudiness, wind speed and gusts, predominant wind periods, etc.
- Other electrical charges correlated with the analyzed load.
- Historical values of generated and consumption values.

For a certain consuming device, its behavior is represented by a load profile corresponding to the electricity consumption for each period; therefore, there is a need to record these values at regular intervals. A solution for smart metering should be implemented on a large scale but keeping the associated costs at a low level. A sufficiently detailed recording of consumption allows the application to finely tune the balance between the generation and consumption and to select harvesting devices and energy storage functionalities depending on the consumption period.

In the traditional approach to distribution system planning, load profiles are used to estimate the maximum load required, in accordance with the simultaneity coefficient of the consumers connected in a network node. Although this approach is appropriate, there are some major disadvantages:

- There are inherent inaccuracies, which must be determined.
- The calculation of energy consumption, with respect to losses, does not have high precision.
- The voltage in the network nodes at different hours may vary or be unknown.
- Load profiles of nodes with random variations in power demand cannot be accurately modeled and evaluated.

Using modern methods of load analysis, it is possible to make load forecasts and based on them the calculation of power and energy losses, for any period, based on load profiles. Among the advantages of using load profiles, the following are mentioned [42]:

- Concurrency coefficients do not need to be estimated or calculated, as load profiles include this information.
- The calculation of energy consumption and power/energy losses can be performed correctly at any point in the network.
- Network charging and voltage are known for any time interval.
- The effect of overloading or increasing the load is modeled with more precision.

4.2. Load-Type Profiles Associated with Nodes in Intelligent Data Hub Distribution Networks

Knowing the load profiles of the nodes, the application should simplify the process of estimating the demand in a certain area. For this reason, it is necessary to know the daily consumption profiles. The load graph of the nodes is constructed using the standard load type profile and their daily consumption.

The shape of the load profiles is influenced, in addition to the category of consumers connected in the node, by the type and season in which the analysis is performed. Since a large number of profile tasks associated with different nodes of the network can create potentially complicated problems, these profiles can be arranged in clusters, based on the existence of certain similarities between them, using clustering techniques. For each cluster, the representative load profile can be determined.

In this sense, all the measurements performed must be processed by arrangement and normalization using a convenient normalization factor (average power, peak power, or more frequently, the energy consumption of the studied period):

$$p_i^h = \frac{P_i^h}{\sum_{h=1}^T P_i^h}, i = 1, \dots, N \quad (21)$$

where:

p_i^h —the normal value of the power measured in node i at hour h ;

P_i^h —the real value of the power measured in node i at hour h ;

$\sum_{h=1}^T P_i^h$ —total energy consumption in the studied period T (generally $T = 24$ h).

It is important to emphasize that following the application of clustering techniques, clusters are obtained coherent and representative (groups) so that the graphs within the same cluster are similar. Finally, each cluster will be associated with a typical task profile, calculated using the average of the graphs corresponding to its representatives.

$$m_{C_k}^h = \frac{\sum_{i=1}^{N_{C_k}} p_i^h}{N_{C_k}}; h = 1, \dots, 24; k = 1, \dots, N_K \quad (22)$$

where:

N_K —number of clusters (groups) resulting from the classification of nodes according to the absorbed load (active power);

N_{C_k} —the number of nodes in each cluster $C_k, k = 1, \dots, N_K$.

4.3. Load Type Profiles Associated with Small Power (Low Voltage) Consumers

This section presents an algorithm for determining the load-type profiles associated with small power consumers according to the energy consumption category in which they fall. Consumption categories are identified from historical information and can be updated following changes in consumer behavior. Due to the large volume of data provided by the intelligent metering system and the need for easy updating of the database, the algorithm provides a clear separation of the various steps based on the application of grouping techniques. The steps of the algorithm are the following:

Step 1. Load analysis and database formation. At this stage, a representative sample from the data collected by the smart metering technique is identified, and the sampling step that will be used in the analysis of load schedules is defined. The database containing the registered load schedules and the consumer category is built.

Step 2. Data preprocessing. In real cases of monitoring consumer tasks involving a large number of meters, from a large geographical area and over a long period of time, technical problems may arise that may alter the accuracy of the database. The most essential and common are communication, interruptions, metering failures, and atypical, irregular behavior of certain consumers. The final result of these problems will be reflected in the records in the database, which may contain null values, missing values, or values that may exceed a certain threshold set by the connection notice. After identifying these records

and applying working techniques with missing data (which can lead to the replacement of missing or equal data with zero with estimated values, respectively deleting records), the database will be prepared for obtaining clusters (consumption categories).

Step 3. Division into macro-categories of consumption. The database containing records of load schedules will be divided into clusters (macro-categories) defined by the type of activity of consumers: sensors, video cameras, local processing systems, communication modules, and display/variable messaging systems.

Step 4. The clustering processes. Within each macro-category of consumption, a classification is made in clusters considering the daily energy consumption of devices connected to the energy network. To achieve this classification, the DBSCAN (density-based spatial clustering of applications with noise) clustering in machine learning method is used. For each cluster, the typical load profile is determined, obtained by averaging the hourly values of the load graphs belonging to this cluster.

Step 5. Assigning task type profiles. To each class of customers is assigned a typical task profile depending on the macro-category of activity to which the consumption category belongs.

The proposed algorithm was tested using a database consisting of 296 load graphs. Following the division into macro-categories of activity, 147 consumers were classified in the category of IoT sensor consumers, 97 in the category of video camera consumers, and 52 in the category of communications module consumers.

The application of the DBSCAN clustering method within each macro-category of activity led to the obtaining of four clusters within the category of IoT sensor consumers and two clusters within the category of video camera and communication module consumers.

Through these standard profiles, consumers are better characterized in terms of load variation than the standard profiles associated with the entire macro-category of activity. This aspect can be highlighted if a comparison is made between the load type profiles within each macro-category of activity and the load-type profiles associated with these macro-categories (Figure 4).

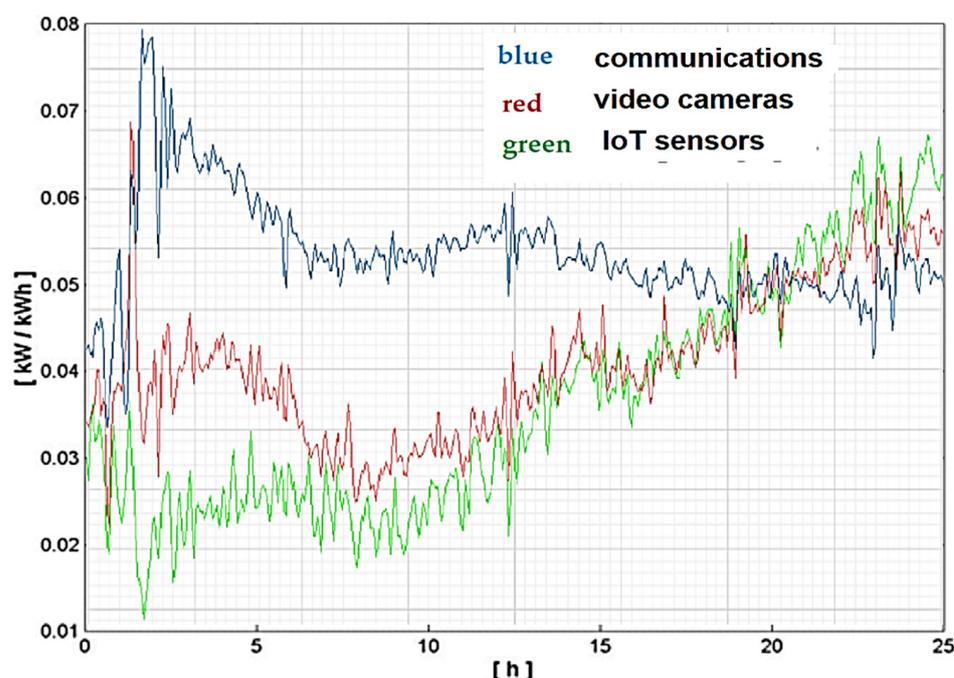


Figure 4. Task-type profiles of macro-activity categories.

Changing energy consumption in consumers raises important issues in planning activities associated with technological processes for the adoption of optimal power supply and operation solutions. Solving problems can be done more productively by using consumption profiles associated with energy carriers.

Here we propose an approach based on clustering techniques for determining load type profiles for the Intelligent Data Hub. The shapes of the standard profile reflect the particularities of the use of electricity by consumers and are influenced by all category of electrical IoT sensors and video cameras used.

The methodology used in the profiling process for Intelligent Networks consumers is presented in Figure 5.

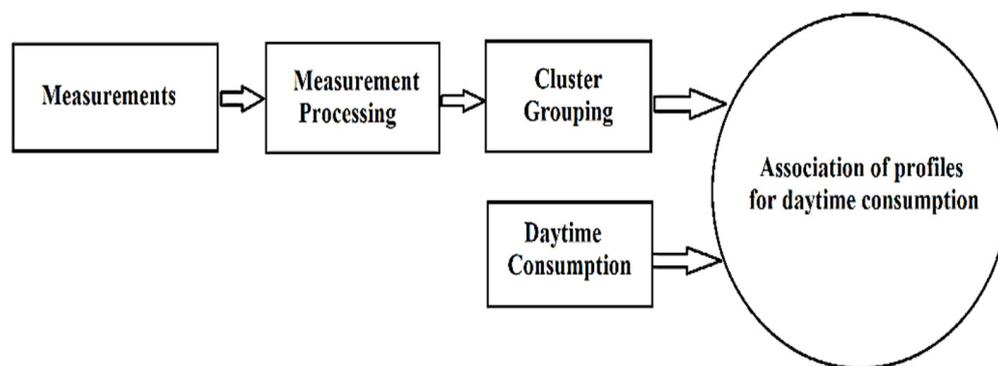


Figure 5. Diagram for determining the load type profiles in the case of consumers of the Intelligent Data Hub.

The significance of each stage of the methodology presented in Figure 5 is the same as for all other profiling processes based on the clustering techniques in the previous paragraphs.

4.4. Stages of the Clustering Process

Clustering techniques are used in many areas of scientific research to group unlabeled elements. These areas already use different terminology, techniques, and assumptions, which refer to the stages of the clustering process, depending on the issues addressed.

In general, the steps to be followed in the clustering process are the following [38,39] (Figure 6):

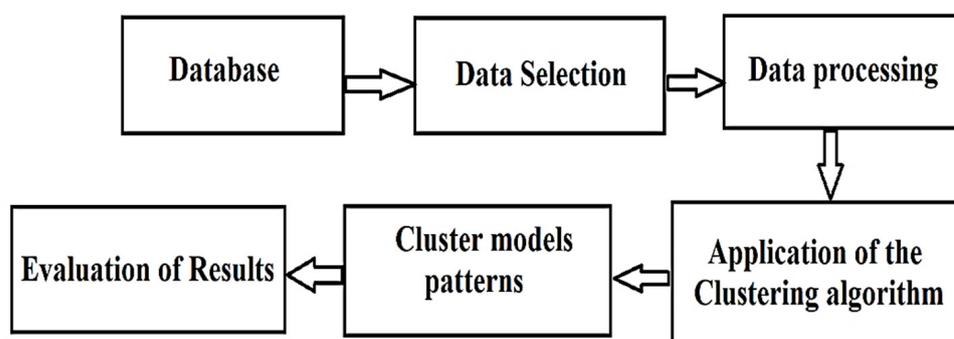


Figure 6. Stages of cluster processing.

Step 1. Establish the elements subject to the clustering process. It considers the choice from the database of the elements that best correspond to the purpose/objective of the problem to be solved. Within this stage you can choose the type and size of the characteristics/attributes available for the clustering process, etc.

Step 2. Extracting the attributes/characteristics of the elements subject to the clustering process. This refers to the identification of the most useful and representative attributes/characteristics of the elements subjected to the clustering process. During the extraction process, one or more transformations of the elements can be performed to obtain new dominant characteristics.

Step 3. Defining a similarity measure. The similarity is usually established by calculating the distance between pairs of elements. This distance presents the similarity between two elements after a vector has been defined for each element. Many distance measurement systems have been defined in the literature, a widely used one being Euclidean distance. These systems will be detailed in the next paragraph.

Step 4. The clustering processes. It can be done in several ways, depending on the methods chosen by the decision maker. All clustering methods should ultimately lead to a number of clusters for any input dataset. If no clusters have been obtained as a result of the process, another method may be applied that gives better results than those previously used. The results obtained can be “clear”, in which the separation of the elements is done in well-defined clusters, or “fuzzy”, in which each element has a degree of belonging for each of the resulting clusters.

Step 5. Extract the results. With the goal of a correct interpretation of the results, it is necessary that their representation be made in a simple form that is easy to interpret by the decision maker.

Step 6. Evaluation of results. The analysis of the validity of the obtained results (represented by clusters) considers a clustering processing evaluation for prediction criterion. A cluster is validated if it does not occur accidentally or for other reasons.

Figure 7 shows the application of modeling of the consumer profile on the integration of renewable energy sources in the Intelligent Data Hub using the DBSCAN algorithm in the machine learning training process, and Figure 8 shows the results obtained for a simulated database using the DBSCAN algorithm in the machine learning deployment process.

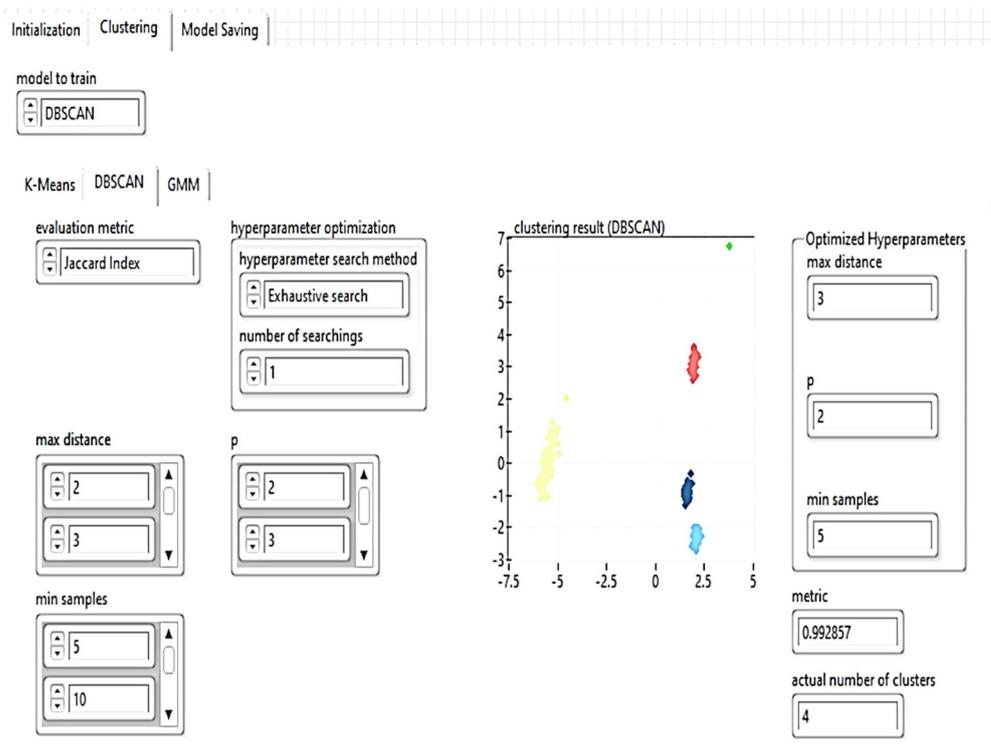


Figure 7. Application of modeling the consumer profile using the DBSCAN cluster training process.

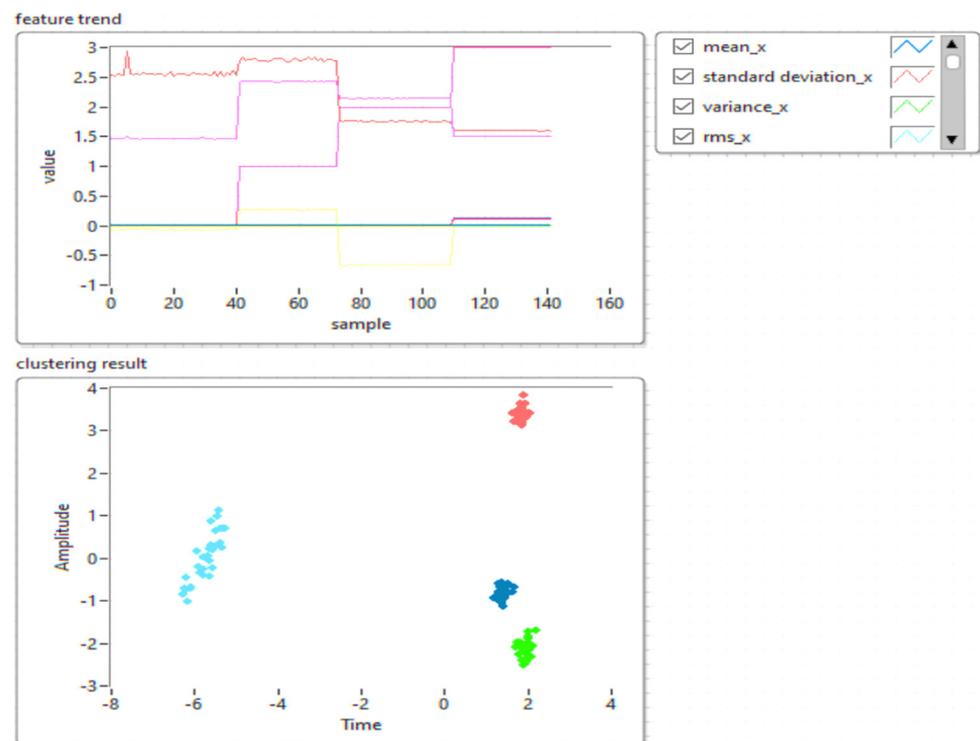


Figure 8. The results obtained for a simulated database consumer profile with the integration of renewable energy sources in the intelligent networks hub.

4.5. Intelligent Data Hub Distribution Network Loading Simulation

In the simulation of the load of the distribution network (DN), the basic element is the simulation of the load of the collection and distribution elements (transformers). Due to the large number of transformers installed in distribution systems, it is very difficult to determine their hourly load. The reason is that in most distribution systems, even very modern ones, which include device-mounted current and voltage sensors, distribution transformers are not equipped with recording meters with real-time remote load transmission capacity. Therefore, without the use of simulation methods, it is complicated to identify those transformers that operate at overload, or to estimate the loads of the connections intended for the transfer of energy between distributors, in the case of reconfiguration.

The most efficient way to estimate the load of transformers, without the need to perform any measurements, is to use simulation programs. To simulate the load of the transformers, we must take into consideration the following elements:

1. The number of consumers connected to each transformer.
2. The category to which each consumer belongs.
3. The annual energy consumption of each consumer.
4. Task type charts corresponding to each category of consumers.
5. Programs capable of calculating the load of transformers.

It was mentioned that in the process of estimating the load of transformers, the maximum and hourly active powers are calculated, on peak days, from different characteristic time periods (winter, summer, average working days of the week, etc.).

Load simulation of distribution transformers using clustering techniques.

The structure of the databases required to simulate the load of the distribution transformers is as follows:

- The database contains “consumer link–substation” (category and number of consumers at each transformer in intelligent network).
- Base profiles include task type profiles for all categories of consumers.

- The consumption database contains data on the annual energy consumption of each consumer connected to the transformer and the consumer category (sensors, communications, video cameras, and processing systems).

To determine the typical load profiles associated with consumers in networks, a database is needed, including as many registered load graphs as possible, in order to be able to represent all consumption classes. The decision-making process regarding the association of a typical task profile to a certain consumer, which belongs to a certain category of consumption, is a complex issue. Thus, a load profiling algorithm was proposed that can be implemented in primary and secondary consumers. This algorithm uses clustering techniques to determine load type profiles.

5. Results

5.1. Testing Solar Cell Panels in the Laboratory

The purpose of this experiment was to determine the efficiency of a solar cell panel in relation to the angle of the incident light. The test conditions (in brief) are as follows:

The test panel was illuminated on different angles with a 3200 K source of light, and output voltages were measured. Results are presented in Table 4 and Figure 9.

Table 4. Output voltage of a solar panel vs. light angle of incidence, artificial light, transversal variation.

Light Angle of Incidence (°)	Output Voltage (V _{DC})	Incident Light Intensity (mW/m ²)
0	5.02	0.4
15	5.50	0.4
30	5.81	0.4
45	6.35	0.7
60	6.41	0.7
75	6.43	0.7
90	6.55	0.9

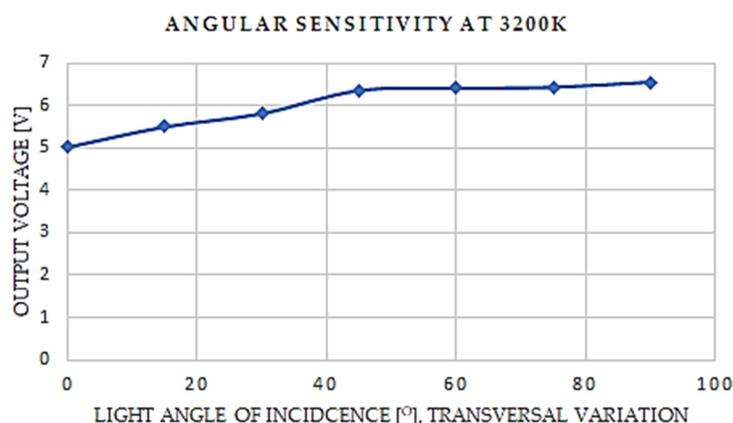


Figure 9. Output voltage dependency on incident angle of illumination at 3200 K.

The test panel was illuminated in different angles with a 7000 K (cloudy sky) and variation around transversal axis. Results are presented in Table 5 and Figure 10.

The test panel was also illuminated in different angles with a 7000 K (cloudy sky) with variation around the longitudinal axis. The results are presented in Table 6 and Figure 11.

Table 5. Output voltage of a solar panel vs. light angle of incidence, natural light, transversal variation.

Light Angle of Incidence (°)	Output Voltage (V _{DC})	Incident Light Intensity (mW/m ²)
0	10.67	1
15	11.40	1.2
30	12.16	1.3
45	12.93	1.4
60	13.35	1.6
75	13.45	1.7
90	13.58	2.4

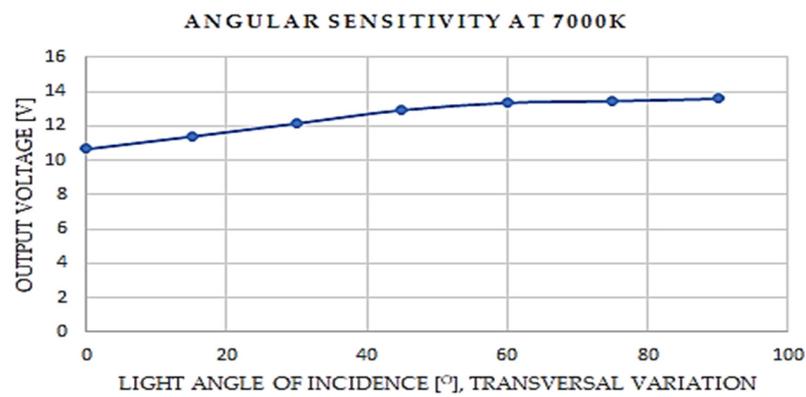


Figure 10. Output voltage dependency on incident angle of illumination at 7000 K, transversal variation.

Table 6. Output voltage of a solar panel vs. light angle of incidence, natural light, longitudinal variation.

Light Angle of Incidence (°)	Output Voltage (V _{DC})	Incident Light Intensity (mW/m ²)
0	10.54	1.3
15	11.48	1.5
30	12.21	1.8
45	12.65	2.1
60	13.04	2.7
75	12.87	2.9
90	13.57	3.2

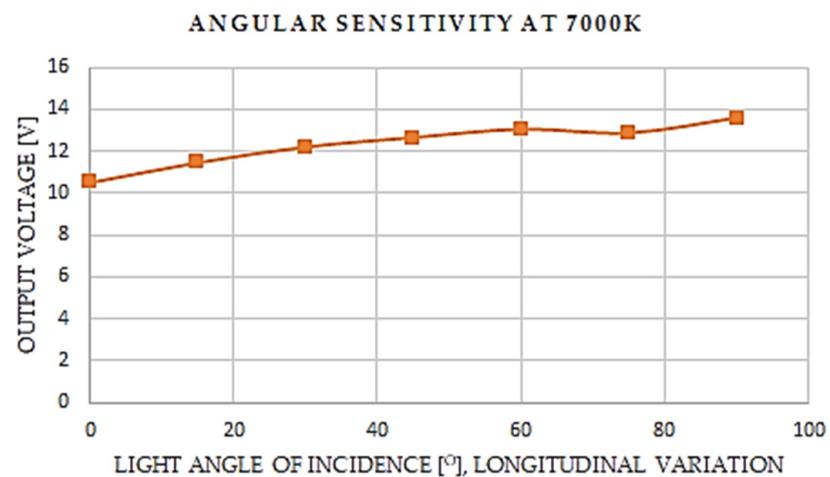


Figure 11. Output voltage dependency on incident angle of illumination at 7000 K, longitudinal variation.

Experimental research on the behavior of photovoltaic panels in variable conditions of solar radiation and operating temperature (according to Tables 4–6)

There is a direct and inverse dependence of the intensity of the incident flow on the distance of the location of the solar panels from the solar radiation.

As the intensity of the incident radiation increases, there is a linear increase in the value of I_{SC} , as well as a logarithmic increase in the case of V_{OC} . Increasing the intensity of the solar radiation is associated with an increase in the cell temperature, the main effect of which is a linear decrease in V_{OC} and photovoltaic conversion efficiency.

Dependency coefficients with the operating temperature for photovoltaic panels regardless of how the solar cells are made (monocrystalline, polycrystalline) show a decrease in conversion efficiency, filling factor, electrical power generated, and idle voltage, as well as an insignificant increase in short-circuit current intensity.

The coefficients of dependence with the intensity of the solar radiation for the photovoltaic panel show an increase of the conversion efficiency, the intensity of the short circuit current, the generated electric power, and the idling voltage, as well as an insignificant decrease of the filling factor.

5.2. Simulation of the Load of Distribution Network Transformers Using Clustering Techniques

The following algorithm is proposed to simulate the load of the distribution transformers from the transformation stations:

Step 1. Database: At this stage, a representative sample of consumers who have installed smart meters will be selected from the database. For each consumer are recorded the typical load graphs from which the main characteristic variables will be extracted: daily energy (W_z), minimum active power (P_{min}), maximum active power (P_{max}), and consumption category.

Step 2. Preprocessing load graphs: all databases containing corrupted data or excluding values or subjected to a processing phase using missing data work techniques. After processing the records, the data obtained are used to obtain consumer profiles using clustering techniques.

Stage 3. Division into macro-categories of consumption: The database containing records of load schedules is divided into clusters (macro-categories) defined by the type of activity of consumers.

Step 4. Clustering process: To determine the load type profiles, a clustering method is used that leads to the best results. Finally, a representative profile for all consumption pattern results is calculated, averaging the hourly values of the load graphs belonging to each cluster.

Step 5. Assigning load profiles: For each category of consumers, depending on their profiling category, a typical load profile is assigned.

Step 6. Estimation of the load of the transformer from the network station. In this stage, a simulation method is conducted using the following relation:

$$P^h = \sum_{k=1}^{C_k} n_k W_{med\ k} p_k^h + \sqrt{\sum_{k=1}^{C_k} n_k (W_{med\ k} \sigma_k^h)^2}, h = 1, \dots, 24[\text{kW}] \quad (23)$$

where:

P^h —load of the transformer from the transformer station at h (kW);

n_k —number of consumers in the cluster (consumption category) k;

$W_{med\ k}$ —average energy consumption of the cluster consumers (category of consumption) K (kWh);

p_k^h —hourly coefficient of transformation of the energy consumed by the consumers from cluster (consumption category) K in average power required by them (kW/kWh);

σ_k —standard deviation of the power distribution required by consumers in the cluster consumption category (kW/kWh);

C_k —number of clusters (consumption categories) corresponding to consumer feeds from the transformer station.

The weight center method (from the category of hierarchical clustering methods) was used to determine the load type profiles, having at its disposal a database consisting of 180 load curves recorded by smart meters mounted on side road consumers in a distribution network of pilot systems.

To determine the typical load profiles, the center of gravity (COG) method was used (in the category of hierarchical clustering methods), having at its disposal a database consisting of 180 load curves recorded by smart meters mounted on side road consumers in a network distribution of pilots located in an urban area of Romania. Each load curve was characterized by 24 hourly values that describe a consumer’s behavior over a one-day interval. Load curves that recorded missing or abnormal values of zero throughout the day were excluded from the clustering process. In the end, only 149 consumers were eligible. Following the clustering process, five consumption categories (clusters) were obtained represented by means. The results obtained for the five consumption categories (statistical parameters, m and σ) are presented in Table 7.

Table 7. Characteristics of consumption categories (the units of measurement are: P_{max} (kW), P_{min} (kW), and W (kWh)).

Consumption Categories	Number of Consumers	P_{max}		P_{min}		W	
		m	σ	m	σ	m	σ
C1	15	0.21	0.02	0.06	0.01	3.41	0.82
C2	5	0.51	0.05	0.02	0.02	4.35	1.20
C3	22	0.46	0.12	0.03	0.01	2.98	0.54
C4	30	0.04	0.06	0.02	0.03	0.25	0.43
C5	72	0.17	0.06	0.03	0.02	1.95	0.41

The analysis of the results shows the representativeness of the clusters; the most representative category of consumption is C5—53% of all consumers, and the representative class is C2—6% of all consumers. The load type profiles associated with each cluster (consumption category) are shown in Figures 12–14. The distribution of consumers in each cluster is shown in Figure 15.

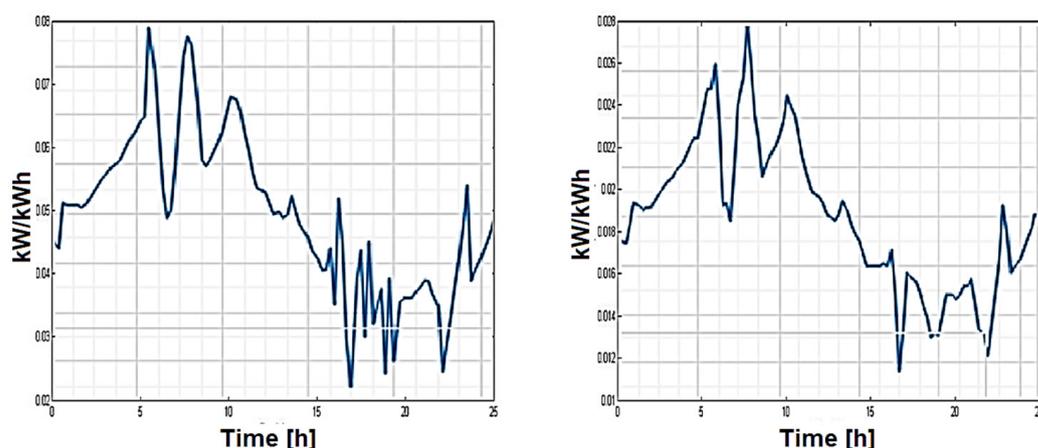


Figure 12. Load type profile associated with consumption category C1 and C2.

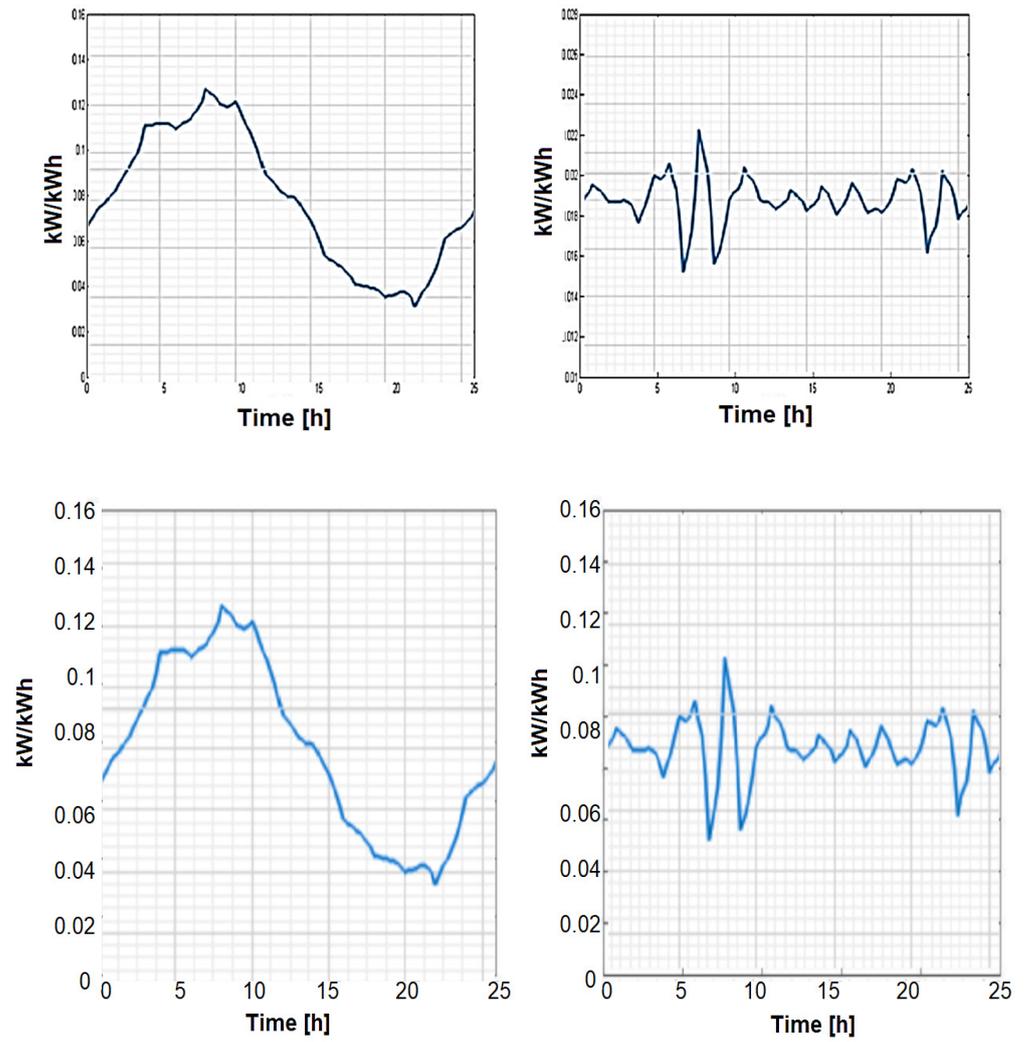


Figure 13. Load type profile associated with consumption categories C3 and C4.

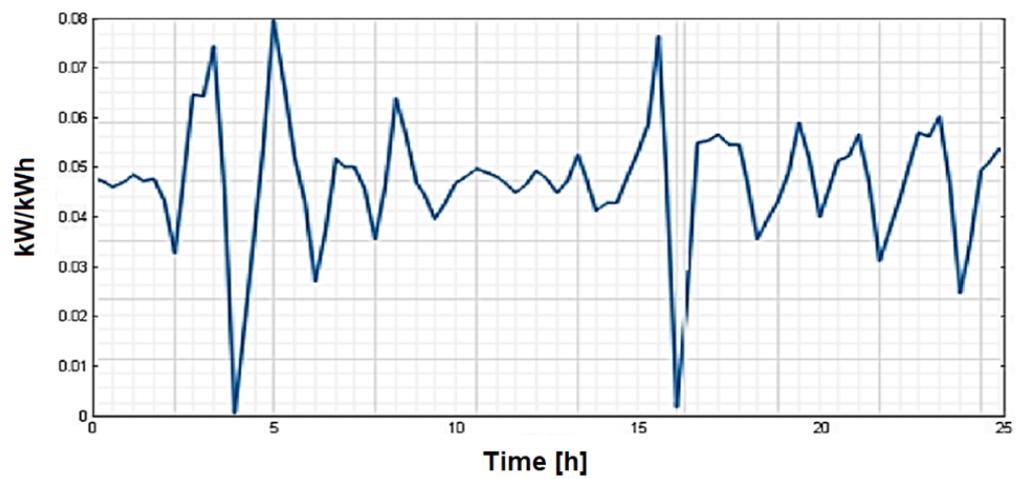


Figure 14. Load type profile associated with consumption category C5.

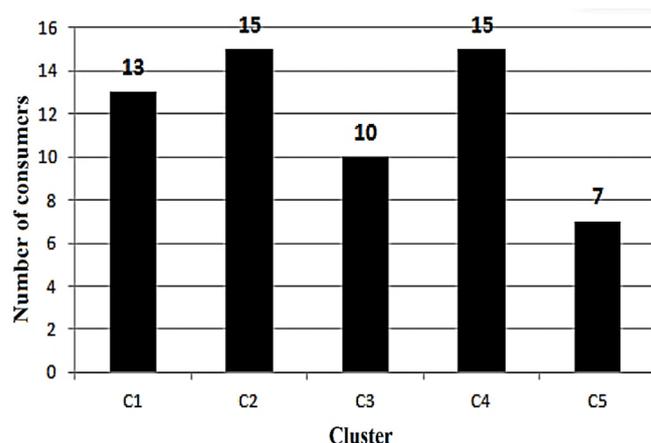


Figure 15. Association of consumers from the test base to clusters (consumption category).

In Figure 16 are presented the real and forecasted values corresponding to the maximum tasks of the consumers in the test base grouped according to the consumption category to which they belong.

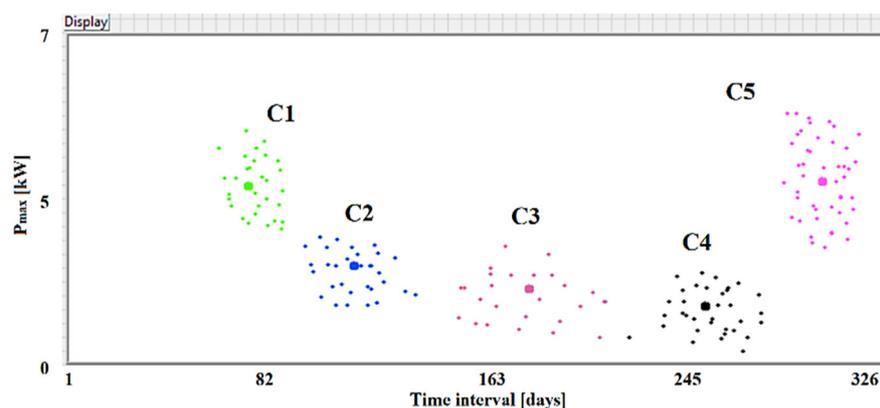


Figure 16. Actual and estimated values of the maximum load—test base.

5.3. 5G Real-Time Monitoring of Battery Charging from Intelligent Data Hub

Failures of the Li-ion battery and charging systems can be classified into internal and external causes. In this section we will briefly present causes and mechanisms that can cause failures. It is important to understand the principles underlying the occurrence of failures, because based on them we can determine useful algorithms for diagnosis and prediction within a BMS system.

Currently, internal battery failures are not yet well controlled. Among the internal defects of the battery, we mention overcharging, decreases of charging capacity, internal and external short circuits, and accelerated degradation of the material and the thermal charging/discharging regime. Among the internal defects mentioned, the most dangerous are the accelerated degradation of the material and the thermal operating regime. Internal faults are identified by abnormal parameters determined in the operation/charging process—state of charge (SOC)—which can be generated by voltage drops, noise in the power energy systems, increased temperature (internal short circuits), and internal resistance (external short circuits) of the battery, as well as physical defects (battery swelling).

External faults also play an important role in generating faults that can affect both the battery and the proper functioning of the BMS. Among the external faults we mention voltage drops (generated by the alternating and direct current electrical network, but also by the noise from the electrical network), current sensor failure, defects due to connections between cells (imperfect contact), and cooling system defects (increase temperature). Cool-

ing system failure is considered the most serious external failure because it can generate both internal and external faults (cumulative defects).

The main function of BMS is to minimize the risks associated with external faults and to predict the occurrence of potential internal battery faults (Figure 17). Dangerous cases are caused, in general, by faults, and the safety and prediction functions of the BMS must minimize the probability of occurrence and the severity of the faults.

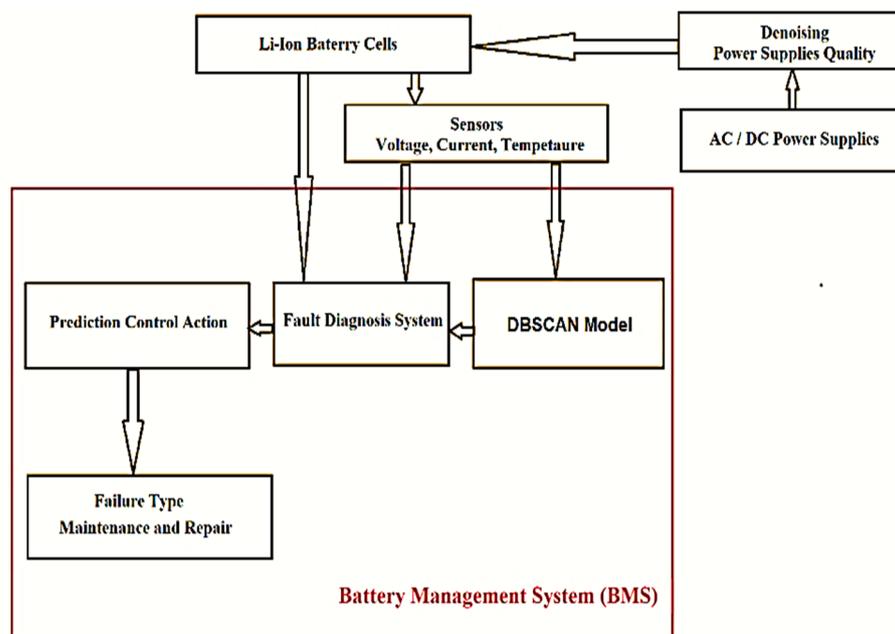


Figure 17. Diagram for detecting and predicting the defects that appear in the process of charging/discharging the batteries within the BMS.

Battery safety is ensured by the quality of sensors, contactors, and insulating material. In addition to the quality of the materials used, operational limits are imposed for the charging voltage and current, and finally the permissible temperature thresholds (thermal operating regime). Voltage, current, and temperature are monitored using sensors connected in a SCADA (IoT) network that monitors each cell. Due to these aspects, the implementation of hardware and software architecture of a BMS becomes very complex. Therefore, the choice of algorithms for detecting loading/unloading failures within a BMS system plays an essential role. These algorithms must perform an early detection of the occurrence of defects, providing (based on the prediction of defects) effective control scenarios with immediate applicability for batteries and users.

6. Conclusions and Future Work

The goal of this paper was to investigate and compare the most relevant technologies related to energy harvesting on a highway with the purpose of determining the efficient ones and to propose a specific architecture for reducing the environmental impact. Novel solutions, such as beamforming and the use of AI, are provided for coping with harvested energy management in small/smart sensor grids. Numerical simulations related to the methodologies, algorithms, and calculation programs developed in this paper have shown that intelligent distribution of consumers in smart grid distribution systems can help smooth the charging curve that can lead to lower electricity prices and facilitate the integration of energy sources that are renewable, resulting in a much safer and more economical operation of smart grid networks. The authors in [40–43] performed analyses of data extraction techniques from the perspectives of different technical approaches to achieve consumer profiles using direct clustering, indirect clustering, clustering evaluation criteria, and customer segmentation. In [44] is presented an approach to the consumer

profile from the perspective of time series, and in [45] the issue discussed was approached with DBSCAN clustering.

As can be seen from the literature, clustering algorithms are frequently used in the field of energy for profiling consumers. The method proposed in this article combines grouping algorithms by clustering techniques and evaluation criteria for clustering results using the regression algorithm with second order polynomials (logistic regression). The use of DBSCAN cluster classification in machine learning can significantly decrease the external factors' influence (e.g., time, weather, day, region) on classifier performance. The results presented showed that the model proposed in this article achieves better classification of the profile of electricity consumers. The technique presented in this article contributes to an overall improvement of consumers' profiles, as it achieves better classification using fewer training samples.

Combining these two algorithms, DBSCAN and fuzzy logic, in the next stage we want to develop an unsupervised machine learning algorithm that will automatically determine the profile of consumers based on historical data and data acquired in real time (data mining).

The technique presented in this article contributes to an overall improvement in the profile of consumers because the proposed method achieves a better classification using fewer samples.

To this end, an approach based on clustering techniques is presented to determine the optimal interconnectivity areas. Consequently, the resulting clusters usually consist of coherent areas where all nodes in a cluster behave in a consistent manner, and therefore a node can be considered representative of that cluster. The obtained areas can be used in the analysis of incidents caused by human errors and weather factors, the optimal location of management devices to increase the observability of the power system, or the determination of pilot nodes in the secondary voltage regulation.

The clustering method adopted in the zoning process depends on the topology of the power system. The main purpose of the zoning process is to compare the elements (which represent power lines between nodes with other nodes) in a binary connectivity matrix A and group them progressively into coherent clusters so that nodes in the same cluster belong to the same areas.

Currently, the short- and medium-term prediction of consumer profiles is very important to implement a robust and reliable system for managing smart grid networks. This article proposes high-performance algorithms for processing and developing learning models for consumer profiling.

The purpose of using the proposed DBSCAN algorithm in machine learning is to improve the prediction so as not to consider the lack of data or their corruption, as is the case in most consumer profile prediction systems.

The model proposed and tested on a pilot project implemented in Romania has a flexible architecture and generates concrete solutions for datasets purchased in real time. Additionally, they can be restructured (rearranged) depending on the applicability pursued, representing a reliable option in cases when complete data cannot be obtained due to their confidentiality.

The analysis made in the article reflects that the proposed method is a robust prediction tool for achieving the profile of consumers, having a high potential for use in various applications such as smart cities and smart grids due to superior performance.

We will continue to develop the architecture by using ledger technology for smart grid management, control, and operation.

Currently, a bridge is being created between the producer and consumer basins beyond the electricity transmission and distribution network: the electricity storage facilities. This bridge, to which will be added micro-networks and energy management systems, will gradually eliminate the differences between producers and consumers scattered on the territory controlled by the current distribution operators and will transform them into entities that consume and produce electricity. Under the new conditions, it is expected to achieve significant reductions in the amount of electricity used by consumers without resorting to new elements of infrastructure, being sufficient only for the simple optimiza-

tion of the way we use this energy. In this context, artificial intelligence and intelligent computing algorithms will certainly be the key technologies to lead the energy sector to the transformations already expected. It is estimated that the new approach to the cities of the future and the power grid will contribute to improving energy efficiency and protecting the environment and will generate a new economic environment. If applications from the smart home will increase human comfort, increasing the number of IoT sensors will have negative consequences on the electricity grid. The impact of the integration of a large number of sensors on the electric power systems largely depends on their charging strategies; by coordinating the charging process of sensors, flexibility services in the electric power system can be obtained, and the necessary investments in the modernization of the infrastructure could be reduced. Thus, companies in the electricity sector must adapt to new technological challenges to improve services to the consumer/customer using intelligent calculations. As future work, we propose to develop a smart energy management platform for small grids dedicated to green highway automation projects. Future research directions are based on the use of AI techniques, mainly clustering and fuzzy techniques, in order to solve the following problems:

1. Electric charge modeling;
2. Analysis of electricity quality;
3. Estimating power/energy losses and methods to increase energy efficiency;
4. The impact of renewable energy sources on electricity networks;
5. Zoning of power systems.

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