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Designing a Comprehensive and Flexible Architecture to Improve Energy Efficiency and Decision-Making in Managing Energy Consumption and Production in Panama

Ivonne Nuñez [1], Elia Esther Cano [1], Edmanuel Cruz [2] and Carlos Rovetto [1,*]

[1] Research Group on Engineering Technologies Applied to Society (GIITAS), Universidad Tecnológica de Panamá, Panamá 0819-07289, Panama; ivonne.nunez@utp.ac.pa (I.N.); elia.cano@utp.ac.pa (E.E.C.)
[2] School of Computer Systems Engineering, Universidad Tecnológica de Panamá, Panamá 0819-07289, Panama; edmanuel.cruz@utp.ac.pa
* Correspondence: carlos.rovetto@utp.ac.pa

Abstract: In recent years, the integration of new elements to the electric grid, such as electric vehicles and renewable energies, requires the evolution of the electric grid as we know it, making it necessary to optimize the processes of production, distribution, and storage of energy. This situation gives rise to introducing the so-called Smart Grids (SG), which would allow a balance between energy supply and demand, thus enabling a system in which the consumer will also become a producer of its surplus energy. Under this scenario, this work proposes an architecture whose technological components, such as the internet of things (IoT), artificial intelligence (AI), cloud computing, and mobile applications, allow users to address the problem of consumption and production of electricity. In the experiments conducted, results were obtained from the components that support the functionality of the proposed platform.

Keywords: energy efficiency; mobile application; internet of things (IoT); artificial intelligence (AI); cloud computing

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1. Introduction

Electric grids are evolving, where capabilities and functionalities are added to the existing infrastructure to improve efficiency and quality of service. To this end, current technology's growing processing and intelligence capabilities are being used, giving rise to the so-called SG or smart grid. It will be the basis for a balance between energy supply and demand and the first step towards smart energy, a system in which the consumer will also become a producer of surplus energy [1–3]. In this way, the digitalization of the energy sector becomes a crucial factor for decarbonization by increasing energy efficiency and supporting the use of renewable energy sources [4–6] through the integration of variable production technologies that improve the quality and security of supply [7,8], thus creating an efficient, resilient, and competitive energy market [9,10].

The SG is defined as an electrical grid that can integrate the actions of all connected users to be efficient in providing a sustainable, economic, and secure electricity supply [11,12]. The transformation of grids towards a smart, secure, and reliable infrastructure will enable the challenges of a complete electrification of the economy, the integration of renewable sources, sustainable mobility, and a more empowered and connected consumer to be met [13].

To reach the full potential of the electricity market in a competitive and robust manner, investment in research and innovation must be made to develop the infrastructure by implementing the necessary technologies. This paper proposes the design of a comprehensive and flexible architecture based on different elements of information and communication technologies (ICT) that allow the processing of data produced by energy sources in the generation phase and consumption data recorded by a low-cost meter. The architecture uses components such as IoT, cloud computing, AI, and mobile technology to allow the user to consult their consumption information, providing the possibility to improve the efficiency of their energy consumption. It raises the level of understanding of disturbances in energy production and consumption, such as fluctuations introduced by system participants dynamically, in turn facilitating planning that not only considers the technical aspects but also how participants respond to changes in economic terms.

This work seeks to present an efficient model that allows the integration of data from various sources, such as consumption meters and energy production sensors. The objective is to facilitate the interpretation and use of information on energy consumption and production in Panama using data analysis and visualization tools. With this solution, it is expected to contribute to the improvement of energy efficiency and decision-making on the management of energy consumption and production.

The structure of this study is as follows: Section 2, background; Section 3, definition of the problem and motivation; Section 4, materials and methods; Section 5, results and discussions; and finally, in Section 6, the conclusions.

2. Background

2.1. Theoretical Context

The smart grid is an electrical network that integrates all connected users' actions to efficiently provide a sustainable, economic, and secure electricity supply. Smart grids use information and communication technologies to collect and analyze real-time data on energy consumption, energy production, and grid capacity. The data is used to optimize energy flow and reduce energy losses [14–17]. Smart grids use a wide variety of technologies to achieve electric power system optimization. Some of the key technologies used in smart grids include:

2.1.1. Internet of Things (IoT)

Thanks to IoT nodes, power grids acquire the flexibility needed to face a more electrified future. Smart grids make it possible to know consumption and demand and to adopt predictive maintenance strategies [18–23]. IoT devices offer many connectivity options in energy infrastructure, helping to monitor all essential energy assets to achieve efficient energy use. Today, it is a technology that has become a benchmark for data collection and processing systems [24–27].

One of the core elements of the SGs is the use of IoT to increase the visibility of the entire environment, providing greater dynamism and efficiency in the collection and distribution of data, which will be used to generate optimization notes for the system [28,29]. IoT is one of the core elements of SGs by providing greater dynamism and efficiency in data collection and distribution and more capacity for direct interaction and control over specific parts of the network [30–33].

In the research of Shahinzadeh and M. Rana [34,35], IoT integration is used to achieve reliable data transmission in communication infrastructures at different levels of SGs:

1. Generation: Monitoring electricity generation from different types of power plants, gas emissions, energy storage, and energy consumption, and predicting the energy needed to supply consumers.
2. Transmission: Monitoring and control of transmission lines and substations, protection of transmission towers.
3. Distribution: Distribution automation, equipment management and protection, fault management.
4. Consumption: Smart home and home appliances, smart charging and discharging of electric vehicles, power load control, multi-grid management.

2.1.2. Artificial Intelligence (AI) Application

The application of AI techniques allows extracting value from generation, transmission, distribution, and consumption data to support decision-making in power grid management, which is transforming and evolving towards an SG [7,36–38]. AI, combined with analytics and monitoring systems, provides clear and complete visibility of the systems within the grid, allowing preventive maintenance actions, real-time incident resolution, and decision-making for operational improvements and optimizations [39–41].

Some practical cases of the use of the application of AI in SGs can be observed in the work of Atef y Eltawil [42], who proposes two intelligent techniques for addressing the electricity price forecasting (EPF) problem using machine learning. First, a support vector regression (SVR) model is used to predict the hourly price. Second, a deep learning (DL) model is implemented and compared with the SVR model. The results show that the two proposed models are effective tools for EPF.

In the work of Ahmad [43], compare tree-based ensemble machine learning models (random forest—RF and extra trees—ET), decision trees (DT) and support vector regression (SVR) to predict the useful hourly energy from a solar thermal collector system. The models developed were compared in terms of their generalizability (stability), accuracy, and computational cost.

In a well-known case implementing an AI platform applied to the design and operation of energy-efficient buildings (EFBs) [44], Yang et al. presented an adaptive ANN which can predict the unexpected behavior of incoming data and adapt to it accordingly. Two models, accumulative training and sliding window training, were tested against simulated and measured data. The sliding window technique had better performance in the case of real measurements. For simulated data, both techniques showed similar performances [45].

Chae et al. proposed a short-term building energy usage forecasting model based on an artificial neural network (ANN) model with Bayesian regularization algorithm to investigate the effects of network design parameters, such as time delay, number of hidden neurons, and training data, on the model capability and generality [46]. The model was used for day-ahead electricity usage of buildings in a 15-min resolution.

Gonzalez and Zamarreno used a feedback ANN to predict short-term electric load consumption in buildings. The biggest advantage of this model lies in its simplicity. It used a minimal number of resources and yet its precision was comparable to other methods used for forecasting [47]. Edwards et al. [48] tested seven different ML techniques on different data sets, and discussed the advantages, disadvantages, and technical benefits for each technique when applied to the prediction of future hourly residential electrical consumption.

On the other hand, in the investigation of Syed et al. [49] evaluates the performance of different feature extraction or dimensionality reduction techniques for short-term energy forecasting applications using smart meter data. The number and type of input feature data are crucial for the performance of energy forecasting models. The results obtained show the importance of dimensionality reduction techniques for higher accuracy and faster training times. While linear principal component analysis (PCA) is a preferred dimensionality reduction technique for faster training times, kernel PCA, non-negative matrix factorization (NMF), independent component analysis (ICA), and uniform manifold approximation and projection (UMAP) yield better accuracies.

2.1.3. Cloud Computing

Intelligent systems, such as, Smart City and SG, are based on the collecting and analyzing of large amounts of data obtained through a macro network of sensors distributed throughout the infrastructure, which must be processed and stored somehow. Here, data centers appear as an essential element for SG to become a settled reality and with it, the cities of the future [50].

Emerging business prospects from the IoT are driving private, public, and hybrid cloud providers to integrate their systems with IoT devices equipped with sensors and actuators to provide a new level of service infrastructure to improve the quality and security of power supply. At the same time, with the advent of IoT, the continued evolution of cloud computing has led to a dramatic change in the design, implementation, and delivery of applications [51,52].

Cloud computing provides geographically distributed computing and storage resources that are essential for the analysis and management of real-time and computationally intensive data in intelligent networks, as is the case of data produced by IoT devices in an SG [53].

2.1.4. Mobile Applications

Nowadays, cell phones have become essential, and thanks to advances in their development in conjunction with the Internet, a wide range of tasks can be performed through them. By using a mobile device, users can access statistics on energy consumption and control household electrical power remotely [54]. There are several studies on the developing mobile smart grid applications that focus on monitoring and controlling energy consumption to interact with an SG network [55–57]. These studies only focus on the technical method of the smart grid system process so that energy consumption can be monitored, organized, and scheduled using a mobile application without going into the process of developing smart-grid-oriented mobile applications.

2.2. Related Work

In this section, we will see some studies related to the development of software architectures oriented to energy efficiency in SG, smart energy, and smart cities.

In the work of Ahsan et al. [58], they propose a distributed smart home architecture involving home sensors that communicate directly with a smart gateway installed inside the home. The gateway decides which data should be sent to the central processor for further analysis. They use an open data set to feed sensor data into the test setup and show that local data processing can improve efficiency by effectively utilizing the available network bandwidth.

Varga et al. [24] present a practical composition method that helps solve IoT interoperability conundrums used in SG. The described approach results in a higher-level abstraction, protecting user applications under a high-level domain API, decisively demonstrating the method's feasibility, power, and utility.

Zhou et al. [59] presents a smart energy community management approach that enables P2P trading and manages domestic energy storage systems. It proposes a smart residential community concept where domestic users and a local energy pool can trade, providing access to cheap renewable energy without new power generation equipment. The proposed energy trading process is modeled as a Markov decision process, and a reinforcement learning algorithm is used to find the optimal decision. A fuzzy inference system is employed to use Q-learning in continuous state space problems (Fuzzy Q-learning) for infinite possibilities in the energy trading process. The performance of the proposed demand-side management system is evaluated by comparing electricity costs before and after its implementation in a community.

Haghgoo et al. [51] presents a cloud-based platform based on a service-oriented architecture to perform service analysis of smart energy systems. It is the result of the European FISMEP (FIWARE for Smart Energy Platform) project to demonstrate an information and communication technology (ICT) architecture for the smart energy sector. The architecture presented is powered by FIWARE, customizable and open-source building blocks for future Internet applications and services. A general list of functional and non-functional system requirements that can be considered in any other system in the energy sector is specified. In addition, the proposed ICT architecture has been demonstrated in the different field tests of the project. In this research, FIWARE has a great potential for application in the investigated use cases. However, due to its modular structure and its goal to provide an API for everything possible, it becomes quite difficult to maintain and requires expert knowledge to operate in production.

In the work of Pau et al. [60], they present a new philosophy for the digitization and automation of distribution networks, based on a modular architecture of microservices implemented through container technology. This architecture enables a service-oriented deployment of the intelligence needed in distribution management Systems, going beyond the traditional vision of monolithic software installations in control rooms. The proposed architecture unlocks a broad set of possibilities, including cloud-based deployments, extension of legacy systems, and rapid integration of machine-learning-based analytical tools.

In the work of Di Santo et al. [61], they present an active demand side management methodology that optimizes energy storage management for domestic consumers with distributed generation. The objective is to reduce electricity costs and postpone investments in grid expansion if the highest load period coincides with the highest electricity tariff of the day. The methodology employs a validated neural network decision-making system trained with optimized data that can be used in households meeting specific conditions: location, electricity tariff, and consumption profile verified by the local electricity company. Three consumption profiles and three solar generation profiles were created and combined to validate the methodology, and the results show that the ANN-based decision-making system efficiently operates the battery to achieve the minimum electricity bill.

In the paper of He et al. [62], they propose an architecture that uses random matrix theory (RMT) to perform anomaly detections for energy flows and data flows, making advanced big data analysis possible within a smart grid. They show that the architecture supports block computation only using a small regional database, proving it to be a data-driven solution sensitive to system situational awareness, and practical for real large-scale interconnected systems.

On the other hand, the research by Sittón-Candanedo et al. [63] proposes the use of an Edge-IoT platform and a social computing framework to build a system for smart energy efficiency in a public building scenario. The system has been evaluated in a public building and the results highlight the remarkable benefits of applying Edge computing to both energy efficiency scenarios and the framework itself. These benefits include reduced data transfer from IoT-Edge to the cloud and reduced network, computing, and cloud resource costs.

3. Problem Description and Motivation

Panama is making significant efforts from various sectors to modernize and innovate the electricity sector, mainly led by the National Energy Secretariat (SNE) [64,65]. One of the open problems identified in the SNE's white paper is the need for studies on the development of software and hardware for intelligent automatic management and control of energy generation and consumption, which is essential because, given a tariff, consumption profile, and customer needs, energy can be saved and sold efficiently. From this, the idea arises to propose an architecture whose technological components will allow us to create an essential innovation in the Panamanian electricity sector.

In this sense, using a low-cost sensor with IoT technology, electric power quality data is collected, measured, and analyzed. Then, from this data stored in the cloud, AI predictive models will be used to assist in the analysis, control, forecasting, consumption, and production capacity of the different energy sources based on historical data to enable better management of the network and generate a different perspective to help make decisions based on data analysis through these robust systems with predictive capabilities. Finally, a system or application is provided to visualize, monitor, and control those mentioned above.

4. Materials and Methods

4.1. Methodology

We will work with the SCRUM agile methodology because it integrates good practices, and better results are obtained through the collaboration of a highly competitive team. This methodology is recommended in projects with complex environments, changing requirements, and needing fast results, where innovation, flexibility, and productivity are fundamental [66].

The SCRUM methodology is an agile framework used in the management and development of software projects and is divided into three main stages: planning and estimation, implementation, and review and retrospective [67,68]:

- Planning and estimation: In this first stage, the development team meets with the objective of defining the project to be developed and establishing a work plan. Requirements are identified, project goals are established, and the product backlog is created, which is a prioritized list of all the functionalities to be developed.
- Implementation: Once the work is planned, work begins in sprints or short development cycles of two to four weeks duration. During each sprint, the team focuses on developing the most important features of the backlog. Each sprint begins with a Scrum Daily Meeting, where progress is reviewed and the work plan is adjusted as needed.
- Review and retrospective: At the end of each sprint, a sprint review meeting is held, in which the functionality developed during the cycle is presented and feedback and other stakeholders are received. This feedback is used to adjust the product backlog and plan the next sprint.

The start of the Scrum methodology begins with sprint planning, which establishes the objectives of the sprint, identifies the tasks to be performed during the sprint, and determines how much work can be completed during the sprint. The product backlog, which is a list of all the product functionality, features, and requirements to be completed in the project, is also developed.

The end of the project lifecycle comes with the final delivery sprint, in which the complete final product is delivered, which is intended to meet the functionalities and requirements defined at the beginning of the project. Figure 1 shows the stages of the methodology used.

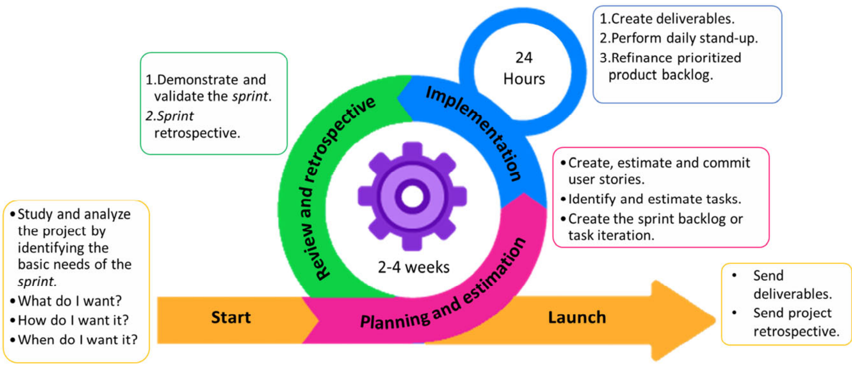


Figure 1. Stages of the methodology used.

4.2. Proposed Architecture

Based on the need to achieve a more reliable electricity supply, a higher quality, more efficient, safe, and sustainable service, an architecture is structured to innovatively manage the monitoring and control level of the electricity grid by integrating storage technology, demand analysis, and electricity consumption interfaces.

Figure 2 shows the general diagram of the architecture, followed by a detailed description of its components for the consumption and prediction of energy consumption in Panama:

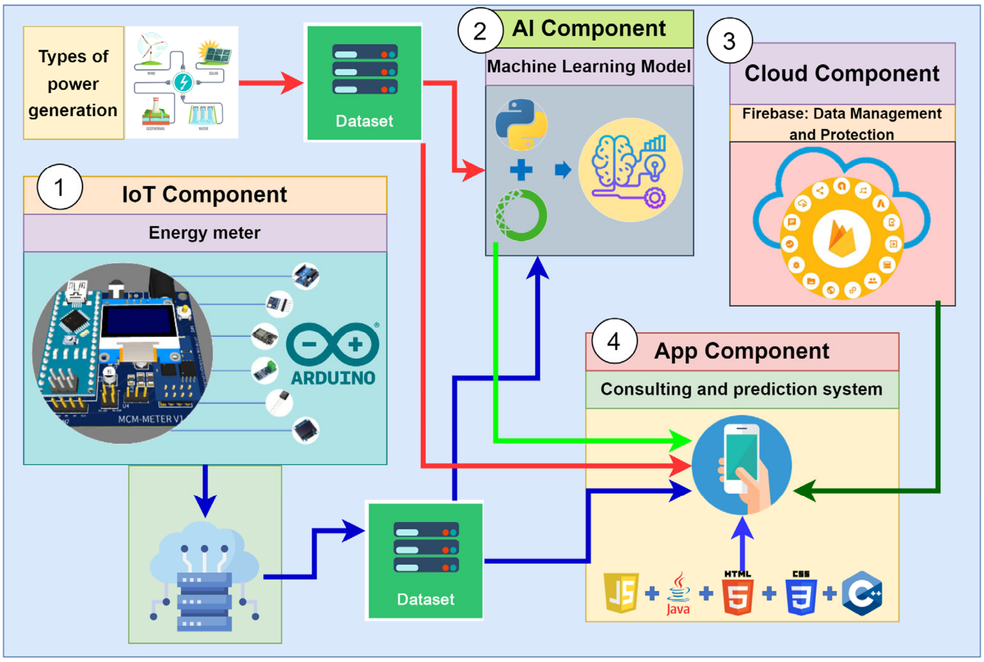


Figure 2. Proposed Architecture.

4.2.1. IoT Component

Access to smart meters is needed to develop an application that uses gamification in SG. However, due to their high cost and implementation, a low-cost electric meter has been developed, which allows capturing important variables or characteristics that generate a set of data to display in the application and the rest to be able to train the AI model.

The electric meter comprises an Arduino board, an ACS712 current sensor, an LM35 temperature sensor, the ML8511 module, an OLED display to observe the data generated from the sensor, and the ESP32 module. The Wi-Fi component sends the data captured by the meter via the ESP32 module. This data is stored in a cloud repository, allowing us to access it at any time and place. Figure 3 shows the Arduino programming of the device.

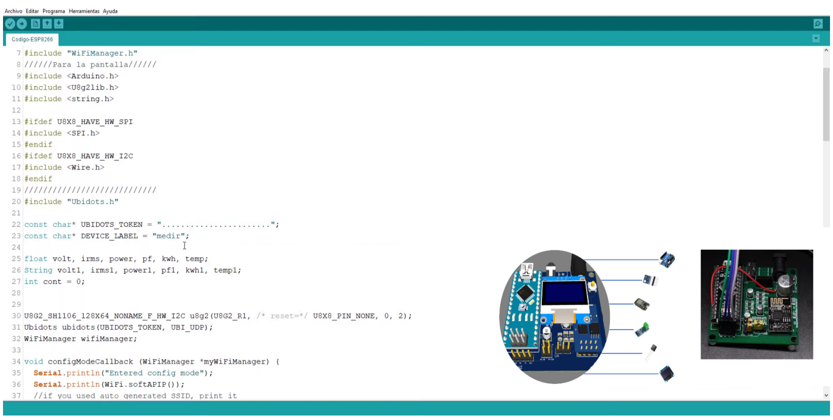


Figure 3. Initial programming of the energy meter.

4.2.2. AI Component

Statistical and AI techniques are increasingly used with numerical models to pro-duce more accurate forecasts. Linear regression (LR) forecasting is one of the AI models used more frequently in electricity consumption and generation forecasting due to the good results obtained.

LR is a data analysis technique that predicts the value of unknown data by using another related and known data value. It mathematically models the unknown or dependent variable and the known or independent variable as a linear equation. The regression model consists of an approach to model the relationship between a dependent scalar variable "Y" and one or more explanatory variables named with "X" and then plots a line that will indicate the trend of a set of continuous data, whose formula is:

$$Y = mX + b$$

where Y is the result, X is the variable, m is the slope (or coefficient) of the line, and b is the constant or also known as the "point of intersection with the Y-axis" on the graph (when $X = 0$).

The predictive models are obtained using simple linear regression using the demand data of each distribution company EDECHI, EDEMET, and ENSA provided by Empresa de Transmisión Eléctrica S.A. (ETESA) [69]. Table 1 shows the data used to train the model.

Table 1. Maximum demand from distributors.

	Maximum Demand (MW)		
Year	**EDECHI**	**EDEMET**	**ENSA**
1998	50.88	354.14	274.59
1999	55.97	369.67	295.49
2000	58.07	394.35	314.83
2001	60.10	412.81	298.63
2002	62.39	441.25	312.41
2003	77.32	439.34	321.69
2004	77.74	454.39	333.22
2005	78.08	466.76	345.24
2006	83.85	492.42	361.86
2007	82.31	509.15	375.99
2008	84.01	530.36	394.87
2009	85.28	567.38	425.71
2010	95.02	601.27	439.29
2011	101.23	626.72	485.75
2012	110.20	664.29	487.15
2013	114.81	695.44	501.29
2014	120.25	738.41	527.33
2015	146.78	778.55	574.37
2016	148.81	798.31	608.45
2017	140.42	809.83	604.82
2018	155.59	797.84	601.76
2019	159.89	839.70	644.88
2020	155.26	806.97	607.63

The demand of the model variables y, x, and z are obtained by applying simple linear regression on the data set that constitutes the annual electricity demand of each of the distributors.

The models for each distributor are as follows:

$$x = i_1 + m_1 D_{EDECHI}$$

$$y = i_2 + m_2 D_{EDEMET}$$

$$z = i_3 + m_3 D_{ENSA}$$

where i_1, m_1, i_2, m_2, i_3, and m_3 are the coefficients of the linear regressions of the distributors.

Using simple linear regression and the demand values of each distributor, the predictive models are obtained.

These data were stored in Pandas DataFrame and were programmed using Python [70,71]. During the training of the models, 80% of the data were used for training and 20% of the data for testing. Tables 2–4 and Figures 4–6 show the values resulting from the model training for each distributor.

Table 2. Results of the prediction model for EDECHI in MW.

Year	Demand	Prediction
2001	60.1	61.114716
2011	101.23	109.672682
2012	110.2	114.937448
2019	159.89	156.9798
2021	160.68	151.096748

Table 3. Results of the prediction model for EDEMET in MW.

Year	Demand	Prediction
1999	369.67	384.96161
2004	454.39	457.108963
2007	509.15	508.185407
2016	798.31	802.397731
2020	806.97	809.546432

Table 4. Results of the prediction model for ENSA in MW.

Year	Demand	Prediction
1999	295.49	282.535085
2001	298.63	302.141461
2007	375.99	378.338353
2010	439.29	443.73054
2014	527.33	541.124566

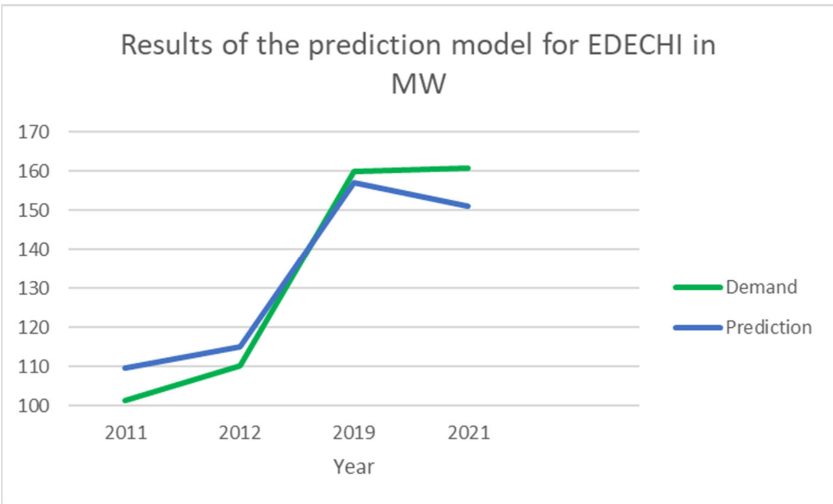


Figure 4. Prediction model for EDECHI in MW.

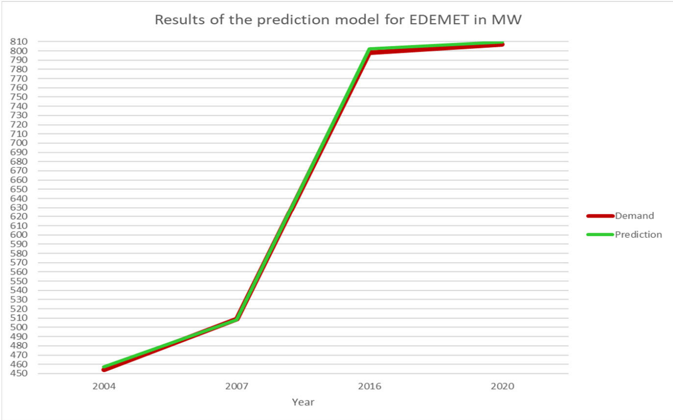


Figure 5. Prediction model for EDEMET in MW.

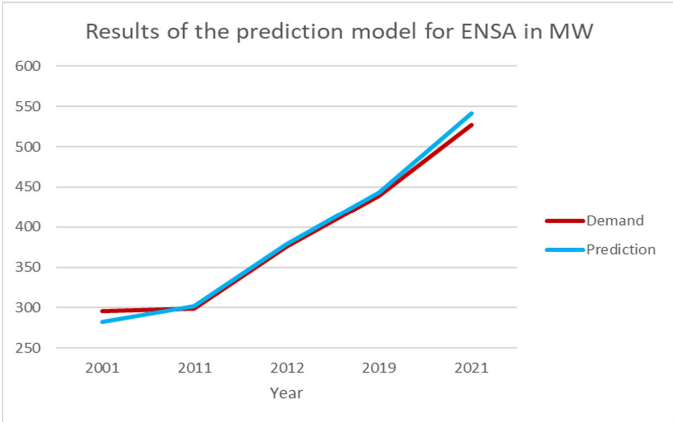


Figure 6. Prediction model for ENSA in MW.

The coefficient of determination (r^2) is used to evaluate how well the data of each model fit. In this, a value of 1 is equivalent to an optimal fit. The coefficients of determination (r^2) for each distributor are shown in Table 5.

Table 5. Coefficients of determination (r^2) by distribution companies.

Coefficients by Distributors	EDECHI	EDEMET	ENSA
r^2	0.97	0.99	0.99

The data set extracted from the national ETESA source and the sensor test data set is verified by the model used to generate the recommendation data displayed in the mobile application.

4.2.3. Cloud Component

This platform manages the user database, ensuring the ethics of the application data, and allows the integration of other components that will make the application robust. It will allow the development cycle of both the mobile application and the web to be carried out harmoniously and simply in less time while maintaining quality [72–74].

This component uses the Firebase mobile cloud platform [75,76], whose main function is to develop and facilitate the creation of high-quality applications in a fast way, so that the user database can be increased. The Figure 7 shows the scripts of the initial programming in Firebase. All programming was based on APIs, JSON, client IDs, and variable logic to make the application functionalities work correctly, as shown in Figure 8.

```
// Import the functions you need from the SDKs you need
import { initializeApp } from "firebase/app";
import { getAnalytics } from "firebase/analytics";
// TODO: Add SDKs for Firebase products that you want to use
// https://firebase.google.com/docs/web/setup#available-libraries

// Your web app's Firebase configuration
// For Firebase JS SDK v7.20.0 and later, measurementId is optional
const firebaseConfig = {
apiKey: "AIzaSyCbWEwEfR_6dVGVQN44PtPwi2YVkNaP208",
authDomain: "sgenergyya.firebaseapp.com",
projectId: "sgenergyya",
storageBucket: "sgenergyya.appspot.com",
messagingSenderId: "694625875868",
appId: "1:694625875868:web:663e3101e8522b370c7a59",
measurementId: "G-NGDWBB30W4"
};

// Initialize Firebase
const app = initializeApp(firebaseConfig);
const analytics = getAnalytics(app);
```

Figure 7. Initial Firebase programming.


```
{
"project_info": {
"project_number": "694625875868",
"project_id": "sgenergyya",
"storage_bucket": "sgenergyya.appspot.com"
},
"client": [
{
"client_info": {
"mobilesdk_app_id": "1:694625875868:android:1081b5370b0a30440c7a59",
"android_client_info": {
"package_name": "com.mycompany.myapp"
}
},
"oauth_client": [
{
"client_id": "694625875868-37sr9ia3tjp9veethf3a5a21cm0eibmu.apps.googleusercontent.com",
"client_type": 3
}
],
"api_key": [
{
"current_key": "AIzaSyDihdA8LejxUasvk4ec9RDZoajsH-wTv5M"
}
],
"services": {
"appinvite_service": {
"other_platform_oauth_client": [
{
"client_id": "694625875868-37sr9ia3tjp9veethf3a5a21cm0eibmu.apps.googleusercontent.com",
"client_type": 3
}
]
}
}
}
],
"configuration_version": "1"
}
```


Figure 8. JSON for making requests to the Firebase and Colab cloud.

4.2.4. App Component

The objective of the architecture is the development of a prototype of a mobile application, where users can consult not only their energy consumption but also other vital factors that will allow them to enter the prosumer concept, that is, people capable of producing and consuming energy, a key figure for energy transition, decarbonization, and smart cities of the future.

The phases of activities involved in the development a prototype of a mobile application is described below:

1. **Analysis and design (identification of needs):** The characteristics and functionalities of various applications related to energy efficiency were analyzed. Information was collected through interviews with various random users to have some data to know the level of experience and usability in specific actions regarding the use of mobile applications. Table 6 shows the attributes of the sociodemographic characteristics of the users of the study.

Table 6. Attributes of the characteristics.

Attributes	Values
Gender	Female Male Prefer not to say
Age (Numeric)	15–20 years old 21–25 years old 26–30 years old Other
What mobile device do you own?	Smartphone Tablet Computer
What operating system do you have?	Android iOS Other
How much experience do you have in handling mobile applications?	No experience Reasonable experience Experienced Very experienced

2. Elevation of requirements: With the results of the previous phase, the key features for using the mobile application and the technological tools used by the participants were identified. The feasibility and technical complexity of each requirement were evaluated to prioritize user requirements:

- Feasibility: an unstructured literature search was conducted to identify accessibility features and services.
- Complexity: the technical complexity of each requirement was evaluated considering the features, services, and development tools available and the difficulty of programming.

Based on these criteria, the priority of each user requirement was rated independently on a 4-point numerical rating scale (see Table 7) according to the Moscow prioritization method [77]:

- 1: must have,
- 2: should have,
- 3: could have,
- 4: will not have at this time.

Table 7. Functional requirements of the mobile application.

Feature	Description	Complexity
Consult energy consumption	View appliance energy consumption patterns in watts per hour.	Yes, high 1
Maps of charging stations, electricity distribution centers	Enable location data to be used to find certain locations	Yes, half 2
Display user contracts	User contracts, whether the user is associated with an electricity distribution company or is a prosumer to whom he transmits energy.	Yes, high 1
Buying assets	Purchase assets to generate renewable electricity from either solar or wind.	Yes, half 2
Learn more	The user can access information on renewable energies, smart energy and SG.	Yes, low 3
Analytics	Future forecast consultation based on the energy the consumer has access to	Yes, half 2

In addition, the technical requirements of the mobile application were established.

3. Development: Because in Panama, 86% of people with smartphones use Android, 13% use the iOS system, and the remaining 1% use other alternatives [78], the application is built using Web standards: HTML, HTML, CSS, JavaScript and making use of other frameworks. Then, the application is combined with Apache Cordova, giving us access to the native features of mobile devices. The Figure 9 shows some screenshots of scripts used in the framework.

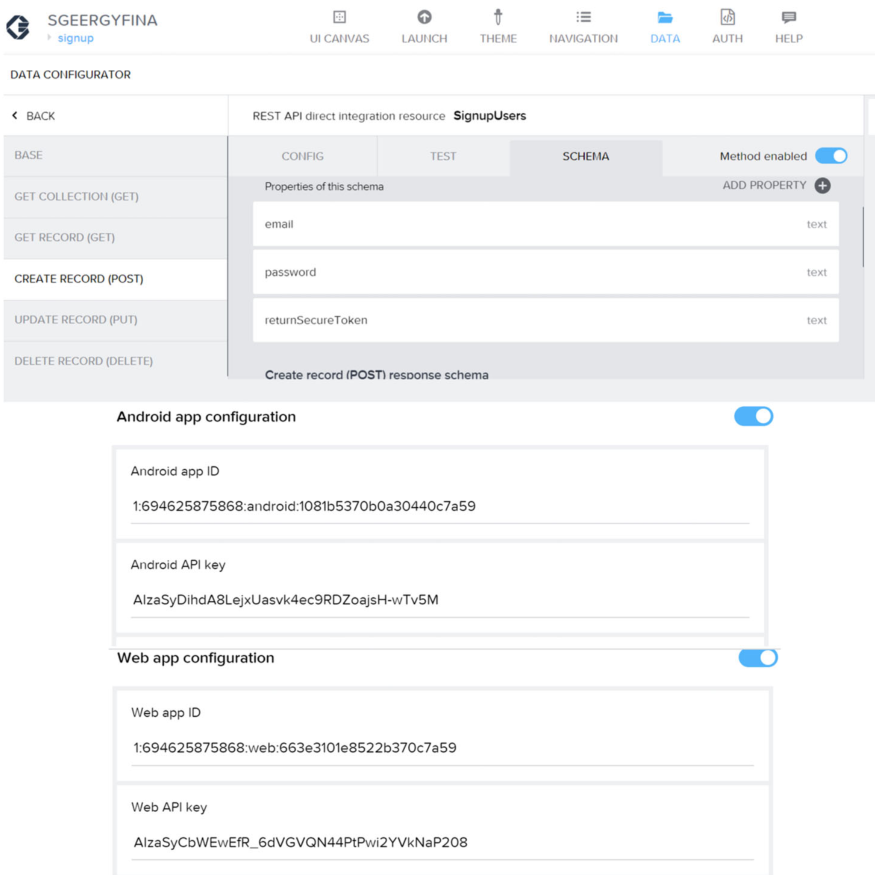


Figure 9. Scripts used in the framework.

4. Protection of user data: To guarantee the privacy of the data handled in the architecture and the mobile application, we will work with the personal data protection Law 81, enacted in March 2019 in Panama [79]. There are principles, obligations, and procedures for data processing in this law that are established to protect the right to privacy and to identify the conditions that must be met by companies or individuals who manage user databases.
5. Testing: Usability tests were performed to ensure the quality of the application on the prototype by applying Nielsen heuristic metrics [80–82] and evaluation techniques, testing, and user satisfaction test and validation [83,84].

For this case, we used the System Usability Scale (SUS) validation technique. Table 8 shows the System Usability Scale (SUS) validation technique. The scale itself consists of 10 questions, each of which can be scored from 1 to 5, where 1 means Strongly Disagree and 5 means Strongly Agree.

Table 8. Validation technique for user satisfaction (System Usability Scale (SUS)).

(+) Positive			(-) Negative	
5	**4**	**3**	**2**	**1**
Strongly Agree	Some Agreement	Neither Agree nor Disagree	Somewhat Disagree	Strongly Disagree
System Usability Scale (SUS)				
Q1: I think I would like to use this application frequently. Q2: I find this application unnecessarily complex. Q3: I think the application is easy to use. Q4: I think I would need support to make use of the application. Q5: I find the various functions of the application well integrated. Q6: I have found too much inconsistency in this application. Q7: I think most people would learn to make use of the application quickly. Q8: I have found the app quite cumbersome to use. Q9: I have felt very confident making use of the app. Q10: I would need to learn a lot of things before I could operate the app.				

The median score of the scale is 68. If the score is below 68, it means that it is very likely that there are serious problems with usability that need to be identified and fixed. A score above 68 is considered positive but denotes that there is some shortcoming in usability.

An interpretation of the SUS scale is proposed in a range of adjectives such as: “worst unimaginable”, “poor”, “acceptable”, “good”, “excellent”, and “best impossible”. Figure 10 shows the relationship of the SUS scale to these easily interpretable adjectives.

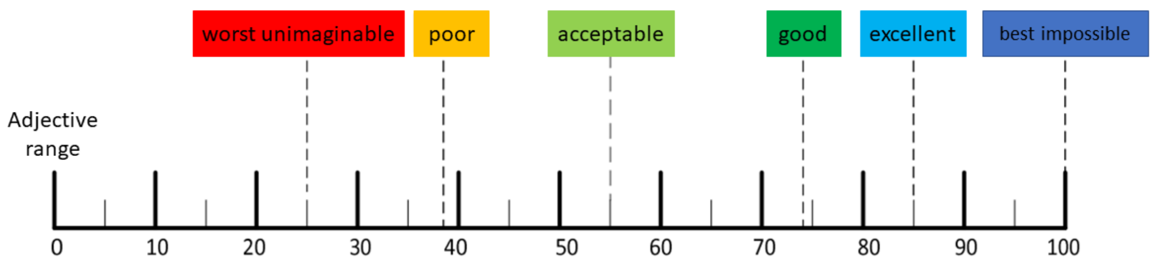


Figure 10. Range of adjectives for SUS scale.

To complement the quantitative analysis provided by the questionnaire, it is supplemented with two qualitative questions to learn a little more about the users’ opinion.

1. What do you think is the best aspect of this interface and why?
2. What do you think needs to be improved and why?

5. Results and Discussions

With the proposed architecture, we observed that, from the implemented components, we could obtain a robust application fed by various services that allow users to have transparency in their energy consumption information.

For the AI component, we measured the accuracy, as shown in Table 5. We consider evaluating other types of models to give even greater robustness to the AI component, and which will be studied in future research.

The information was handled quickly and versatilely regarding the means of communication to send the data with the developed sensor.

On the other hand, prototype of a mobile application meets the functional requirements previously stated in Table 6 for managing energy consumption and demand data through a distributed process and serving as a prelude to structuring a much more robust mobile architecture in the framework of the SGs. Figure 11 shows the interface of the proposed mobile application within the architecture.

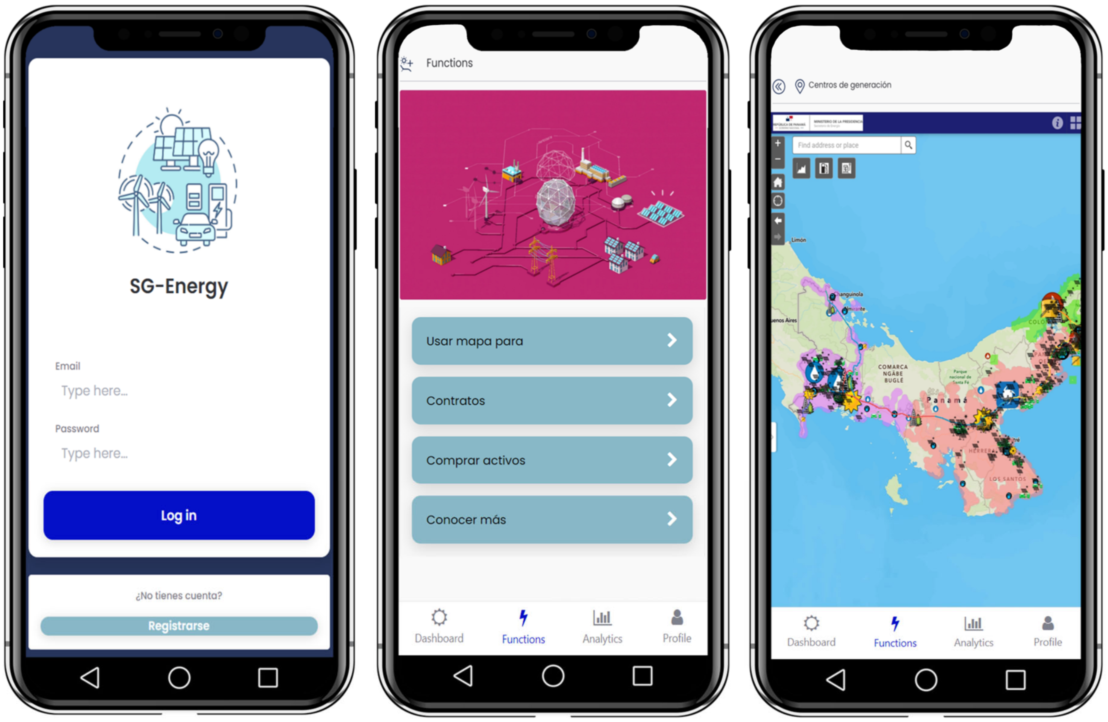


Figure 11. Mobile interface of the prototype application.

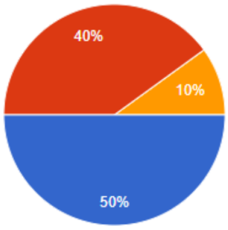
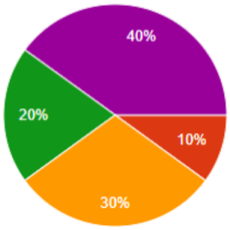
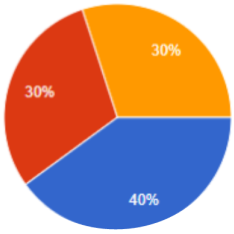
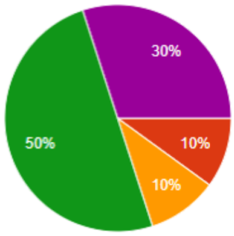
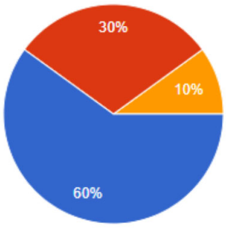
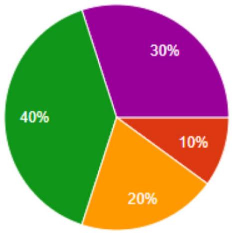
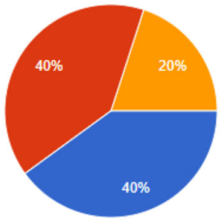
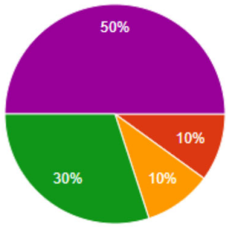
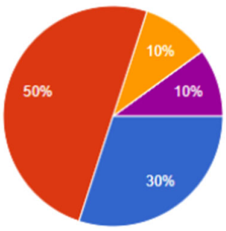
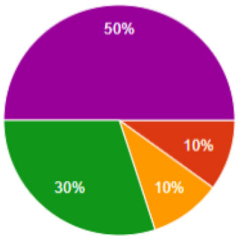
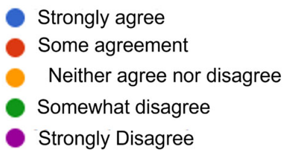
The application consists of four sections, which are:

- Dashboard: In this panel, the user can see the location of his home, the total energy consumption in watts consumed, appliance consumption, real-time consumption, and billing.
- Functions: Here, the user gets to see a menu that allows him/her to use the map functionalities to see his/her location, electric vehicle charging stations, and maps of electricity generation, transmission, and distribution centers in the province Panama.
- Analytics: In this panel, the user can see predictions about energy consumption patterns, and the system offers a series of recommendations based on previous data. In addition, the user can consult accurate data from Panama regarding electricity generation.
- Profile: In this section, users can view their registration data, passwords, and security issues.

This study uses SUS adapted with adjective rating scale to measure the usability of mobile applications. To obtain the results of the usability test of the application, the average results obtained from the user questionnaire are added up, considering the following: the odd questions (1, 3, 5, 7, and 9) will take the value assigned by the user, and 1 will be subtracted from it.

For the even questions (2, 4, 6, 8, 10), it will be 5 minus the assigned value. Once the final number is obtained, it is multiplied by 2.5. Table 9 shows the results obtained from the application of the test to the users.

Table 9. Results for the user satisfaction validation technique (SUS Scale).

SUS Scale Evaluation Percentages			
Q1 	Q2 	Q3 	Q4 
Q5 	Q6 	Q7 	Q8 
Q9 	Q10 	What do you think is the best aspect of this interface and why? R: I consider its appearance to be the best, as it has a very good balance of information and colors.	What do you think needs to be improved and why? The names of the activities should be a little more intuitive.
			

1 to 5, where 1 means Strongly Disagree and 5 means Strongly Agree.

According to what was described above in the use of the SUS scale, we have that:

According to the data in the graphs found in the table, the results obtained in the questions, in order, were: 5,1,5,2,5,2,2,4,1,4,1.

We assign the new values according to the SUS algorithm, and our new values will be:

$$((5-1)+(5-1)+(5-1)+(5-2)+(5-1)+(5-2)+(4-1)+(5-1)+(4-1)+(5-1))\ {}^{*}2.5$$

Then, the SUS score is 90. Given that the theoretical maximum is 100 points and looking at the Figure 10 in the range of adjectives, this result indicates that the level of user satisfaction in using the application is excellent.

The proposed architecture model shows that investment in energy transformation can significantly influence future socioeconomic development and position Panama as a clean technology energy hub at the forefront of the Latin American and Caribbean region.

For the projections to be fully achieved, it is necessary to modernize and innovate by aligning the governance of energy policy and international cooperation, expanding the supply of innovation aimed at the energy sector, addressing critical gaps, increasing the demand for clean and sustainable energy technologies and innovation, taking advantage of digitalization while closing the digital divide, improving data collection, management and application, and data systems.

6. Conclusions

The energy sector is undergoing a revolution, with disruptive and innovative solutions and new approaches emerging, which need to be implemented under the context of the national market to facilitate its contribution to the energy transition. There is great potential for the modernization of the Panamanian electricity system. Investing in the energy transition would stimulate economic activity in the recovery phase 2020–2024, providing a net stimulus to investment in clean technologies and eliminating fossil fuel subsidies. It would boost real GDP by an additional 0.52% in 2024.

A mobile technology architecture was proposed based on which mobile interface oriented to energy query and prediction was designed and developed for user use in the SG framework using innovative technologies such as IoT, AI, the cloud, mobile applications, software engineering methodologies, security, and user-centered design processes. This architecture contributes as a small foundation for innovation in Panama's electricity sector and to migrate to a resilient electricity sector.

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