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Advanced Data Systems for Energy Consumption Optimization and Air Quality Control in Smart Public Buildings Using a Versatile Open Source Approach

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Abstract: This work discusses smart building applications involving the Internet of Things (IoT) which are focused on energy consumption monitoring and forecasting systems, as well as indoor air quality (IAQ) control. Low-cost hardware integrating sensors and open source platforms are implemented for cloud data transmission, data storage and data processing. Advanced data analytics is performed by the seasonal autoregressive integrated moving average (SARIMA) method and a long short-term memory (LSTM) neural network with an accurate calculation performance about energy predictions. The proposed results are developed within the framework of the R&D project Data System Platform for Smart Communities (D-SySCOM), which is oriented to a smart public building application. The main goal of the work was to define a guideline-matching energy efficiency with wellness in public indoor environments, by providing modular low-cost solutions which are easily implementable for advanced data processing. The implemented technologies are suitable to define an efficient organizational user protocol based on energy efficiency and worker wellness. The estimated performance of mean square error (MSE) of 0.01 of the adopted algorithms proves the efficiency of the implemented building monitoring system in terms of energy consumption forecasting. In addition, the possibility of designing and implementing a modular low-cost hardware–software system was demonstrated utilizing open source tools in a way that was oriented to smart buildings approaches.

Keywords: Internet of Things (IoT); SARIMA; LSTM; smart building; energy efficiency

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1. Introduction

In energy systems, taking decisions on the basis of data collected by a powerful energy monitoring is the only way to minimize consumption and to try to avoid high simultaneous loads. The energy data processing is a key element for the estimation of Key Performance Indicator (KPI) in smart buildings [1]. Energy monitoring, and the related efficiency management can severely reduce costs (such as electrical utility costs), thus increasing the lifetime of energy storage systems [2]. The first step in managing electric load consumption is to know the electricity consumption profile versus time. Electrical power consumption generally varies due to both user behaviors [3] and ambient conditions [4], which leads to the demand of continuous control. According to data analytics, data mining techniques are used for energy data classification, clustering and prediction [5]. Cloud systems [6] are good candidates to process data detected by Internet of Things (IoT) sensors.

The energy consumption data can be collected and processed by the data center facilities through a wireless communication network using the message queuing telemetry transport (MQTT) protocol [7] (a lightweight protocol specifically designed for machine-to-machine—M2M—communication). In recent years, electrical load forecasting is getting more and more important due to electricity market deregulation and to the integration of renewable energy production, operated in large plants as well as small ones on buildings [8]. To overcome the incoming challenges and ensure accurate power prediction, predictive algorithms can be adopted such as seasonal ARIMA (SARIMA) [9], and long short-term memory (LSTM) [10]. Specifically, SARIMA model is very similar to the autoregressive integrated moving average (ARIMA) model [11], except for an additional set of autoregressive and moving average components; LSTM is a kind of recurrent neural network (RNN) [12]. Both are used in general as forecasting methods. The ever-increasing energy consumption and utility costs of building operations requires the exploration of new strategies to optimize usage performance, to reduce energy waste, and to minimize environmental impacts [13]. A successful approach to reach a high energy efficiency in building spaces is the adoption of advanced energy management systems (EMSs) [14], for instance those based on the combination of web interfaces monitoring energy consumption and switching electric power [15], indoor environmental quality (IEQ) for efficient indoor comfort (thermo-hygrometric, lighting, air quality and acoustics) [16], and user activity checks [17].

The overall state of the art suggests the importance of smart building applications to combine wellness functions with energy consumption aspects. The main goal of this work is to provide modular and easily applicable design criteria for energy control systems by focusing attention on the energy savings in public buildings generated by means of low-cost electronic components. Two interfaces were so designed and implemented for a basic prototype demonstrator: one collecting data to calculate energy consumption of the different loads of the building, and one dedicated to indoor air quality (IAQ) monitoring, capable of detecting light intensity, temperature and humidity. A low-cost Arduino-based interface was then developed for sensors data collection and web publication as well as to drive electronic components actuating energy-saving strategies. The use of a cloud-based web interface provides for the formulation of the organizational protocol based on the automated interventions when either anomalous energy consumption occurs, high values of energy consumption are predicted or bad air quality conditions are found (see scheme of Figure 1). The flowchart summarizes the organizational protocol adopted in this study for the public building energy control. The protocol is made of different levels:

- the "field" level with the electronic interface for active data detection,
- the data monitoring levels accounting for results prediction,
- the adjusting final level, containing the procedures for energy efficiency enhancements.

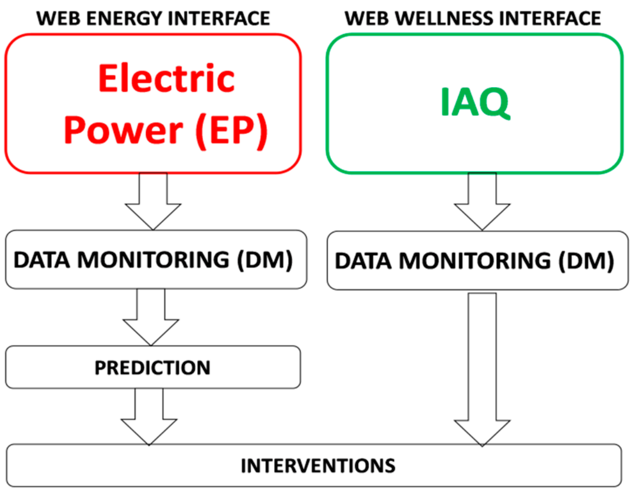
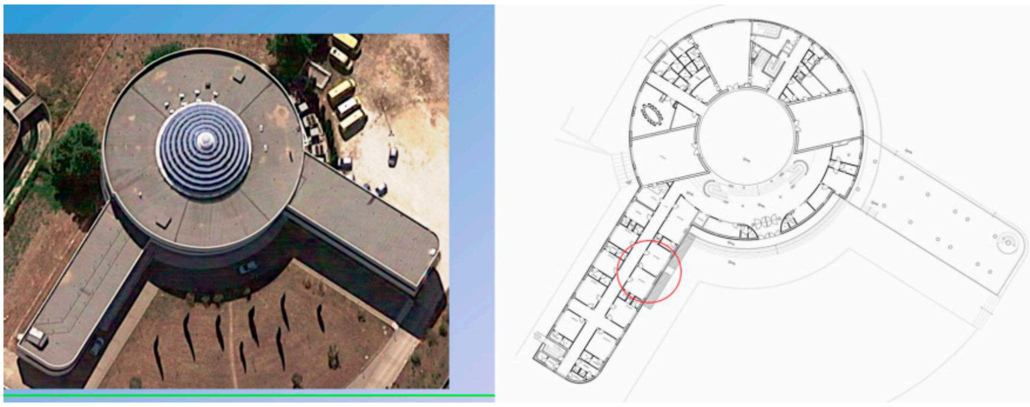


Figure 1. Organizational protocol used for the project web interfaces in a public smart building.

What is depicted in Figure 1 was developed within the framework of the Italian project Data System Platform for Smart Communities (D-SySCOM) [18] (Lead company: SIT srl, Partners: Aliser srl, Eulogic srl, Geatecno srl, Interdisciplinary Laboratory of Design and Integrated Management of Industrial Plants—section of Applied Thermodynamics of the

University of Salento, New Technologies Center for the Social Integration of the Disabled at the University of Salento).

In Figure 2 the image and the floor plan of the building adopted for experimental results are reported.



(**a**) (**b**)

Figure 2. (**a**) Photo and (**b**) floor plan (right) of the building adopted for the testing of the protocol indicated in Figure 1 (Municipal building of the municipality of Nardò in the South of Italy). Experimentations were performed in the rooms indicated with the red circle.

The building in Figure 2 was provided with a modular information system architecture which can simultaneously detect energy and IAQ data, thus ensuring at the same time working quality and energy efficiency. A solution was found that was easily interfaceable with advanced algorithms predicting indoor parameters. Both real-time and predicted parameters are able to allow the optimization of the working environment, according to the activities carried out inside. The chosen low-cost prototypes allow the extension of monitoring to all the rooms of the building and the provided solution can be easily transferred to other public buildings.

2. Materials and Methods

2.1. Energy Monitoring Modular Architecture (EP Interface)

The architecture of the developed IoT-based power consumption monitoring system has the following four-layers: perception, network, application and cognition layers.

At the perception layer, sensor devices are provided which measure and acquire power process variables. At the network layer, information is sent to a cloud-based server. At the application layer, the real-time information is stored and displayed. At the cognition layer, data are post-processed while using machine learning for data analysis and forecasting for assisting in the decision making. Figure 3 highlights the architecture of the system, integrating both energy and IAQ modules: the first three layers (perception layer, network layer, and application layer) are common for both modules; the cognition (the fourth layer) only applies to the energy module and is finalized to improve the energy control by means of machine learning algorithms.

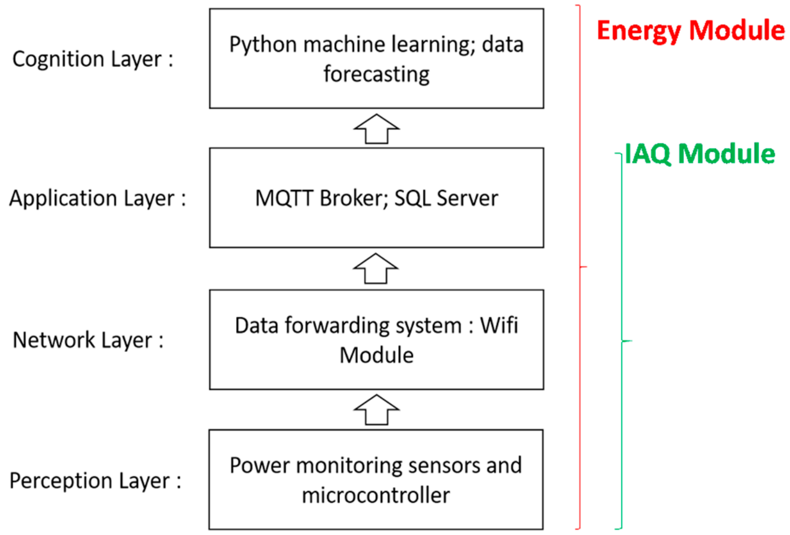


Figure 3. System structure of the system: modularity implementation of the technologies monitoring energy parameters and indoor air quality.

2.1.1. Perception Layer (EP Interface)

The perception layer is directly linked to the central power supply node for power measurement. The system measures the root-mean-square (RMS) instantaneous power, by calculating the RMS current and RMS voltage from the electrical network (the Italian network provides 220 V as an AC voltage level). The voltage is measured on the electric lines passing through the step-down transformer and a voltage regulator adjusting the DC output into a range acceptable for the MicroController Unit (MCU). The adopted microcontroller is the Arduino Nano board, based on the ATmega328P. It is an Alf and Vegard's RISC (AVR) based microcontroller with 5 V supply, 8 bit and 16 MHz clock frequency. The software code is the Arduino's Wire programming language, executable on the Arduino Integrated Development Environment (IDE). The electronic components of the setup measuring electrical parameters is illustrated in Appendix A. The AC voltage measurement is adopted to calculate the real power, the apparent power and the power factor. This measurement is performed by using the ZMPT101B AC to AC voltage transformer which has high accuracy, good consistency for voltage and power measurement and can measure up to 250 V AC.

To achieve the requested accuracy (error < 5%), the system underwent a calibration procedure with an oscilloscope and a multimeter. The RMS current and voltage were sampled approximately 50 times in 20 milliseconds (2.5 kHz) sampling frequency, and the results were saved to a database. Then, the rolling average (a calculation to analyze data points by creating a series of averages of different subsets of the full data set) of ten measurements was used to calculate the power by means of the microcontroller. The data was after passed to the ESP8266 Wi-Fi module uploading data to the AdafruitIO cloud structured query language (SQL) server supporting MQTT protocol.

2.1.2. Network Layer (EP Interface)

This layer mainly transmits the detected data from the smart energy monitor to the cloud sever. Data pre-processing methods, such as filtering and outlier removal processes, are executed by the controller, reducing the quantity of transmitted data and the computational cost (are processed only useful data). After pre-processing, data are transferred to the Wi-Fi module interfaced with the microcontroller, or stored in the transmit queue, depending on the data effectiveness data length. The ESP8266 is a low-cost Wi-Fi chip operating with the TCP/IP protocol and supporting IEEE 802.11 b/g/n Wi-Fi standards.

2.1.3. Application Layer (EP Interface)

Data are published by the remote MQTT broker directly through the ESP8266 gateway (publish/subscribe system). MQTT requires low bandwidth and has a data packet size with low overhead minimum (>2 bytes) so that it has smaller supply power consumption. This protocol is a data-agnostic protocol that can transmit data in various forms such as binary data, text, XML, or JSON. As the web server is published, the dashboard-based web application is accessible anywhere and anytime, thus enabling remote energy management.

2.1.4. Cognition Layer (EP Interface)

This layer defines the process following the cognitive computing algorithm. The main functions of the cognitive layer are

- data pre-processing
- the data mining processing.

This layer is able to execute SARIMA and LSTM algorithms. The whole data mining processing workflow is depicted in Figure 4: it is characterized by five phases (the first step is the pre-processing phase, and the other four steps are related the data processing). The dataset is split into training (75%) and test (25%) datasets to be processed by the machine learning algorithms (best choice concerning algorithm optimization).

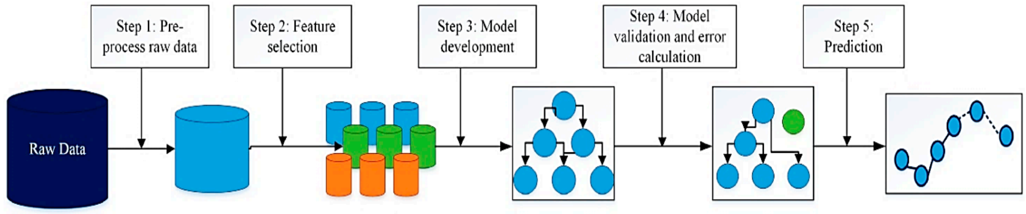


Figure 4. Advanced architecture adopted for data detection and processing.

The predicted values are compared to the actual values (measured) using different metrics such as mean absolute error (MAE), mean squared error (MSE), root-mean-square error (RMSE) [18].

The architecture in Figure 4 defines the steps of the cognition layer of Figure 3: data are pre-processed extracting features, developing the forecasting model (validating it) and predicting results. The main parameter used for the graphical forecasting view is the electric energy.

2.2. Air Monitoring System Modular Architecture (IAQ Interface)

The modular IAQ architecture is characterized by three layers (see Figure 2): perception, network and application layers. In the perception layer, sensors acquire environmental parameters. In the network layer, information is sent out to the cloud-based server. At the application layer, the real-time information is displayed and the detected digital data are archived.

2.2.1. Perception Layer (IAQ Interface)

The perception layer is the physical system composed by sensors and by the Arduino-based MCU to collect and forward the parameters to the Wi-Fi node. Specifically, about indoor air quality, the following parameters are measured (see Appendix B).

2.2.2. Network Layer (IAQ Interface)

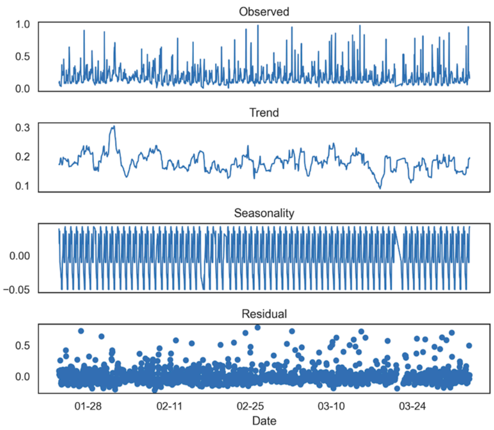
This layer mainly transmits the data detected by the IAQ system to the cloud server by using an ESP266-based NodeMCU v3 ESP8266 Wi-Fi chip. This layer forwards, transfers, and sends data from the Arduino board to the cloud server.

2.2.3. Application Layer (IAQ Interface)

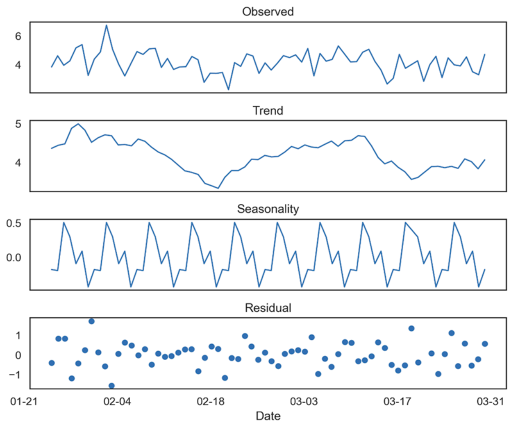
Data are published by the remote MQTT broker through the ESP8266 gateway. The adopted cloud server is ThingsBoard IO (open source IoT platform for device management, data collection, processing and visualization). The graphical dashboards were developed using Python.

2.3. Automatic Time-Series Decomposition and Dashboards

Decomposition is a useful abstraction for time series analysis and to inform forecasting models. Decomposition is performed on the experimental dataset estimation. It is helpful in breaking down the usage consumption in systematic and non-systematic components. The estimated series are classified in four main components: the observed values, the trend (the increasing or decreasing value in the series), the seasonality (the repeating short-term cycle in the series), and the residual noise (the random variation in the series). This series decomposition helps in understanding the complexity of the forecasting modeling to be applied. Decomposition is performed both on hourly (Figure 5a), and daily (Figure 5b) data. The statistical trends of Figure 5 show the possible dataset decomposition forms (on hourly and daily basis) of the forecasting model.



(**a**)



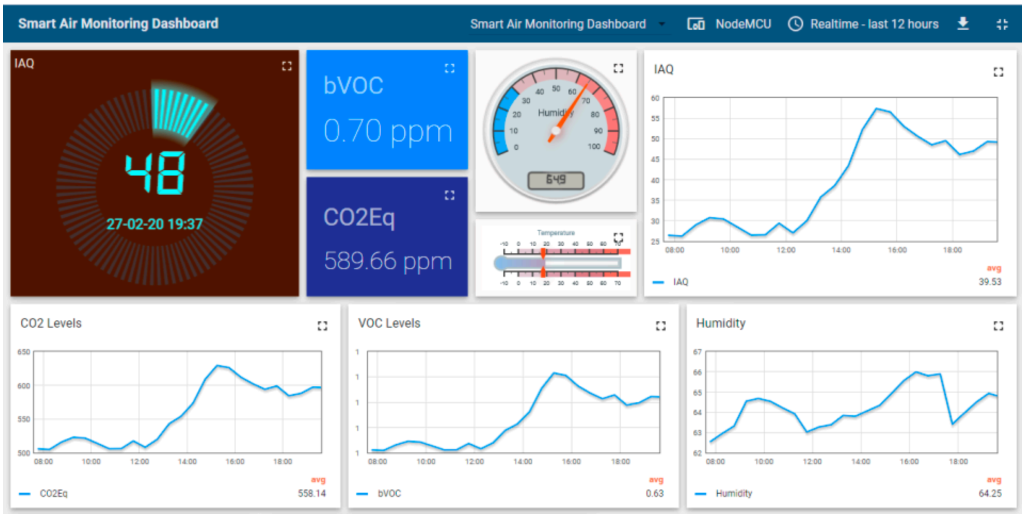
(**b**)

Figure 5. (**a**) Time series decomposition hourly basis. (**b**) Time series decomposition daily basis.

3. Results

3.1. Energy Monitoring and IAQ Dashboards

First results concern the frontend dashboards of energy monitoring and IAQ system. In Figure 6a, the Adafruit IO dashboards enabling remote energy control is illustrated. The dashboards represent the real time signals and historical weekly energy consumption, (every 7/15/30 days) indicating current, voltage and power trends. Figure 6b shows the implemented web ThingsBoard, displaying both real time and historical IAQ data (temperature, humidity, CO_2, VOC levels, dust density).



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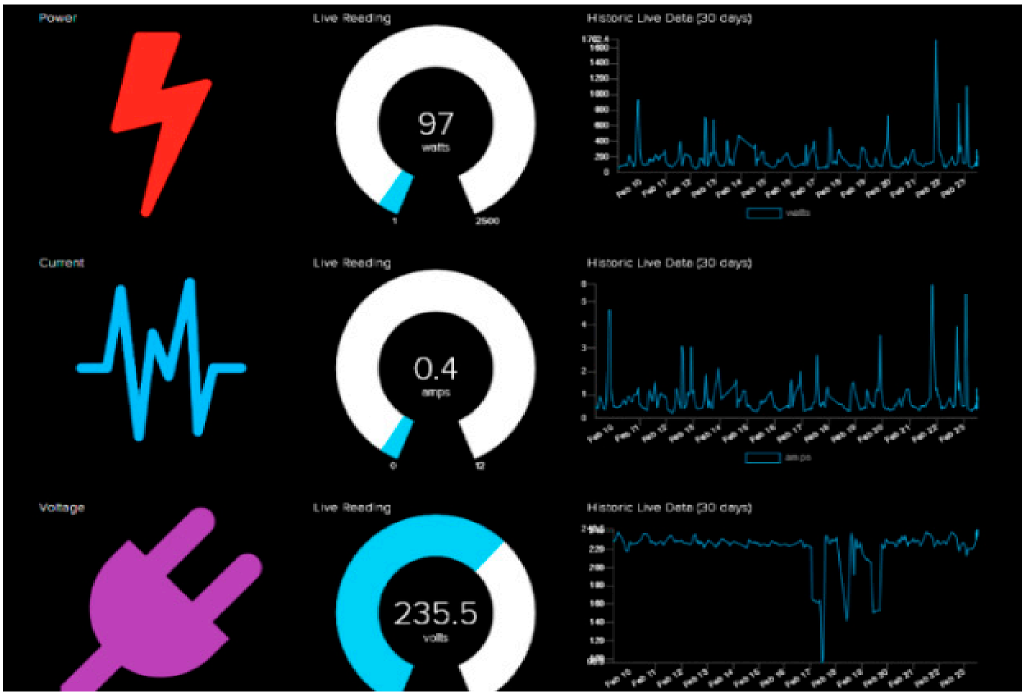
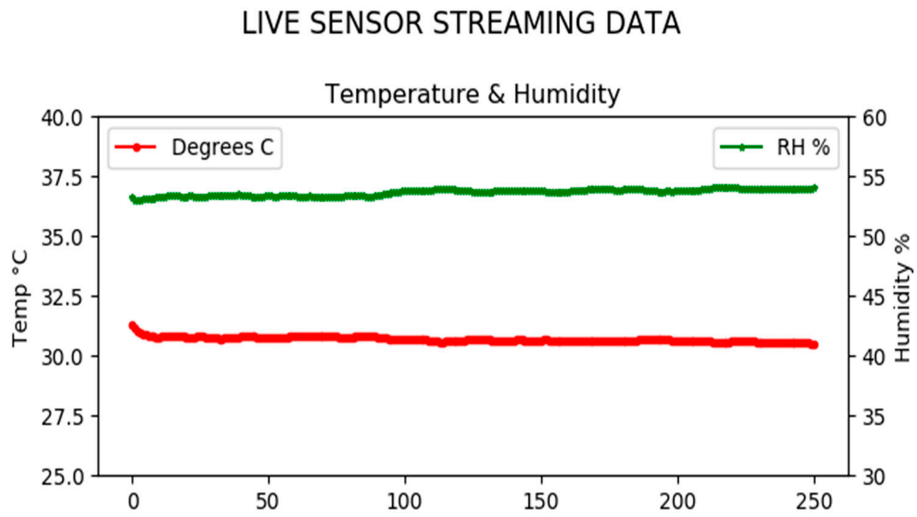


(**b**)

Figure 6. Dashboards of the implemented platform, monitoring air quality (**a**) and energy (**b**) tested for a public building.

3.2. IAQ Parameter Monitoring

Figure 7 represents the real-time serial output of only BME sensor (see Appendix B) evaluating the indoor air quality (IAQ) parameters (VOC concentration): in Figure 7a, the real-time temperature is reported (expressed in °C) as well as relative humidity (see related description in Appendix B); in Figure 7b, the $PM_{2.5}$ IAQ index versus the time (measurements of VOCs concentration) can be read. The adopted dust sensor (see Appendix B) counts the dust particles into a range between 0 to 3000 particles (PCS) per 0.01 contamination factor (CF) [19,20]. Specifically, the sensor measures the $PM_{2.5}$ IAQ index versus the time. The "wellness" scale of $PM_{2.5}$ level of house can be seen in ordinary ranges below 150 pc/0.01 cf. Figures 7b and 8 report the IAQ "wellness" bands.



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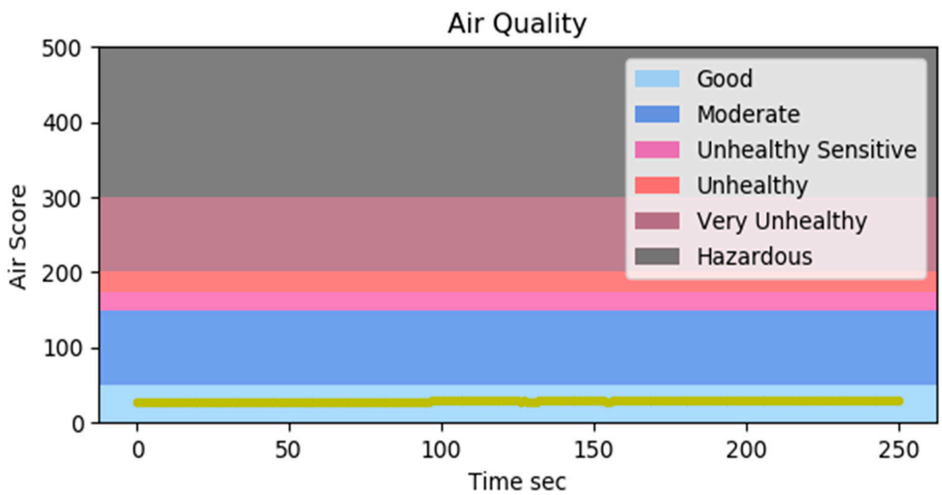


(**b**)

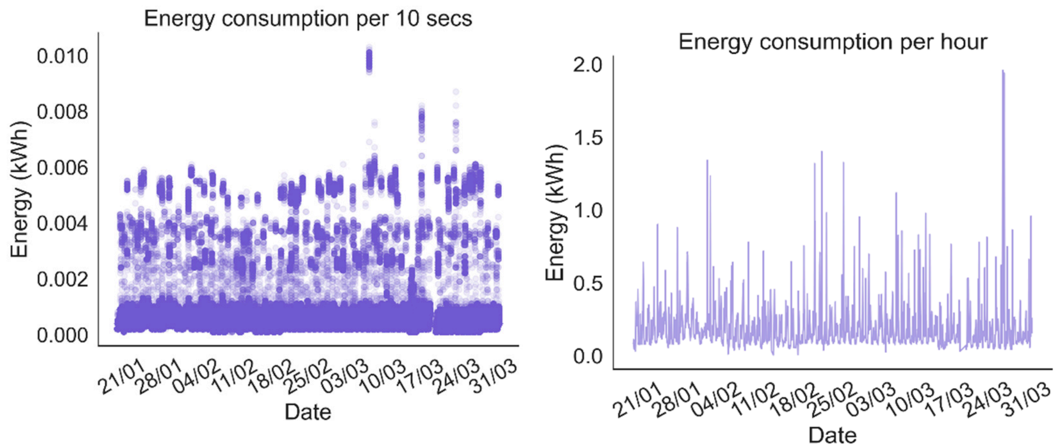
Figure 7. IAQ BME Serial Output: (**a**) temperature in °C and humidity percentage versus seconds. (**b**) IAQ index (VOCs concentrations) and related "wellness" bands.

IAQ INDEX	AIR QUALITY
0–50	Good
51–100	Moderate
101–150	Unhealthy Sensitive
151–200	Unhealthy
201–300	Very Unhealthy
301–500	Hazardous

Figure 8. IAQ "wellness" bands indicated in the estimation of IAQ value of Figure 7b.

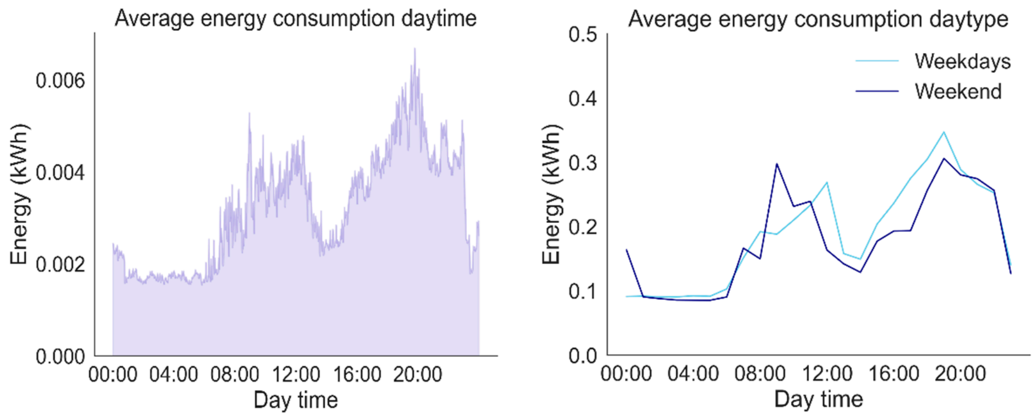
3.3. Data Mining to Understand Energy Consumption Behavior

The developed prototype platform for energy dashboards provides energy data grouped as energy consumption per minute (Figure 9a), total energy consumption per hour, (Figure 9b), average energy consumption based on the time of the day (Figure 10a), or types of day (weekdays/weekends) (Figure 10b), and average weekly energy distribution by days of week, both (Figure 11a) percentage-wise and (Figure 11b) consumption-wise.



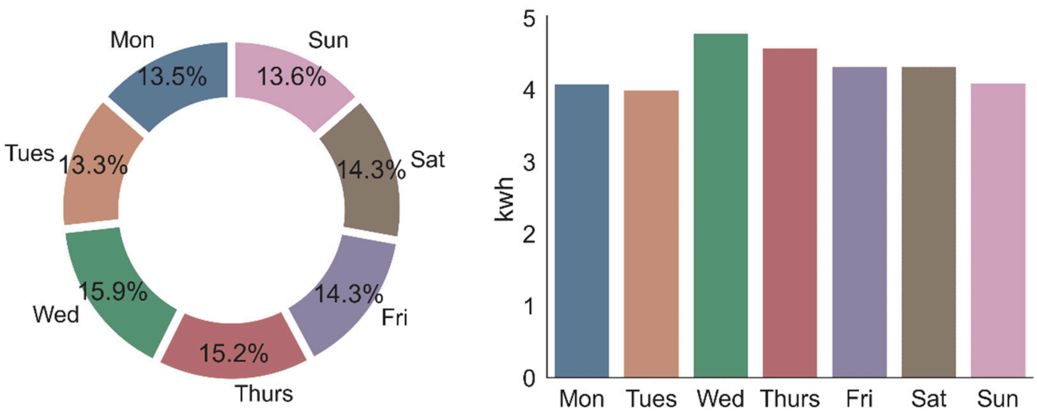
(a) (b)

Figure 9. (**a**) Energy consumption per 10 s; (**b**) Average energy consumption per hour.



(a) (b)

Figure 10. (**a**) Hourly average energy consumption versus time. (**b**) Hourly average energy consumption per weekday type.



(a) (b)

Figure 11. Average weekly energy distribution by days of week. (**a**) Percentage-wise; (**b**) Consumption-wise.

3.3.1. SARIMA Forecasting Results

Figure 12 compares the SARIMA forecasting plot (one-step ahead forecasts) obtained by the experimental results (blue lines show the real values, the orange is one step ahead forecast values, and the gray color indicates the calculus error margin). Some details about the SARIMA algorithm optimization are given in Appendix A.

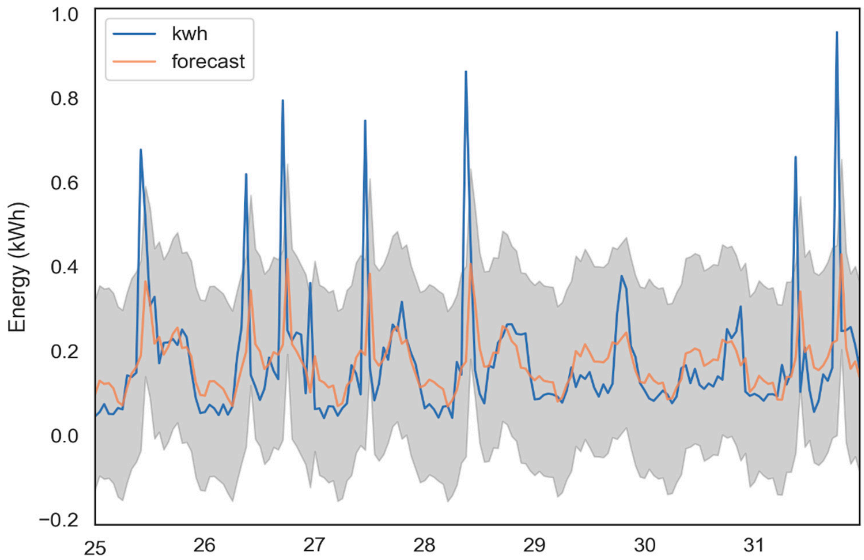


Figure 12. SARIMA dashboard forecasting: energy consumption hourly forecasting.

3.3.2. RNN/LSTM Results

Alternatively, to the SARIMA approach, an RNN approach has been adopted for energy forecasting. To further improve the performance of the SimpleRNN mode, LSTM networks have been used. Hyperparameter tuning has been performed, and the parameters used were time lag = 24, layer depth = 64, epochs = 500. Figure 13 depicts the performance comparison of measured and forecasted values on 7 days test data, while utilizing SARIMA, RNN and LSTM approaches. Figure 14 is the dashboard, depicting one-week ahead load forecast utilizing LSTM as the preferred approach, based on the best reported performance measures. Some details about the LSTM testing environment are shown in Appendix A.

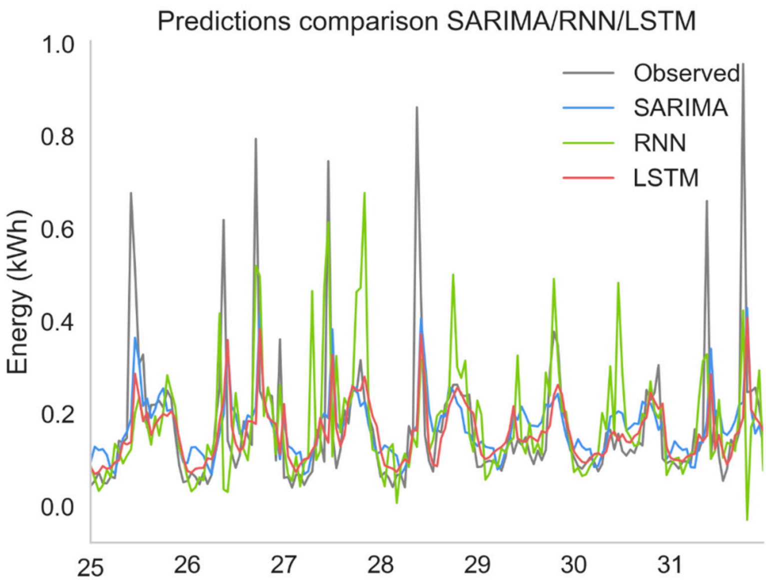


Figure 13. Prediction comparison of 3 different forecasting algorithms—SARIMA, RNN and LSTM.

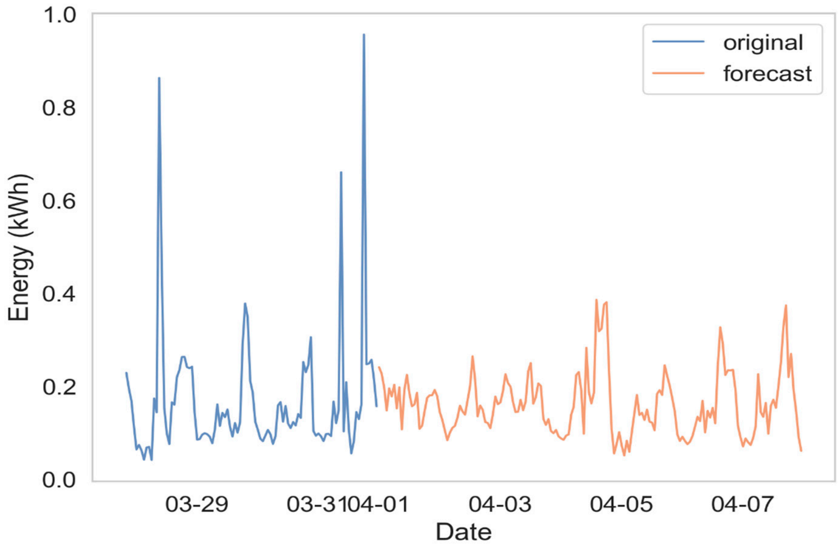


Figure 14. One week ahead load forecast by LSTM Predicted (red line) vs. actual load (blue line).

4. Discussion

In Table 1 LSTM can be observed to provide better error measurements if compared with RNN and SARIMA, thus confirming the suitability of the LSTM algorithm for the analyzed dataset.

Table 1. Performance metric comparison among the three algorithms.

Performance Metric	SARIMA	RNN	LSTM
MAE	0.075166	0.080148	0.067111
MSE	0.018464	0.019442	0.018558
RMS	0.141396	0.139434	0.136226

A total 102,464 datapoints were processed for each of the two monitored room of the experimental building of Figure 2 (one room is energy efficient by means of lighting and temperature control and the other one is not efficient). A comparison between the rooms has been performed concerning the period from April–December 2020:

- thermal energy savings were of 233 kWh (62.2%);
- ventilation electrical energy savings were of 17.5 kWh (25.1%);
- lighting electrical savings were of 282.2 kWh (88.6%).

The modular implementation can simultaneously show dashboards concerning, respectively, energy monitoring and IAQ controls, stored in the same cloud platform: the methodology based on the development of the different architecture layers (as illustrated in Figure 3), integrates other sensors providing other possible information [1] (ventilation, number of persons for room, lighting, energy renewable KPI, etc.), and other dashboards (for example for noise level data [21]). Monitored and predicted energy consumption data are of primary importance to the planning of work activities in an efficient way. An example is planning efficient electrical load switching operations [22,23] according to the workers activities inside the public building, as well as load priorities [23]. The use of both energy consumption and IAQ modules allows the formulation of intervention plans (bottom level of Figure 1) based on the following procedure:

1- energy consumption interventions based on the use of electricity, avoiding energy waste and using energy either from renewables or from storage (thermal and electrical), and possibly choosing low-cost hours;

2- reengineering working spaces based on intelligent deactivation of electrical loads in empty rooms;
3- new definition of the rooms occupation based on either work activities or electric loads distribution;
4- engineering of new layouts by taking into account the "wellness" level provided by the IAQ module;
5- other interventions can be performed in real time by continuously analyzing building energy and IAQ dashboards.

The use of the very low cost electronic components described in the Appendices A and B, and the adoption of an open source platform, makes it possible to install the modules in each room of the building and to control all the parameters in the cloud. This aspect is important for big public buildings which have several floors and many rooms.

Concerning advantages and disadvantages of the proposed technologies, in Table 2 some features are reported compared with commercial solutions.

Table 2. Comparison with commercial solutions.

Feature	Proposed Technologies	Commercial Technologies
Mechanical stability of the electronic modules	The mechanical stability can be achieved after an accurate design of the package containing electronic components and printed circuit board (PCB) connections.	The mechanical stability is guaranteed by the industrialized package tasted during the industrialization process.
Communication stability	Both accurate design and maintenance are necessary to ensure communication stability.	Commercial solutions normally provide a sure communication stability.
Time forecasting (setting parameters)	It is possible to set each parameter of the forecasting algorithm.	Typically, commercial solutions do not implement forecasting algorithms.
Sensor setting	The proposed solution allows us to optimize important parameters (such as sampling time), and transmission protocol.	The setting is a function of the availability of the third-party company providing the software.
Integrability	The solutions are fully integrable with standard protocols, and the modules are designed to integrate in the same framework as other low-cost sensors detecting other indoor parameters. The use of a possible software development kit (SDK) and of the open source software, allow favoring the integration of the hardware and the software.	The modules are typically integrable with other ones of the same company.
Cost	The low cost is fundamental to implementing modules when many rooms have to be controlled.	The cost of the components may limit the implementation (especially for big buildings).
Data availability	The availability of raw data allows to estimate different KPI also considering a large number of variables/parameters (as for complex KPI [1]).	Data are typically available on third party databases, and cannot be easily used to calculate other KPI which can be referred to in the particular case study.

In Table 3, some research topics matching with the proposed technology by highlighting its potential advantages are listed. The main issues can be summarized as follows:

- simultaneous energy and IAQ monitoring system are applied on the same building;
- a good error performance of the adopted algorithms (LSTM and SARIMA) can be useful for energy forecasting;
- low-cost and open source solutions are suitable for the hardware integration of different sensors and for the data processing software libraries;
- a method to design platform architectures, implementing standard communication protocols (such as MQTT), is available.

Table 3. Comparison with commercial solutions.

Research Topics and references	Applicability of the Proposed Technology to the Research Topic	Advantages of the Proposed Technology Matching with the Research Topic
Energy Management Systems (EMS) [24–27]	EMS monitoring heavy loading, fault conditions, energy consumption (considering environment parameters),battery charging, and estimating problems in electric power systems.	Easy implementation for each type of monitoring system, integrating versatile synoptic panels controlling parameters (open source platforms adaptable for the specific environment or system to control and able to estimate other non-standard parameters).
Energy Forecasting [28–36]	Methods such as artificial neural network (ANN), SARIMA and LSTM for load, active and reactive power forecasting.	Possibility to integrate for cloud or local forecasting calculus different algorithms by using the same software platform.
Smart metering network [37]	Long RAnge (LoRA) technology for residential electricity metering networks.	Compatibility with LoRA protocol constructing a LoRA IoT network (by means of a specific access control layer).
Wireless Sensors Network (WSN) [38–40]	WSN implementing long-range wide-area networks (LoRaWAN), bluetooth low-energy mesh long-Range (BLE-M-LR), and data aggregation technologies.	Possibility to also structure the complex WSN, adopting a low-cost Arduino-based technology managing different wireless nodes (simply constituted by a microcontroller unit, a radio frequency transmitter, and a battery) structured in different architectures.
Electronic Integrated Chips [41–43]	Integration in boards of Bluetooth Low Energy (BLE), and in general of low-cost systems-on-chip solutions, allocating resources efficiently.	Presence in the market of sensor technologies compatible with different Arduino-based boards, ensuring a full integration for embedded BLE or Global Positioning System (GPS).
Indoor air quality [44]	Indoor air quality (IAQ) monitoring technology.	Possibility to integrate IAQ with EMS by considering the same backend system.

Possible future developments of the present system will be addressed in future to energy routing and strategy actuation features based on alerts detected by the platform. Actually, on the same hardware, both energy management and building security would be provided based both on sensors detection or AI prediction algorithms.

5. Conclusions

The paper proposes some hardware and software low-cost solutions which are useful for smart building energy and IAQ monitoring. The low-cost modules allow for the installation of the components in each room of the public building. The goal of the paper was to propose a modular approach to electronic control modules. Acquired datasets have been adopted to define optimization strategies for electrical energy consumption reduction and worker wellness increase. The provided solutions are compatible and integrable with other "open" modules controlling other parameters, and which are devoted to further improve energy savings and wellness conditions. Interventions can be planned which are also based on predicted energy consumption.

Compared to existing commercial solutions, the technology proposed here uses a predictive LSTM algorithm, which is demonstrated to be more efficient than a SARIMA one, for the specific dataset typology.

The formulation of more complex key performance building indicators, taking into account priorities of electrical loads, is under investigation.

The adopted open source tools are fully integrated into an information system managing front-end interfaces with dashboards and back-end data systems collecting data. The paper provides a low-cost solution to build up an advanced platform, suitable to control whole buildings with a modular implementation of the hardware solutions and compatible with different sensor technologies and data transmission standard protocols.

The implementation of two main functions, such as energy and indoor air quality monitoring, proves that managing sensors data displaced in complex networks is possible. In addition, Python with the related open source libraries is compliant with the implementation of different machine learning algorithms, provided that there is a dataset to be processed and performance to be achieved.

The adoption of more algorithms and sensors is fundamental to estimate innovative KPIs as outputs of complex monitoring systems such as energy routing. In future works, implementing synchronized electronic boards will be the goal, both for control and actuation functions for cloud computing platforms or for edge computing systems interfacing microcontrollers with data processing units. This achievement is possible as the modularity of the solutions depicted here allows the design and to implementation of hybrid networks constituted by cloud and edge data processing systems.

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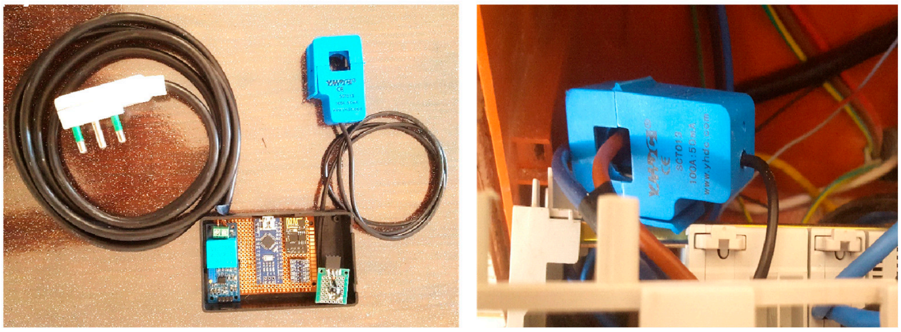
Abbreviations

AC	Alternating Current
ANN	Artificial Neural Network
ARIMA	AutoRegressive Integrated Moving Average
AVR	Alf and Vegard's RISC
BLE	Bluetooth Low Energy
BLE-M-LR	Bluetooth Low Energy Mesh Long Range
CF	Contamination Factor
DM	Data Monitoring
D-SySCOM	Data System Platform for Smart Communities
EEPROM	Electrically Erasable Programmable Read-Only Memory
EP	Electric Power
EMS	Energy Management System
GPS	Global Positioning Systems
IAQ	Indoor Air Quality
IEQ	Indoor Environmental Quality
IoT	Internet of Things
IDE	Integrated Development Environment
IP	Internet Protocol
IRED	Infrared Emitting Diode
KPI	Key Performance Indicator
LoRA	Long RAnge
LoRaWAN	Long-Range Wide-Area Networks
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MCU	MicroController Unit

MOS	Metal Oxide Semiconductor
MQTT	Message Queuing Telemetry Transport
MSE	Mean Square Error
M2M	Machine to Machine
PCB	Printed Circuit Board
RMS	Root Mean Square
RNN	Recurrent Neural Network
SDK	Software Development Kit
SQL	Structured Query Language
TCP	Transmission Control Protocol
VOC	Volatile Organic Compounds
WMS	Wireless Sensors Network

Appendix A

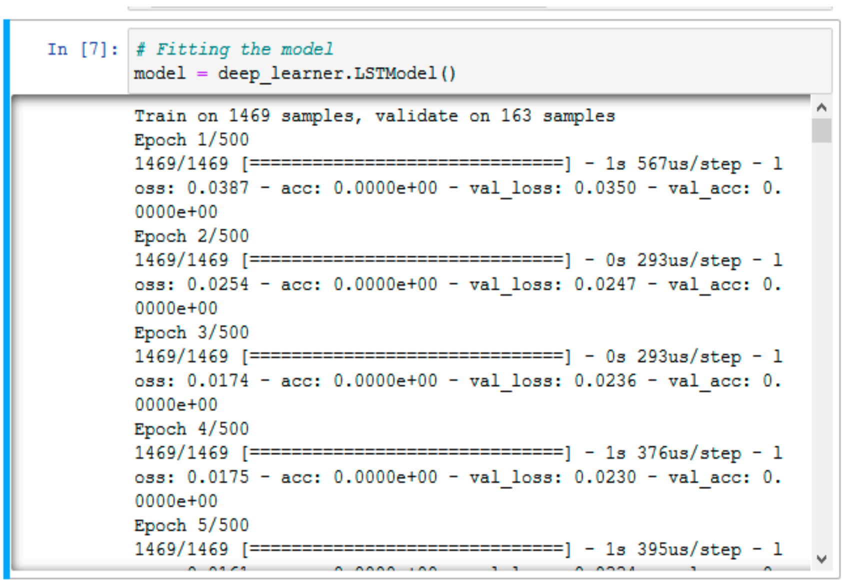
Figure A1a shows the whole electronic setup used for energy monitoring measuring electrical current and voltage. The measurement system is non-invasive, i.e., the user does not need to disconnect any wires or modify any connections within the distribution board of the house (Figure A1b).



(**a**) (**b**)

Figure A1. (**a**) Components of the energy monitor system. (**b**) CT coupled in a distribution board of a residential home.

Data collected in cloud are processed by the SARIMA and LSTM algorithms. In Figure A2 is illustrated the testing framework used for the algorithm optimization.



```
In [7]: # Fitting the model
        model = deep_learner.LSTMModel()

Train on 1469 samples, validate on 163 samples
Epoch 1/500
1469/1469 [==============================] - 1s 567us/step - l
oss: 0.0387 - acc: 0.0000e+00 - val_loss: 0.0350 - val_acc: 0.
0000e+00
Epoch 2/500
1469/1469 [==============================] - 0s 293us/step - l
oss: 0.0254 - acc: 0.0000e+00 - val_loss: 0.0247 - val_acc: 0.
0000e+00
Epoch 3/500
1469/1469 [==============================] - 0s 293us/step - l
oss: 0.0174 - acc: 0.0000e+00 - val_loss: 0.0236 - val_acc: 0.
0000e+00
Epoch 4/500
1469/1469 [==============================] - 1s 376us/step - l
oss: 0.0175 - acc: 0.0000e+00 - val_loss: 0.0230 - val_acc: 0.
0000e+00
Epoch 5/500
1469/1469 [==============================] - 1s 395us/step - l
```

Figure A2. Testing framework of LSTM prediction.

Figure A3a–d illustrates some plots used for the check of the SARIMA performance algorithm, where are some plots related the optimization of algorithm checking testing data distributions.

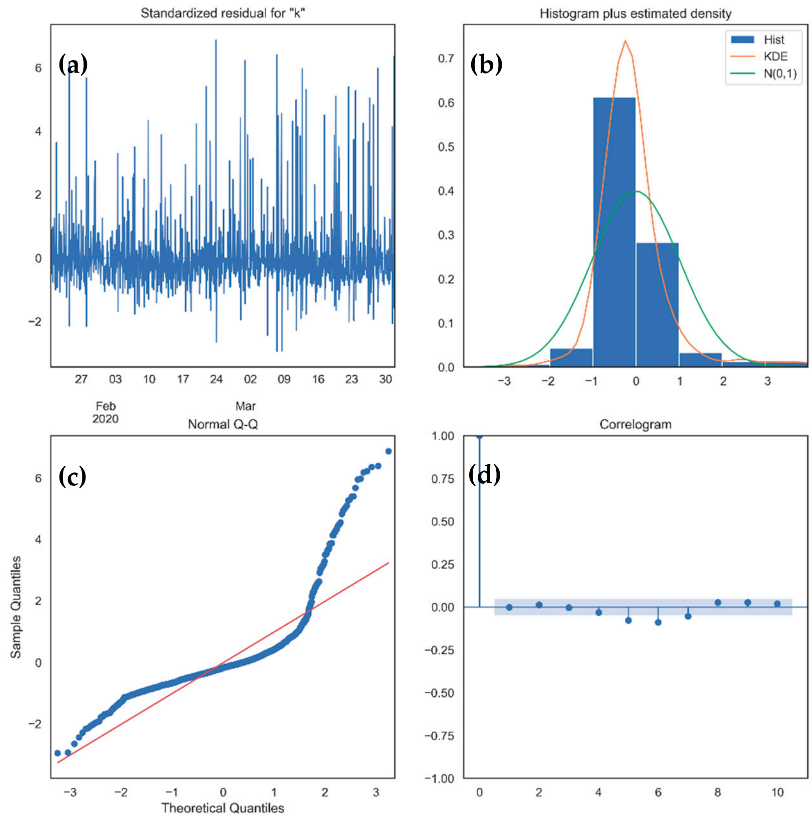
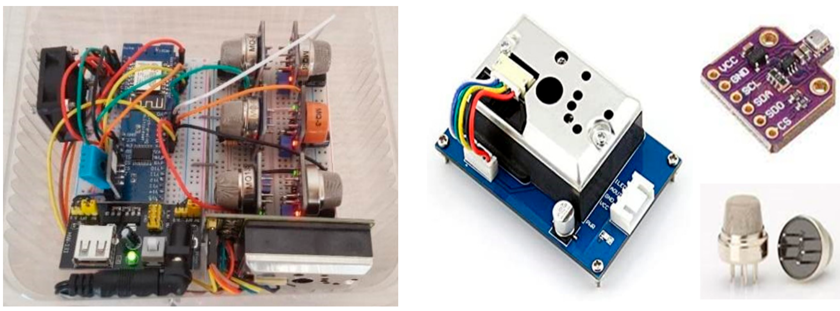


Figure A3. Testing of the SARIMA algorithm checking the best algorithm performance: (**a**) standardized residual, (**b**) histogram of the estimated density distribution, (**c**) normal probability Q-Q plot, (**d**) correlagram.

Appendix B

Arduino based MCU (Figure A4a) is able to collect and forward data of sensors (illustrated in Figure A4b) to the WiFi node.



(**a**) (**b**)

Figure A4. (**a**) IAQ Monitoring sensor setup. (**b**) BME, MQ, SHARP Sensors.

- BME680 is a low power consumption sensor unit that includes an environmental VOC, temperature, humidity and barometric sensors. The operating current consumption ranges from 5 to 25 mA. The sensor precision for temperature is ±1.0 °C, the humidity is ±3% r.H and atmospheric pressure of ±0.6 hPa. The BME680 sensor calculates the sum of VOCs in the surrounding air to provide qualitative air quality data. This sensor also incorporates a background auto-calibration feature in order to provide reliable

IAQ qualitative data. The data is stored in Electrically Erasable Programmable Read-Only Memory (EEPROM), which is then used for baseline correction for subsequent readings. This process regards the recent measurement records to guarantee that IAQ index ~25 matches to typical good air and IAQ index ~250 states for typical polluted air. The sensor output resistance value varies according to VOCs concentrations, as the higher the concentration of reducing VOCs, the lower the resistance and vice versa. The IAQ qualitative range is from 0 to 500.

- Sharp GP2Y1010AU0F is a dust sensor with an optical sensing system. An infrared emitting diode (IRED) and a phototransistor are integrated into this device, detecting the reflected light of dust in air. In particular, the sensor can detect fine particles like those contained in cigarette smoke, with a capability for detecting them due to the pulse pattern of output voltage. The features of compact size and low current draw of 20 mA are particularly important for wireless embedded applications. The sensor outup is an analog voltage proportional to the measured dust density, with a sensitivity of 0.5 V per 0.1 mg/m^3. The detecting range of the sensor is from 0 mg/m^3 to 0.5 mg/m^3.
- MQ Sensors are metal oxide semiconductor (MOS)-type gas sensors, also known as chemiresistors. Their detection is based upon the change in resistance of the sensing material when the gas comes into contact with the material. They have high sensitivity for different gasses like ammonia, NOx, alcohols, aromatic compounds and smoke. The conductivity of the sensor increases with the concentration of pollutant gas. The sensitive material of MQ sensors is SnO_2, which has lower conductivity in clean air. When the target combustible gas exists, conductivity of the sensor increases proportionally to gas concentration. The sensor module voltage is 5 V. The resistance variation in the sensor module is converted into proportional voltage variation by the use of external load resistance.
- BH1750FVI is a photodiode-based analog ambient light intensity sensor integrated into a circuit with a two wires serial bus interface. BH1750FVI has high resolution when measuring light in a range between 1 and 65535 lx.

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