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Occupancy Detection in Smart Home Space Using Interoperable Building Automation Technologies

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Abstract

To detect whether people are occupying individual rooms in a smart home, a range of sensors and building automation technologies can be employed. For these technologies to function in tandem and exchange useful data in a smart home environment, they must be interoperable. The article presents a new interoperable solution which combines existing decentralized KNX building automation technology with a KNX/LabVIEW software application gateway using visible light communication to track occupancy in a room. The article also describes a novel KNX/IoT software application gateway which uses an MQTT protocol for interoperability between KNX technology and IBM Watson IoT platform. We conducted an experiment with the originally designed solution to detect occupancy in an office room. We used KNX and BACnet building automation technology to produce an interoperable KNX/BACnet hardware gateway which allowed the application of artificial neural network mathematical methods for CO_2 waveform prediction. The best results in detecting occupancy in a room were R = 0.9548 (Levenberg–Marquardt algorithm), R = 0.9872 (Bayesian regularization algorithm), and R = 0.8409 (scaled conjugate gradient algorithm), which correspond to the results obtained by other authors and a minimum system prediction accuracy of 96%.

Keywords

Smart Home, Sensors, Building Automation, Visible Light Communication, KNX, Internet of Things, Prediction, Interoperability, Occupancy, Neural Network

1. Introduction

Automation technologies and methods are currently experiencing rapid development and providing sophisticated management solutions for operational and technical features in residential, administrative, and industrial buildings. These technologies can be applied to minimize energy consumption, reduce operating costs, and raise comfort for building occupants [1]. Smart homes provide practical solutions in the world of the Internet of Things (IoT) [2]. IoT mechanisms enable the management of home environments because they can be developed as IoT-based information systems [3]. An important parameter for optimal control of operational and technical functions in intelligent buildings is correct detection of occupants in living spaces. The range of technologies available in IoT allows new scenarios in which home automation has a significant role [4]. Using IoT, future homes, or smart homes, will

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seamlessly integrate physical smart objects and enable their interactivity with the surrounding environment [5]. Unfortunately, the use of multiple technologies (Zigbee, EnOcean, X10, and Z-Wave device communication, Coap, MQTT, and XAMPP application protocols) in building automation does not guarantee interoperability with data communications security [6]. In phase with the development of technical concepts such as smart homes, smart metering, smart grids, and smart cities, new methods are being sought for the transmission of information through suitable communications media with an emphasis on security, transmission speed, resilience and interworking of wireless and wired technologies [7]. Future smart homes and power management systems will incorporate many interconnected smart wireless devices (e.g., wireless sensors & IoT nodes) [8]. Visible light communication (VLC) is an emergent communications technology for IoT services with appealing benefits not found in existing radio-based communications for smart homes [9, 10].

The article describes our own recently proposed hardware and software solutions to enable communications and interoperability in smart home technology used to detect human occupants. The solution employs the KNX open data protocol, which provides interoperability and interworking with other technologies. Novel methods of enabling interoperability between KNX technology (smart home automation) and a VLC testing platform, IoT platform, or BACnet technology are also described.

The research contribution contains three main parts as follows (Fig. 1).

Part 1: A proposed architecture (for the interoperable solution) is applied to existing decentralized KNX technology in a smart home for the purpose of monitoring occupancy in individual rooms. An interoperable implementation of KNX technology LabVIEW and VLC technology is described, and an experiment was conducted with an interoperable LabVIEW/KNX communication solution for a VLC testing platform to measure the VLC communication parameters for detecting occupancy in a room. Part 1 includes a novel software application gateway which is interoperable with KNX/ LabVIEW.

Part 2: An interoperable implementation of KNX technology and IBM Watson IoT platform, which uses the MQTT protocol, is applied to a novel KNX software application gateway/IoT solution in an experiment to detect occupants in an office room.

Part 3: An interoperable implementation of KNX (KNX outdoor temperature sensor) and BACnet building automation technology (BACnet CO_2, RH, & indoor temperature sensors) is applied through a KNX/BACnet hardware gateway. PXC001.D is used in a novel prediction method which uses an artificial neural network—comparison of Levenberg-Marquardt algorithm (LMA), Bayesian regularization algorithm (BRA), and scaled conjugate gradient algorithm (SCGA)—to detect occupancy in a room.

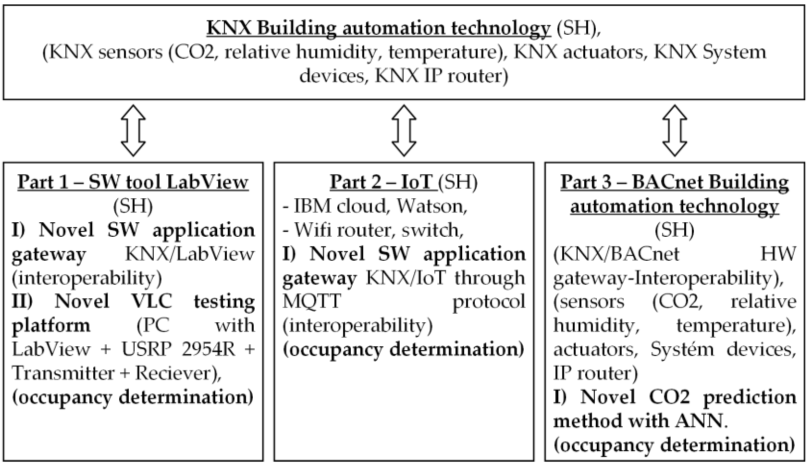


Fig. 1. Block diagram: interoperability between KNX and BACnet technologies, LabVIEW (VLC testing platform), and IoT platform for smart home automation

The proposed architecture was applied to existing decentralized KNX technology in a smart home environment for the purpose of monitoring occupancy in individual rooms. The article is structured as follows: Section 2 introduces relevant studies and key technologies in smart home solutions which apply VLC, KNX, LabVIEW, and IoT platforms; Section 3 presents a description of VLC technology, an experiment conducted with an interoperable LabVIEW/KNX communication solution for a VLC testing platform, measurement of VLC communication parameters for detecting occupancy in a smart home; Section 4 presents a designed solution and experiment to detect occupancy in a laboratory room (EB312); Section 5 presents a new method which uses an ANN to detect occupancy in a smart house (room R203); and lastly, Section 6 concludes the study and discusses future research directions.

2. Related Work

Building automation technologies used to detect occupancy in interior spaces of houses, offices, malls, or hospitals will be ready to adapt interoperable VLC systems and IoT & soft computing methods in the near future [11–15]. A summary of state-of-the-art VLC, IoT implementations and soft computing methods—artificial neural network (ANN), fuzzy system (FS), linear regression model (LRM)—applied in smart home automation is presented in Table 1 [16–51].

Table 1. Studies to investigate the application of VLC & IoT in smart homes

Topic of the article	Observation	Reference
VLC in smart home applications	VLC, smart home	[16–18], [21–24], [27–31]
VLC, smart home, IoT applications	VLC, smart home, IoT	[19], [20], [25], [26]
Smart home automation employing VLC, an Arduino, or KNX technology	VLC, smart home, KNX	[32], [33]
Smart home or smart city with IoT implementation	Smart home, SC, IoT	[34]
IoT learning – Practical case for smart home automation	Smart home, IoT	[35], [44]
A smart home gateway architecture based on blockchain to prevent data forgery	Smart home	[36]
Deep block scheme – Scheme for secure SC based on deep learning and driven by blockchain	Smart home, secure	[37]
IoT data processing in smart home for occupancy 88% detection	Smart home, IoT, occupancy	[38]
ADL, IoT, smart home with over 96% classification accuracy	Smart home, IoT, ADL, SM	[39]
Overall user energy consumption of IoT devices	Smart home, IoT, SM	[40]
Open home automation bus – IoT-supported security	Smart home, IoT, security	[41], [42]
A predictive model for battery life in IoT networks	Smart home, IoT,	[43]
Comparison of (RNN) prediction methodology with ANN and linear regression models (LRM)	Smart home, RNN, ANN, LRM	[45]
Predictive control for lighting systems in smart home with 97.4% accuracy	Smart home, prediction	[46]
A fuzzy system (FS) based on occupancy for predicting energy consumption in a building	Smart home, FS, SM, occupancy,	[47]
Dirichlet process (DP) mixture model implemented with Gibbs sampling of user behavior	Smart home, DP	[48]
HVAC systems in multi-occupant offices with an ANN	Smart home, ANN, occupancy	[49]
Mining big data streams (MBDS) – Business analytics tools	MBDS	[50]
Extreme gradient boost classification (GBC)	GBC	[51]

None of the articles mentioned in the research described a comprehensive solution for interoperability using VLC, KNX, BACnet, or IoT for monitoring occupancy in smart homes.

In the current study, we applied an interoperable implementation of KNX technology and VLC in LabVIEW to the VLC testing platform to measure VLC communication parameters for the purpose of detecting occupancy in a smart home. The study also investigated an interoperable implementation of KNX technology (providing a security standard) and IBM Watson IoT platform which used the MQTT protocol for communication. The design is a novel solution for indirectly detecting occupancy in office rooms (with commonly use KNX technology sensors to detect or measure motion, CO_2, temperature, & humidity). KNX technology is suitable for monitoring occupancy in buildings because it is resilient, applies an open communication protocol, provides interoperability, conforms to a worldwide standard, and commonly finds use in the smart home technology market. In the said study, we present a new prediction method which uses an ANN (comparing the LMA, BRA, SCGA) to detect occupancy in smart homes with a minimum prediction accuracy of 96% in certain conditions without additive noise cancelling.

3. Providing Interoperability between KNX Technology & VLC Testing Platform with LabVIEW

As developments in smart homes accelerate, the number of different telecommunications technologies required for efficient operation of individual smart components also increases. The majority of households today use either Wi-Fi-based connections (based on the older 802.11n, newer 802.11ac, or new 802.11ax standards), metallic networks (Ethernet), or optical fibers. Wireless networks are frequently preferred for connecting end devices to the local network. Newer Wi-Fi standards offer transmission parameters comparable to physical cable connections. However, Wi-Fi carries the risk that available and non-overlapping radio channels may be depleted, especially in denser residential areas. By its very nature, this technology passes through walls, and so the networks of individual living areas overlap, inferring that they are able to interact with each other. An alternative to these wireless radio frequency technologies is the relatively modern technology of VLC. This technology functions on the basis of high-frequency modulation of light, which can then be used as a transmitting element. A photodetector, solar panel, camera, or CMOS chip can be used for reception, all of which are devices which are able to identify rapid changes in the luminous flux intensity of a light source (e.g., on/off states in the case of phase shift keying). The rapid development of this technology is mainly due to the rate of development of LEDs. Compared to conventional lights, LEDs enable high-speed switching through their very design. Any alternative technology which functions in the free and currently unlicensed band is a much sought-after item. In addition, VLC-based telecommunications channels do not interfere with sensitive technology, and thus it is possible to apply this technology to link medical equipment or for assembly halls. A commercial VLC-based solution would fill some of the gaps in the concept of smart homes or smart cities, and could work as complementary or sister technology alongside existing Wi-Fi or next-generation networks. Research of experimental VLC platforms has been underway at VŠB–TUO for several years. From the start, it was clear that the concept must focus primarily on the modularity of the end solution. The combination of data communications with adaptively controlled smart lights according to human presence is a perfect fit for the concept of smart cities. In view of our requirements for high modularity, we have selected the LabVIEW tool from the National Instruments, a company which has extensive experience in virtual instrumentation, for prototyping and constructing the alpha model. The combination of virtual instrumentation and a robust hardware platform offers many significant benefits. The code can be quickly compiled and modified, while any significant changes can be tested immediately. The software is not directly dependent on the hardware, so any modifications to modules do not interfere with software and can be executed without complication. The hardware itself is also partially customizable. Communication can be tested in scenarios that involve cars or interior lights.

3.1 Interoperability between LabVIEW (VLC Testing Platform) & KNX Technology

LabVIEW software contains libraries for creating applications. These provide measurements in individual phases (collection, analysis, and presentation of data), thus offering a fully developed programming environment. We used the programming tool ETS, currently ETS-5, for programming and parameterization of individual KNX technology components (i.e., sensors, actuators, system components). KNX technology delivers interconnection for its modules using a twisted pair (TP) communications medium. Parameterization requires an individual address to be assigned to each KNX device, while a building structure, KNX installation topology, and group address structure must also be created. We selected UDP communication for communicating between the application created in LabVIEW and KNX building technology (Fig. 2).

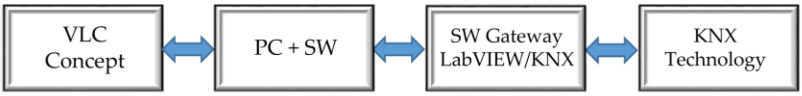


Fig. 2. Block diagram: description of ensuring interoperability between VLC testing platform, LabVIEW, and KNX building automation technology.

3.2 Visible Light Communication

The third and latest version of our platform was based on USRP 2954R, which is the latest SDR (software define radio) from the National Instruments (LabVIEW). This USRP was modified as follows: The internal cards were replaced with an Ettus LFTX/LFRX kit which operates in the baseband (DC -30 MHz). For now, commercial lights can only be modulated in the DC -10 MHz band due to limitations in the LED diodes themselves. A 1.6 W amplifier operating in the 1–200 MHz band was connected to the USRP output. Modulation of the light source itself was performed via a commercial ZX85-13G+ bias-tee. For the physical transmission component, we used a Philips Fortimo ceiling light unit, which is used widely in the corridors at VŠB–TUO. Its affordable price also means it is installed in many state institutions throughout the Czech Republic. The receiving component is a Thorlabs PDA36A-EC commercial photodetector, whose output was also connected to the USRP. The entire system was based on orthogonal frequency-division multiplexing (OFDM) digital modulation, which is well-known from new generation networks, some Wi-Fi standards and digital television. Because of the synchronization requirements, both the transmitter and receiver were housed in a single SDR, allowing synchronization through the device bus. A powerful PC built on an Intel Core i9 Extreme platform was connected to the SDR via a PCI-E cable. The entire system is depicted in Fig. 3.

To acquire optimal energy segmentation of the infrared and visible image contours, we applied Bregman's iterative approach, while the nonsubsampled contourlet transform (NSCT) transform was used to decompose the source image, with corresponding rules applied to integrate the coefficients with the light in the segmented background. To maintain a level of data authenticity, we defined a specific measurement scenario. A Philips lighting unit was mounted to a ceiling at a height corresponding to the usual height of a room in a smart home. The receiving component, a photodetector, was placed on a movable trolley. For the first measurements, the trolley was placed directly below the lighting unit, so that the photodetector was located directly in the center of the illuminated area. The trolley was then moved in increments to the edge of the illuminated surface, which formed the shape of a cone. Because the entire cone was symmetrical, the parameters measured from the center to the edge of the cone directly correlated in all directions. Thus, it was not necessary to perform multiple sets of measurements, a fact verified with test measurements that confirmed the hypothesis. A carrier frequency of 3 MHz was used for measurement. We selected this due to the nonlinearity of the amplifier used at ambient frequencies (Fig. 4).

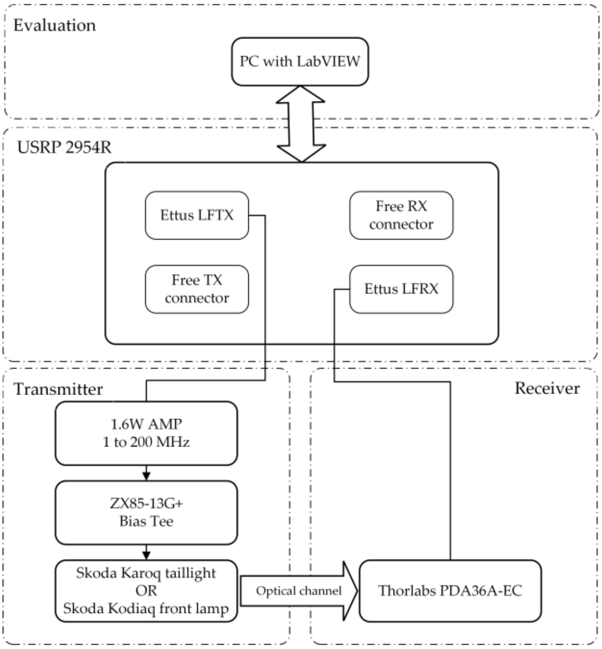


Fig. 3. Flowchart of VLC testing platform.

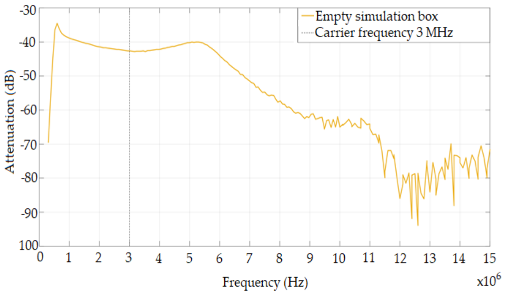


Fig. 4. Frequency-attenuation characteristics of the amplifier with 3 MHz carrier frequency providing the most linear gain in its vicinity.

During measurement, the order of N-QAM modulation of the subcarrier OFDM symbols was changed from 4- to 64-QAM. The bandwidth was gradually changed from 500 kHz up to the system's limit. The charts in Figs. 5 and 6 represent the results of the combinations of different bandwidths and orders of N-QAM modulation. Fig. 5 represents the best-case scenario as the moment when the receiver was at the center of the illuminated area, while Fig. 6 represents the boundary of the radiated cone. The charts indicate that some error rates were very high, and the main limiting factors were the system's hardware components, which are not ideal. However, the modularity of the system will allow for gradually eliminating these limiting factors and achieving superior results. Despite the problems, the system functions adequately and allows the transmission of data through a commercial and affordable LED ceiling light. In this respect, VLC technology offers benefits that can be integrated into the concept of SH or smart cities in the future. However, further experiments in this area are necessary, but the test platform still has a number of bugs that require fixing. The system is also unoptimized and thus places high demands on the computing power of the connected PC.

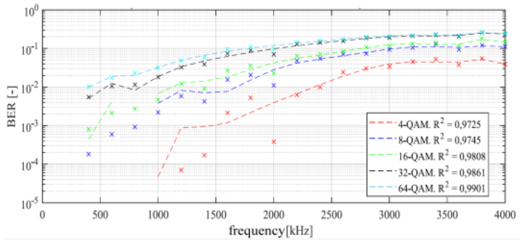


Fig. 5. Error rate dependence on bandwidth (ideal scenario).

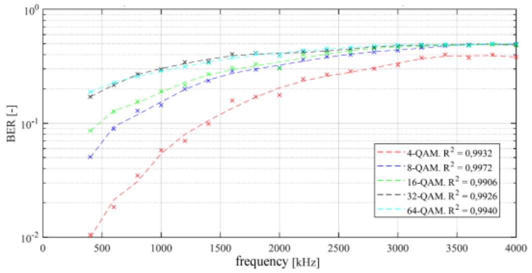


Fig. 6. Error rate dependence on bandwidth (limit values).

Fig. 7 illustrates the constellation diagrams of different orders of M-QAM modulation in ideal conditions. All these diagrams were derived from measured values as follows: The photodetector was positioned exactly at the center of the radiated cone, and the system used the narrowest possible bandwidth in combination with a carrier frequency with low attenuation, treated as ideal conditions.

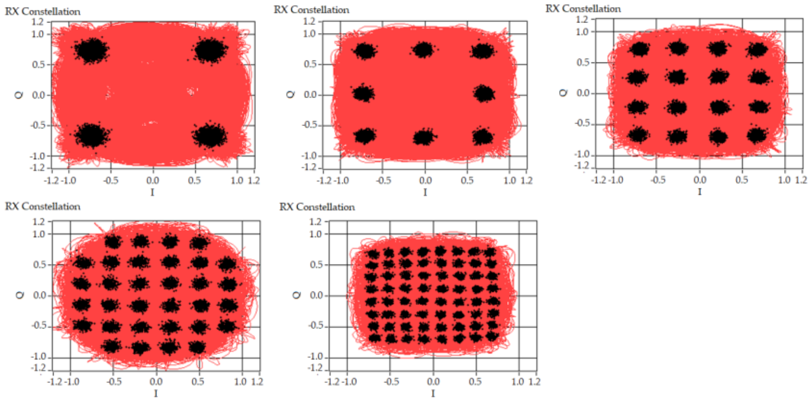


Fig. 7. Constellation diagrams of various M-QAM modulation schemes directly in the center of illuminated area.

3.3 Using VLC to Monitor Occupancy

VLC can be used to determine the location of a person or object within an environment. The coordinates of a monitored object can be roughly estimated with Cell-ID identification. Each VLC access point can be tagged with a unique Cell-ID, and when the monitored object enters the illuminated area, it is automatically pinpointed with a level of precision corresponding to the diameter of the illuminated area. This method can also be applied conversely as follows: the receiver is used as a fixed solution, whereas the object is mounted with the receiving component. Other well-known RF localization solutions can also be applied and are generally based on triangulation variants (laceration & angulation). Another alternative is advanced computer vision analysis, which involves a geometric relationship between the 3D position of a monitored object and its 2D position projected onto an image sensor. While these techniques have the greatest accuracy, they are also computationally intensive, and so modern and more expensive hardware capable of ray tracing is often required, with a centralized server evaluating the collected data. Both passive and active visible light positioning (VLP) techniques can be used to monitor objects. Active localization techniques require a tag or active component which must be directly mounted on a monitored object or person. These techniques also rely on a direct line of sight between the receiver and transmitter. By comparison, passive solutions can work with both direct line-of-sight rays and scattered or diffused rays, although the infrastructure must be scanned and analyzed in advance and requires no dedicated wearable equipment. Both active and passive VLP techniques can be used, and their deployment is highly dependent on the specific scenario and backbone system capabilities. These technologies can be incorporated into the presented concept and thus be used to track objects of interest or persons in real time. The concept has not yet been implemented, while the end solution is still in the draft phase.

4. Interoperability between KNX Technology & IoT Platform

4.1 Interconnection of KNX/IoT Technologies Using MQTT Protocol

To provide connectivity to KNX technology and an IoT platform using the MQTT communication protocol, we created a software gateway between KNX and IoT (Fig. 8). We applied several third-party libraries in our work, mainly libraries for communication with the KNX bus, IBM Watson IoT platform, and Cloudant databases, and for work with JSON files. For the development environment, we selected Microsoft Visual Studio 2017, and for programming with C# language, we used the .NET Framework since it has sufficient support for this platform in the form of libraries from both KNX Association and IBM. As a hardware solution to run the developed software, we used a personal computer (PC) installed with a Windows 10 operating system. To access the KNX installation in IoT, we required software which is able to mediate the connection and communication between the KNX installation itself and selected web service. In this case, we applied IBM Watson IoT platform web services. This software was required to function continuously on the selected device and maintain a connection for two-way communication. KNX technology parametrization was implemented using the ETS-5 software tool. The HW components of KNX technology were a CO_2 sensor (0–9999 pm), relative humidity sensor (1%–100%), temperature sensor (0°C–40°C) MTN 60005-0001, and motion sensor MTN 630819.

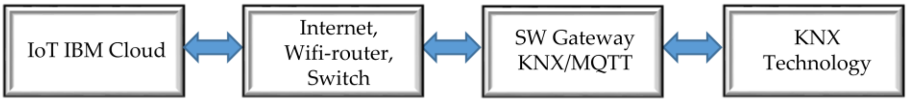


Fig. 8. Block diagram: interconnectivity of KNX/IoT cloud.

4.2 Implementation of Console Application

Implemented as a console application, Console Gateway maintains a continuous connection between the KNX installation and Watson IoT platform (Fig. 9).

When connected, the application monitors the KNX bus to capture predetermined telegrams, and transfers them to the Watson IoT platform service. The console application was created primarily for quicker implementation and high reliability, and then deployed on the laboratory's PC, running continuously for as long as necessary to maintain the connection between the cloud service and KNX installation. When launched, the application informs the user of the success or failure of the connection to the KNXnet/IP router and Watson IoT cloud services. If both connections are established, the user is prompted to commence the data transfer. The data transferred to the cloud is then written to the console.

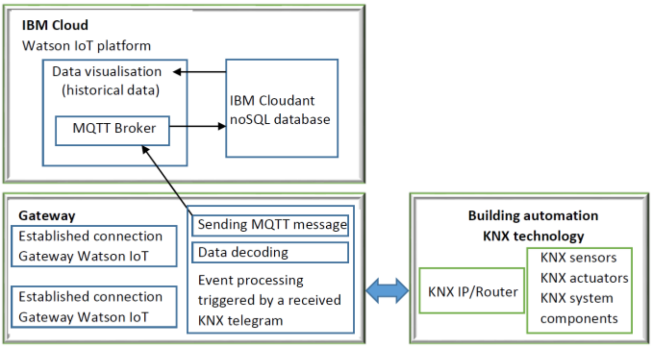


Fig. 9. Diagram of the solution for KNX/IoT interoperability.

4.3 Experiment – Using KNX Technology in IoT Platform

This section describes the effect of human presence on the air quality of the indoor environment of monitored classroom EB312. The experiment revealed that human presence in the room not only affected its CO_2 level, but also relative humidity and temperature. The regular teaching schedule and other real-time recorded activities in the classroom provided a model for comparison of the measured data with the actual occupancy of the EB312 classroom laboratory. During the measured period in April 2019, the class schedule in classroom EB312 at VŠB–TUO was as follows:

- Monday: 9:00–10:30, 10:45 a.m.–12:15, 2:15–3:45 p.m.
- Tuesday: 9:00–10:30, 10:45 a.m.–12:15, 2:15–3:45 p.m.
- Thursday: 12:30–2:00, 2:15–3:45 p.m.

The following sections describe the experiments for monitoring activity in the EB312 laboratory classroom over the course of a month.

4.3.1 Measurement interval of 1 month

To obtain a clearer view of the differences in the measured values when a room was either empty or occupied, the charts below plot the course of all measured quantities for the month of April (Fig. 10).

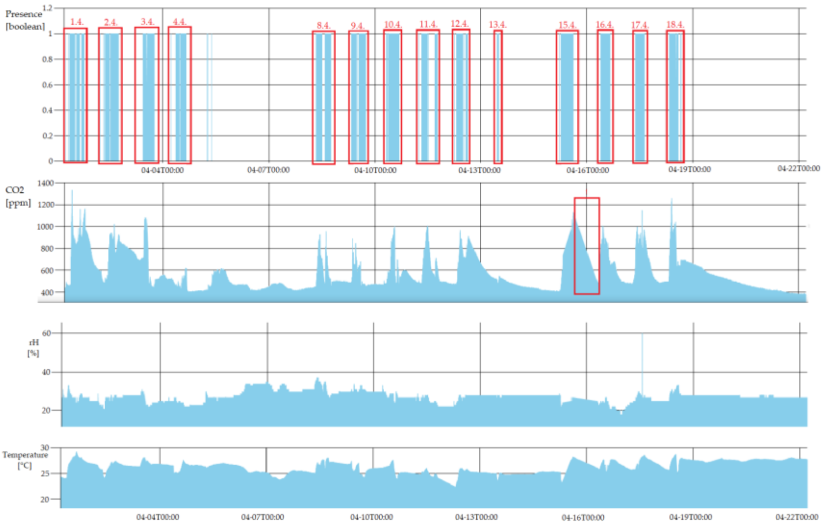


Fig. 10. Plot charts of measured values of CO_2, relative humidity, temperature, occupancy: measurement interval of 1 month (April 2019).

The maximum and steady-state values in the charts are immediately apparent. Motion sensors respond to human presence by changing the logic state from 0 to 1. If no motion is detected, the sensor changes the state to 0. This type of sensor is very sensitive. If the classroom is full of people, it is virtually always in the 1 state since the frequency of detected motion increases with an increasing number of people. During lessons in the laboratory, the occupancy sensor values were in the 1 state most of the time because several people were continuously present. It is interesting to study the progress of CO_2 levels, which increased sharply with the arrival of students to the classroom and then gradually decreased as the room emptied, eventually attaining concentration levels close to that of atmospheric CO_2. Leakage via windows, doors, and permeable masonry allows CO_2 levels to decrease even when the room is closed.

5. KNX/BACnet Interoperability

5.1 Description of Technology

This section describes the interoperable BACnet and KNX automation technologies (Fig. 1) that we used in experiments for a smart woodhouse. Interoperability between KNX and BACnet technologies was achieved with a hardware BACnet/KNX gateway and PXC001.D. BACnet technology was used for HVAC control (humidity, temperature, and CO_2 measurement), while KNX technology was used to control the lights and blinds, and switch off sockets. The following parameters were measured as follows: CO_2 (ppm) (0–2000 ppm, ±50 ppm), indoor temperature T_{in} (°C) (0°C–50°C/-35°C–35°C, ±1°C); indoor humidity RH (%) (0%–100%, ±5%) via the BACnet QPA 2062 sensor; and temperature T_{out} (°C) (-30°C–80°C, resolution 0.1°C) via the KNX AP 257/22 sensor. The AP 257/22 sensor was implemented with KNX technology, and the measured data was collected and used to train an ANN to predict CO_2 levels. The objective is to eventually dispense with the CO_2 sensors and rely on other parameters. This will be achieved by comparing the predictions in different contexts with different inputs to determine the optimal and most efficient method (Fig. 11).

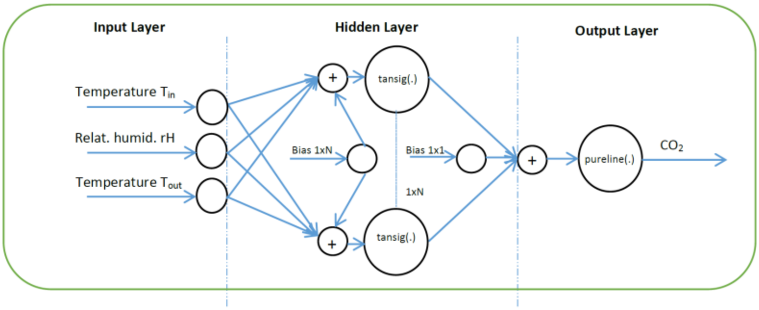


Fig. 11. Architecture of ANN trained with test data for three input quantities of T_{in}, RH, and T_{out}.

5.2 Mathematical Methods

Three optimization algorithms were to train the ANN in the experiments, LMA, BRA, and SCGA.

5.2.1 Levenberg–Marquardt algorithm

The LMA was designed to approach second-order training speed without having to compute the Hessian matrix. The LMA changes adaptively when the parameter upgrades from the gradient descent update and Gauss-Newton update, as denoted in Equation (1) below:

$$[J^T WJ + \lambda I\,]h_{lm} = J^T W\,(y - \hat{y}), \tag{1}$$

where small values of the algorithmic parameter λ cause a Gauss-Newton update and large values of the algorithmic parameter λ cause a gradient descent update. The parameter λ is initially large, so that the first updates represent small steps in the direction of steepest descent. If any iteration results in a worse approximation ($x^2(p + h_{lm}) > x^2(p)$), then λ is increased. In other words, as the solution improves, λ decreases, the LMA method approaches the Gauss-Newton method, and the solution distinctively accelerates towards the local minimum. According to Marquardt's updated relationship, Equation (2) is denoted as:

$$[J^T WJ + \lambda diag(J^T WJ)\,]h_{lm} = J^T W\,(y - \hat{y}). \tag{2}$$

The values of λ are normalized to the values of J^T.

5.2.2 Bayesian regularization algorithm

The Bayesian evidence framework proposed by MacKay (1992) provides a unified theoretical treatment of learning in neural networks. In the Bayesian evidence framework, the weights and biases of the network are assumed to be random variables with specified distributions. Typically, training aims to reduce the sum of squared errors in the following Equation (3) denoted as:

$$F(\omega) = \alpha E_W(w, M) + \beta E_D(D|w, M), \tag{3}$$

where $E_W(w, M)$, is the sum of squares of architecture weights, *M* is the ANN architecture, and α and β are objective function parameters (also referred to as regularization parameters or hyper-parameters and take positive values) that must be estimated adaptively. The inference task is specified in the model using Bayes' theorem (4) denoted as:

$$P(w|D, \alpha, \beta, M) = \frac{P(D|w, \beta, M).P(w|\alpha, M)}{P(D|\alpha, \beta, M)}. \tag{4}$$

In the previous equation, *D* is the training sample, while the prior distribution of weights is defined as $P(w|\alpha, M) = (\alpha 2\pi)m/2\exp\{-\alpha 2w'w\}$. *M* is the specific ANN, and w is the network weights vector. $P(w|\alpha, M)$ states our knowledge of weights before any data is collected, and $P(D|w, \beta, M)$ is the likelihood function, which is the probability of occurrence, thereby providing the network weights.

5.2.3 Scaled conjugate gradient algorithm

The SCGA is a supervised learning algorithm for feedforward neural networks and a member of the class of conjugate gradient methods (CGMs). Let $p = \exp\,(\frac{-\Delta E}{T})$ be a vector, ***N*** be the sum of the number of weights and number of biases of the network, and ***E*** be the error function we want to minimize. SCGA differs from other conjugate gradient methods in two ways:

- Each iteration ***k*** of a CGM computes ω_i, where $R^N$is a new conjugate direction, while $\omega_{k+1} = \omega_k + \alpha_k.p_k$ is the size of the step in this direction. p_k is actually a function of α_k, the Hessian matrix of the error function, i.e., the matrix of the second derivatives. In contrast to other CGMs, which avoid the complex computation of the Hessian and approximate α_k with a **time-consuming** line search procedure, SCGA makes the following simple approximation of the term $E''(\omega_k)$, a key component of the computation of α_k: s_k.
- Because the Hessian is not always a positive definite, which prevents the algorithm from achieving good performance, SCGA uses a scalar α_k, which is meant to regulate the indefiniteness of the Hessian. This resembles the LMA, and is done by setting the following Equation (5) denoted as:

$$s_k = E''(\omega_k).p_k \approx \frac{E'(\omega_k + \alpha_k.p_k) - E'(\omega_k)}{\alpha_k}\,, \qquad 0 < \alpha_k \ll 1 \tag{5}$$

and adjusting λ_k at each iteration.

5.2.4 Description of the experiments

The data set contains parameters measured on June 28, 2018 in the smart home (Room 203). In this experiment, we measured CO_2, relative humidity, indoor & outdoor temperature, illuminance, wind, and occupancy. The data was pre-processed to improve the efficiency of neural network training by normalizing the values to fall between 0 and 1 (in Step 1 of Fig. 12).

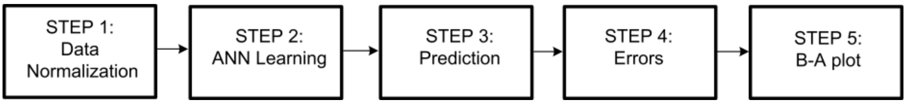


Fig. 12. Block scheme: summary of experimental steps.

We applied the *nftool* function (Neural Fitting) in MATLAB, with neurons varying from 10 to 100, and the three above-mentioned methods. The data samples were divided into three sets, namely training (used to teach the ANN) (Fig. 11), validation, and testing (to provide an independent evaluation of network training) (in Step 2 of Fig. 12).

Because the learning date is different from prediction dates, the procedure is called *cross-validation*. In this step, we applied the *nntool* function in MATLAB (in Step 3 of Fig. 12). When the results were ready, the next step calculated the parameters which allowed us to quantify the precision of the results and thus compare the prediction quality between the different neural networks (in Step 4 of Fig. 12). The experiments were dependent on the three parameters of R (correlation coefficient), MSE (mean squared error), and MAPE (average absolute percentage error). After calculating them, we plotted two charts. The first chart references and predicts CO_2 over time, while the second chart is a Bland-Altman plot. Bland-Altman method is a technique that allows a comparison of two measurements of the same sample. The differences between measurements are quantified using a graph which consists of a scatterplot with the average and differences represented on the X and Y axes, respectively. The plot also contains horizontal lines drawn at the mean difference and limits of agreement, which are defined as the mean difference plus and minus 1.96 times the standard deviation of the differences (in Step 5 of Fig. 12). The final step was a comparison of the results and the plots to determine which conditions and methods were optimal for future predictions. The CO_2 level in the smart home (Room 203) on June 28, 2018, with indoor temperature (T_{in}), relative humidity (RH), outdoor temperature (T_{out}) as inputs, was predicted using an ANN (Fig. 11). Table 2 shows the calculated R, MSE, and MAPE values, followed by plots of reference and predicted CO_2 (Fig. 13(a)), and BA (Fig. 13(b)).

5.2.5 Results and discussion

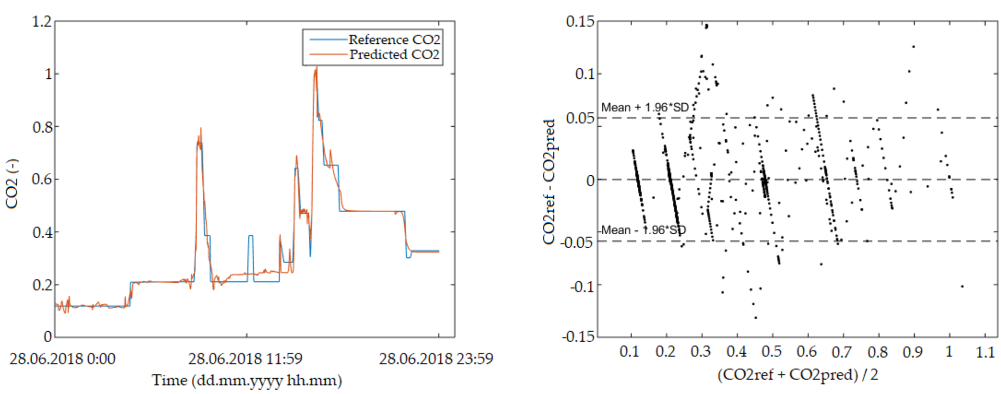
A comparison of LMA, SCGA, and BRA backpropagation algorithms for CO_2 concentration waveform prediction using a multilayer perceptron feedforward neural network ensues. Because of the volatile and non-stationary nature of the CO_2 time series, CO_2 forecasting proved a challenging task which required significant care and caution. Recent studies show that ANNs are sufficiently capable of forecasting CO_2 levels [34–37]. In the said study, a 3-layer perceptron feedforward neural network was used to compare three training algorithms (LMA, SCGA, and BRA backpropagation) as to their ability to perform daily CO_2 waveform prediction (Table 2).

The advantage of SCGA is that it does not place much strain on system memory. LMA is more time-efficient than SCGA, but at the cost of higher memory requirements. BRA differs from the previous two in that it does not work with a validation set and can generalize very small or complicated datasets or those which contain additive noise. The training ends when the weights are minimized. To classify prediction quality, a correlation analysis (correlation coefficient R) calculated MSE and MAPE, while the Bland-Altman method was used. The best results in detecting occupancy were R = 0.9872 for BRA, R = 0.9548 for LMA and R = 0.8409 for SCGA. The results correspond to the results of other authors, with a system prediction accuracy of better than 88% [38], 96% [39], and 97% [46]. The experiment showed that the BRA algorithm had an obvious preference in terms of prediction accuracy with MAPE (0.0611), followed by the LMA and SCG algorithms with MAPE (0.1086 and 0.1899). For the purposes in the current study, the BRA algorithm was more suitable in building a multistep ahead CO_2 prediction model. For Room 203 on June 28, 2018, the results varied considerably for the parameters T_{in}, RH, and T_{out} but were generally good, with a maximum correlation of 0.9872 and minimum MSE of 8.8975×10^{-04} for 10 neurons (BRA) (Table 2). The result of the BA graph in Fig. 13(b) indicates a higher number of outlying measurements in the interval 0.1 to 0.5 (-) and partially in the interval 0.6 to 0.7 (-), caused by changes (transient phases) in the predictions associated with people entering or leaving the room. The majority of values fall in the interval 0.1 to 0.3 (-), indicating the absence of people in the monitored space. For the entire data set, 96% of the values lie within the ±1.96 SD range for detecting human presence. The experimental results of the study are significant in demonstrating the possibility of using ANN to predict a specific CO_2 waveform, based on other measured variables (T_{in}, RH, and T_{out}) to monitor occupancy with interoperable technology in a smart home. To implement the proposal, the building automation technology must be secured against cyberattacks. In the context of the application of a security standard to individual KNX devices, KNX technology fully ensures secure operation and protection against internal and external attacks.

Table 2. Trained ANN using LMA, BRA, SCGA for prediction, with cross-validation for Room 203 on June 28, 2018 (T_{in}, RH, and T_{out})

No. of neurons	LMA			BRA			SCGA		
	MSE	R	MAPE	MSE	R	MAPE	MSE	R	MAPE
10	0.0201	0.6519	0.2908	0.0009	**0.9872**	0.0624	0.035	0.2159	0.4756
20	0.0036	0.9471	0.1480	0.0009	0.9864	0.0611	0.0143	0.7679	0.2610
30	0.0031	**0.9548**	0.1086	0.0111	0.8262	0.1996	0.0194	0.6696	0.2897
40	0.0052	0.9228	0.1339	0.0046	0.9313	0.1307	0.0203	0.6474	0.2908
50	0.0061	0.9082	0.1340	0.0094	0.8562	0.2009	0.0141	0.7731	0.2309
60	0.0114	0.8204	0.1686	0.0102	0.8417	0.1808	0.0140	0.7739	0.2306
70	0.0053	0.9211	0.1343	0.0089	0.8642	0.1712	0.0138	0.7777	0.1899
80	0.0050	0.9251	0.1282	0.0043	0.9365	0.1279	0.0201	0.6551	0.3300
90	0.0041	0.9401	0.1100	0.0088	0.8651	0.1907	0.0102	**0.8409**	0.2256
100	0.0054	0.9202	0.1280	0.0064	0.9037	0.1319	0.0197	0.6598	0.3033

Bold font indicates the best performance in each test.



(a) (b)

Fig. 13. Comparison of reference CO_2 and predicted CO_2 waveforms in Room 203 on June 28, 2018 from a neural network of 10 neurons using (a) BRA and (b) Bland-Altman graph.

6. Conclusion

Different types of sensor and building automation technology (KNX, BACnet, VLC, IoT) were applied in experiments to determine occupancy in individual rooms in a smart home. The article described a new architecture (interoperability solution) for existing decentralized KNX technology (KNX/BACnet, KNX/IoT, & KNX/LabVIEW) for the purpose of smart home automation and monitoring the occupancy of individual rooms. To provide interoperability and a communications interface between KNX technology, a VLC and PC, we created a new software tool in LabVIEW for real-time communication with separate KNX technology devices and VLC technology to measure the data transmission quality. The experiment measured the frequency attenuation characteristics of the VLC amplifier, error rate dependence on bandwidth in an ideal scenario, error rate dependence on bandwidth with limit values, and constellation diagrams of various M-QAM modulation schemes directly in the center of the illuminated area. The system functioned adequately and allowed the transmission of data through a commercial and affordable LED ceiling light. To provide interoperability and a communication interface between KNX technology and IoT, we developed new software for a single-purpose console application, which provides connectivity between separate KNX components and IBM Watson IoT services, allowing interoperability through the MQTT protocol. This original program was created with an emphasis on simplicity and reliability. The program runs continuously and was controlled with a web browser and internet connection. The Watson IoT platform provides a user-friendly web interface for visualizing the received occupancy monitoring data in a smart home. The user is able to monitor the data and CO_2 sensors, and thus determine whether the monitored area is occupied. To provide interoperability between KNX and BACnet technologies for the purpose of monitoring in a smart home, a PXC001.D system controller was used. The new proposed method was able to predict levels of CO_2 concentration from the indoor temperature, indoor relative humidity, and outdoor temperature input values. An ANN, which applied LMA, BRA, and SCGA algorithms, was used in the experiments. A comparison of the reference measured CO_2 and the ANN's predicted CO_2 was discussed in relation to the quality of the selected ANN. LMA provided an accuracy of 95.48%, SCGA an accuracy of 84.09%, BRA an accuracy of 98.72% (Table 2). The respective Bland-Altman plot also indicated that, in this case, the values beyond the limits of agreement were minimal. We can conclude that an ANN with BRA is sufficient for good quality predictions of CO_2 levels in a smart home. The authors' future work will investigate the use of new, practical implementations which optimize operational and technical control of the functions in intelligent buildings through an IoT platform and VLC. This will aid in improving the proposed method for monitoring the building occupancy and detecting the daily living activities of seniors and persons with disabilities in the context of smart home care.

Author's Contributions

Conceptualization, JV, RM. Funding acquisition, RM, PB. Investigation and methodology, JV, RM, LD. Project administration, JV, RM, PB. Resources ,JV, RM, PB. Supervision JV, RM, JN. Writing of the original draft, JV, LD, RM. Writing of the review and editing, JV, LD, RM. Software, JV, LD, RM. Validation, JV, LD, RM, JN. Formal analysis, JV, LD, RM. Data curation, JV, LD, RM. Visualization, JV, LD, RM. All the authors have proofread the final version.

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Competing Interests

The authors declare that they have no competing interests.

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