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Sustainable Smart City Building Construction Methods

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Received: 3 April 2020; Accepted: 6 June 2020; Published: 17 June 2020

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Abstract: In a global world, the human population invariably increases while resources gradually decrease as cities and towns constantly consume resources to satisfy their needs and requirements. At this point, it is very necessary to focus on making these urban areas more sustainable and greener. The need for some advanced and automated systems improves the situation, which leads to the innovation of smart cities. Smart city is the concept that helps in developing sustainable cities via optimized resource utilization methods. In smart city development, various sensing technologies can be used that can sense and utilize natural resources in better ways, like storing rainwater to use afterward, intelligent and smart control system, smart infrastructure monitoring system, smart healthcare system, smart transportation system, and smart system for energy consumption and generation by various facilities. To make the city smart and sustainable with efficient energy consumption, we propose renewable solar and wind energy-enabled hybrid heating and cooling HVAC-DHW (heating, ventilation, and air conditioning-Domestic Hot Water) system in which energy consumption is evaluated using optimized NARX-ANN and fuzzy controller based on user needs, dynamic behavior of the atmospheric environment, and spatial distribution of energy supply. To achieve the proposed goal, first, via sensor, heating and cooling effect of environment and building is sensed and these sensed inputs are then fed into deep-learning-based NARX-ANN that forecast internal building temperature. This forecasted temperature is fed into a fuzzy controller for optimizing output based on user demand. This processed information leads to energy distribution based on their requirement using a smart energy sensing system. Based on the experimentation result and performance analysis, it was found that the proposed system is more robust and has a high control response in comparison to the existing systems with minimum energy consumption. The analytical results support the feasibility of the proposed framework architecture to facilitate energy conserving in smart city buildings.

Keywords: NARX-ANN (non-linear autoregressive artificial neural network); DHW (domestic hot water); fuzzy controller; PID controller; RES-PP (renewable energy source power plant)

1. Introduction

In recent decades, the advancement in modern technologies, such as Bluetooth mesh networks and location service competences, has led to the development of advanced smart buildings. Smart buildings connect enterprises with public systems and provide sustainable development to smart cities by adding importance to owners, operators, and occupants [1]. The processes of construction of buildings have become more compound and dynamic with numerous different systems and devices requiring multiple standards. With the evolution of innovative technologies, it is very difficult to maintain the trend of present-day techniques with progressing approaches. To safeguard the success of smart buildings, it is always necessary to be aware of the pros and cons associated with new technologies. At present, most of the building management systems have started paying attention to intelligent building techniques, such as control systems and wireless sensor networks. In addition, energy management remains to be the major focus of the existing building management systems. Along with this, the organizations further require optimization of sustainability, productivity, space utilization, and operational efficiency factors [2].

Smart buildings are the integration of advanced technologies for building systems. Some of them include the automation of buildings, telecommunications, user life safety, and facility management systems. The smart building provides actionable information through which the building owner or the occupants manage the building in an automated manner. In general, smart buildings monitor and control the activities inside the building using advanced technologies. The information obtained from the buildings is further used to automate various processes such as heating, ventilation, air conditioning, security, etc. [3,4]. In traditional building management systems, there is an increased risk of building overheads resulting in higher cost expenses and energy consumption for both the owners and building occupants. This is due to the reason that buildings are not intelligently maintained. For instance, light facilities in unused rooms and rooms heated up when there are no people inside are some of the scenarios that lead to wastage of energy and resources.

Smart buildings act as an effective alternative for traditional building construction methods. In older days, the buildings were constructed through various steps, such as design, installation, and operation processes. Each step was performed separately in a consequent manner. The construction of smart buildings is far away from the traditional approaches and requires a single designer to design every building technology system in a unified manner with reliable construction documents. The construction document contains the details of all the subsystems and identifies the common elements between the subsystems. This comprises database systems, equipment rooms, cable pathways, and communication protocol between the devices. The contractor then installs a single consolidated design called a master system integrator. This process improves efficiency measures with lesser time and cost expenses [5]. During the stage of building operation, the building technology systems are incorporated both horizontally and vertically between the subsystems. This enables the flow of the data from subsystems to facility management systems and then to the business systems, allowing the building operation data to be used across several individuals for building occupation and management purposes. Smart buildings make use of advanced information technologies to operate different subsystems in a smart environment.

Smart buildings reduce energy consumption and improve the sustainability of buildings as well as the smart electric grids. The operational energy efficiency of the building is determined through various building automation factors, such as HVAC control, metering, lighting control, and power management processes. Thus, smart buildings form the basis for smart electrical grids. Some of the potential key drivers for smart buildings include energy, economy, and technology. Efficient use of mainstream information technology with emerging advanced technologies form the basis of sustainable smart buildings. Some of the main features of the smart buildings include system connectivity, data, automation, sensor, and actuators [6]. Among them, system connectivity remains to be the most important factor. The subsystems within the building should always be tightly interconnected so that they can easily communicate with each other. For example, power supply, lighting, fire alarms, and water meters are always interconnected in a smart building environment. Sensors and actuators form an essential part of smart buildings. Sensors collect the data about smart appliances and direct with a decision for efficient resource allocation processes, they measure physical quantity and translate the real-world measurements into data for the digital domain. For example, the use of footfall counters detects the building location with the high crowd in a day and predicts the high traffic areas.

The information collected from the various parts of the smart buildings is continuously processed and analyzed in real-time through the use of centralized servers. The centralized server continuously monitors smart buildings to automate the control and management processes of buildings. Further, smart buildings may generate a huge volume of data of their own. The process of storage and analysis of this data provides significant benefits in terms of cost and energy management [6].

The use of the smart buildings has numerous advantages for both the occupants and the owner. Smart buildings increase the productivity of the occupants by providing an optimal level of air quality, security, lighting, physical comfort, sanitation, and space availability measures. Further, the use of smart devices, such as cameras and sensors, provides precise data on the usage of smart buildings that assist the effective decision-making processes. Sensors provide precise data that assist in making effective decisions. Sensors detect changes, such as air quality, temperature, occupancy, motion, etc., and feed that information to the building management systems. This system helps to monitor conditions, where users can automatically alter the settings according to their own preferences in particular areas of the building. Moreover, lighting is an integral part of smart buildings. It is designed for energy efficiency and it derives real operational benefits and makes adjustments based on conditions like daytime accessibility and use. In addition, significant operational savings and data protection are the other significant benefits of the smart building systems. Some of the key components of the smart building include sensor and actuators, network and communication medium, software platforms, HVAC systems, and smart control devices [7].

A clear illustration of smart building components is given in Figure 1. Sensors monitor and send the building information (data) to a computer processor for further data processing and storage processes. Usually, sensors communicate through the access points situated inside the building and then communicate across a gateway. The gateway acts as an aggregate point that collects the sensor data and sends it to the storage medium, such as cloud systems. The network defines the collection of sensors through which the data are collected and organized at a central location. Software platforms act as a host through which the services are offered to the smart building users. HVAC is heating, ventilation, and air conditioning systems. HVAC is a sensing device mainly used to reduce energy consumption across smart devices. It compares the actual state with the target state and derives the conclusion. Smart devices control appliances and outlets. It enables the owners and occupants to control their devices remotely. Some of the considerable examples of smart devices include home alarms and sensor. Smart buildings devise corrective action and automation as a response to alarms created by a system. However, the homeowner uses a mobile phone to set his alarm and control their appliances by enabling and disabling or performing other tasks [8].

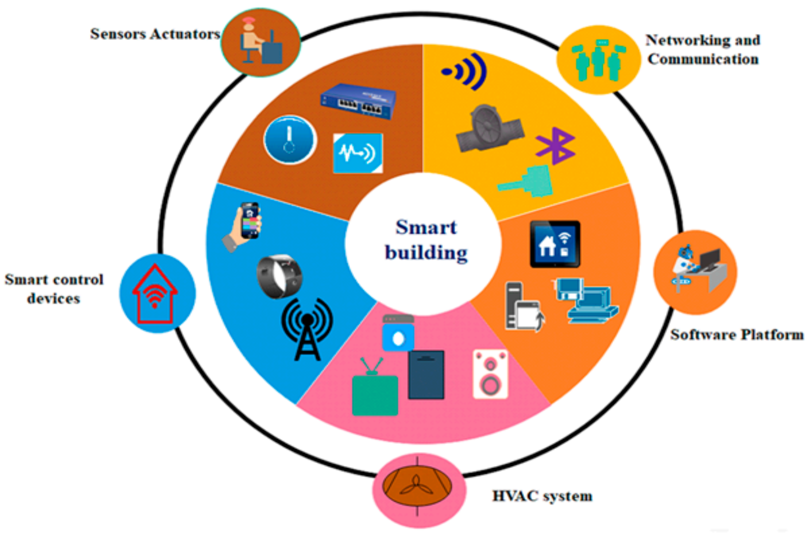

Figure 1. Smart building and its components.

In simple terms, the working of the existing smart buildings is described as follows: The sensor devices are installed across the building, that continuously monitor the building and collect data. The sensed data are transferred to the storage platforms through the network and communication medium. Based upon the data or input received from the sensor networks, the services to the end-users are offered through the software platforms. The HVAC equipment acts as an energy management unit that takes care of heat, air conditioning, and ventilation facilities. The owner and occupants control smart building facilities using smart control devices [9].

Recently, researchers have started paying attention to neural networks and machine learning techniques for smart buildings. The algorithms, such as Convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN), are widely used across the smart building construction processes. A Convolutional Neural Network (CNN) is a DL algorithm which can take an input image and assign importance to various aspects/objects in an image and it is able to differentiate one from the other. Modern buildings adapt to both internal and external elements and thrive on increasing data sources, such as sensors and smart devices. CNN in a smart building helps in relevance analysis of a large set of parameters, including indoor facade temperature, solar radiation outdoor temperature history, outdoor humidity, and many more. ANN algorithms are inspired by the abilities of the human brain and it predicts the patterns from the sensor data through the use of learning and recall processes. These algorithms are mainly used in smart building construction systems to predict the rate of buildings' energy consumption and to optimize the flow of energy across various smart devices [10].

The process of implementation of smart systems within a building has numerous benefits that range from cost efficiency to eco-friendly building construction measures. Smart buildings are considered a new technology today, with their wide variety of benefits, they will soon become an inevitable part of the modern smart cities. For the property owners and developers, smart buildings raise the value of the asset. For property managers, smart buildings offer the most efficient subsystems with various management options. Similarly, for the engineers, architects, and building construction contractors, smart building enables efficient project management and scheduling activities. Even though the smart buildings have numerous advantages for the occupants and building owners, it has considerable drawbacks. At present, there exists a variety of approaches for energy and power consumption management for smart buildings, but it still requires greater improvements. Such drawbacks are cost, security and privacy, system compatibility, sedentary lifestyle, and many more. Due to scarcity of non-renewable resources, research areas gain attention towards utilizing renewable resources, based on this concept, we proposed solar and wind energy based RES-PP (Renewable Energy Small Power Project) to supply power to HVAC-DHW system as well as to the main electric power grid and to make the city smart and sustainable with efficient energy consumption supply. In order to solve the issue, the proposed approach energy-efficient solution for the construction of smart buildings with NARX-ANN and fuzzy controller systems. First, via a sensor, heating and cooling effect of environment and building is sensed and these sensed inputs are then fed into deep-learning-based NARX-ANN that forecast internal building temperature. This forecasted temperature is fed into a fuzzy controller for optimizing output based on user demand. This processed information leads to energy distribution based on their requirement using a smart energy sensing system.

Without sensors, the records created for storing the data obtained from the manual intervention for energy consumption in city buildings may lead to severe stress and may miss some information. However, due to the utilization of sensors, the estimation of sensors is precise and accurate so that manual working can be avoided, which reduces human error to the minimum in collecting data. Due to gathering data by means of sensors, they can be accessed whenever required by utilizing an online dashboard with the help of a device with internet accessibility. It makes humans redundant for data collection round the clock and sending the data collected for storing online and visualization. Apart from faster data collection by sensors, it can actually track a higher number of metrics when compared to other human interventions.

Utilization of data gathered from the sensor around the smart building will help in preventing the anomalies around the buildings for false detection of data, which is not possible with manual human calculation. In addition to gathering data continuously, the sensors in smart buildings store all collected data for years in a certain format, which makes the data accessible for years.

Lighting plays a significant role in smart city building enhancement due to the fact that it provides handling capabilities as well as simplicity to utilize and monitor. A significant feature of the lighting method is its innovative handling technology that can normally provide unique luminaire to give lightning systems which control the building environment in smart cities. This states that there exists a control solution methodology, which is capable of making intelligent decisions for smart buildings and helps in forming smart buildings quickly after installations. The existing microprocessor in every lighting system automatically absorbs the incoming luminaires, which makes it easy for sensor to gather data from smart city buildings.

Users are able to handle the settings of a lighting control model of every individual lighting present in the buildings through application in mobile devices, making it a user-friendly and enabling interaction with luminaries without the need to run the controlling system. Solutions provided by lighting system have the capability of forming valuable data about buildings in smart cities.

The transmission system integrated into every luminaire enables automatic transmission between them.

The paper is organized as follows: Section 1 provides a brief introduction to the proposed approach. The literature review is given in Section 2. Section 3 describes the proposed energy-efficient solution. Results and discussions are given in Sections 4 and 5 concludes the proposed approach with future enhancements.

2. Literature Review

This section provides a brief literature review on some of the existing technologies that relate to the process of construction of smart buildings in smart cities.

An approach called toward learning-based thermal comfort modeling via pervasive sensing (i-TCM) for smart buildings is given in [11]. This approach aims to offer indoor thermal comfort satisfaction for smart building users. An effective learning-based solution for thermal comfort modeling is built using machine learning approaches. The data from the smart building are collected and utilized using wireless sensor networks and interconnected IoT devices. Here, the data collected from the sensor networks are stored across the cloud computing platform for easy retrieval and management processes. Next, a black-box neural network method is implemented that improves the satisfaction and comfort level of the building users. The experimental results state that this approach provides better results with improved performance measures. However, it fails to meet the increased energy consumption demands.

A graph-optimization based method for indoor navigation system is given in [12]. This approach is user-friendly and can be easily used across buildings without any prior knowledge. It makes use of the crowd-sourced data from sensor networks to find the activity landmark of the most engaged area in the smart buildings. Through the use of the graph optimization techniques, it finds the trajectory alignment and constructs an indoor map. Finally, the relative coordinates are transformed into absolute coordinates with reference points that reduce redundant segments with dynamic time warping methods. This approach is implemented in real-time across smart office buildings and shopping malls. The result provides improved navigation with a minimal amount of data.

Another approach for smart building construction using asymmetric and multi-block space time code is presented in [13]. It provides three methods, such as multi-input multi-output (MIMO) setting method, blocks diagonal method (BDM), and smart puncturing method (SPM). The BDM method produces multi-block space-time codes to achieve a diversity-multiplexing tradeoff (DMT). Increasing the density of the new block-diagonal asymmetric space-time (AST) codes is considered equivalent to the minimization of the particular order. Thus, the implicit lower bound density is made explicit for most important special cases. Further, the use of SPM generalizes the process of subfield construction and applies it across an increased number of transmission and lesser reception antennas. The generalized method constructs sphere decodable codes using cyclic division algebra (CDA). This approach works well in most cases, but with an increased number of density orders, it fails to provide an efficient solution for the construction building process.

A Wi-Fi-based city radio map construction scheme is given in [14]. In general, Wi-Fi roadmaps are constructed using a database of Wi-Fi fingerprints across various points in a building. Similarly, a city radio map deals with the collection of radio maps for every building in a city. However, the manual calibration city radio map construction methods require increased time and effort. In order to overcome this drawback, this approach presents an efficient method for city radio map construction through the use of crowdsourcing of Wi-Fi fingerprints from various smartphones. First, it classifies the buildings in a city into three categories, such as residential area, commercial area, and public area. Then, the fingerprints are collected from the buildings of each category using location-labeling techniques. The results state that this approach could construct efficient city radio maps with minimal time and cost. Further, the development of city radio maps solves the problem of global indoor positioning in smart buildings. However, this approach can lead to various system-level issues.

An unsupervised learning approach for crowd-sourced indoor localization in wireless networks is given in [15]. It provides a novel unsupervised model for unlabeled fingerprints using global-local optimization techniques. Using unsupervised learning models, this approach determines optimal placement of fingerprint sequences over the indoor map. It is performed under the constraints enforced on the inner structure of the map, such as walls and partitions. The efficient interaction between the global and the local optimization techniques in a hybrid approach gradually reduces the complexity of the learning task. The experimental observations are made across single and multi-story buildings, and the results state that this approach provides precisely localized models with lesser efforts to labeled sample collections. The hybrid techniques are proposed in [16–19], using various machine learning techniques for analyzing huge amounts of data and also enhancing the optimization algorithms to improve the performance.

Observe, Learn, and Adapt (OLA) algorithm for energy management in smart homes using wireless sensor networks and artificial intelligence techniques is given in [20]. It integrates artificial intelligence (AI) with wireless sensor networks (WSN) to derive an efficient management technique called Observe, Learn, and Adapt (OLA) algorithm. It adds more intelligence to the programmable communicating thermostat (PCT) through which the energy is consumed across smart homes. The OLA algorithm is developed and verified using a house simulator which acts as an "expert system shell". The use of PCT reduces energy use and manages data efficiently. The results are analyzed and compared in terms of zone-controlled home with OLA and knowledge base versus a home without zone control knowledge base or OLA.

An approach of peer to peer energy sharing in smart buildings using distributed transaction methods is given in [21]. The major objective of this work is to provide sustainable energy management for energy building clusters using distributed transactions. Building clusters include various types of energy buildings, such as professional, industrial, academic, and commercial places. First, the energy utilization functions are computed using controllable loads of the building. The optimal energy sharing profiles are identified in a distributed manner through which the total social energy cost is minimized. Next, mutual energy sharing's modeled using non-cooperative games, and descriptions to the existence of the equilibrium of the games are provided. The existence of equilibrium is searched using relaxation-based algorithms. This approach is computationally energy-efficient, but it fails to incorporate the sustainable needs of the emerging smart cities.

A deep reinforcement-based learning approach for smart builds are given in [22]. This approach makes use of smart grid techniques with deep reinforcement learning for efficient energy management across smart cities. Deep learning with reinforcement learning enables efficient online optimization schedules for the construction of energy-efficient building management systems. Learning procedures constructed using deep Q-learning and deep policy gradient mechanisms that perform multiple actions simultaneously. The simulations are validated on the Pecan Street Inc. database, and the results provide comparatively improved energy consumption measures than the existing approaches.

Machine learning-based approaches for short-term load balancing in smart residential buildings are given in [23]. This work presents a big data framework for smart buildings. The data collected from various sensors are loaded into a NoSQL database, which is capable of storage and processing of significant volumes of heterogeneous data. Then, a set of machine learning algorithms is designed and implemented to predict the rate of electricity consumption across smart residential buildings. This work makes use of a Feed-Forward Artificial Neural Network (FF-ANN) algorithm with backtracking adjustment for prediction and classification processes. The performance measure of FF-ANN is compared against six algorithms, such as random forests, non-linear autoregressive algorithms, Nesterov, deep neural networks, and gradient tree boosting, and exogenous algorithms. The results are evaluated using the real cases of the smart building. It is observed that this approach provides better efficiency measures. However, it fails to provide a cost-effective solution.

Parallel building, a complex approach for smart building management, is given in [24]. This approach presents novel hybrid deep learning predictions that make use of an encoder and a decoder with ACP (algebra of communicating processes) theory. The long short-term memory acts as an encoder and gate recurrent acts as a decoder. The simulations are performed using the real-time datasets and the results state that this approach provides efficient energy management across smart buildings, but it fails to meet the increased demands of big data. It is envisioned from the literature [25–27] that the present-day solution for smart cities is not sufficient, and it fails to provide energy-efficient and cost-effective solutions smart building construction process. Thus, throughout the proposed system, an energy-efficient solution for the smart building will be provided with cost-efficient constraints.

3. Proposed Methodology

To construct a sustainable smart city, integration of electrical power grid with renewable energy natural sources and energy consumption management systems of commercial and residential building play a very crucial role. It was observed that overall, 70% of electrical energy is utilized by these residential buildings and Figure 2 flow diagram of the proposed self-tuned HVAC–DHW system with RES power plant commercial buildings shows that energy consumption can be reduced by 29 to 30% by using sustainable, optimized, and self-tuning hybrid solar heating and cooling HVAC system. Earlier, the researches in this area focused to building level. In order to enhance the energy saving with solar and wind energy utilization we proposed self-tuning HVAC–DHW system utilizing solar and wind energy by using fuzzy controller based nonlinear autoregressive artificial neural network (NAR-ANN). The schematic flow diagram of the proposed HVAC-DHW system powered by renewable solar and wind energy is shown in Figure 2.

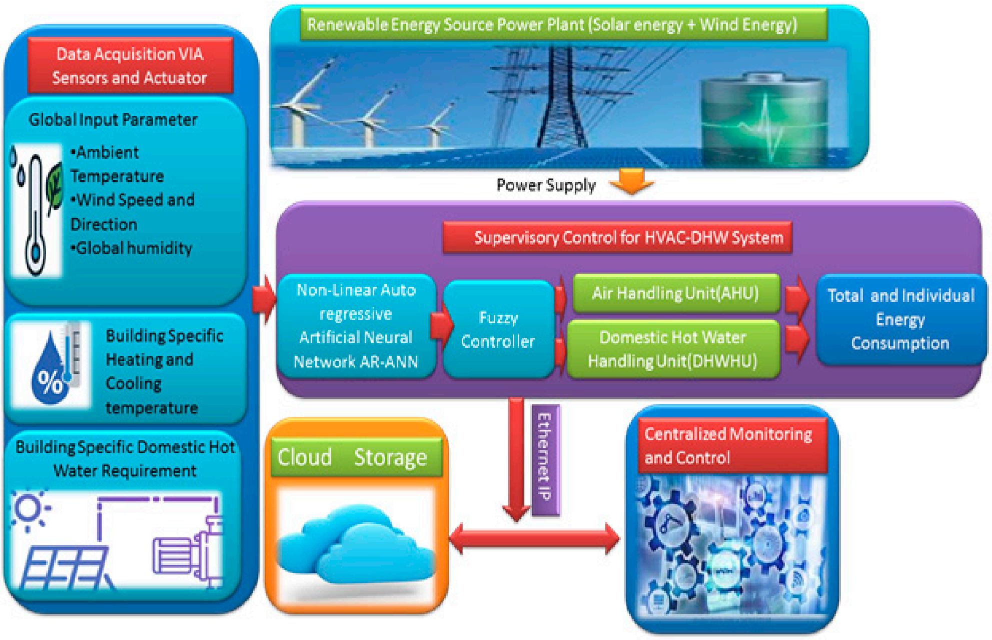

Figure 2. Flow diagram of the proposed self-tuned HVAC–DHW system with RES power plant.

The proposed HVAC-DHW model does not involve user intervention for data collection.

3.1. Data Acquisition

Atmospheric temperature, humidity, wind speed, and wind direction, as well as the heating and cooling temperature of residential and commercial buildings, are obtained by various sensor and actuators. These sensors are connected to the HVAC-DHW System Unit. All the contextual information regarding the atmosphere and building is captured by sensors and these sensing data are further used for determining energy consumption.

Data gathered through various sensors, in this case, the functioning sensors, are analyzed using alarm systems. Functions of sensors may cause some variation due to different environmental conditions, this type of situation can lead to false notification of data by sensor, here, alarm plays a significant role in capturing the functions of sensor where abnormal functioning of sensor will lead to alarm sound, thus preventing the damage caused by over functioning of sensors and providing significant protection to a smart building during data collection and working environment.

Human intervention does not exist in the model due to the fact that sensors collect precise information where the metrics involved have more accuracy, here, user intervention may mislead the sensors which are placed in centralized control and monitoring system. Based on the environmental situation in the building, the sensors analyze the metrics and collect information, such as temperature, speed of wind, ambient, humidity, etc., where this may not be possible for humans to measure manually.

Supervisory Control for HVAC-DHW System

The HVAC-DHW System is a supervisory control unit that gets the weather input from various sensors, this input information is then fed into non-linear autoregressive artificial neural network with external input (NARX-ANN), as shown in Figure 3, that processes these data and produces the internal building temperature as output. This forecasting internal temperature is then fed into a fuzzy logic controlling system that controls the temperature based on user comfort. Based on different weather conditions, the proposed NAR-ANN divides input parameter in two categories: Summer and winter for simulating the temperature. For summer NARX-ANN models are constructed with 10 hidden layer neurons with network weight and bias, while for winter, the model is constructed with 30 hidden layer neurons. In addition, we use five input values, including external ambient temperature

(Amb_T in °C), global humidity effect (GH(%), wind speed and direction $\left(WSD\left(\frac{m}{s}\right)\right)$, internal building temperature (Int_T in °C), and DHW temperature ((DHW_T in °C). The input value of the considered parameters (Amb_T, GH, WSD, Int_T, DHW_T) is sensed at time τ and gives NARX-ANN model computes desired internal building temperature at time τ + 1. Afterward, the difference between the internal temperature at τ and τ + 1 represented by $\Delta\tau$ is applied as an input to a fuzzy controller. The equation for NARX-ANN [28] based on the given parameter is defined as given in Equation (1):

$$\hat{\gamma}(\omega) = \hat{\gamma}(\tau - 1, \omega) = f(\varphi(\tau), \omega) \tag{1}$$

where $\hat{\gamma}$ is the value of γ at time τ forecast by the NARX-ANN model, ω is a weight vector of the neural network, f is the fitness function recognized by the ANN and $f(\varphi)$ is the regression vector function. The dataset is divided into two phases: Training and testing. In training, performance evaluation is performed by RMSE, which calculates the forecasting model error given by Equation (2).

$$FE_i = \sqrt{\gamma_i - \hat{\gamma}_i} \tag{2}$$

where, γ_i represents actual value and $\hat{\gamma}_i$ represents forecast output.

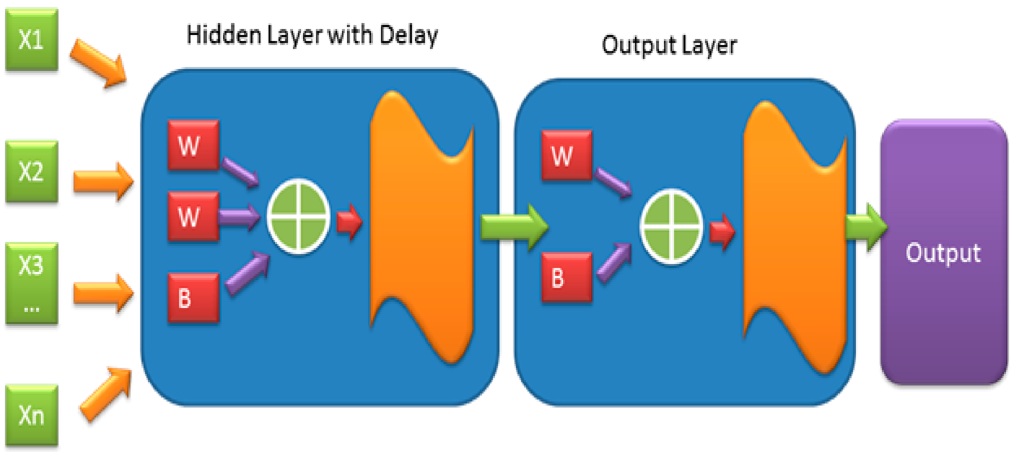

Figure 3. Architecture of non-linear autoregressive artificial neural network with external input (NARX-ANN).

3.2. Fuzzy Controller

The fuzzy controller is activated by providing input activation parameter $\Delta\tau_i$, which is obtained by the difference between parameter values of $\tau_i(n)$ of the forecasted internal temperature at time n and the value $\tau_i(n-k)$ of measured internal temperature at time $(n-k)$, where k = 5, 10, 15 … , 60 min. The fuzzy controller architecture is shown in Figure 4, which handles the HVAC-DHW system by on/off switch and controls the air inlet speed. The fuzzy control system takes rough input value of $\tau_i(n)$ and $\Delta\tau_i$, which is further transformed into output values in linguistic form by using a selected set of membership functions. The linguistic forms used are:

- Extremely Cold (EC)
- Pleasantly Cold (PC)
- Moderate Cold (MC)
- Normal
- Extremely Hot (EH)
- Pleasantly Hot (PH)
- Moderate Hot (MH)

The main task of the controller is to intricate the rough input values in linguistic form using an inference method on the basis of fuzzy rules in if-then form. These fuzzy rules are joint in the fuzzy controller, which produces a membership function [29]. The equation for this Gaussian membership function is defined as given in Equation (3):

$$g(x, \delta, \rho) = e^{\frac{-(x-\rho)^2}{2\delta^2}} \quad (3)$$

where, ρ represents the center of membership function and δ determines the width of the membership function. By using this membership function, output values in linguistic form are determined. The Gaussian membership function accepts input crisp values and generates outputs crisp values. This is performed based on the fuzzy rule defined by the user using Gaussians operation rule accomplished in the following three phases:

1. Fuzzification: In this phase input crisp value is transformed into fuzzy output variable using fuzzy rules defined by the user.
2. Fuzzy interface mechanism: Output of each user fuzzy rule is then determined and given to its antecedent. After that, collective output is determined to define fuzzy rules.
3. Defuzzification: In this phase fuzzy based output is transformed into output crisp values.

3.2.1. Air Handling Unit

The air handler unit of HVAC-DHW system consists of air dampers, cooling loop coil, cold water propel, and regulatory valve. The cooling loop coil unit (CLCU) has two physical loops: Cold water coil loop, and air coil loop. T_{DB}^{On} and T_{WB}^{On} are the dry and wet bulb temperature of on-coil air while R_a^{On} represents the rate of flowing air. Similarly, for off-coil temperature of a dry and wet bulb and the rate of water flow is T_{DB}^{Off}, T_{WB}^{Off}, and R_w^{Off}. The off-coil temperature of dry bulb T_{DB}^{Off}, and rate of water flow R_w^{Off} are the controlled process output and workable variable while on-coil temperature are considered to be constant with variation in the rate of air flow R_a^{On} based on the cooling demand of occupant space. Thus output T_{DB}^{Off} can be defined as a function f, as given in Equation (4):

$$T_{DB}^{Off} = f\left(T_{DB}^{On}, T_{WB}^{On}, R_a^{On}, R_w^{Off}\right) \quad (4)$$

3.2.2. Domestic Hot Water Handling Unit (DHWHU)

The DHWHU of the HVAC-DHW unit consists of a hot water reservoir with electric heater backup, fluid coil loop, and pumps for hot and cold water, and a processor for processing weather data. Based on the computation of hot water demand using membership function and fuzzy rule defined by the user, the load factor L_F for overall user profile demand is defined as followed by Equation (5):

$$L_F = \frac{avg_D}{Peak_D} \quad (5)$$

where, avg_D represents the average of hot water demand from different users. $Peak_D$ is the highest hot water temperature demand.

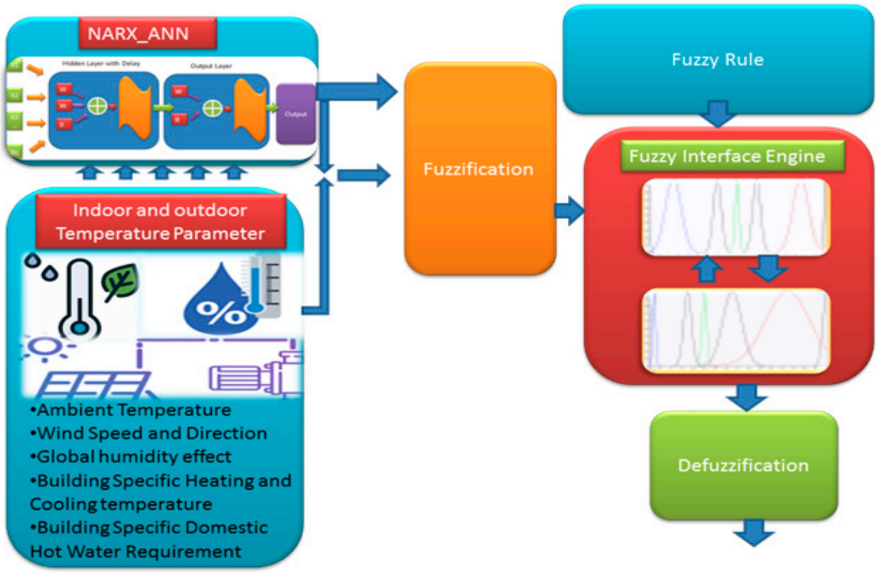

Figure 4. Architecture for fuzzy controller.

3.2.3. Energy Consumption

The total energy consumption EC_{Tot} is computed by following Equation (6):

$$EC_{Tot} = \sum_{i=1}^{l} \alpha_{Hi} + \beta_{Pi} + \mu_{CUi} + \vartheta_{Ai} \quad (6)$$

where, α_{Hi} represents the energy consumed by ith heater, β_{Pi} represents the energy consumed by ith pump, μ_{CUi} represents the energy consumed by ith cooling unit, ϑ_{Ai} represents the energy consumed by another ith auxiliary electric device of HVAC-DHW system.

3.2.4. Centralized Monitoring and Control Module

All the input information generated by sensor and processed inside HVAC-DHW system using NARX-ANN and fuzzy controller for domestic hot water demand and air cooling demand is transmitted to centralized monitoring and unit via Ethernet IP for monitoring the user demand in the whole city. The processed information is also sent to cloud for storage for further reference.

3.3. RES-Power Plant (Solar + Wind Energy)

To provide the electricity power to HVAC–DHW system, we use RES-Power Plant System that consists of solar and wind energy power units, a backup energy storage battery system and several HVAC-DHW systems enabled commercial and residential buildings. The RES-power plant (RES-PP) is considered as a price evaluation meter. Based on the electricity cost of the whole day, the RES-PP computes the real time power generation schedule, including fluctuation intervals on an hourly basis, and delivers it to the main grid. Using this information, the main grid makes decisions, including the actual energy consumption of HVAC-DHW systems and decision of charging/discharging of energy storage battery system.

Solar and Wind Power Computation

The solar output power for solar entity e at maximum power point (MPP) [30,31] can be written as Equations (7) and (8).

$$SOP^{c}_{e,t,i} = SOP_{e,\,STP}\frac{SI^{c}_{t,i}}{SI_{STP}}\left(1 - 0.00450\left(COT^{c}_{e,t,i} - Temp_{STP}\right)\right) \quad (7)$$

$$COT^{c}_{e,t,i} = AT_{t,i} + \frac{SI^{c}_{t,i}}{800}(MOCT - 20) \tag{8}$$

where, e, t, i represent indexing solar entities, hours and intra hours, $SOP_{e,t,i}$ represents solar output power of solar entity e in intrahour i and t hour, STP is standard testing parameter, $SI_{t,i}$ represents solar-irradiance at i interval in t hour, $SI_{STP} = 1000\frac{W}{m^2}$, $COT_{e,t,i}$ is the cell operating-temperature at i interval in t hour, $Temp_{STP} = 25$ °C, $AT_{t,i}$ is the ambient temperature at i interval in t hour. MOCT is the minimum operating cell temperature. c is the time-series of speed of wind, irradiance of solar power, temperature ambience of working day.

The wind output power $WOP_{u,t,i}$ for wind generating unit u [5] is given by Equation (9):

$$WOP^{c}_{u,t,i} = \{0, \quad if\ WS_t \leq WS^{bi}_u\ or\ WS_t \geq WS^{bo}_u WOP^{r}_u \frac{WS^{c}_{t,i} - WS^{bi}_u}{WS^{r}_u - WS^{bi}_u}, \quad if\ WS^{bi}_u \leq WS^{c}_{t,i} \leq WS^{r}_u, WOP^{r}_u, \quad Otherwise \tag{9}$$

where, WS_t is the wind speed in time t hour, WS^{bi}_u, WS^{bo}_u, WS^{r}_u are break-in, break-out, rated wind speed, $WS^{c}_{t,i}$ is the wind speed in time t hour at interval in case c.

4. Simulation Results

In our research, in order to enhance the energy saving with solar and wind energy utilization, we proposed a self-tuning HVAC–DHW system utilizing solar and wind energy by using fuzzy controller-based nonlinear autoregressive artificial neural network (NAR-ANN). To achieve the proposed goal, first, via sensor, heating and cooling effect of environment and building is sensed and these sensed inputs are then fed into deep-learning-based NARX-ANN that forecast internal building temperature as mentioned in Figure 5. This forecast temperature is fed into a fuzzy controller for optimizing output based on user demand as mentioned in Figure 6. This processed information leads to energy distribution based on their requirements using a smart energy sensing system.

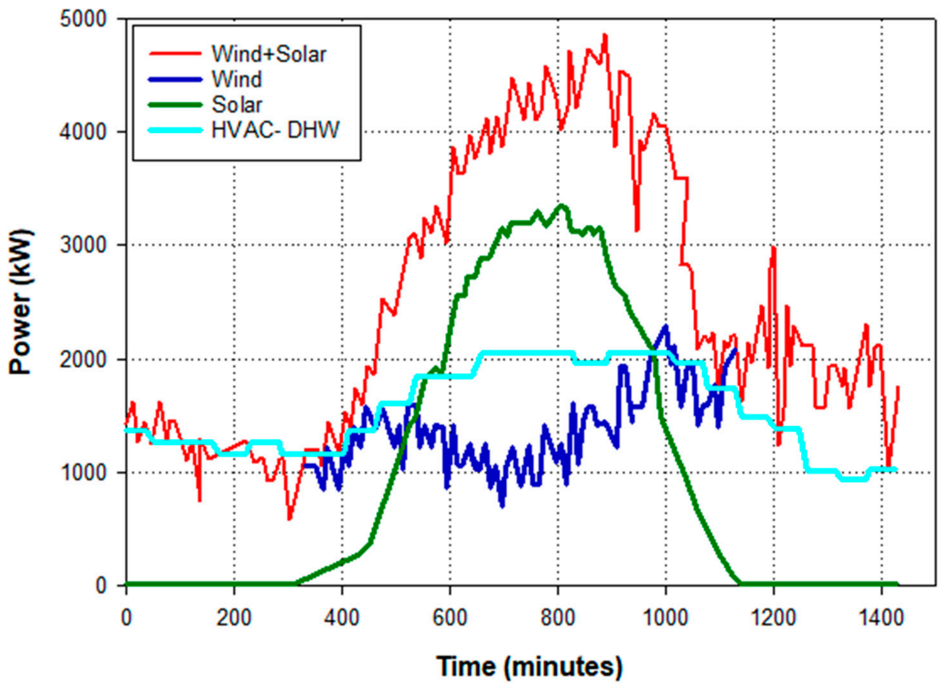

Figure 5. Energy consumption representation of individual auxiliary devices of HVAC-DHW system.

We consider a RES-PP consisting of four equal size turbines of wind, one Photovoltaic Solar panel and 2500 HVAC-DHW systems. The break-in, break-out, and rated wind speeds of all wind turbines are 4 m/s, 30 m/s, and 12 m/s, respectively. The power rate of all turbine wind is 1.5 MW and of all solar power entities is 4.5 MW. For different cases, including speed of wind, irradiance of solar power, temperature ambience of wind and solar power and using Equations (7) and (9), forecasting of power generation of solar and wind entity per 10 min is represented. On the basis system forecasting uncertainties and power utilization of all individual components of HVAC-DHW system, the total energy consumption of the proposed system to maintain all buildings at preferred temperature and preferred DHW demand is shown and energy consumption of individual auxiliary devices of HVAC-DHW system as mentioned in Figure 7.

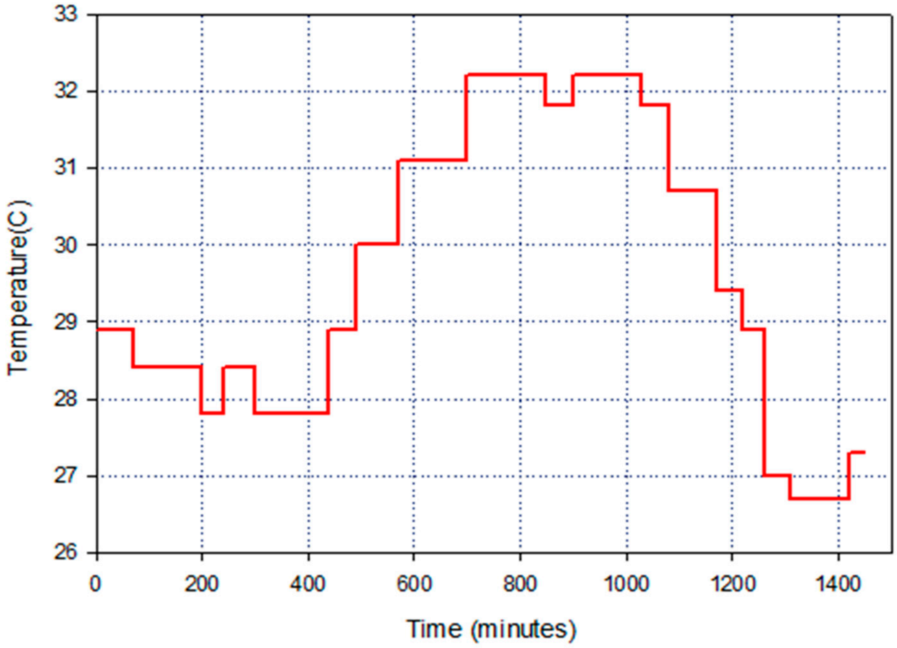

Figure 6. Weather forecasting as a function of temperature.

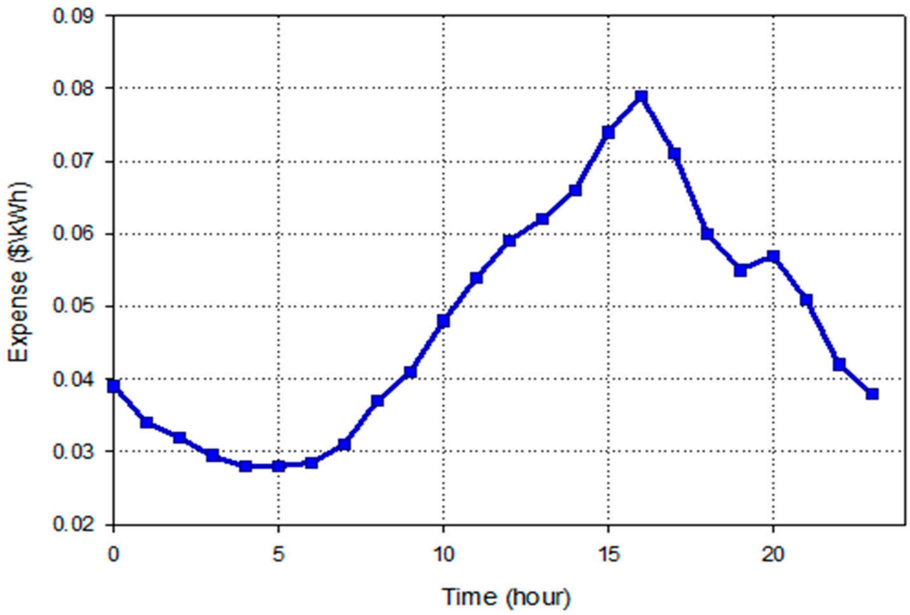

Figure 7. Electricity expense cost per-hour based on historical electricity data.

The performance of the proposed fuzzy controller-based HVAC-DHW system is evaluated by comparing it with PID controller-based HVAC system. Figure 8 shows that the proposed fuzzy controller has a stronger and more extraordinary control response ability than PID controller.

To evaluate the robustness of the proposed system, the experimentation is performed under different favorable and unfavorable conditions like keeping cold temperature water supply fixed with variable load distribution through water and air flow rates. The results depicted in Figure 8 show that the proposed control strategy of fuzzy system can be applied to control and regulate dry-bulb off-coil temperature T_{DB}^{Off} of AHU unit. From the results depicted in Figure 9, it is clearly seen that the proposed fuzzy control system is more robust than PID controller.

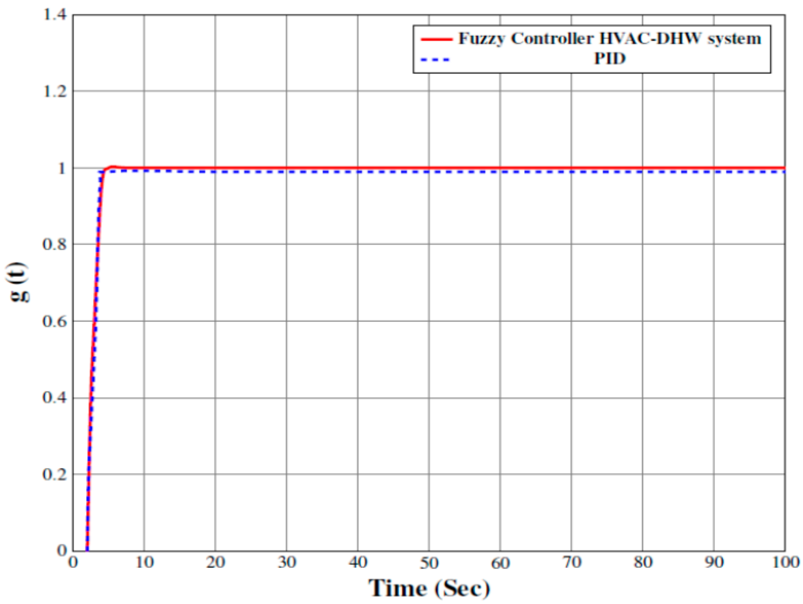

Figure 8. Performance analysis based on the system's control response.

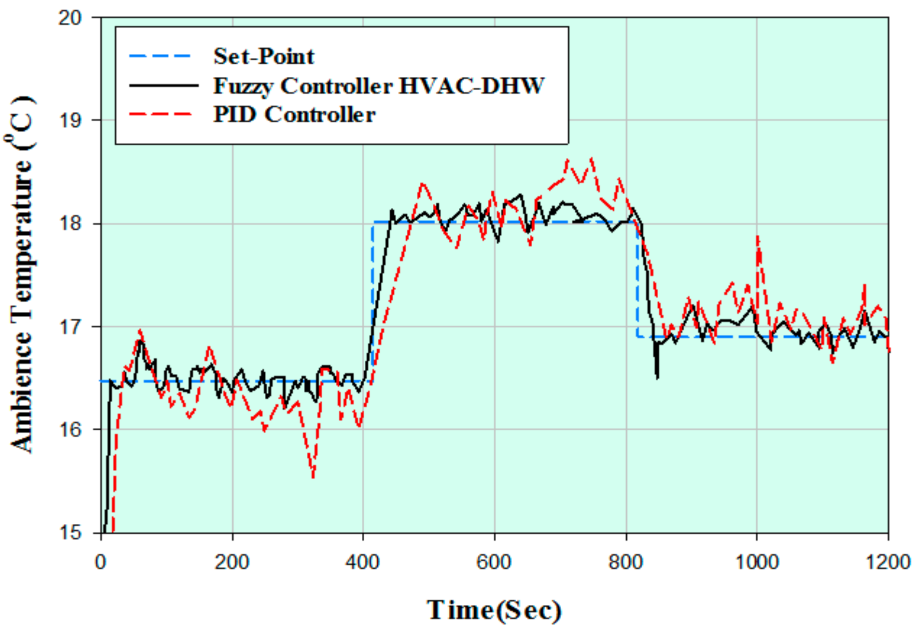

Figure 9. Performance analysis based on the robustness of system.

5. Conclusions

Due to scarcity of non-renewable resources, research areas gain attention towards utilizing renewable resources, based on this concept we proposed solar and wind energy-based RES-PP to supply power to HVAC-DHW system as well as to the main electric power grid. To satisfy the heating and cooling requirements of domestic hot water demand of residential and commercial buildings we propose a self-tuned HVAC-DHW system using the concept of NARX artificial neural network and fuzzy system. The indoor temperature of buildings and outdoor temperature of the atmosphere with domestic hot water demand is sensed by using various sensors and actuators. These sensor data are fed into NARX-ANN for accurate forecasting of indoor temperature. This forecast temperature is then fed into a fuzzy controller for controlling the AHU and DHWHU to satisfy user demand. The experiment results show the individual and total energy consumption of the proposed system. The performance evaluation of the proposed systems is compared with the existing PID controllers in terms of robustness and controlling response of the system. From the experimentation results, it was seen that the proposed system performs better than the existing PID controller with more power savings. The limitation of this proposed work is that it can only be adopted for the analysis of the electric power grid as it trained based on the parameters obtained from solar and wind energy data and the applicability of other sorts of energy parameters should be analyzed for that particular aspects. In future, this work can be extended with zero energy building concepts to make the system more environmentally friendly with less energy consumption.

Author Contributions: Conceptualization, J.Z.; formal analysis, B.A.M.; investigation, H.Z.; project administration, J.Z.; resources, S.C.B.; software, H.Z.; validation, S.C.B.; writing—original draft, J.Z.; writing—review & editing, B.A.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

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