

## Self-powered Gas Sensor Monitoring

# SDN-IoCE for Intelligent Self-Powered Gas Sensor Monitoring

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**Abstract**—Detection of harmful gases and their real-time monitoring in a closed as well as open environment find applications such as safety in industrial setting, health monitoring, air quality tracking, etc. This article discusses the issue in a framework of Internet of Consumer Electronics (IoCE). The model integrates Internet of Things (IoT)-based low cost self-powered sensors deployment for gas sensing, and Software Defined Network (SDN)-driven control, leading to SDN-IoCE. Reliable transmission of gas sensing data is essential and done through reconfigurable intelligent surface (RIS) aided underlay cognitive radio network (CRN). Radio frequency (RF) energy harvesting (EH) to be done for self-powering of sensor nodes. Two deep Q-networks (DQNs) are used where the first one ensures seamless connectivity on gas sensing data transmission while the other one performs its time-critical analysis. The proposed SDN-IoT architecture achieves 33 sec and 46 watt less values in delay/latency and energy consumption, respectively over existing work.

**Index Terms:** Gas sensing (GS), Internet of Consumer Electronics (IoCE), DQN, EH, RIS

■ **RECENTLY CONSUMER ELECTRONICS (CE) DEVICES** find widespread applications in diverse fields as technological advancement leads to low-cost and simple fabrication on sensor. Along with this, integration of intelligent operations on it gives rise to the emergence of Internet of Consumer Electronics (IoCE). On the other side, the ever-increasing functionalities of

CE result in increased energy consumption, posing challenge on battery capacity and environmental sustainability [1]. Inclusion of diverse consumer applications with intelligent operations on Internet of Things (IoT) need extensive wireless connectivity for Wireless Consumer Application Networks (WCAN) into CE [2]. Applications include trustworthy intelligent operations on health monitoring [3], on consumer-centric electric vehicle charging in industry 5.0 environment [4], on unmanned aerial vehicles (UAV) networks [5], UAV scheduling and task offloading [6], CE data auditing scheme [7], consumer-centric service prediction

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scheme [8], e-commerce system for CE [9], security-by-design (SbD) concept in energy harvesting (EH) for sustainable and secured IoT to support smart village and cities [10], smart home [11], citizens' cognition and decision-making in smart sustainable cities [12] etc. Applications also demand sustainable consumer-centric sixth-generation (6G) networks, supporting industry 5.0 [13], and also involving reconfigurable intelligent surface (RIS) [14] for link improvement.

Rapid urbanization and rising industrialization have detrimental impacts on the environment through the emission of several harmful gases, volatile organic compounds (VOCs), suspended particles, etc. Reliable detection of harmful gases and their continuous monitoring provide essential information about air quality, and potential hazards followed by employing proper control mechanism. Gas sensors (GS) with high-sensitivity, low-cost, robust and simpler (in-house) fabrication metal-oxide-semiconductor (MOS) based make their usages affordable in diverse applications even for broader deployment that demand extensive coverage and thus create a revolution on CE market. VOCKit, an IoT sensor kit that combines fluorometric sensors with machine learning (ML)-driven embedded imaging system for VOC detection and classification [15]. Performance can be improved through clustering, as explored in smart agriculture systems [16], and the neural network used [17] in the Wireless Sensor Network (WSN).

Ambient Wi-Fi RF signals at 2.4 GHz [1], [10] typically provides incident power in the range of  $-20$  to  $-10$  dBm at indoor distances of 2–5 meters. Rectification yields tens to hundreds of microwatts in EH using high-efficiency rectennas (rectification efficiencies of 75–90 % [1] [10]. On hardware side, compact rectenna modules with integrated matching networks (e.g., Powercast P2110B and EnOcean radio frequency (RF)-EH kits), supercapacitor-based energy buffers (10–100 mF) for stabilizing harvested energy, and ultra-low-power microcontroller units (MCUs)/wireless chips such as advanced reduced instruction set computer machine (ARM) Cortex-M0+, TI CC2650, and ESP32-C3 operating in sub-milliwatt active modes, are reported.

#### A. Challenges and Contributions

Continuous monitoring and time-critical analysis of GS data through deployment of low-cost MOS devices face challenges of integration of IoCE, artificial intelligence (AI)/ML for automatic decision and emerging wireless technologies for low-latency high-speed connectivity. To address the issues, this article discusses

the scope of deployment of low-cost sensors as CE devices for VOCs sensing, RF-EH for self-powering with RIS-aided underlay cognitive radio (CR) for high-speed low latency seamless connectivity. Deep Q-Networks (DQNs) facilitate time critical analysis, altogether leads to an software radio network (SDN)-IoCE architecture. The contributions of the present work are as follows:

- i. Time frame structure consists of RF-EH slot, gas sensing by low-cost GS and sensing data transmission. The optimal value of RF-EH slot is determined to enable harvested energy self-powered to the GS node.
- ii. RIS aided underlay CR mode enables seamless reliable transmission of GS data by minimizing the link outage probability. To implement in cost-sensitive consumer environments, RIS panels can be realized using low-cost meta surfaces fabricated with printed circuit techniques that substantially reduce hardware expenses. In indoor industrial or consumer spaces, RIS should be mounted on existing infrastructure i.e. walls, ceiling, etc. thus avoiding standalone installation cost. Furthermore, a modular panel design with different sizes and shapes enables scalable RIS deployment, allowing additional panels to be added incrementally to meet performance demands.
- iii. Two separate DQNs are used to solve optimization problems, the first one (DQN1) in data transmission and the other one DQN2 for decision policy on gas monitoring.

The proposed SDN-IoCE gas monitoring system illustrates how CE devices, when integrated with AI-driven decision-making (DQNs) and 5G/6G network enablers such as RIS-assisted CRNs, can provide sustainable, intelligent, and ultra-reliable monitoring in industrial and smart-home IoCE environments.

The paper is organized as follows: proposed system model, optimization problems with constraints, DQN framework, results and discussions and finally conclusion and comments.

## PROPOSED SYSTEM MODEL

This suggested system model comprises of two modules (i) GS-EH-RIS-CR involved in gas sensing and its transmission and (ii) SDN-IoCE architecture for time critical analysis of gas sensing data. Figure 1 presents the proposed SDN-IoCE-Gs-CR-RIS-EH (SIGSCRISEH) system model involving self-powered gas sensing, followed by DQN based optimized sensor data transmission and decision policy of gas monitor-

ing with time critical data analysis at edge nodes.

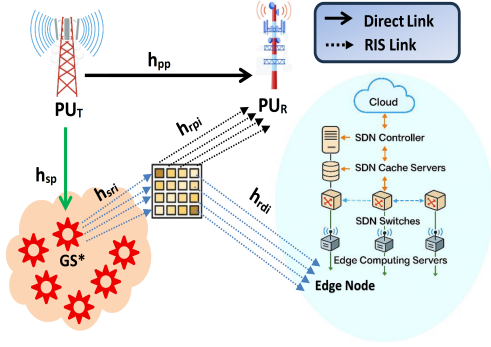


Figure 1: System Model with SDN-IoCE architecture

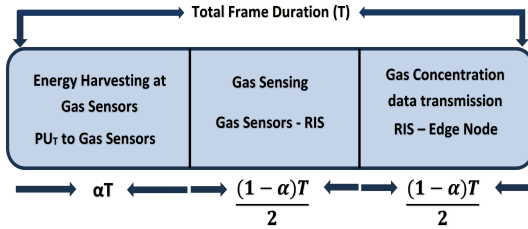


Figure 2: Frame Structure

### GS-EH-RIS-CR sensor data transmission

Figure 2 shows the periodic frame-structure that includes operations of EH, gas sensing and sensor data transmission. Frame consists of three slots where over some fraction of time  $\alpha T$ , GS harvests energy from primary user (PU) i.e. existing WiFi RF signals. The optimal value of  $\alpha$  is determined so that harvested energy keeps it ON and powered for gas sensing operation and transmission. The remaining time  $(1 - \alpha)T$  is divided in two equal slots where during the first slot gas sensing is done and simultaneously sensed gas data is transmitted from GS to RIS. The last time slot is used for data transmission from RIS to edge devices for time-critical analysis.

The phase shift (PS) matrix at RIS is given as

$$\Theta_k = \mathcal{A}_k \text{diag}(e^{j\phi_{k1}}, e^{j\phi_{k2}}, \dots, e^{j\phi_{kM}}) \in \mathbb{C}^{M \times M},$$

where,  $\mathcal{A}_k$  and  $\phi_k$  ( $k \in \{sr_i, sp_i\}$ ,  $i \in 1, 2, \dots, M$ ) denote the amplitude reflection coefficient and phase shift of all RIS elements, respectively [18]. Finding the optimal values of phase shift (PS) matrix is a design issue for reliable and seamless connectivity.

### Optimization Problems with Constraints

The closed indoor gas monitoring environment leads to severe signal attenuation and quality degradation. Hence, for its real-time monitoring and critical

analysis need reliable data transmission to edge nodes and cloud server. Mathematically, a reliable link is ensured by minimizing the GS outage probability ( $P_{\text{out}}^{\text{GS}}$ ), as the objective function shown in Eq. (1).

Self-powering operation of GS needs sufficient EH so that its residual energy  $E_{\text{res}}$  be positive as given by Eq. 1 (i). Since the proposed GS data transmission follows underlay CR model, PU i.e. the existing WiFi communication data rate no way be hampered. This is ensured by maintaining the PU desired data transmission rate  $\mathcal{R}_{pr}$  above a predefined threshold  $\mathcal{R}_p^{\text{th}}$  and is considered Eq. 1 (ii) constraint. High-speed connectivity in 5G/6G network is an essential requirement for the proposed IoCE based GS to meet the desired throughput  $\mathcal{R}_{sr}$  above a specified threshold  $\mathcal{R}_s^{\text{th}}$  as specified in Eq. 1 (iii). Constraint in Eq. 1 (iv) in RIS phase-shift ensures implementation of the optimal intelligent reflection in the 5G/6G environment.

Following the above discussion, GS-EH-RIS-CR data transmission can be stated as to minimize  $P_{\text{out}}^{\text{GS}}$ , by finding out the optimal values of  $P_s$ ,  $\alpha$  and  $\Theta_{sr_i}$ , while maintaining the energy causality at GS, PU and GS throughput constraints.

$$\begin{aligned} & \min_{\alpha, P_s, \Theta_{sr_i}} P_{\text{out}}^{\text{GS}} \\ & \text{s.t. } i) E_{\text{res}} \geq 0, \\ & ii) \mathcal{R}_{pr} \geq \mathcal{R}_p^{\text{th}}, \quad iii) \mathcal{R}_{sr} \geq \mathcal{R}_s^{\text{th}}, \\ & iv) 0 < \phi_k < 2\pi, k \in \{sr, sp\}, \end{aligned} \quad (1)$$

where,  $E_{\text{res}}$ ,  $\mathcal{R}_{pr}$ ,  $\mathcal{R}_{sr}$ ,  $\mathcal{R}_p^{\text{th}}$  and  $\mathcal{R}_s^{\text{th}}$  denote the total residual energy (self-powering), PU data rate, GS (SU) data rate, target PU throughput constraint (PU protection) and GS throughput constraint (high speed data rate), respectively.

### Solution:DQN Framework

The controller connects to a cloud-based analytics engine that trains the two separate DQNs. The first one i.e. DQN1 provides high speed reliable link connection in IoCE and the other one i.e. DQN2 is used for the optimal decision policies on gas monitoring system. While DQN1 model is deployed in controller having global view of IoCE network, DQN2 is housed in edge nodes, makes time critical decisions through collaborative operation with DQN1.

#### A. DQN1 for Reliable Data Transmission

In the DQN1 model, the state comprises of distance information of the GS, RIS, PU transmitter-receiver, edge devices, cloud server, EH duration,

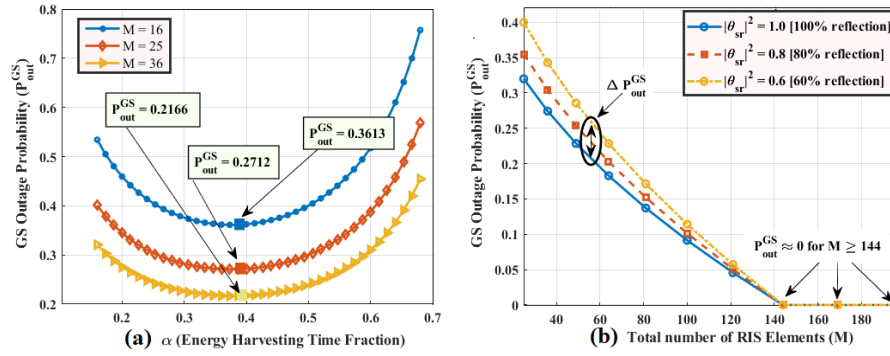


Figure 3:  $P_{out}^{GS}$  versus (a) EH duration ( $\alpha$ ), (b) total number of RIS elements ( $M$ )

sensor data transmission power, and phase shift  $\Theta$ . Thus the input state is defined as  $S = \{d_{p-g}, d_{p-R}, d_{S-RIS}, d_{RIS-PU}, d_{RIS-Edge}, \alpha, P_s, \Theta\}$ .

The action state space consists of adjusting phase shift, EH duration and sensor transmit power, hence,  $\mathcal{A} = \{\Theta_{old}, \alpha_{new}, p_{new}\}$ .

After installation, the placement of RIS is fixed; consequently, the distances in set  $S$  are found, so the action space contains adjustment of EH duration, transmit power and phase shift, each one is changed in discrete steps. At iteration  $t$ , the action  $a_t \in \mathcal{A}$  contains three components:

- 1) Phases:  $\Theta_n \in \{\Delta\Theta_1, \dots, \Delta\Theta_N\}, \forall_n \in N$
- 2) EH duration:  $\alpha_m \in \{\alpha_1, \alpha_2, \dots, \alpha_m\}$
- 3) Transmit power:  $P_{s_m} \in \{P_{s_1}, P_{s_2}, \dots, P_{s_m}\}$

with  $m \in M$ , discrete values of EH and power. At iteration  $t$ , for successful transmission i.e., no outage with EH (Eq. 1 (i) satisfied) and constraints Eq. 1 (ii) and (iii) satisfied, the reward is given by  $r_s = R_{sr}$ . Now if any one of the constraints Eq. 1 (ii) or (iii) is not met, the constrained objective fails, new reward is

$$r_f = \begin{cases} R_{pr}, & \text{if Eq. 1 (ii) not satisfied,} \\ R_{sr}, & \text{if Eq. 1 (iii) not satisfied} \\ 0, & \text{otherwise.} \end{cases}$$

Thus, the overall reward function is expressed as

$$r_t = \begin{cases} r_s, & \text{if Eq. 1 (i) and (ii) satisfied,} \\ r_f, & \text{otherwise,} \end{cases}$$

The above reward calculation follows [18]. Following Bellman equation, the optimal policy of action selection that maximizes

$$Q^*(s_t, a_t) = \mathbb{E}_{s_{t+1}} \left[ r_t + \gamma \max_{a' \in \mathcal{A}} Q^*(s_{t+1}, a') \mid s_t, a_t \right]$$

Inclusion of a neural network (NN) for function

approximation enables the estimation of the action function as  $Q(s_t, a_t; W) \approx Q^*(s, a)$ . Hence, in DQN1 model, the state  $S$  is the input, while evaluated Q-value is the output for each state-action pair.

The DQN training process aims to minimize the error function, defined as the loss function, obtained from the target and the realistic Q-values. Thus, the loss function and target Q-value are

$$\text{Loss}(W) = \mathbb{E} \left[ (Q_{\text{target}} - Q(s_j, a_j; W))^2 \right], \quad (2)$$

$$Q_{\text{target}} = r_j + \gamma \max_{a'} Q(s_{j+1}, a'; W^*), \quad (3)$$

for mini batch  $j$ . Here,  $W$  and  $W^*$  denote the weights for the evaluation and target network, respectively.

SDN controller maintains a global view of active SUs (multiple GSs), RIS nodes, edge devices and PU activity. It allocates transmission slots and RIS update windows using a time-slotted schedule (TDMA style) and enforces an admission control policy so that the aggregate secondary interference stays below a configured interference-temperature threshold at PU receivers. DQN policy enables fine-grained power adaptation within each allocated slot to minimize collisions and reduce aggregate interference, through RIS element phase profiles maximizing SU link gain while nulling or reducing radiated power toward PU locations.

#### B. DQN2 for Gas monitoring and decision policy

The proposed framework starts operation at the sensing layer, where a smart sensor or an array of sensors (multiple GSs), continuously monitor, say an indoor environment of a chemical factory, for sensing of VOCs. The sensor nodes comprise of sensing unit, limited power supply, low power processing unit, limited storage unit and wireless link with RIS aided Wi-Fi (Primary) for edge nodes and remote server. GSs periodically send sensing data to nearby edge nodes,

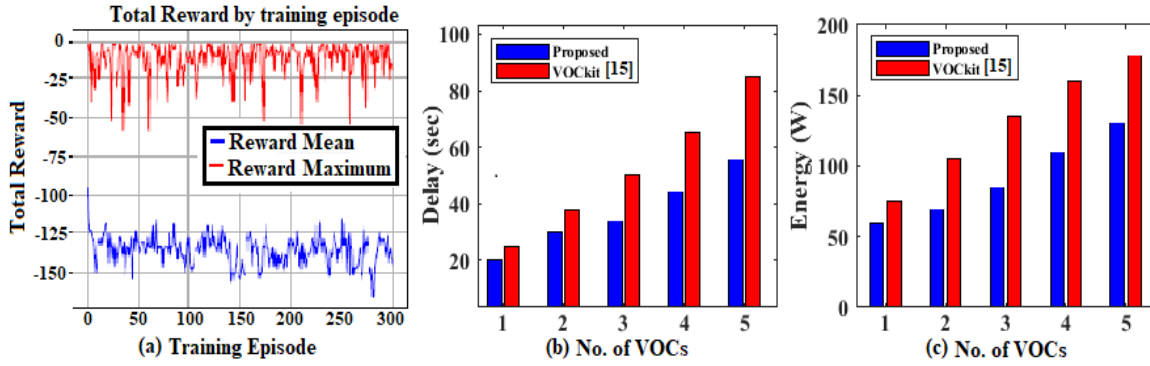


Figure 4: (a) Mean and Max reward vs no. of epoch, (b) Delay in sec. and (c) Energy in watts vs no. of VOCs

typically handle lightweight processing, thereby offer low-latency and energy efficiency.

The proposed architecture also contains SDN switches and cache servers, equipped with reliable wireless connections through RIS. SDN controller acts as a centralized decision-making entity representing the core of the proposed system. Upon receiving the aggregated data from edge nodes, updates from SDN switches, and control policies from the cloud, SDN controller computes risk assessment and scenario prediction considering the real-time hazards, presence of different gases, and their concentration.

DQN2 operates on a Q-value approximator  $Q(S_m, a_m; \Theta)$  and a target approximator  $Q(S_m, a_m; \Theta^-)$ . The loss function and the target value follow the similar forms of Eqs. 2 and 3.

The proposed SDN-IoCE framework can support indoor chemical factory environment monitoring of VOCs in real time, by deploying low-cost MOS-based gas sensors across different factory zones. Sensor readings are transmitted to nearby edge servers for time-critical analysis using DQN1, while DQN2 provides intelligent decision support (e.g., triggering ventilation, generating alarms, or activating safety protocols).

## RESULTS and DISCUSSION

Simulations were done on a Ubuntu workstation, equipped with AMD Ryzen hexa-core CPU, sixty-four gigabytes of RAM, and a 1408 CUDA GPU. Table 1 shows the parameter values of SDN architecture and DQN settings.

Figure 3 (a) illustrates  $P_{out}^{GS}$  versus  $\alpha$ ,  $P_{out}^{GS}$  decreases initially as EH at GS enhances. With further increase in  $\alpha$ ,  $P_{out}^{GS}$  increases as transmission slot reduces. It is observed that  $P_{out}^{GS}[M = 36] < P_{out}^{GS}[M = 25] < P_{out}^{GS}[M = 16]$  and  $P_{out}^{GS}$  attains

Table 1: DQN parameters and performance

Category	Parameter and Value
General Settings	Fleet size: 5; Nodes: 50; Edges: 100; Edge feature dimension: 10; Maximum steps per agent: 50.
DQN Hyper-parameters Settings	Update rate ( $\alpha$ ): 0.001; $\gamma$ : 0.99; $\epsilon$ range: 0.1–1.0; Decay rate: 0.995; Batch size: 64; Replay memory: 10,000; Target update: every 10 steps.
Proposed work, work reported in [15]	VOCs:5; Delay:54s,Energy:130W [15]: Delay:87s, Energy:176W.

0.2166, 0.2712 and 0.3613 for  $M = 36, 25$  and  $16$ , respectively. Figure 3 (b) shows  $P_{out}^{GS}$  vs RIS dimension ( $M$ ) where the former decreases with an increase in  $M$  value. It is also observed that  $P_{out}^{GS}[|\theta_{sr}|^2 = 1] < P_{out}^{GS}[|\theta_{sr}|^2 = 0.8] < P_{out}^{GS}[|\theta_{sr}|^2 = 0.6]$  since  $|\theta_{sr}|^2 = 1$  implies 100 % reflection with full power from RIS. The value of  $P_{out}^{GS}$  saturates to zero (0) for all cases after  $M = 144$ .

Figure 4 (a) shows improved performance on rewards values up to 200 with smooth convergence and network stability over the training episodes. Delay/latency and energy consumption with different number of VOCs for the proposed SD-IoT architecture and [15] are shown in Figure 4 (b) and Figure 4 (c), respectively, with 33 sec and 46 watt less values for the former considering 5 VOCs (Table 1) due to RIS-CR data transmission and trainable DQN2 operation.

## CONCLUSION AND COMMENTS

This article discusses an SDN-IoCE low-cost gas monitoring system ensuring self-powering of sensor nodes, low latency, high-speed connectivity and energy efficiency on intelligent decision making.

Low-cost MoS sensors with intelligence in

SDN leads to CE devices widespread applications that include industrial settings, air quality tracking, environment-friendly health monitoring etc. CE devices market can influence significantly exploiting sensor reversibility, meaning that once the detected VOCs disappears, sensor can go back to the original state, hence, they can be reusable. The proposed model also shows potential application using reversible GSs.

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