
Sudip Misra, Senior Member, IEEE, Samaresh Bera, Student Member, IEEE, Achuthananda M.P., Sankar K. Pal, Fellow, IEEE, Mohammad S. Obaidat, Fellow, IEEE, Fellow, SCS

Abstract—In this paper, a situation-aware protocol switching scheme is proposed for software-defined wireless sensor networks (SDWSNs) to support application-specific requirements in real-time. The proposed scheme consists of two phases — decision making and protocol deployment. In decision making, we use the supervised learning approach to choose the suitable routing protocols to be deployed in different time periods according to application-specific requirements. In the second phase, the chosen protocol is deployed in the network by the SDN controller in an adaptive manner. It is noteworthy that the proposed scheme can be integrated on top of the SDN controller in WSN to deploy a suitable routing protocol dynamically in the network. Extensive simulation results are analyzed to show the effectiveness of the proposed scheme, while varying the application-specific requirements. We see that the proposed scheme outperforms the existing schemes, in which a particular protocol is used in different time periods, in terms of energy consumption, throughput, packet delivery ratio, and delay in the network. It is shown that situation-aware protocol switching is capable of enhancing the network performance of SDWSNs.

Index Terms—Wireless Sensor Networks, Software-Defined Networking, Supervised Learning, Network Performance

I. INTRODUCTION

Wireless sensor networks (WSNs) are widely used for military applications, environment monitoring, wild-habitat monitoring, target tracking, intelligent traffic monitoring and energy management [1]. Consequently, multiple sensor nodes are deployed in a region to get real-time information. According to the received information, users are capable of taking adequate decisions for improved decision-making. Recently, different mechanisms are introduced to change the activities of a sensor node in run-time. The Software-defined networking (SDN) technology can be used in WSN to change the activities of sensor nodes in real-time to meet application-specific requirements [2].

Due to the growing interests of supporting application-specific requirements, it is required to manage the deployed nodes in WSNs dynamically in real-time from different aspects. For example, the AODV [3] routing protocol may be suitable for use on DSDV [4] in a specific time period for energy-efficient WSN applications. However, the latter one may be useful for minimizing network delay over the former one. Therefore, it is required to manage the routing protocols used in the network in different time periods depending on the requirements in order to get optimal network performance. However, the existing WSN frameworks [5] do not support such features to change the protocols in real-time. In contrast, SDN-enabled WSNs can be configured in real-time, while separating the control logic from the physical sensor devices [6]. Consequently, different application-specific requirements can be supported in real-time, which are platform-independent. However, there is a research lacuna on how to choose optimal routing protocols to get optimal network performances, and then how to deploy them in the network as well. The existing schemes either focused on the static requirements from the users or considered value-based information forwarding, i.e., the sensed information is forwarded if it crosses a predefined threshold value.

A. Contribution

To address the above-mentioned issues, we propose a situation-aware protocol switching scheme in software-defined wireless sensor networks (SDWSNs). The proposed scheme consists of two phases — determination of an appropriate routing protocol and deployment of the protocol at the nodes. In the first phase, we determine the suitable routing protocol to be deployed for which network performance increases. To determine the protocol, we use supervised learning approach [7] at the controller end. The controller collects network statistics from the sensor nodes and application-specific requirements from application layer to take adequate decisions. In the second phase, the determined protocol is deployed at the individual sensor nodes. It is also noteworthy that multiple routing protocols can be used in a specific time period, as the software-defined framework supports protocol independent packet processing techniques [8]. Consequently, a WSN can be divided into multiple subnetworks, and multiple routing protocols can be deployed depending on the application-specific requirements to get optimal network performance. Extensive simulation results show that the proposed scheme is useful to optimize network performance from the aspects of energy consumption, throughput, packet delivery ratio and delay, while changing the routing protocols according to application-specific requirements. In brief, the contributions in this work are as follows:

- We propose a situation-aware routing protocol switching scheme in SDWSN to meet application-specific requirements of users.

S. Misra, S. Bera and Achuthananda M.P. are with the Computer Science and Engineering Department, Indian Institute of Technology, Kharagpur, 721302, India, Email: smisra@sit.iitkgp.ernet.in, s.bera.1989@ieee.org, achuthananda@gmail.com

S. K. Pal is with the Indian Statistical Institute, Kolkata, 700108, India, Email: sankar@isical.ac.in

M. S. Obaidat is the Chair and Professor of the Dept. of Computer and Information Science, Fordham University, New York, 10458, USA, Email: mobaidat@fordham.edu
We interweave supervised learning-based algorithms for protocol selection and deployment, which train the SDN controller, so that it adaptively switches between routing protocols, as per the application-specific requirements. This contribution is a carefully artificed rhetoric, which elicits the embedding of adaptive learning to improve the performance of SDWSN.

- We present the framework for decision making and protocol deployment, which can be integrated with the existing SDWSN framework to improve overall network performance, without affecting the underlying architecture.

The rest of the paper is organized as follows. Section II discusses the existing works from the perspectives of WSN. Detailed system model is presented in Section III. Section IV describes the proposed solution approach. Simulation results are presented in Section V. Finally, Section VI concludes the paper with some future research directions.

II. RELATED WORK

In this Section, we discuss the existing works from two different perspectives — reconfigurable WSN [9]–[12] and software-defined WSN [6], [13]–[17] — which are useful to change the activities of a sensor node in real-time.

A. Reconfigurable WSN

Bouabdallah et al. [9] proposed an energy consumption minimization scheme for sensor nodes deployed in a vehicular network. The authors claimed that energy consumption can be minimized by sending data traffic through multiple paths rather than using a single path in the network. A load balancing approach is studied to determine the multiple paths, in order to minimize energy consumption. FPGA-based re-configurable sensor nodes are developed by Krasteva et al. [10]. The developed systems consist of re-configurable hardware platforms which can be configured in real-time, while introducing a middle-ware. Likewise, Guevara et al. [12] proposed a design for hardware-centric re-configurable wireless sensor nodes. Additionally, transducer electronic data sheet architecture and management policy are proposed for the nodes. Gao and Piao [11] proposed a dynamic routing protocol deployment strategy for WSNs in real-time. In such a scheme, the use of the protocols for information routing can be changed in real-time, depending on the requirements and network conditions.

Although different useful schemes are proposed to configure activities of sensor nodes in real-time, they are either distributed in nature or constrained by their capacity. Due to the distributed nature of decision making, the existing solutions may not be adequate in a global scenario to meet application-specific requirements.

B. Software-defined WSN

Luo et al. [6] proposed flow-table implementation rules, named as Sensor-OpenFlow, for use in sensor networks. Two different flow-table rules are proposed — value-based and ID-based. In the value-based approach, the value of the sensed information is compared before forwarding it to other nodes in the network. On the other hand, in the ID-based approach, the ID of sensor node is compared to forward the sensed information to sink nodes in the network. Galluccio et al. [13] designed a prototype for SDWSN, in which sensor nodes can be reconfigured in a stateful manner, while reducing the message exchange between the node and the controller. Anadiotis et al. [14] proposed an SDN-enabled WSN framework in order to deploy map-reduce functions optimally in the network. In such a scheme, the desired map and reduce functions are deployed at individual sensor nodes in the network using the SDN concept. Zeng et al. [15] proposed an energy consumption minimization scheme in WSN, in which a node consists of multiple sensor devices to perform different tasks. Therefore, the sensors can be activated according to the application-specific requirements. The authors proposed a hierarchical controller/manager architecture for the proposed scheme. Similarly, an SDN-based WSN architecture is proposed by Wang et al. [17] to control sleep-scheduling of sensor nodes in the network in an energy-efficient manner. Recently, Bera et al. [16] developed a platform, named as Soft-WSN, for controlling and monitoring WSN using the concept of SDN. The proposed system provides facility to control device-specific and network-specific tasks in a WSN. The authors claimed that the proposed system can be integrated into an existing WSN, without affecting underlying technologies.

We synthesize that most of the existing SDN-based schemes focused on the device-specific reconfiguration, which can be done in real-time to meet application-specific requirements. However, suitable information routing strategy also plays an important role to maximize the network performance, such as minimization of energy consumption and delay, and maximization of throughput and packet delivery ratio. Therefore, we intend to propose a scheme to select and deploy suitable routing protocol, in order to maximize network performance.

III. SYSTEM MODEL

A. Architecture

Figure 1 presents a schematic architecture of SDN-enabled WSN. We follow the generalized architecture of SDN, which consists of infrastructure, control and application layers. At the infrastructure layer, sensor nodes and access devices (ADs) are deployed. The sensor nodes send the sensed information to the ADs, and the ADs forward the information to the data center for computation. Leveraging the SDN concept in WSN, the sensor nodes can be controlled in a centralized manner, depending on the application-specific requirements. Therefore, the controller takes adequate decisions and controls the entire network. On the other hand, application-specific requirements are provided to the controller from application layer.

B. Objectives

The objective of the proposed scheme is to maximize network performance. Therefore, we consider four metrics to form the objective function — energy consumption, packet delivery ratio, throughput and delay, which are discussed below.

1) Energy Consumption: Energy consumption at a sensor node depends on the required energy for transmission and reception. In addition to the circuitry energy consumption in
transmission and reception, the transmission energy also depends on the distance between sender and receiver. Therefore, total energy consumption of a sensor node for transmitting data to a neighbor node located at a distance $d$ is calculated as $E_t = E_{ckt}^{rx} + E_{ckt}^{tx} + \frac{P_{trans}}{h^{\eta}}$, where $\eta$ is a constant, and $h$ denotes the path loss exponent. The parameter $d$ is the distance between the sending and receiving nodes, and $\sigma$ is the path loss exponent. For simplicity, we consider that the path loss exponent is always constant. Consequently, energy consumption for a given pair of source and destination nodes (consider it as a path $l$) located at $h$ multi-hop distance is calculated as follows:

$$E(l) = \sum_{k=1}^{h-1} E_{ckt}^{rx} + \sum_{k=1}^{h} \left( E_{ckt}^{tx} + \frac{P_{trans}}{h^{\eta}} \right)$$  \hspace{1cm} (1)

($h - 1$) hops are considered for energy consumption due to reception, as destination node is typically powered by external source. Consequently, the objective of the controller is to minimize the energy consumption for all pairs of source and destination nodes in the network, while deploying the suitable routing protocol $r \in R$. Mathematically,

$$\text{Minimize } \sum_{t=1}^{T} \sum_{r \in R} E(l,t,r), \ r \in R$$  \hspace{1cm} (2)

$$\text{subject to } E_{ckt}^{rx}, E_{ckt}^{tx}, d > 0, \text{ and } \eta \leq 1$$

Equation (2) denotes that $E_{ckt}^{rx}, E_{ckt}^{tx}, d$ are always greater than zero. On the other hand, $\eta$ is always less than or equal to 1, as the maximum drainage efficiency is 100%. $L$ and $T$ denote the total number of paths used for routing in the network and total time, respectively. $r$ is the routing protocol used at the node.

2) Packet Delivery Ratio: Packet delivery ratio is calculated as the ratio between the number of packets successfully received ($P_{rx}$) at the destination nodes and the number of packets transmitted ($P_{tr}$) at the source nodes, i.e., $\rho = P_{rx} / P_{tr}$. The objective is to maximize the packet delivery ratio in order to improve the network performance. Mathematically,

$$\text{Maximize } \sum_{t=1}^{T} \rho(t,r), \ r \in R \text{ subject to } P_{tr} > 0$$  \hspace{1cm} (3)

The constraint $P_{tr} > 0$ confirms that the number of packets transmitted $P_{tr}$ is always greater than zero.

3) Throughput: We calculate the network throughput for a path $l$ as follows: $\Upsilon(l) = \sum_{k=1}^{L} \sum_{t=1}^{T} \frac{W_{i,k}}{RTT_{i,k}} / h$ [19]. Our objective is to maximize the throughput to improve the network performance. Mathematically,

$$\text{Maximize } \sum_{t=1}^{T} \sum_{l=1}^{L} \Upsilon(l,t,r), \ r \in R$$  \hspace{1cm} (4)

subject to $W_{i,k} > 0$, and $RTT_{i,k} > 0$ where $C_l$ is the total number of available channels. $W_{i,k}$ is the received TCP window size, and $RTT_{i,k}$ is the round-trip time for $i^{th}$ channel in $k^{th}$ hop. It is noteworthy that performance of TCP in WSN is very poor. Therefore, we adopt the distributed TCP caching mechanism, in which the sensor nodes locally retransmit the lost segments [19]. Consequently, the lost segment is not re-transmitted from the original source node, so that the required network performance is preserved.

4) Delay: We consider the delay as the combination of processing, queuing, transmission, and propagation delay.

Therefore, total delay in a path between the given source and destination having $h$ hops is calculated as: $D(l) = \sum_{k=1}^{h} (D_{prop}^{i,k} + D_{tx}^{i,k} + D_{q}^{i,k} + D_{ckt}^{prop})$. Consequently, the objective is to minimize the network delay for all paths $L$ used for routing, which is represented as follows:

$$\text{Minimize } \sum_{t=1}^{T} \sum_{l=1}^{L} D(l,t,r), \ r \in R$$  \hspace{1cm} (5)

subject to $D_{prop}^{i,k}, D_{tx}^{i,k}, D_{q}^{i,k}, D_{ckt}^{prop} > 0$ The constraint in Equation (5) denotes that all the delays are always greater than zero.

In the proposed scheme, we consider that there always exists a path between a source and a destination. We do not focus on the connection establishment problem in sensor network, as main objective of the proposed scheme is to determine an appropriate routing protocol to be deployed in the network, so that overall network performance increases.

C. Overall Objective Functions

We combine all the individual objective functions together as a multi-objective function. We consider weight-based ap-
suitability of a routing protocol to be used to get optimal statistics collection.

A. Determination of Suitable Protocol

Determination of a suitable routing protocol is critical for optimizing network performance. For this purpose, we use a supervised learning approach [20] to train the controller through which the SDN controller can take adequate decisions with given conditions, such as the number of nodes, available energy, node speed, and application-specific requirements. Further, the training phase consists of three phases — feature extraction, classification, selection of the best classifier.

1) Feature Extraction: We consider different network-specific parameters such as network size, pause time, node speed, communication range, and packet sending rate, to extract various features from different network statistics. All the parameters are elaborated below.

- **Network Size**: It is defined as the number of nodes present in the network. Typically, in a WSN environment, the total energy consumption in the network increases with an increase in the number of nodes for information routing. Therefore, we consider network size as one of the important parameters to extract the features from network statistics.
- **Pause Time**: It defines whether the network is static or dynamic. If the nodes maintain an equal pause time, the nodes are static in nature. Otherwise, the nodes are dynamic. Pause time is considered to deal with the nodes’ movement patterns in order to take adequate decisions.
- **Node Speed**: This indicates the speed of the nodes in the network. If the speed of nodes is high, then the network topology also changes very frequently. Consequently, flow table entries are required to be updated frequently at individual nodes, which, in turn, maximizes the energy consumption. Therefore, we need to select a suitable routing protocol to deal with the node speed in the network.
- **Communication Range**: It is used to calculate the neighbor lists of the nodes. We assume that the nodes are distributed in a uniform-random manner in the network, and initially, the network is connected.
- **Packet Sending Rate**: This parameter indicates the number of packets sent from the source in the network at each time period. This also affects the amount of energy consumption and packet delivery ratio in the network.

Therefore, the above mentioned parameters are used to extract the features in order to classify the network statistics. The controller collects the network statistics consisting of different tuples as follows: <Pause Time, Speed, Energy,

Flow-tables are maintained at SDN-enabled devices to route information.
Communication Range, Packet Sending Rate). The nodes periodically send these information to the controller.

2) **Classification:** After extracting different features, as mentioned in Section [21], they are classified based on the optimization problem defined in Section [III-C]. We calculate a cost value for which the network performance is optimized, while application-specific requirements are given [23]. Therefore, for a given application requirements, we assign different weights of energy, throughput, delay and packet delivery ratio, as mentioned in Section [III-C]. Mathematically, it is represented as follows [21]:

\[
h_\theta(x) = \sum_{i=1}^{k} \theta_i x_i
\]  

(7)

where \( \theta_i \) denotes the weights considered for the application-specific requirements. \( k \) denotes the number of objective functions considered. In the proposed scheme, we have considered \( k = 4 \), i.e., energy, packet delivery ratio, throughput and delay. Accordingly, weight for \( \theta_i \) is assigned, which is further reflected in the results and discussion (please refer to the Section [V]). It is noteworthy that \( \theta_i \) are the parameters (also known as weights) parameterizing the space of linear functions mapping from \( X \) to \( Y \) [21]. Therefore, \( Y \) is a linear function of \( X \) with coefficient \( \theta_i \). In order to learn the values of \( \theta_i \), the objective of the learner is to make \( h_\theta(x) \) as much as possible accurate to meet the application-specific requirement. Therefore, Equation (7) is represented as follows:

Minimize \( C(\theta) = 1/2 \sum_{i=1}^{k} (h_\theta(x^{(i)}) - y^{(i)})^2 \)  

(8)

It is noteworthy that \( x \) stands for different parameters considered in the work, such as energy, delay, packet delivery ratio and throughput. \( y \) is the target value based on cost calculated using Equation (8) for a particular routing protocol. Therefore, for given values of \( x \), the objective is to minimize the target value \( y \). Thus, the learner determines which routing protocol minimizes \( y \) for given \( x \).

Finally, value of \( \theta_i \) is determined as follows [21]:

\[
\theta_j = \theta_j + \lambda \left( y^{(i)} - h_\theta (x^{(i)}) \right) x^{(i)}
\]  

(9)

where \( \theta_j \) is the initial value, and the process is repeated until the value of \( \theta_j \) converges. The parameter \( \lambda \) is the learning rate. Consequently, we get the values for \( \theta_j \), in order to meet application-specific requirements according to the training dataset. We select the ‘Classification via Regression’ approach, as it gives the best network performance (refer to Table [II]). The Mcnemar’s significance test [22] is conducted to validate the accuracy of the extracted features from the sensed data. For simplicity, we limit our discussion on the Mcnemar’s significance test, as our prime objective concerns the deployment of a suitable routing protocol in the network, depending on the application-specific requirements.

**TABLE II:** Comparison of classification accuracy with different classifiers

<table>
<thead>
<tr>
<th>Name of the classifier</th>
<th>Percentage of accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naive Bayes</td>
<td>0.782</td>
</tr>
<tr>
<td>KNN(K = 10)</td>
<td>0.894</td>
</tr>
<tr>
<td>Random Forest</td>
<td>0.898</td>
</tr>
<tr>
<td>Best Fit Decision Tree</td>
<td>0.880</td>
</tr>
<tr>
<td>Classification via Regression</td>
<td>0.903</td>
</tr>
<tr>
<td>Function tree</td>
<td>0.854</td>
</tr>
<tr>
<td>Decision Table</td>
<td>0.901</td>
</tr>
</tbody>
</table>

We present the algorithm for classification in Algorithm [1].

**Algorithm 1:** Algorithm for classification

**Input:** Set of routing protocols \( R \), Network statistics

**Output:** Classify the features and stored them in the Class \( C \)

1. Assign \( U_{min} = \infty \), \( r = 1 \), \( C = 0 \);
2. while \( r \leq |R| \) do
3. \( U_r = \sum_{l,t} \alpha E(l,t,r) + \beta \gamma \rho(l,t,r) \)
4. if \( U_r \leq U_{min} \) then
5. \( U_{min} = U_r \);
6. \( C = r \);
7. \( r = r + 1 \);
8. return \( C \);

B. **Protocol Deployment**

After selecting a suitable routing protocol decided in Algorithm [1] to optimize the network performance, we need to deploy it in the network. Algorithm [2] presents the protocol deployment in the network in a periodic manner similar to the network statistics collection. The algorithm checks the classes obtained using Algorithm [1] for which cost is minimized with the given network condition. Finally, the controller deploys the desired protocol in the network. The periodic update interval \( T_{itr} \) depends on users’ requirements.

V. **PERFORMANCE EVALUATION**

We evaluated the performance of the proposed scheme, SAPS, using simulator NS-3 (www.nsnam.org), in which, required modules are developed to change the routing protocols in run-time. We use the term ‘SAPS’ to denote the proposed scheme in the rest of the paper. Different simulation parameters are considered, as shown in Table [III]. We compare the performance of the proposed scheme with the following routing protocols: OLSR [23], DSDV [4], AODV [3], and DSR [24]. In SAPS, multiple routing protocols are deployed based on the decision taken by the controller in order to improve the network performance, while considering application-specific requirements. On the other hand, we present the results for benchmark schemes, while considering that a particular routing protocol is used in the entire simulation time. The controller
Algorithm 2: Algorithm for appropriate protocol deployment

Input: Set of classes $C$, Time interval $T_{itr}$, Total time $T$
Output: Deployment the best routing protocol $r \in R$ in the network
1 Assign $r_{best} = 1$, Elapsed time $T_{elsp} = 0$;
2 Start the WSN with protocol $r$;
3 while $T_{elsp} <= T$ do
4    if $T_{elsp}/T_{itr} == 0$ then
5        Collect network statistics $S$;
6        Choose the suitable protocol $r \in R$ with $S$ from
7        $C$ obtained in Algorithm 1;
8        if $r \neq r_{best}$ then
9            $r_{best} = r$;
10           Deploy the protocol $r_{best}$ at individual nodes
11           $i \in N$;
12    else
13        $T_{elsp} = T_{elsp} + 1$;

TABLE III: Simulation parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of nodes</td>
<td>100</td>
</tr>
<tr>
<td>Communication Protocol</td>
<td>IEEE 802.15.4</td>
</tr>
<tr>
<td>Node speed</td>
<td>0 – 20 m/s</td>
</tr>
<tr>
<td>Deployment strategy</td>
<td>Uniform Random</td>
</tr>
<tr>
<td>Communication range</td>
<td>0 – 100 m</td>
</tr>
<tr>
<td>Simulation time</td>
<td>100 min</td>
</tr>
<tr>
<td>Traffic</td>
<td>CBR</td>
</tr>
<tr>
<td>Mobility model</td>
<td>Random-waypoint</td>
</tr>
<tr>
<td>$\alpha$, $\beta$, $\gamma$, and $\zeta$</td>
<td>0.15 and 0.35</td>
</tr>
</tbody>
</table>

Fig. 3: Network performance with $\alpha = 0.15$, $\beta = 0.35$, $\gamma = 0.15$, and $\zeta = 0.35$

A. Application 1: Priority on Throughput and Delay

We consider an application in which maximization of throughput and minimization of delay are important, while considering other constraints such as energy consumption and PDR. Therefore, we set the values for coefficients $\alpha$, $\beta$, $\gamma$, and $\zeta$ as 0.15, 0.35, 0.15, and 0.35, respectively. Figure 3 presents the results with desired application-specific requirements. We see that network throughput is maximized using SAPS over some of the existing protocols such as AODV and DSR, as shown in Figure 3(c). On the other hand, it is almost equal with OLSR and DSDV, due to the proactive nature of the schemes. Moreover, network delay is minimized using SAPS over the existing schemes, while changing the routing protocols dynamically depending on the application-specific requirements, as shown in Figure 3(b). On the other hand, compared to the existing schemes, energy consumption and packet delivery ratio are moderate using the proposed scheme. Therefore, it is evident that the proposed scheme is capable of deploying suitable routing protocols in the network according to the application-specific requirements. Figure 6(a) depicts the results after solving the overall optimization problem, as presented in Section III-C. We see that the proposed scheme, SAPS, is capable of minimizing the cost compared to the fixed routing strategies.
In contrast, if we use a particular protocol in the entire simulation time, we see that network performance is not optimized, and it does not support the application-specific requirements as well. For example, using OLSR and DSDV, we can maximize the throughput, while incurring increased network delay, which is not sufficient to meet users’ requirements.

**B. Application 2: Priority on Throughput and PDR**

In this scenario, network throughput and PDR are prioritized over energy consumption and network delay. Therefore, different values of the coefficients are considered as $\alpha = 0.15$, $\beta = 0.35$, $\gamma = 0.35$, and $\zeta = 0.15$. Figure 4 presents the obtained results for energy consumption, throughput, PDR, and delay in the network. We see that SAPS is more capable of enhancing the network performance over the existing schemes, i.e., maximization of throughput and PDR in the network.

In this scenario, we see that the value of PDR increases using the proposed scheme, unlike Figure 3(c), as it is prioritized. Similarly, network throughput is also maximized, as shown in Figure 4(c). On the contrary, energy consumption and delay are not optimized, as our main focus is to maximize the network throughput and PDR in the network. Consequently, the proposed scheme maximizes the network performance, depending on different application-specific requirements. Additionally, the overall cost is also minimized using the proposed scheme, as depicted in Figure 4(b).

**C. Application 3: Priority on Energy Consumption and Delay**

In the third scenario, we prioritize energy consumption and delay over throughput and PDR in the network. Therefore, we select the following values of the coefficients: $\alpha = 0.35$, $\beta = 0.15$, $\gamma = 0.15$, and $\zeta = 0.35$. Figure 5 shows the results obtained corresponding to different performance metrics. As in other scenarios, the proposed SDN controller takes adequate decisions to deploy different routing protocols in different time periods. From Figures 5(a) and 5(b), we observe that the energy consumption and delay in the network are minimized using the proposed scheme. Additionally, we get moderate results for throughput and PDR. On the other hand, although the use of AODV and DSR minimizes the energy consumption, the network delay is not optimized. Therefore, we see that the use of a particular protocol does not serve the purposes of application-specific requirements.

Figure 6(c) depicts that the proposed scheme is also capable of minimizing the overall cost compared to the fixed routing strategies.

Consequently, it is evident that the proposed scheme outperforms the existing schemes from different sensor networking perspectives such as energy consumption, throughput, PDR, and delay, as presented in Figures 5(a), 5(b), and 5(c). Additionally, it is also capable of minimizing the overall cost in the network as depicted in Figures 6(a), 6(b), and 6(c) according to the optimization problem presented in Section III-C.

**VI. Conclusion**

In this paper, we proposed a situation-aware protocol switching scheme in SDWSN to optimize network performance, while considering different application-specific requirements. We designed an adaptive controller to take appropriate decisions based on the network condition and application-specific requirements. To take adequate decisions, we used a supervised learning approach at the controller end. Finally, the decided protocol is deployed in the network in real-time. We evaluated the performance of the proposed scheme under different application scenarios, and showed that the proposed scheme is capable of enhancing network performance over the existing schemes, in which a particular routing protocol is deployed for all the time.

In this work, we observed that it takes some time to deploy the updated routing protocol at each sensor node. Therefore, during the switching phase, few packets are unnecessarily retransmitted and may be lost, which, in turn, minimizes PDR in the network. We plan to address this issue as a future extension.
of this work. Further, due to the movement of the sensor nodes, there always exists a gap in status reporting to the controller from the physical nodes. Consequently, the controller does not have real-time information due to the reporting delay and changes in the network. This is a limitation of SDN-based approaches. We also plan to address this issue as a future extension of this work. Additionally, discussion on control overhead in network status collection and corresponding results are also included as a future extension of this work.

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REFERENCES


Fig. 6: Overall cost with different application-specific requirements

(a) $\alpha = 0.15$, $\beta = 0.35$, $\gamma = 0.15$, and $\zeta = 0.35$ (b) $\alpha = 0.15$, $\beta = 0.35$, $\gamma = 0.35$, and $\zeta = 0.15$ (c) $\alpha = 0.35$, $\beta = 0.15$, $\gamma = 0.15$, and $\zeta = 0.35$