Artificial Intelligence-Driven Mechanism for Edge Computing-Based Industrial Applications

Ali Hassan Sodhro, *Member, IEEE*, Sandeep Pirbhulal, and Victor Hugo C. de Albuquerque, *Senior Member, IEEE*

***Abstract*—Due to various challenging issues such as, computational complexity and more delay in cloud computing, edge computing has overtaken the conventional process by efficiently and fairly allocating the resources i.e., power and battery lifetime in Internet of things (IoT)-based industrial applications. In the meantime, intelligent and accurate resource management by artificial intelligence (AI) has become the center of attention especially in industrial applications. With the coordination of AI at the edge will remarkably enhance the range and computational speed of IoT-based devices in industries. But the challenging issue in these power hungry, short battery lifetime, and delay-intolerant portable devices is inappropriate and inefficient classical trends of fair resource allotment. Also, it is interpreted through extensive industrial datasets that dynamic wireless channel could not be supported by the typical power saving and battery lifetime techniques, for example, predictive transmission power control (TPC) and baseline. Thus, this paper proposes 1) a forward central dynamic and available approach (FCDAA) by adapting the running time of sensing and transmission processes in IoT-based portable devices; 2) a system-level battery model by evaluating the energy dissipation in IoT devices; and 3) a data reliability model for edge AI-based IoT devices over hybrid TPC and duty-cycle network. Two important cases, for instance, static (i.e., product processing) and dynamic (i.e., vibration and fault diagnosis) are introduced for proper monitoring of industrial platform. Experimental testbed reveals that the proposed FCDAA enhances energy efficiency and battery lifetime at acceptable reliability (∼0.95) by appropriately tuning duty cycle and TPC unlike conventional methods.**

***Index Terms*—Artificial intelligence (AI), battery model, duty cycle, edge computing, forward central dynamic and available approach (FCDAA), industrial Internet of things (IIoT), mobile devices, predictive transmission power control (PTPC).**

Manuscript received December 3, 2018; revised February 13, 2019; accepted February 14, 2019. Date of publication March 4, 2019; date of current version July 3, 2019. This work was supported by CENIIT project 17.01 which is led by Professor Andrei Gurtov at Linkoping University, Linkoping-58183, Sweden. There is no conflict of interest between all authors. Paper no. TII-18-3268. *(Corresponding author: Sandeep Pirbhulal.)*

A. H. Sodhro is with the IDA-Computer and Information Science Department, Linkoping University, Linkoping SE-58183, Sweden (e-mail: ali.hassan.sodhro@liu.se).

S. Pirbhulal is with the CAS Key Laboratory of Human-Machine Intelligence-Synergy Systems and the Institute of Biomedical and Health Engineering, Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, Shenzhen 518055, China (e-mail: sandeep@siat.ac.cn).

V. H. C. de Albuquerque is with the University of Fortaleza, Fortaleza 60811-905, Brazil (e-mail: victor.albuquerque@unifor.br).

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Digital Object Identifier 10.1109/TII.2019.2902878

I. Introduction

INDUSTRIAL revolution has caught the attention of Internet of things (IoT)-enabled smart world by integrating edge artificial intelligence (AI) mechanism with mobile technologies while transmitting multimedia (i.e., text, images, video, etc.) content. An integration of the heterogeneous networks and wearable devices on one hand can facilitate each and every corner of the world, while on the other hand several challenges are faced by customers or users. With the advancement in mobile devices, industrial sector is revolutionized at large extent. At present, the AI-driven edge computing mechanism for industrial applications is very vital for the entire world to solve most the relevant issues at global level.

Main challenging problem that most of the industrial applications are facing is the resource-constrained (i.e., power hungry and short battery lifetime) nature of the IoT-enabled portable devices in the integrated platform. AI has become the center of attention to several applications [1]. In industrial platforms, IoT devices continuously monitor event triggered information which is further transmitted to a remote server, so apprehending monitoring of the industrial outcome [3]. However, for providing ease and comfort through IoT-enabled portable devices, there are problems of high energy drain, shorter battery lifetime, and complex computational process [4], [5]. There is a requirement for conventional batteries to be regularly recharged/replaced in IoT-based sensor devices. One of the examples is that in the fault diagnosis and recovery sensors, it is very cumbersome to frequently change their batteries. Therefore, energy drain optimization and battery lifetime extension in IoT-based sensor devices are the challenging task to be focused [1]. Fig. 1 shows the proposed AI-enabled framework for industrial applications. It comprises four sections with different functionalities, such as adaptive edge node, adaptive network node, adaptive application node, and service node. First, edge node which contains six key blocks (power controller, duty-cycle optimizer, reliability optimizer, sensors and actuators, microcontroller and ADC, and connectors) collects data, stores in cloud, process, analysis, and monitors with the help of edge intelligence which is based on cognitive knowledge of the entire industrial mechanism. Second, adaptive network node gets information from adaptive node and manages that data with router, repeater, satel-

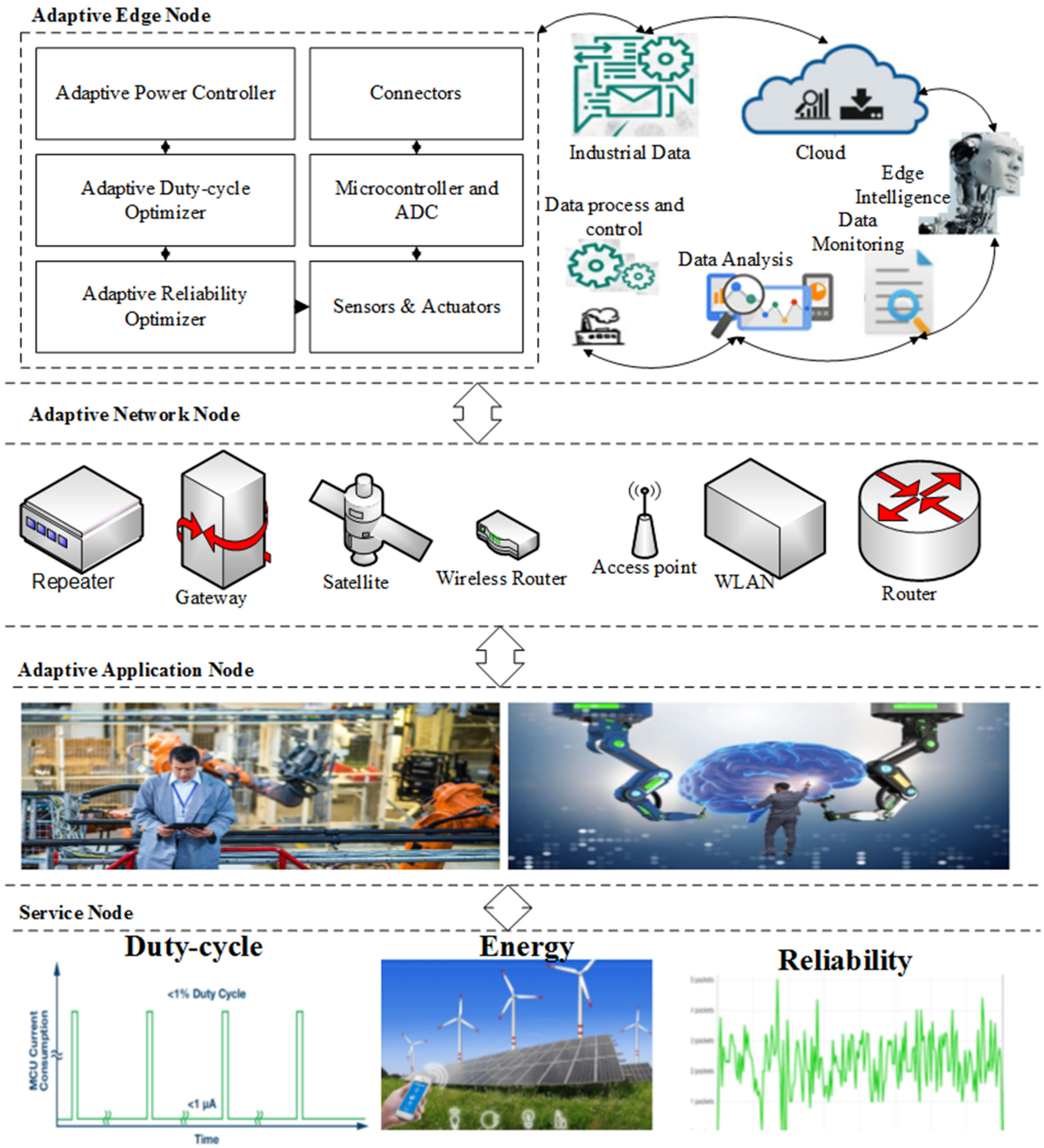

Fig. 1. Proposed architecture of AI-based edge computing platform for industrial applications.

lite system, access point, router and wireless local area networks. Third, adaptive application node gets information from upper layers by handling the fault diagnosis and monitoring of the entire platform to the last service node. Fourth, service node deals with the duty cycle and energy optimization in the overall industrial system. Currently, most of the researchers show their concerns over the energy depletion in edge AI-based IoT devices due to power hungry, tiny size, and poor performance of conventional approaches [1], [6], [7]. Nevertheless, few researchers comprehend optimization of duty cycle and energy drain in industrial sector via energy harvesting. In general, energy in the IoT-based industrial platforms is scavenged by different methods, such as wireless power transfer (WPT), wind turbines, vibration, etc. [1], [8]. But due to their unsteady, random results, an inappropriate load cannot be used for real-time industrial applications [9], [10]. WPT benefits to industrial application by scavenging energy from wind, RF sources [11]. Also, the simultaneous wireless information and power transfer is not the viable solution to fix the issues of fair resource allocation and energy drain optimization. It is discussed and examined by authors in [12] and [13] that WPT can be a suitable option for the current industrial applications due to emerging wireless technological trends and practices. Actually, the miniaturized and resource-confined nature of the IoT-based edge AI devices results in a significant proportion of energy dissipation during sensing and transmission phases, and it is apparently impossible to neglect energy depletion of these tasks. Traditional sensor networks cannot be re-energized due to static node distribution mechanism and battery's empty level; thus, huge amendment is needed to bring these up to current needs of the industrial world

TABLE I
RELATED WORK

Ref. No	Applications	Proposed Solution	Merits	Demerits
[1,3,4]	AI, Energy Energy optimization, delay	TPC based	Energy and Charge efficient	Complex and inefficient
[2,5,8]	IoT signal for industrial system	TPC, Channel and battery-aware	Duty-cycle, data rate	High energy and battery drain during media transmission
[6,7]	Edge and AI based industrial platforms	Cloud and battery enabled	Fairy and battery efficient	Less power-aware and battery-efficient
[9,10]	Energy-aware IoT for Industrial platform	Frameworks and protocols	Extensive survey for AI-based industrial application	Not focused on Industrial applications
[11,12]	AI based edge computing and WSN	Energy-aware and routing protocols	Energy optimization and efficient routing	Complex and less battery-efficient
[13]	WPT and Industrial WSN	Energy harvesting and duty-cycle enabled	Battery and energy-aware	Inappropriate for industrial platform
[14]	IIoT , AI, Adaptive methods	QoS optimization based	Efficient QoS management	Less Battery and energy - efficient for Industrial IoT
[15]	Machine Learning and Cellular networks	TPC and relay selection based	Novel Architecture and resource allocation method	High battery and energy drain in industrial system
[16]	WSN and communication systems	TPC and resource allocation	Energy optimization in wireless and sensor networks	Complex and less reliable for dynamic industrial platform
[17]	Industrial IoT, WSN	Energy and battery-based frameworks and method	Efficient resource allocation	Complex and less battery-aware for Industrial services
[18]	WPT and Radio networks	TPC and radio-aware	Intelligent resource monitoring in radio networks	Unsuitable for IIoT system
[19]	Future Networks, WSN	QoS and Energy Scavenging	Novel energy and QoS efficient	Complex and less reliable for Industrial system
[20]	WPT for IIoT	TPC and QoS-aware framework	Detailed survey	Not focus at joint duty-cycle and TPC
[21]	IoT for Edge computing	Energy and battery-oriented	Novel Physical layer and framework for industrial applications	Complex, less reliable without duty cycle
[22]	Industrial platforms	Fuzzy based secure	Secure home monitoring	High energy drain
[23]	Energy-aware and secure WSN	TPC and battery-based	Efficient media transmission	More battery drain
[24]	IoT based edge platform	Framework and battery-aware	Efficient lifecycle management	Less energy saving
[25]	QoS-aware IIoT and CPS	Optimal resource allocation	QoS monitoring and management	More energy and battery drain
[26]	Ubiquitous and Smart IIoT	TPC based and framework	Novel process monitoring algorithm and framework	More battery drain
[27]	AI, QoS, IoT,	Routing protocols and framework	Routing and battery-based	More energy dissipation
[28]	Power allocation in Industrial systems	AI-aware	Novel Framework and methods	High energy drain

[15]. Thus, to meet the required needs of each application, a hybrid adaptive transmission power control (TPC) and duty cycle has become potential candidate for AI-based edge computing in industrial applications. Our proposed forward central dynamic and available approach (FCDAA) optimizes the power, extends the battery lifetime with high reliability in AI-based edge computing industrial application for the first time as per author's knowledge. The proposed FCDAA tunes transmission power level and duty cycle of IoT devices in industrial applications by adopting static (product processing) and dynamic (vibration and fault diagnosis) platform at acceptable reliability or packet loss ratio (PLR).

The contribution of this paper is threefold.

1) First, an FCDAA is proposed for managing the execution time of sensing and transmission tasks in AI-based IoT devices for industrial applications.
2) Second, system-level battery model of edge AI-enabled IoT devices for industrial applications is proposed by examining the duty cycle and energy optimization.
3) Third, data reliability model of IoT-based handheld devices over hybrid TPC and duty-cycle network is proposed to effectively monitor the industrial IoT (IIoT).

The rest of this paper is arranged as follows. Section II rigorously reviews the existing works. FCDAA and battery model are developed in Section III. Data reliability model is proposed for hybrid TPC and duty-cycle industrial networks in Section IV. Experimental testbed is developed in Section V. Section VI concludes this paper.

II. EXISTING WORKS

This section provides the rigorous literature about duty-cycle-based techniques, and power-aware algorithms, architectures, reliability models for AI-based industrial applications.

Because of the high inspiration from every domain, sensor networks have caught the attention in the industrial corner to examine and observe the processing, monitoring, and outcome. But these heterogeneous networks are facing the critical challenges due to the power hungry and limited battery lifetime, hence are not offering accurate and timely services at economical level. Energy harvesting has been employed to increase the lifetime of nodes as a substitute to supplement batteries. Hybrid TPC and duty-cycle-based approach plays the critical role for the energy-aware industrial system with distinct methods, for

$Inputs: TP, \chi_{tx}(TP), \chi_{DAA}, C_{leak}$
$Output: BatteryLifetime(T_{tx}), Energydrain(E), \mathrm{Re}liability$
for
$If\ \kappa \geq \kappa_{th}$

$$T_{tx} = \left\lceil \frac{\chi_{sense}(TP) + \chi_{tx}(TP) + \chi_{DAA}}{\kappa - (\gamma_{sense} + \gamma_{tx} + C_{leak})} \right\rceil$$

else

$$BatteryLifetime = \frac{DC}{T_{ON} - (T_{off} + \sigma) \times \kappa_{th}}$$

If
$T_{FC} = T_{tx}$

$$E = \sum_{i=1}^{S} \left(E_{sen_i}(b) + E_{tx_i}(b, d_{ij}) \right)$$

$$DC_S = \frac{T_{ON}}{T_{ON} + T_{OFF}}$$

elseif

$$BatteryLifetime(DC_S) = \sum_{i=1}^{S} [\gamma - (E + C_{leak})] \times T_{ON}$$

else

$$\mathrm{Re}liability = \frac{\sum_{i=1}^{n} (RSSI_{th} - TP) + \sum_{i=1}^{n} (RSSI_{th} + TP)}{n \times \sigma} \times DC$$

end
end
end

Fig. 2. Proposed FCDAA.

example, modulation-level control, duty-cycle optimization, network scheduling at physical, medium access control (MAC) and network layers accordingly. Energy neutral operation (ENO) is widely accepted mechanism during harvesting the energy and manages the power by typically adjusting the duty cycle or wake-up duration of the sensor nodes as shown in Table I.

In this paper, for the first time, an FCDAA and data reliability models are proposed for AI-based industrial application over hybrid TPC and duty-cycle network to save energy. TPC levels and duty cycle, i.e., wake-up and sleep periods of IoT-based devices are adapted while taking into account the deviations of the wireless channel, i.e., static (product processing) and dynamic (vibration and fault diagnosis) cases.

III. Proposed FCDAA

This section describes in detail the two key parts first proposed FCDAA and second system-level battery model by integrating both TPC and duty cycle for AI-driven industrial applications. One of the vital energy and battery lifecycle management methods in IoT-based industrial applications is presented in [14]. The key purpose of the proposed FCDAA is to extend the battery lifetime and save the power in AI-based edge computing platforms for industrial application. Besides, the TPC and duty-cycle entities of the IoT-based portable devices are optimized by properly following ENO during sensing, processing, and transmission of industrial data. Assume that $\chi_{tx}(TP)$ and χ_{FC} are the battery charge depletion at adopted power levels and CPU's extra energy drain by forward central consequently as depicted in Fig. 2. Besides, the duty-cycle management mechanism is presented in Fig. 3. In duty-cycle analysis, harvesting energy

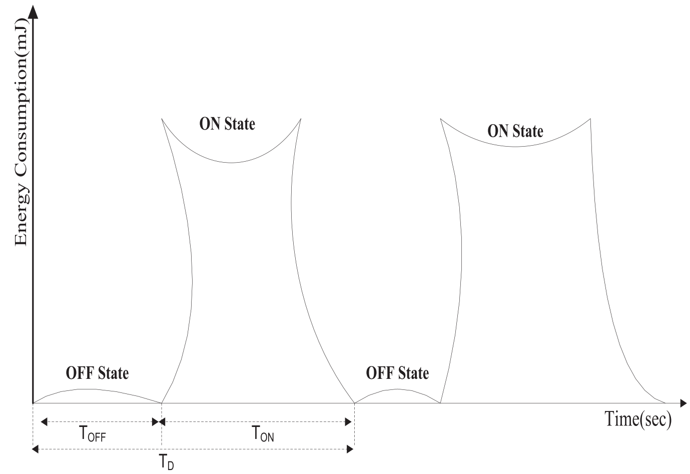

Fig. 3. Duty-cycle management in IoT devices for industrial applications.

from access point to nodes is playing remarkable role in examining the overall network performance. When harvesting energy rate is greater than the threshold amount $(\kappa \geq \kappa_{\mathrm{th}})$, next active period can be predicted by using (4) and Fig. 2.

Otherwise, negative energy state will be obtained by the proposed FCDAA when sufficient energy is not harvested. Besides, FCDAA's key functionality is to optimize the sleeping time, transmission power level at zero-energy interval time duration. Also, a deviation factor (σ) is introduced for achieving the targeted threshold by rectifying the problem during battery lifetime maximization. A transmission time is then calculated and be suitable for full cycle as in Fig. 3. The running time of the forward central control (T_{FC}) is adopted according to the next transmission task and n accordingly. The trade-off between forward central control, CPU's overhead bits and sensitivity will be established by tuning associated parameters [14]. Finally, node will be in sleep mode before the FCDAA's new assignment with active duration (T_{ON}) appears. Energy drain can be rectified with the use of duty-cycle and dynamic transmission power. With efficient and accurate energy scavenging mechanism, less transmission power is used with acceptable PLR. It is analyzed that T_{ON} is nonlinearly related to battery lifetime. The proposed system-level battery model comprises two periodic functions, such as sensing and transmission in industrial applications. In each task, IoT device's active time is represented by T_{ON}. Various tasks lie in the active duration, such as processing, sensing, and transmission, while more energy is saved and hence less battery charge consumed during inactive, i.e., sleep mode. Battery charge dissipation (χ) and T_{ON} of the nodes provide current (χ_i) value as presented in

$$\gamma_i = \frac{\chi_i}{T_{\mathrm{ON}}}. \tag{1}$$

Average current value is obtained either by monitoring task load (χ_i) or execution time (T_{ON}). Hence, duty cycle of IoT-

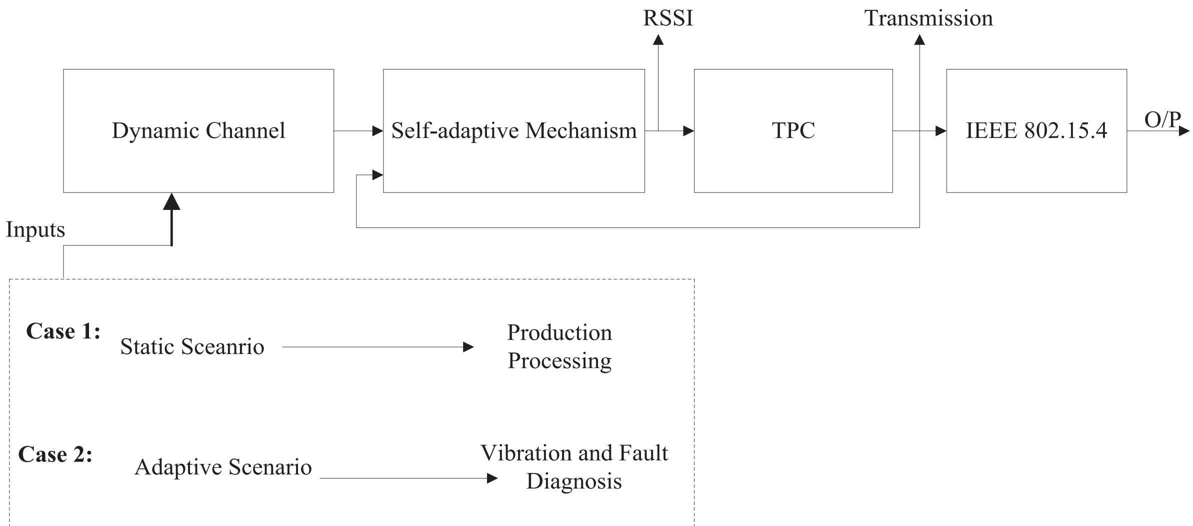

Fig. 4. Framework of reliable data transmission in AI-based edge computing platform over hybrid TPC and duty-cycle network.

based sensor devices S is given in (2) and Fig. 3

$$\mathrm{DC}_S = \frac{T_{\mathrm{ON}}}{T_{\mathrm{ON}} + T_{\mathrm{OFF}}} \tag{2}$$

where T_{ON} and T_{OFF} are the active and sleep time of nodes, respectively. The energy deletion of sensing and transmission tasks of IoT devices in industrial applications is analyzed by operation of transmitter and base station. Industrial data are measured, recorded, and communicated to the intended destination with the help of the sensor-enabled devices, but the key problem is their power hungry and resource-constrained nature. To resolve these issues, the duty cycle of the transceiver must be properly managed and monitored. For instance, the time period of sensor "i" where $i = 1, 2, \ldots, S$ is computed merely during the sensing and transmission tasks. Energy dissipation of former and later tasks while transmitting b bits at distance d_{ij} for sensor j is $E_{\mathrm{sen}_i}(b)$ and $E_{tx_i}(b, d_{ij})$ consequently. So, battery charge level or state of charge (SoC) of these miniaturized sensor nodes is measured according to the energy (sensing and transmission) depletion level as in (4). Besides, SoC heavily depends upon the current consumption during sensing (χ_{sense}) and transmission (χ_{tx}), respectively, and the energy scavenging (β) entities. Battery SoC for the next active slot (T_{ON}) can be predicted according to (4)

$$E = \sum_{i=1}^{S} \left(E_{\mathrm{sen}_i}(b) + E_{tx_i}(b, d_{ij})\right) \tag{3}$$

$$\text{Battery Lifetime}\,(\mathrm{DC}_S) = \sum_{i=1}^{S} [\gamma - (E + C_{\mathrm{leak}})] \times T_{\mathrm{ON}}. \tag{4}$$

IV. Data Reliability Model for Hybrid TPC and Duty-Cycle Networks

A novel data reliability model for the AI-based industrial applications over hybrid TPC and duty-cycle network is proposed.

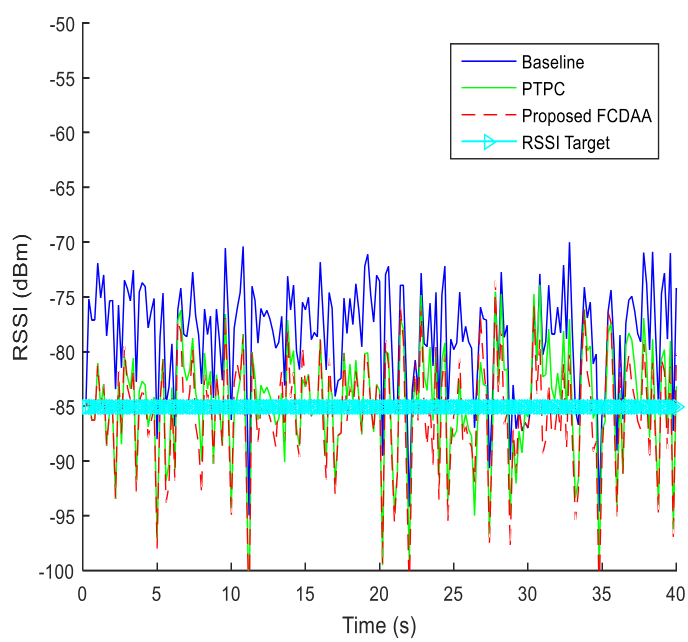

Fig. 5. Reliability optimization in hybrid TPC and duty-cycle network.

In these networks, received signal strength indicator (RSSI) and PLR are the key performance indicators for examining the entire system

$$\text{Reliability} = \begin{cases} \mathrm{RSSI}_{\mathrm{th}} - 1, \mathrm{TPC} = \pm 1 \\ \mathrm{RSSI}_{i-1} \leq \mathrm{RSSI}_{\mathrm{th}}, \mathrm{TPC} = 1 \\ \mathrm{RSSI}_{i-1} \geq \mathrm{RSSI}_{\mathrm{th}}, \mathrm{TPC} = -1 \end{cases} \tag{5}$$

$$\text{Reliability} = \frac{\sum_{i=1}^{n} (\mathrm{RSSI}_{\mathrm{th}} - TP) + \sum_{i=1}^{n} (\mathrm{RSSI}_{\mathrm{th}} + TP)}{n \times \sigma} \times \mathrm{DC}. \tag{6}$$

Fig. 4 reveals the framework of the reliability optimization in the AI-based edge commuting platform for industrial

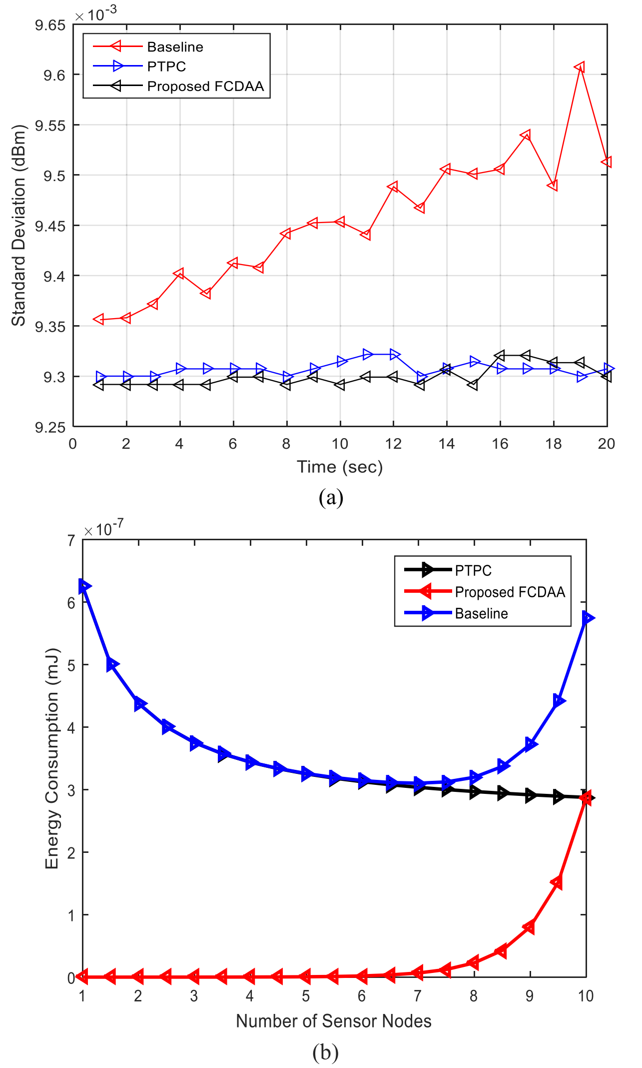

Fig. 6. (a) Relationship between time and standard deviation. (b) Number of sensor nodes and energy consumption level.

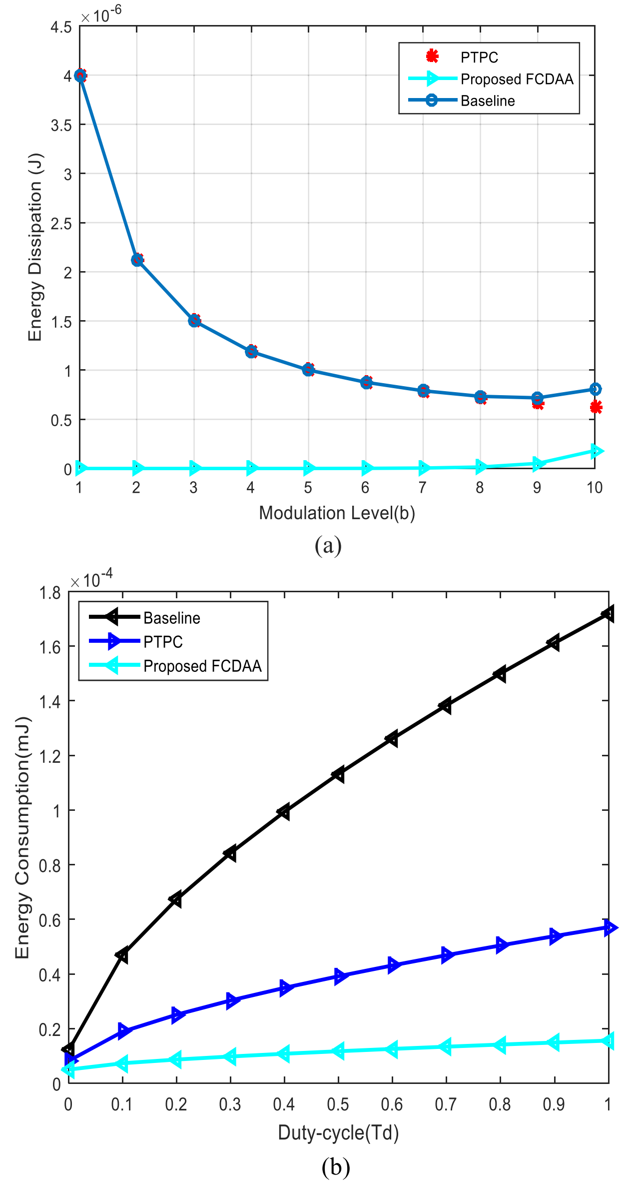

Fig. 7. (a) Tradeoff between modulation and energy drain. (b) Duty cycle versus energy depletion.

application by adopting Case 1 (static: product processing) and Case 2 (dynamic: vibration and fault diagnosis) self-adaptive mechanisms. In addition, TPC and RSSI level are taken at the physical layer while duty cycle is considered at the MAC layer. TPC is adapted according to the variation in the wireless channel which impacts a lot on the RSSI level, PLR, and hence the reliability. Cases 1 and 2 are given as the inputs to the wireless channel, which feeds to the adaptive TPC techniques from where signal's level is examined and then transmission is started to monitor and manage the power by adopting the IEEE 802.15.4. Besides, Cases 1 and 2 in Fig. 4 are very vital for accurately analyzing the behavior of the IoT-based portable devices in industrial platform.

Fig. 5 reveals the relationship between time (in second) and the RSSI (in dB·m) value or reliability of the proposed FCDAA and conventional methods, i.e., baseline and predictive transmission power control (PTPC) over hybrid TPC and duty cycle network. It is examined that there is less variation in the RSSI level of the proposed FCDAA unlike the traditional methods at the predefined RSSI target value. Stable RSSI level shows high reliability and reasonable energy drain. Fig. 6(a) reveals the tradeoff between the time and the standard deviation of the proposed FCDAA, and conventional, i.e., PTPC and baseline methods. It is observed that there is more deviation in the later than the former due to unstable nature of the wireless channel which affects a lot to the overall performance of the industrial environment. Fig. 6(b) reveals the relationship between sensor nodes and the energy drain for the proposed FCDAA and the conventional, i.e., PTPC and baseline. It is examined that as the number of sensor nodes is increasing the energy dissipation increases too, which is higher for the traditional methods and less for the proposed FCDAA. Relationship among modulation level, duty cycle, and energy drain is drawn in Fig. 7(a) and (b) accordingly for the proposed FCDAA, PTPC, and baseline by adopting AI-based edge computing mechanism in industrial

TABLE II
EXPERIMENTAL PARAMETERS

Parameter	Value
RSSIth	-85 dBm
Standard deviation (σ)	5dBm
Harvesting rate (β)	1000 Hz
Dutycycle	1%
Carrier frequency	5 GHz
Bandwidth	5 MHz
TP levels	{-5,-4, -3, 2, 1,0,1,2,3,4,5}
Maximum Transmission Power	0 dBm
Minimum Transmit power	-20 dBm
Operation time (T)	5 mints
Delay	300 sec
Data packet length	200 bytes
Data packet interval	100 sec
Data Rate	250 Kbps
Noise figure	7 dB
Noise PSD	-174 dBm/Hz
Wireless Channel	IEEE 802.15.4 (PHY and MAC)
Processing delay	2 mints

TABLE III
RELATIONSHIP BETWEEN PERFORMANCE METRICS

X/Y Axis	Standard Deviation(dBm)			Energy Consumption(mJ)		
	FCDAA	PTPC	Baseline	FCDAA	PTPC	Baseline
Sensor Nodes	Low	moderate	High	Low	High	High
Modulation Level	Low	High	High	Low	moderate	High
Duty-cycle	Low	High	High	Low	High	High
Time	Low	High	High	Low	High	High

applications. Modulation level or data rate varies with respect to the requirement of sensors and static and dynamic industrial scenarios, and then there will be change in the energy dissipation level. Increase of data rate makes the power drain and battery lifetime in IoT-based portable devices for industrial applications as a critical challenge. In industrial applications, large data rate consumes significant amount of power in both processing and transmission phases as shown in Table III while Fig. 7(b) shows the interconnection between the duty cycle and the energy drain for the proposed FCDAA and the traditional methods, i.e., baseline and PTPC. Besides, it is analyzed that network congestion is linearly related to the delay and hence the energy drain in the traditional techniques unlike the proposed FCDAA.

V. EXPERIMENTAL RESULTS AND DISCUSSION

An extensive experimental testbed for AI-based industrial applications is established with the support of IoT devices. Adopted industrial datasets show the impact power and battery lifetime of the IoT-driven portable devices product monitoring and process with high reliability. There are several experimental parameters as shown in Table II.

Several key issues are examined during the industrial process and monitoring by gathering large datasets [25] and developing novel mechanisms to manage the power and extend the battery lifetime of portable industrial devices. Moreover, overall testbed consists of transmitter sensor node and base station with static and dynamic mechanisms, operation time T of 5 min, and delay t_0 of 200 ms. It must be noted that RSSI deviation is linearly proportional to the channel characteristics, i.e., Case 1: static (product processing) and Case 2: dynamic (vibration and fault diagnosis) cases. Faster the vibration and fault diagnosis process, higher the channel deviation and less stable the RSSI values, hence less reliability and vice versa. Hence, it can be said that the proposed FCDAA shows high reliability unlike orthodox methods, i.e., baseline and PTPC. In addition, the connection between data packet size w and energy depletion rate is established for different sensor platforms with clear representation. Besides, high deviation and unstable nature of the channel dissipates more energy in baseline and PTPC than the proposed FCDAA. We observed that with the increase of the duty cycle more energy is depleted for the conventional methods unlike the proposed FCDAA. In addition, the high sleep time of the sensor nodes strengthen the energy saving but the large wakeup time leads to more energy consumption for the traditional methods than the proposed FCDAA in the industrial environment. Moreover, duty cycle or wireless channel utilization is merely concerned with the data traffic generation, i.e., discrete or continuous mechanism in the industrial applications. With the increase of the duty cycle, PLR will increase to large extent in the conventional methods unlike in the proposed FCDAA. We analyzed that distance and energy drain are linearly proportional, i.e., more energy is consumed by baseline and PTPC and less with the proposed FCDAA. But there is less energy drain in the proposed FCDAA, more in baseline, and slightly more in the PTPC. Let us assume that the threshold distance d_{th} is 1 km, where energy consumption can be reduced by using some resource scheduling algorithms with the condition $d \leq d_{\mathrm{th}}$, whereby distance between IoT devices in industrial application is denoted by d (which is 100 m).

VI. Conclusion and Future Research

Power and battery-aware communication through portable IoT devices is very vital for industrial application due to rapid progress in the technological trends and practices. Also, industrial sector has revolutionized the entire landscape to boost the societal and economical needs. The challenging issue with today's industrial evolution is the resource-constrained nature of IoT-based portable devices. To resolve these challenges, this research contributes in three distinct ways. First proposes FCDAA by tuning duty cycle and transmission power levels of the IoT-based portable devices during sensing, processing, and transmission tasks by considering large number of real-time datasets. Second, the system-level battery model of IoT-based portable devices is proposed. Third, the data reliability model is proposed for IoT devices in AI-driven edge computing platform for industrial platform. Through theoretical analysis with extensive real-time datasets and Monte Carlo simulation in MATLAB, we concluded that significant amount of transmission power is dissipated at relatively less PLR and stable RSSI by baseline (with very low energy saving), acceptable by the proposed FCDAA (with high energy saving) and medium by PTPC (low energy saving). It has also been examined and interpreted that FCDAA fulfills the main requirement of RSSI and PLR by adopting AI-driven edge computing platform for industrial applications. Hereafter, it can be claimed that the proposed FCDAA is the potential candidates for energy saving in AI-driven edge computing mechanism for industrial applications. Following are the limitations of the proposed FCDAA.

1) Relatively more complexity in integrating TPC and duty cycle for AI-driven IoT devices.
2) Hybrid duty cycle and TPC mechanism saves more energy with larger delays at base station or receiver side in AI-driven IoT devices.

In near future, machine learning-based self-adaptive joint WPT, modulation and coding techniques for big data management in industries will be focused. Besides, AI-driven use case for the smart industrial city will be proposed.

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Ali Hassan Sodhro (M'11) received the Ph.D. degree in computer application technologies from the University of Chinese Academy of Sciences, Beijing, China, in 2016.

He is currently a Postdoctoral Research Fellow with IDA-Computer and Information Science Department, Linkoping University, Linkoping, Sweden, and an Assistant Professor with the Department of Electrical Engineering, Sukkur IBA University, Sukkur, Pakistan. Before that, he was an Erasmus Mundu's Postdoctoral Fellow under SMARTLINK Project with University Lumiere Lyon 2, France (August 2017 to August 2018). He is the author of 45 research journal and international conference proceeding papers, and 7 book chapters. He has ten years of research and teaching experience. His main research interests include green and battery-aware biomedical systems, medical IoT, and machine learning for healthcare applications.

Dr. Sodhro is recipient of several research awards, i.e., Third Best Paper Award with Cash Prize and Certificate at Guangzhou Annual Report Competition at Guangzhou, China, 2015, Best Graduate Award 2016, etc.

Sandeep Pirbhulal received the Ph.D. degree in pattern recognition and intelligent systems from the University of Chinese Academy of Sciences (CAS), Beijing, China, in 2017.

He is currently a Postdoctoral Fellow with the CAS Key Laboratory of Human-Machine Intelligence-Synergy Systems, Shenzhen Institutes of Advanced Technology, CAS. He has a vast experience of seven years in academia and research. He has authored or coauthored more than 40 international journal articles including IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, IEEE SENSOR JOURNAL, IEEE ACCESS, and IEEE JOURNAL OF BIOMEDICAL AND HEALTH INFORMATICS among others, more than 7 international conference proceeding papers, and 6 book chapters with 370 citations on Google scholar, and H-index of 13. His current research interests include wireless body sensor networks, privacy and security for wireless sensor networks, and Internet of medical things.

Dr. Pirbhulal is the Guest Editor of peer-reviewed international journals, i.e, Multidisciplinary Digital Publishing Institute (MDPI) Sensors, etc. Moreover, he served as a Reviewer for more than ten international journals such as IEEE SENSOR JOURNAL and IEEE ACCESS.

Victor Hugo C. de Albuquerque (M'17–SM'19) received the Graduation degree in mechatronics technology from the Federal Center of Technological Education of Ceará, Fortaleza, Brazil, in 2006, the M.Sc. degree in teleinformatics engineering from the Federal University of Ceará, Fortaleza, in 2007, and the Ph.D. degree in mechanical engineering with emphasis on materials from the Federal University of Paraíba, João Pessoa, Brazil, in 2010.

He is currently an Assistant VI Professor of the Graduate Program in Applied Informatics, and the Coordinator of the Laboratory of Bioinformatics, University of Fortaleza, Fortaleza. He has experience in computer systems, mainly in the research fields of applied computing, intelligent systems, visualization and interaction, etc. He has authored or coauthored more than 160 papers in refereed international journals, conferences, four book chapters, and four patents.