Artificial Driven Mechanism for Edge Computing with Deep Neural Network based Industrial Application

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Abstract : Nowadays, accurate and intelligent resource management by Artificial Intelligence (AI) has become the center of attention particularly in industrial applications. With the organization of AI at the edge will outstandingly enhance the computational speed and range of Internet of Things (IoT) based devices in industries. However, there is main challenge is the short battery lifetime and power hungry. A Forward Central Dynamic and Available Approach (FCDAA) was proposed for power saving and battery lifetime saving of IoT based devices in industries by adopting the running time of sensing and transmission processes in IoT-based portable devices. Moreover, a system level battery model and data reliability model were proposed for edge based IoT devices. In this paper, the FCDAA is improved by proposing Machine Learning-based Self-adaptive Joint wireless Power Transfer, Modulation and Coding technique (MLSJPTMC). In a deep learning technique called Deep Neural Network (DNN) is introduced to learn the duty-cycle and energy consumption of IoT-based portable devices. DNN consists of single input layer, multiple hidden layers, and single output layer. Finally DNN returns duty-cycle and energy consumption of IoT-based portable devices with mining error. The learned duty-cycle and energy consumption of IoT-based portable devices are used in FCDAA which enhance the performance of power and battery lifetime-aware communication in AI-based IoT devices in industrial application. The experimental results prove that the proposed MLSJPTMC technique has better performance in terms of energy consumption and energy dissipation.

***IndexTerms* – Artificial Intelligence, Edge Computing, Forward Central Dynamic and Available Approach, Internet of Things, Machine Learning-based Self-adaptive Joint wireless Power Transfer, Modulation and Coding technique.**

I. Introduction

Due to the advance in networking technologies, a large number of smart devices can now connect to the Internet in the form of Internet of Things (IoT) (Singh & Singh, 2015). Based on the Cisco report, these devices will generate 507.9 ZB of data by 2019. Data generated by IoT-devices are more essential for industrial applications which are interested in improving their productivity and revenues. However, analysis and management of such large amounts of data are burdensome and challenging for industries that rely on conventional computing paradigms. Edge computing (Khan et al, 2019) is gaining popularity in this context because IoT is becoming common in processing data on the edge of the networks.

Industrial applications attracted towards the IoT-enabled smart world which integrates edge Artificial Intelligence (AI) mechanism (Dwivedi et al, 2019) with mobile technologies while transmitting multimedia content. A combination of the wearable devices and heterogeneous networks on the one hand can make possible each and every concern of the world, while on the other-hand various challenges are faced by users or customers. Nowadays the AI driven edge computing mechanism for industrial applications is very important for the entire world to solve most the relevant issues at global level. The most challenging issue in industrial revolution is the resource constrained (i.e., power and battery lifetime) nature of IoT-based portable devices. Predictive Transmission Power Control (PTPC) was a dynamic wireless channel which not be supported by the typical power saving and battery lifetime techniques.

A Forward Central Dynamic and Available Approach (FCDAA) (Sodhro et al, 2019) was proposed for power and battery-aware communication through portable IoT devices. A system-level battery model of IoT based portable devices was proposed by combining both Transmission Power Control (TPC) and duty-cycle for AI based industrial applications. In these networks, Received Signal Strength Indicator (RSSI) and Packet Loss Ratio (PLR) were the key performance indicator to examine the whole system. Moreover, a data reliability model was proposed for IoT devices in AI driven edge computing platform for industrial platform. FCDAA fulfilled the main requirement of RSSI and PLR by adopting AI drive edge computing platform for industrial applications.

In FCDAA, the energy consumption is assigned based on the energy dissipation of former and later tasks while transmitting particular bits at a particular distance for sensor. Moreover, duty-cycle is assigned based on the active time of nodes, charge dissipation and energy. The computational complexity is high while setting the energy and duty-cycle for different AI-based IoT devices. So in this paper, MLSJPTMC is proposed to learn duty-cycle and energy consumption using DNN. The duty-cycle and energy consumption are processed in input, hidden and output layer for learning process. The learned duty-cycle and energy consumption is given as input to FCDAA to enhance the performance of power and battery lifetime-aware communication in AI-based IoT devices in industrial application.

II. Literature Survey

A Multiple Algorithm Service Model (MASM) (Zhang et al, 2019) was proposed for energy-delay optimization in edge AI. In MASM, the computing Virtual Machines (VMs) were equipped with heterogeneous algorithm with different computation complexities and uploaded various data sizes. An optimization model was proposed based on MASM which jointly assigning the proper workload assignment weights and the computing capacities of the VMs to reduce delay and energy costs. A Tide Ebb Algorithm (TEA) was developed to determine robust solutions to the energy delay optimization problem. However, this model is more complex.

An Energy-Efficient Algorithm (EEA) with power control principle (Sodhro et al, 2018a) was proposed for media transmission in remote healthcare systems. EEA adjusted transmission power with respect to dynamic and time-varying channel characteristics. However, this model has high energy drain problem during media transmission.

Flexible deep learning model in edge computing (Sureddy et al, 2018) was proposed for IoT. This model combined deep learning into edge computing and it used flexible edge computing architecture with multiple agents. A novel offloading strategy was designed to optimize the performance of IoT deep learning applications with edge computing. However, this model face high computational complexity problem.

A joint transmission power control and duty-cycle approach (Sodhro et al, 2018b) was proposed for smart healthcare system. An Adaptive Energy-Efficient TPC (AETPC) and duty-cycle adaption based framework was developed by changing the temporal variation in the on-body wireless channel amid static and dynamic body postures. A feedback control-based duty-cycle algorithm was proposed to adjust the execution period of tasks. However, this approach is less battery efficient.

Dynamic algorithm (Dong et al, 2015) was proposed for joint power control and time switching in Simultaneous Wireless Information and Power Transfer (SWIPT). The dynamic algorithm used the stochastic optimization theory which trade average power consumption by jointly allocating the transmission power and time switching factor. A control parameter was described in the dynamic algorithm to facilitate the tradeoff. However, the dynamic algorithm is complex and less reliable without duty-cycle.

Second-order continuous-time algorithm (Wang et al, 2018) was proposed for optimal resource allocation in power systems. This algorithm converged exponentially to the optimal solution of the resource allocation problem starting from any initial states over an undirected and connected graph. In addition to this, obtained results were further extended to the optimal resource allocation problem in case of switching communication topologies. However, the second-order continuous-time algorithm has high energy drain problem.

III. Proposed Methodology

In this section, the MLSJPTMC is described in detail for power and battery lifetime-aware communication in AI-based IoT devices in industrial application. In MLSJPTMC, the duty-cycle and energy consumption are learn using DNN. The duty-cycle and energy consumption are given to train the DNN classifier. DNN has three layers namely input, hidden and output layer. The probabilities are denoted as $f(x) = x$ are given to the input layer of neurons. The hidden layer of DNN is defined as tan-sigmoid transfer function.

$$f(x) = \frac{2}{1+e^{-2x}} - 1 \tag{1}$$

Each input has its own weight values as $w_1, w_2, \dots, w_n$ and the weighted sum of the inputs is done by the adder function as follows,

$$u = \sum_{i=1}^{n} w_i x_i \tag{2}$$

The output layer of DNN is described by the following equation.

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b_i\right) \tag{3}$$

In Eq. (3), y is the output neuron value; $f(x)$ is the transfer function, w_i refers the weight values, x_i denotes input data values and b_i refers to the bias value. Based on the output neuron values, the duty-cycle and energy consumption is assigned in FCDAA.

DNN consists of multiple hidden layers between input and output layers. Here also, the input layer assigns weights to the input parameters and transfers those to the next layer. Each subsequent layer also assigns weights to their input and generates their output. At the output layer, the final output value is obtained and error function is calculated to determine how correctly learned those duty-cycle and energy consumption parameters. This training cycle is repeated until a termination criterion is satisfied. The learned duty-cycle and energy consumption value is used in FCDAA.

Deep Learning Algorithm

Input: Training dataset D and Learning Rate l

Output: Trained neural network

Initialize all weights and biases in network;

$while(termination\ condition\ is\ not\ satisfied)$

{

$for(each\ training\ parameter\ X\ in\ D)$ //X is the duty-cycle and energy consumption

{

$for(each\ input\ layer\ node\ j)$

{

$O_j = I_j$ //Output of an input layer

$for(each\ hidden\ or\ output\ layer\ node\ j)$

$H_j = \frac{2}{1+e^{-2j}} - 1;$

$O_j = f\left(\sum_{i=1}^{n} w_{ij} x_i + b_j\right)$

$for(each\ node\ j\ in\ output\ layer)$

$E_j = O_j(1 - O_j)(H_j - O_j)$

//Error of an output layer

$for(each\ weight\ w_j\ in\ network)$

$w_j = w_j + \Delta w_j$ //weight update

$for(each\ bias\ b_j\ in\ network)$

```
            b_j = b_j + Δb_j //bias update
        }
    }
}
```

After learning the duty-cycle and energy consumption, FCDAA and data reliability models are processed for AI-based industrial application over hybrid TPC and duty-cycle network to save energy. Consider that, $\chi_{tx}(TP)$ is the battery charge depletion at adopted power levels and χ_{FC} is the CPU's extra energy drain by forward central. In duty-cycle analysis harvesting energy 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 $(k \geq k_{th})$ than next active period can be predicted by,

$$BatteryLifetime\ DC_S = \sum_{i=1}^{S}[\Upsilon(E + C_{leak})] \times T_{ON} \tag{4}$$

$$E = \sum_{i=1}^{S}\left(E_{sen_i}(b) + E_{tx_i}(b, d_{ij})\right) \tag{5}$$

Or else, negative energy state will be obtained by FCDAA when sufficient energy is not harvested. As well, FCDAA optimize the sleeping time, transmission power level at zero-energy interval time duration. In order to achieve the targeted threshold, a deviation factor σ is used where the problem is rectified during battery lifetime maximization. A transmission time is then calculated and be suitable for full-cycle. The running time of the forward central control T_{FC} is adopted according to the next transmission task and n accordingly. The tradeoff between forward central control, CPU's overhead bits and sensitivity will be established by tuning associated parameters. In the last 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 non-linearly 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 lies 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 provides current χ_i value as presented

$$\Upsilon_i = \frac{\chi_i}{T_{ON}} \tag{6}$$

Average current value is obtained either by monitoring task load χ_i or execution time T_{ON}. Hence duty-cycle of IoT based sensor devices S is calculated as,

$$DC_S = \frac{T_{ON}}{T_{ON}+T_{OFF}} \tag{7}$$

In Eq. (7), T_{ON} is the active time of nodes and T_{OFF} is the sleep time of nodes. The energy deletion of sensing and transmission tasks of IoT devices in industrial applications is analysed by operation of transmitter and base station. Industrial data is 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 remedy these issues the duty-cycle of the transceiver must be properly managed and monitored. For example, the time-period of sensor i where $i = 1,2 \dots S$ is calculated just during the sensing and transmission tasks. Energy dissipation former and later tasks while transmitting b bits at distance d_{ij} for sensor j is $E_{sen_i}(b)$ and $E_{tx_i}(b, d_{ij})$ respectively. So batter charge level or state of charge (SoC) of these miniaturized sensor nodes is measured according to the energy (sensing and transmission) depletion level. Besides, SoC heavily depends upon the current consumption during sensing χ_{sense} and transmission χ_{tx} respectively and the energy saving entities. Battery SoC for the next active slot T_{ON} can be predicted according to equation 4.

A novel data reliability model for the AI-based industrial applications over hybird TPC and duty-cycle network is proposed. In these networks, received signal strength indicator (RSSI) and packet loss ratio (PLR) are the key performance indicators for examining the entire system.

$$Reliability = \begin{cases} RSSI_{th} - 1, & TPC = \pm 1 \\ RSSI_{i-1} \leq RSSI_{th}, & TPC = 1 \\ RSSI_{i-1} \geq RSSI_{th}, & TPC = -1 \end{cases} \tag{8}$$

$$Reliability = \frac{\sum_{i=1}^{n}(RSSI_i - TP) + \sum_{i=1}^{n}(RSSI_i + TP)}{n \times \sigma} \times DC \tag{9}$$

The framework of the reliability optimization in AI based edge computing platform for industrial application is introduced which adopts 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. The case 1 and case 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.

IV. Result and Discussion

In this section, the performance of PTPC, FCDAA and MLSJPTMC are tested in terms of energy consumption and energy dissipation. The simulation is conducted in MATLAB 2017b based on the experimental parameters which are listed in Table1. An extensive experimental test-bed for AI based industrial application is established with the support of IoT devices. The adopted industrial datasets show the impact power and battery lifetime of the IoT-driven portable devices product monitoring and process with high reliability.

Table 1 Experimental Parameters

Parameter	Value
RSSIth	-85 dBm
Standard deviation (σ)	5 dBm
Harvesting Rate (β)	1000 Hz
Carrier frequency	5GHz
Bandwidth	5MHz
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 mins
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 min

4.1 Energy Consumption

Energy consumption is the amount of energy consumed by the IoT devices in industries. Table 2 show the energy consumption of PTPC, FCDAA and MLSJPTMC under different duty-cycle.

Table 2 Energy Consumption vs. Duty-cycle

Energy Consumption ($\times$ **10^{-3}**)			
Duty-cycle	**PTPC**	**FCDAA**	**MLSJPTMC**
0	0	0	0
50	0.0013	0.0008	0.0006
100	0.0014	0.0011	0.0008
150	0.0018	0.0013	0.0011
200	0.0021	0.0015	0.0013
250	0.0023	0.0018	0.0016
300	0.0024	0.0020	0.0018
350	0.0026	0.0022	0.0021
400	0.0029	0.0025	0.0024
450	0.0032	0.0028	0.0026
500	0.0034	0.0031	0.0028

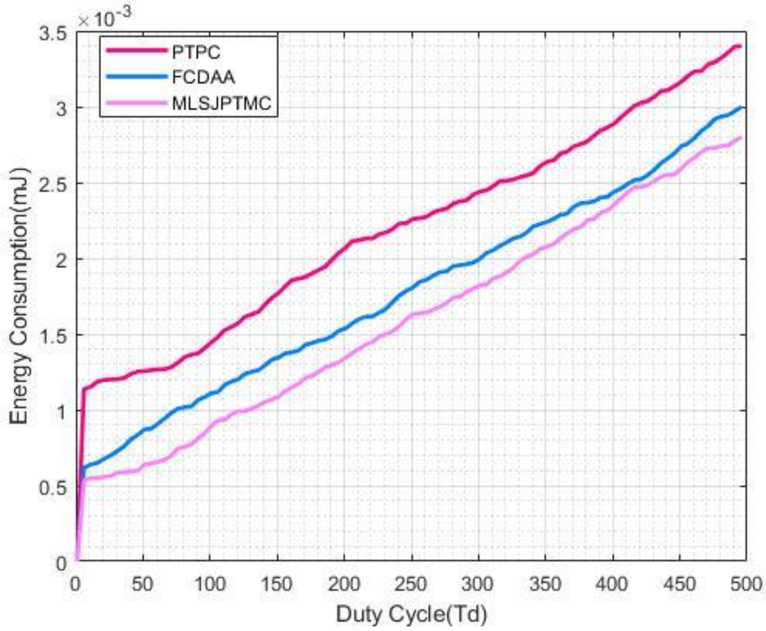

Figure 1 Energy Consumption vs. Duty cycle

Figure 1 shows the comparison between PTPC, FCDAA and MLSJPTMC in terms of energy consumption for different duty-cycle. X axis denotes the duty-cycle and Y-axis denotes the energy consumption in terms of mJ. From Figure 1, it is proved that the proposed MLSJPTMC has low energy consumption than PTPC and FCDAA.

Table 3 reveals the relationship between sensor nodes and the energy consumption for PTPC, FCDAA and MLSJPTMC.

Table 3 Energy Consumption vs. Sensor Nodes

Energy Consumption ($\times$ **10^{-3}**)			
No. of Sensor nodes	**PTPC**	**FCDAA**	**MLSJPTMC**
0	0.0049	0.0048	0.00478
50	0.0042	0.0040	0.0034
100	0.0039	0.0034	0.0029
150	0.0031	0.0030	0.0024
200	0.0030	0.0025	0.0021
250	0.0026	0.0021	0.0013
300	0.0021	0.0016	0.0009
350	0.0017	0.0012	0.0003
400	0.0012	0.0007	0.0002
450	0.0006	0.00091	0.00008
500	0.0002	0.00002	0.00007

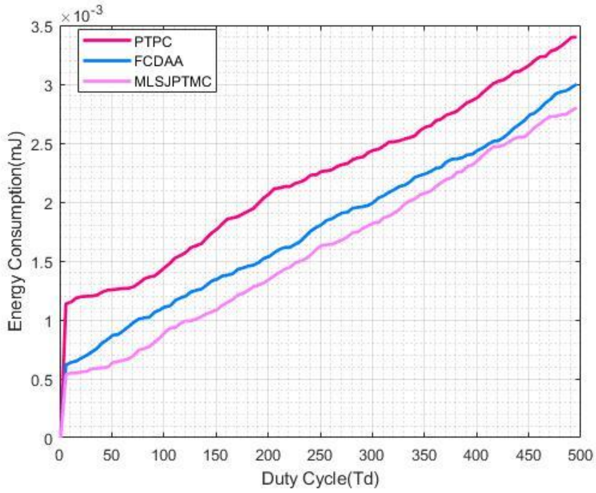

Figure 2 Energy Consumption vs. Sensor Nodes

Figure 2 shows the comparison between PTPC, FCDAA and MLSJPTMC in terms of energy consumption for different number of sensor nodes. X axis denotes the number of sensor nodes and Y-axis denotes the energy consumption in terms of mJ. From figure 2, it is proved that the proposed MLSJPTMC has low energy consumption than PTPC and FCDAA.

4.2 Energy Dissipation

Energy dissipation is the amount of energy dissipated by the IoT devices in industries. Modulation level varies with respect to the requirement of sensors and static, dynamic industrial scenarios then there will be change in the energy dissipation level. Table 4 shows energy dissipation for different modulation level.

Table 4 Energy Dissipation vs. Modulation Level

Energy Dissipation ($\times$ **10^{-3}**)			
Modulation Level	**PTPC**	**FCDAA**	**MLSJPTMC**
0	0.0021	0.0019	0.0015
50	0.0020	0.0018	0.0013
100	0.0018	0.0016	0.0012
150	0.0015	0.0013	0.0009
200	0.0013	0.0010	0.0007
250	0.0010	0.00073	0.0005
300	0.00076	0.00043	0.0002
350	0.0054	0.00018	0
400	0.00294	0	0
450	0	0	0
500	0	0	0

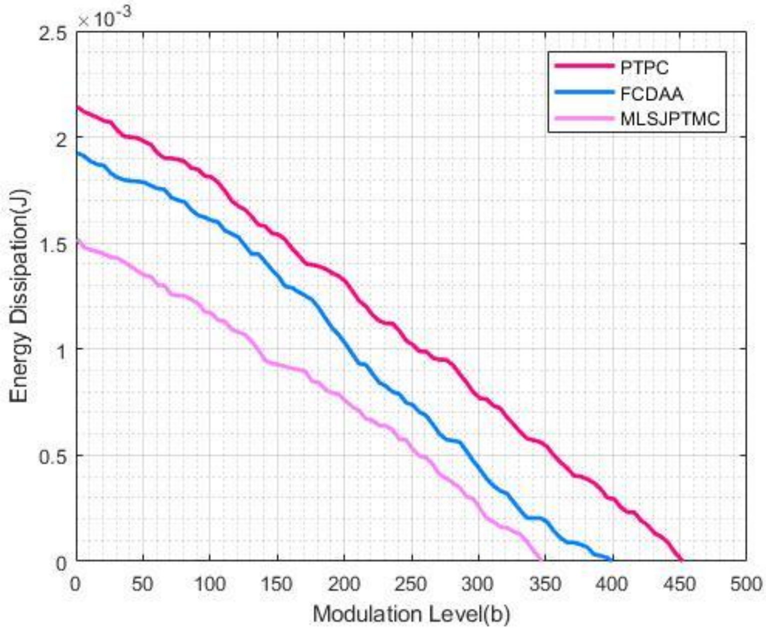

Figure 3 Energy Dissipation vs. Modulation Level

Figure 3 shows the comparison between PTPC, FCDAA and MLSJPTMC in terms of energy dissipation for different modulation level. X axis denotes the modulation level and Y-axis denotes the energy dissipation in terms of J. From figure 3, it is proved that the proposed MLSJPTMC has low energy dissipation than PTPC and FCDAA.

Table 5 shows the energy dissipation for different time intervals.

Table 5 Energy Dissipation vs. Time Interval

Energy Dissipation ($\times 10^{-3}$)			
Time (sec)	**PTPC**	**FCDAA**	**MLSJPTMC**
0	0	0	0
50	0.0779	0.0522	0.0324
100	0.0878	0.0644	0.0416
150	0.0991	0.0678	0.0517
200	0.1090	0.0761	0.0635
250	0.1191	0.0950	0.0735
300	0.1273	0.1091	0.0824
350	0.1347	0.1205	0.0947
400	0.1430	0.1301	0.1005
450	0.1500	0.1340	0.1102
500	0.1900	0.1796	0.1326

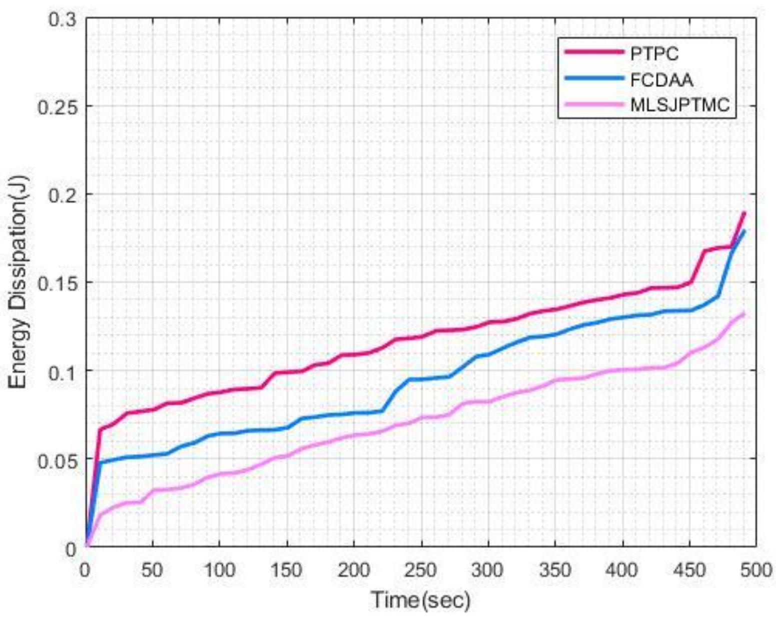

Figure 4 Energy Dissipation vs. Modulation Level

Figure 4 shows the comparison between PTPC, FCDAA and MLSJPTMC in terms of energy dissipation for different time interval. X axis denotes the time and Y-axis denotes the energy dissipation in terms of J. From figure 4, it is proved that the proposed MLSJPTMC has low energy dissipation than PTPC and FCDAA.

V. Conclusion

In this paper, MLSJPTMC is proposed to enhance the power and battery-aware communication through portable IoT devices for industrial applications. Initially, MLSJPTMC used DNN to learn duty-cycle and energy consumption for AI-based IoT devices. The DNN consists of three layers are input layer, hidden layer and output layer. Each layer process the duty-cycle and energy consumption with their weight values. Finally the output layer returns the duty-cycle and energy consumption value with minimal error. The learned duty-cycle and energy consumption is used in FCDAA which extends the battery lifetime and save the power in AI based edge computing platforms for industrial applications. By learning, duty-cycle and energy consumption of IoT devices the performance of power and battery-aware communication through portable IoT devices for industrial applications is enhanced.

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