An Optimal Resource Allocation Method for IIoT Network

Pratik Goswami
School of Computer Science and Communication Engineering, Jiangsu University
Zhenjiang, Jiangsu, China

Amrit Mukherjee*
amrit1460@ieee.org
School of Electronics and Information Engineering, Anhui University
Hefei, Anhui, China

Pushpita Chatterjee
Old Dominion University
Norfolk, Virginia, USA

Lixia Yang*
lixiayang@yeah.net
School of Electronics and Information Engineering, Anhui University
Hefei, Anhui, China

ABSTRACT

The recent technical evolution is revolving around Internet of Things (IoT). The Internet of Softwarized Things (IoST) as a subset of IoT, is making its mark mostly towards industrial applications to connect all the devices and improve the computation capability and networking flexibility. The Industrial IoT (IIoT) consists of a large network, where the multiple works are processed continuously at a time. Therefore, multi-objective interference issue in the path remains as obstacle, for which the networking resources are lost. The existing works were performed with fixed resources and dedicated channel states which make the network less flexible with more time response. In this paper, the problem is addressed with optimal resource allocation using convolutional neural network (CNN) to extract the optimal channel state for different applications, which ease the computations along with efficiency. Furthermore, the proposed method is validated with the mathematical analysis and simulation.

CCS CONCEPTS

• **Networks** → *Wireless personal area networks*; **Network performance analysis**.

KEYWORDS

CNN, IIoT, Signal-interference-ratio (SIR), resource allocation, Wireless Sensor Network (WSN)

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*Corresponding authors

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1 INTRODUCTION

The emergence of IoT in each and every field of applications has also made its presence for the development of industrial applications. This introduces a new phenomenon called Industrial IoT (IIoT): a subset of IoT [2][4]. It has evolved for the betterment of industrial production in terms of efficiency and sustainability [19][21][23]. The IIoT has come up as an impressive technology which comprises of machine-to-machine (M2M) connection as well as industrial communication technologies with automation to make a comprehensive system. In IoT paradigm, Wireless Sensor Network is an integral part of it. The sensor nodes or devices communicate each other and process the data after collecting it and feedback to the environment. Similarly in IIoT, a huge number of devices are connected to the internet which demands the system to be fast, secure, along with energy and cost efficient. Therefore, our work mainly focuses on the resource allocation challenges in IIoT and this problem is dealt with the consideration of WSN for secure, cost and energy efficient system. The large range connection between machines through 5G technologies [3] requires a good infrastructure in resource constrained network as well as for such huge network the desired value of different utilities can be achieved with optimal resource allocation in network. The authors of different literatures formulated different approaches for resource allocation in varying wireless channel. But most of those approaches are hard to manage in terms of large network due to the non-convex nature [17]. In some cases, Lagrangian dual domain [24], dual descent [8] and other heuristic approaches are used to achieve those purposes. Eventually, in these methods the computational cost is very high and it requires a fixed system model. In recent scenario, the emergent applications adapted different machine learning (ML) and statistical regression techniques for wireless resource allocation in sensor network. The well-known ML method neural network (NN) is quite an impressive technique for prediction of resource allocation strategies. In case of supervised learning, the optimal solution cannot be achieved due to the limited availability of heuristic as well as fully connected neural networks (FCNNs), though having universal approximation property are not able to achieve large scale requirements. But, FC-NNs can achieve the scalability for large network by processing the signals in time and space with CNNs.

In this paper, we have considered (CNNs) for resource allocation purpose for IIoT network, due to its spatial arrangement feature.

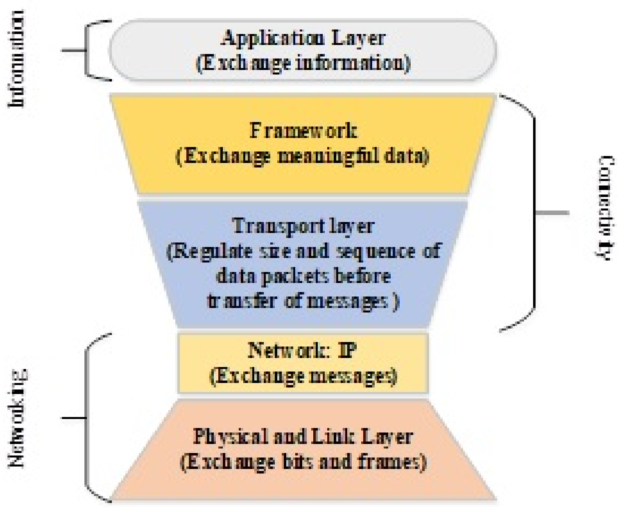

Figure 1: Network Topology of IIoT Communication

Table 1: List of Symbols

Symbols	Definitions
i	Transmitters
$r(j)$	Single receiver
$\mathbf{G}(t)$	Chanel matrix
$\mathbf{Y}(t)$	Chanel matrix for system variables
$\Phi(t)$	Resource allocation function
S	Signal power
I	Channel interference power

It is used to get the optimal resource allocation feature from the channel state map. The state-of-art of our work can be summarized by the following points:

• Problem formulation for resource allocation

• Finding the signal-to-interference ratio (SIR) for the each interfering channel

• Optimal feature extraction in terms of channel state: the channel matrices are used as input and SIR value of each interfering channel as convolutional filter evaluates optimal resources.

The rest of the paper is organized as follows: Section 2 reviews some of the literatures of existing related works and techniques. The system assumption for the proposed method and the proposed model is presented in Section 3, Section 4 discusses the proposed method and analyses the working of CNN and optimal resource allocation of the network. Section 5 shows the simulation results and discuss the network performance compare to other existing methods. The paper is concluded discussing the significance of the proposed work and future possibilities in Section 6.

We have given Table1, for some of the important symbols and definitions for the ease of readers.

2 RELATED WORK

The resource allocation policy is discussed and proposed in many literatures. In [12] efficient resource allocation for heterogeneous WSN is proposed based on SACHSEN algorithm. According to the authors, this algorithm performs as middleware platform by which multiple applications share their resources to each other whenever it is needed, without compromising quality of service (QoS). In another case, a collaborative approach is attained by the authors in WSN. Energy efficient resource allocation and optimization is well-known fact in any sensor network. Therefore, optimization techniques along with artificial intelligence are well developed for this purpose [15]. Power is allocated based on that data classification in [20]. The process was accomplished by comparing perfect and imperfect channel state information (CSI) to achieve the proper distribution of power. The deep neural network (DNN) based optimal resource allocation scheme is proposed in [25] for Cognitive Radio Network. Similarly deep learning is being used by the authors of literature [13] for wireless resource allocation in vehicular networks. As our work considers CNN for the resource allocation purpose, we have also discussed some literatures where CNN is considered for various application purposes. As a part of deep learning CNN is used for industrial WSN for physical layer authentication purpose to enhance the security of the industrial WSN (IWSN) [14]. As a great tool for feature extraction, CNN is used in one of the literatures for the data prediction in WSN [5]. In [1] the authors designed a classification based system with compressed WSN images. As well as power control scheme [22] using CNN, power allocation strategy Utilizing CNN [11] and to represent signals in graphs CNN is also used to design an architecture [9].

3 NETWORK ASSUMPTIONS AND PROPOSED METHOD

In IIoT network [16], the communication depends on different parameters like location of nodes, hardware conditions, and dynamic power consumption of nodes. Therefore, for energy efficient communication it is better to have a strategy to achieve enough power for completion of task. Considering this we have proposed a method for optimal power allocation in sensor channel. The network architecture considers some specific assumptions to design the system model.

• The position of nodes are fixed and randomly distributed in 100m X100 m area.

• The network is comprised of heterogeneous nodes. These nodes are responsible for communication of different applications.

• The sensor nodes in the network are capable of transmit and receive power continuously.

• The Rayleigh fading is taken under consideration in channel

The work flow of the proposed method is shown in Figure 2. The optimal resource allocation scheme is mainly considered for dynamic environment of the channel. At first the number of channels are estimated in a network [6]. After that based on channel parameters the general resource allocation policy is considered. Then the path interference [7] of the different applications is calculated. We have considered the path interference due to the large scale IIoT network as there are multiple tasks occur at a time. This is explained in Section 4.

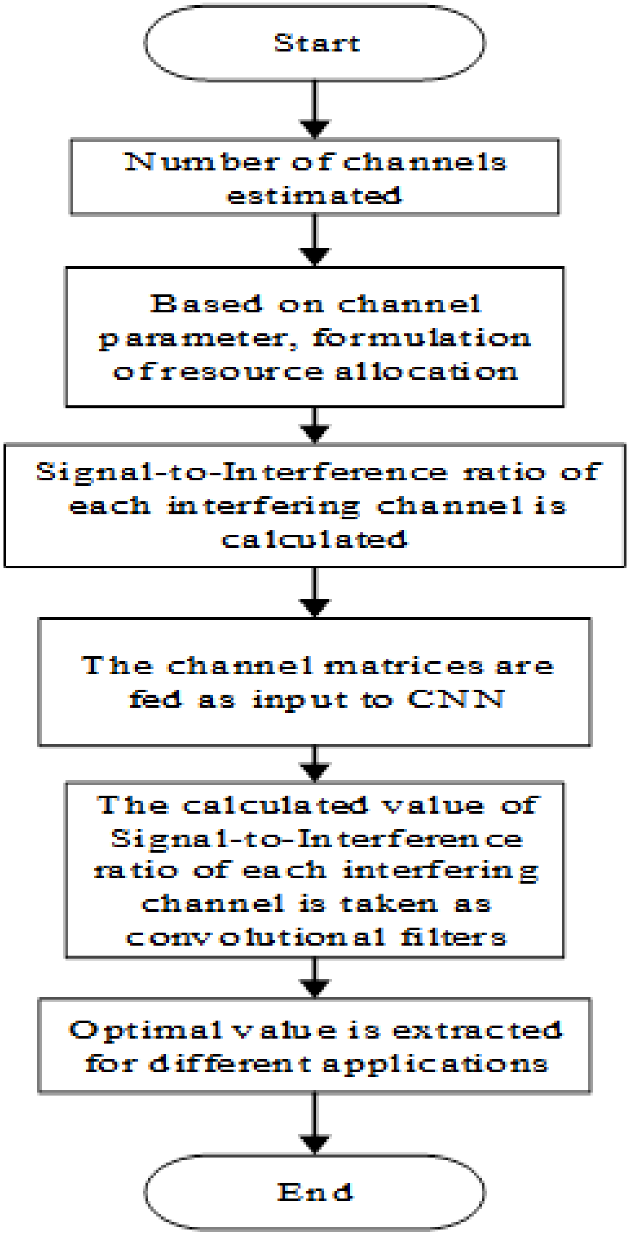

Figure 2: Workflow of the Proposed Method

The CNN is considered for further process of optimal resource allocation. The channel matrix is taken as input map and the SIR value of each interfering channel is considered the convolutional filter. It results as different feature maps as different images. After that the pulling operation is done which gives optimal channel state output feature in terms of interference. By which the resource allocation is done.

4 MATHEMATICAL ANALYSIS OF THE PROPOSED METHOD

4.1 Problem Formulation

As mentioned above in Section 2, the nodes are heterogeneous and these are responsible for the communication of different applications. In this condition, in IIoT at the time of communication between devices, each device possibly can be used for multiple purposes. Therefore, there is a high chance of path interference of the signal at the time of communication. Considering this, we can assume that there are m number of transmitting nodes and n number of receiving nodes. We have taken under consideration for both the cases, where m>n and m=n. In that case, each transmitter $i \in (1, m)$ can be connected to single receiver $r(j) \in (1, n)$ and multiple transmitter can also be connected to single receiver, which can be represented as $\Re_j$:=i:$r(i)$=j.

As the small scale Rayleigh fading is considered in channel between each nodes in multipath scenario, the fading coefficients influence the resources for each communication timeslot t. The channel between i and $r(j)$ can be represented as $g_{ij}(t)$ and between i, $r(i)$ the channel is denoted as $g_{ii}(t)$. A channel matrix $\mathbf{G}(t) \in \mathbb{R}^{m \times n}$ is represented as a collection of all the channels, where the channel state $|\mathbf{G}(t)| = g_{ij}(t)$. At the time of communication, the data packets are transferred through nodes and these can be considered as random vectors as $\mathbf{Y}(t)$, where $|\mathbf{Y}(t)| = y_i(t)$ as a single input. Therefore the required resources to complete any task can be represented as [24]:

$$\Phi(t) = \Phi(\mathbf{G}(t), \mathbf{Y}(t)) \tag{1}$$

This equation further can be represented as a vector in receiving end by the function of joint space resource allocation:

$$\mathbf{r}(t) = \mathsf{f}(\Phi(t); (\mathbf{G}(t), \mathbf{Y}(t))) \tag{2}$$

Now, this paper concerns about the resource allocation policy with respect to path interference of the communicating signals. The power provided by the system for the processing of tasks is not fully utilized due to the co-channel interference and the dynamic resource allocation is possible if the path interference taken care of as a condition.

If we consider the number of interfering channels i_0, the signal power is S and I is the interference power, then the signal-to-interference ratio can be calculated as:

$$SIR = \frac{S}{I} = \frac{S}{\sum_{i=1}^{i_0} I_i} \tag{3}$$

The interference power I_i can be calculated as the function of distance between nodes from transmitting end to receiving end D and number of nodes R as:

$$I_i = S \times (\sqrt{\frac{D}{R}})^2 \tag{4}$$

This power value is calculated for further process of CNN in next subsection.

The energy efficient optimal value P_{ee}^{opt} can be calculated as:

$$P_{ee}^{opt} = max(r(t)) \tag{5}$$

Model.png

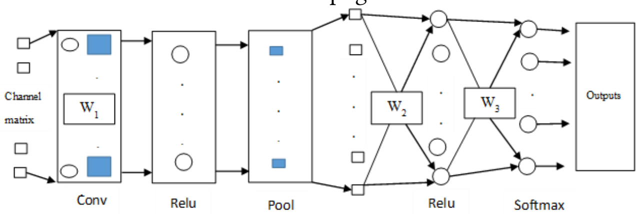

Figure 3: CNN Model

The maximum matrix value for the power calculation is the final output for each application based resource allocation in channel.

4.2 Convolutional Neural Network and Optimal Resource Allocation

The CNN is a great technique for feature extraction and classification [10]. In CNN the huge set of data is reduced in small scale. Here, we have considered 1-D convolution layer and 1-D pooling to get the optimum resource allocation. As per our network consideration we have taken the channel matrix $\mathbf{G}(t)\mathbf{Y}(t)$ as input map for 100mX100m =10000 nodes. Then we have considered the 10 convolution filters (10X10). These convolutional filters or the Kernels are adjusted with the SIR of the 10 channels. Now, the 2X2 submatrices are considered for pooling layer. It means the number of feature maps are generated are 10. This is considered because we assume that in our network the number of different applications or tasks are processing through IIoT network is 10. In the pooling part among the feature maps the maximum and minimum value is calculated. It means from which we get the reduced size of the map by which after the training in FCNN [18] we get the optimal value of resource in channels for different applications. Here, the Relu activation function $R(z, 0) = max(0, z)$ is used for both the cases of convolution layer and feedforward neural network. The reason behind the use of Relu is that it is non-linear, which is very much necessary for any deep learning and for our proposed model.

The convolutional layer is different from FCNN, as it is hidden, it is only connected to some part of the network. It can be explained with some considerations. If we consider number of weights x1 to x6 are inputs and c1 to c4 are feature maps. Then the single unit of hidden one dimensional output is connected to only three inputs. In this type of network training process get faster due to decrement of number of parameters.

The convolutional layer mainly consists of kernel size, stride and padding. Based on this three variables decides the size of feature map. Kernel size is basically the number of input used for each feature map and stride is the distance between two feature maps and the padding is the addition of variable to make the number of feature maps equal to the number of units. The size of the feature map can be calculated as [5]:

$$W_{out} = \frac{W_{in} + 2 * padding - F}{stride} + 1 \tag{6}$$

Here, and are the size of output and input feature map and is the size of kernel.

Table 2: Simulation Parameters

Parameters	Values
Network diameter	100mX100m
Number of nodes	10000
Total network energy	1J
Number of simulations	10000

The pooling layer also consists of three variables, pool size, stride and padding. The operation of stride and padding are same as convolutional layer but the pool size is depends on the number of data required for calculation. The main principle of pooling layer is to reduce the size of feature map.After the operation of pooling layer, we are now able to classify the channel input as different application features. Therefore, for classification purpose, we have used a hidden layer of 100 nodes in FCNN. This FCNN is great for the learning of non-linear features in cheap way. As our goal is to find the optimal allocation policy for different applications we have taken 10 output nodes.

5 ANALYSIS OF NETWORK PERFORMANCE

In this section, the network performance is analyzed in terms of simulation results. The assumed simulation parameters are shown in Table2.

The residual energy of the network after each simulation is calculated and shown in Figure 4. If the system residual energy is less, then the system is considered good in terms of energy utilization. The amount of residual energy remain in our proposed method is less, compare to IEEE 802.11 and conventional approach it utilizes more of the power. Therefore, our proposed method can be considered as efficient for optimal allocation of the resource.

energy.png

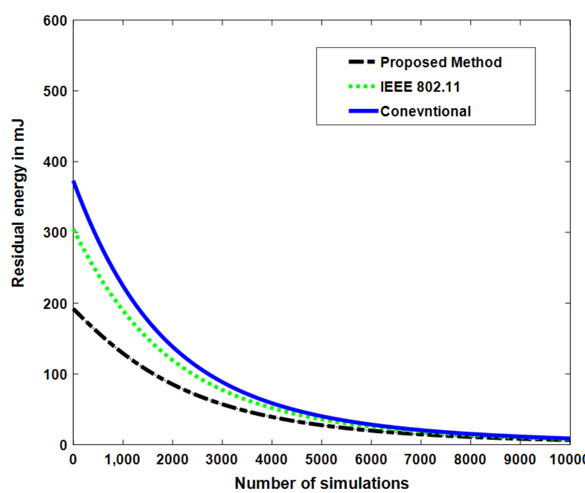

Figure 4: Residual Energy of the Proposed Method

In the simulation result Figure 5, the response time of the system is shown. The comparison is shown for two processes, one is executed with our proposed work using CNN implementation and another is the without CNN or the normal resource allocation in the channel, which means the channel resource allocation is done conventionally. It can be seen that in both cases initially the curve rises smoothly, and then stable down after some fluctuations. The increase in response time after each simulation is less in our proposed method with CNN. It means the system responses fast in our approach.

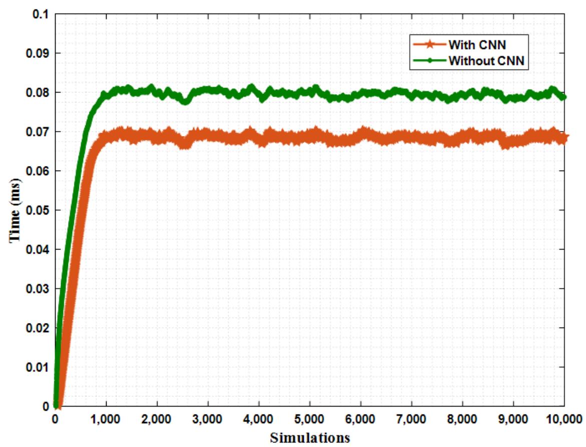

Figure 5: System Response of the Network

In Figure 6, the optimal allocated energy is shown with respect to per task. It can be seen clearly as the number of simulations are increased the allocated energy also get decreased smoothly for both the cases. In the proposed resource allocation method using CNN the allocated energy for each task is high. Whereas; the conventional process as per the simple channels state estimation the energy per task is less. It proves that our proposed method of resource allocation good enough to utilize the maximum resources of the network.

The total energy consumption of the network is compared with two different methods, one is proposed method of resource allocation with CNN and the conventional method without CNN (normally calculated through channel estimation) in Figure 7, The value of each techniques decreases smoothly, among these bars our method results least in terms of energy consumption with respect to number of simulations. In that case our method outperforms other techniques, which validates the significance of our work.

6 CONCLUSION

In this paper, an optimal resource allocation scheme is proposed for IIoT network. The optimal value is achieved by the feature extraction method of CNN. To attain the model free instantaneous resource allocation, the SIR of each interfering channel in the process of communication for IIoT applications is taken under consideration. These SIR values are adjusted with Kernel or convolutional filters, which filter out the feature map from the channel input matrix. Further, with pooling and classification the optimal value of channel state is achieved and then the resource is calculated.

per task.png

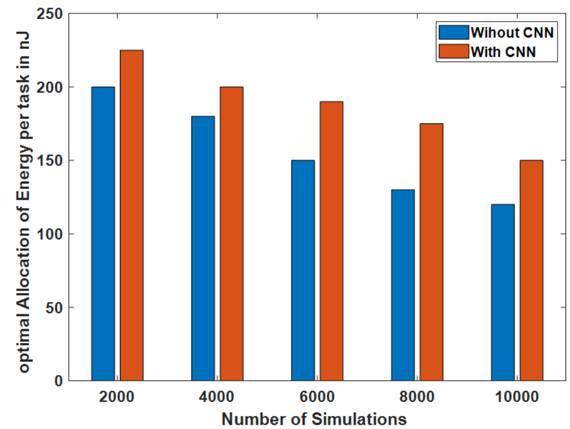

Figure 6: Comparison of Energy Consumption Per Task

consumption.png

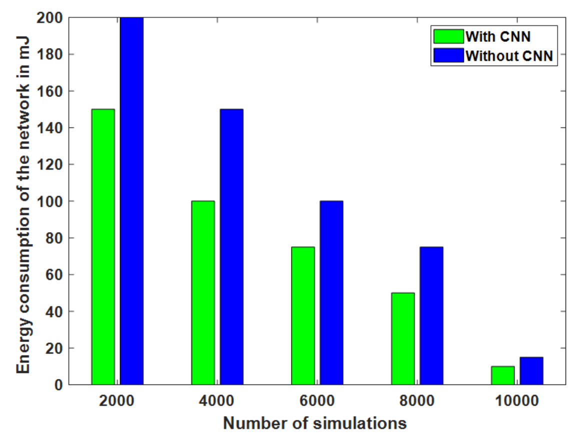

Figure 7: Energy Consumed in the Network in proposed method

The work is validated by showing the network performance with simulation and mathematical analysis, which out-perform the other methods. This work can be extended considering other parameters like residual energy for further improvement and as well as increasing number of layers it will give better performance.

REFERENCES

[1] Jungmo Ahn, JaeYeon Park, Donghwan Park, Jeongyeup Paek, and JeongGil Ko. 2018. Convolutional neural network-based classification system design with compressed wireless sensor network images. *PLoS One* 13, 5 (2018), 1–25. https://doi.org/10.1371/journal.pone.0196251.eCollection2018

[2] Debasis Bandyopadhyay and Jaydip Sen. 2011. Internet of things: Applications and challenges in technology and standardization. *Wireless Personal Communication* 58, 1 (2011), 49–69.

[3] Deborsi Basu, Abhishek Jain, Raja Datta, and Uttam Ghosh. 2020. Optimized Controller Placement for Soft Handover in Virtualized 5G Network. In *2020 IEEE Wireless Communications and Networking Conference Workshops (WCNCW)*. IEEE, 1–8. https://doi.org/10.1109/WCNCW48565.2020.9124902

[4] Jim Chase. 2013. *The evolution of the internet of things*. Technical Report. Texas Instruments. 1–7 pages.

[5] Hongju Cheng, Zhe Xie, Yushi Shi, and Naixue Xiong. 2019. Multi-Step Data Prediction in Wireless Sensor Networks Based on One-Dimensional CNN and Bidirectional LSTM. *IEEE Access* 7 (2019), 117883–117896. https://doi.org/10.1109/ACCESS.2019.2937098

[6] Wei Cui, Kaiming Shen, and Wei Yu. 2019. Spatial Deep Learning for Wireless Scheduling. *IEEE Journal on Selected Areas in Communications* 37, 6 (2019), 1248–1261. https://doi.org/10.1109/JSAC.2019.2904352

[7] Paul de Kerret; David Gesbert; Maurizio Filippone. 2018. Team Deep Neural Networks for Interference Channels. In *2018 IEEE International Conference on Communications Workshops (ICC Workshops)*. IEEE, 1–6. https://doi.org/10.1109/ICCW.2018.8403662

[8] Mark Eisen and Alejandro Ribeiro. 2020. Optimal Wireless Resource Allocation With Random Edge Graph Neural Networks. *IEEE Transactions on Signal Processing* 68 (2020), 2977–2991. https://doi.org/10.1109/TSP.2020.2988255

[9] Fernando Gama, Antonio G. Marques, Geert Leus, and Alejandro Ribeiro. 2019. Convolutional Neural Network Architectures for Signals Supported on Graphs. *IEEE Transactions on Signal Processing* 67, 4 (2019), 1034–1049. https://doi.org/10.1109/TSP.2018.2887403

[10] Sujeet More; Jimmy Singla; Sahil Verma; Kavita; Uttam Ghosh; Joel J. P. C. Rodrigues; A. S. M. Sanwar Hosen and In-Ho Ra. 2020. Security Assured CNN-Based Model for Reconstruction of Medical Images on the Internet of Healthcare Things. *IEEE Access* 8 (2020), 126333–126346. https://doi.org/10.1109/ACCESS.2020.3006346

[11] Woongsup Lee, Minhoe Kim, and Dong-Ho Cho. 2018. Deep Power Control: Transmit Power Control Scheme Based on Convolutional Neural Network. *IEEE Communications Letters* 22, 6 (2018), 1276–1279. https://doi.org/10.1109/LCOMM.2018.2825444

[12] Wei Li, Flávia C.Delicato, Paulo F.Pires, Young Choon Lee, Albert Y.Zomaya, Claudio Miceli, and Luci Pirmez. 2014. Efficient allocation of resources in multiple heterogeneous wireless sensor networks. *J. Parallel and Distrib. Comput.* 74 (2014), 1775–1788.

[13] Le Liang, Hao Ye, Guanding Yu, and Geoffrey Ye Li. 2020. Deep-Learning-Based Wireless Resource Allocation With Application to Vehicular Networks. *Proc. IEEE* 108, 2 (2020), 341–356. https://doi.org/10.1109/JPROC.2019.2957798

[14] Run-Fa Liao, Hong Wen, Jinsong Wu, Fei Pan, Aidong Xu, Yixin Jiang, Feiyi Xie, and Minggui Cao. 2019. Deep-Learning-Based Physical Layer Authentication for Industrial Wireless Sensor Networks. *Sensors* 19, 11 (2019), 1–17. https://doi.org/10.3390/s19112440

[15] Amrit Mukherjee, Pratik Goswami, Ziwei Yan, Lixia. Yang, and Joel J. P. C. Rodrigues. 2019. ADAI and Adaptive PSO-Based Resource Allocation for Wireless Sensor Networks. *IEEE Access* 7 (2019), 131163–131171. https://doi.org/10.1109/ACCESS.2019.2940821

[16] Amrit Mukherjee, Pratik Goswami, Lixia Yang, Sumarga K. Sah Tyagi, U. C. Samal, and S. K. Mohapatra. 2020. Deep neural network-based clustering technique for secure IIoT. *Neural Computing and Applications* 32 (2020), 16109–16117. https://doi.org/10.1007/s00521-020-04763-4

[17] Alejandro Ribeiro. 2012. Optimal resource allocation in wireless communication and networking. *EURASIP Journal on Wireless Communications and Networking* 2012, 1 (2012), 1–19. https://doi.org/10.1186/1687-1499-2012-272

[18] Amrit Mukherjee; Deepak Kumar Jain; Pratik Goswami; Qin Xin; Lixia Yang; Joel J. P. C. Rodrigues. 2020. Back Propagation Neural Network Based Cluster Head Identification in MIMO Sensor Networks for Intelligent Transportation Systems. *IEEE Access* 8 (2020), 28524–28532. https://doi.org/10.1109/ACCESS.2020.2971969

[19] Emiliano Sisinni, Abusayeed Saifullah, Song Han, Ulf Jennehag, and Mikael Gidlund. 2018. Industrial Internet of Things: Challenges, Opportunities, and Directions. *IEEE Transactions on Industrial Informatics* (2018), 1–11. https://doi.org/10.1109/TII.2018.2852491

[20] Houlian Wang and Gongbo Zhou. 2017. Power Allocation Based on Data Classification in Wireless Sensor Networks. *Sensors(Basel)* 17, 5 (2017), 1–13. https://doi.org/10.3390/s17051107

[21] Martin Wollschlaeger, Thilo Sauter, and Juergen Jasperneite. 2017. The future of industrial communication: Automation networks in the era of the internet of things and industry 4.0. *IEEE Industrial Electronics Magazine* 11, 1 (2017), 17–27.

[22] Di Xu, Xiaojing Chen, Changhao Wu, Shunqing Zhang, Shugong Xu, and Shan Cao. 2019. Energy-Efficient Subchannel and Power Allocation for HetNets Based on Convolutional Neural Network. In *2019 IEEE 89th Vehicular Technology Conference (VTC2019-Spring)*. IEEE, 1–5. https://doi.org/10.1109/VTCSpring.2019.8746493

[23] Li Da Xu, Wu He, and Shancang Li. 2014. Internet of Things in Industries: A Survey. *IEEE Transactions on Industrial Informatics* 10, 4 (2014), 2233–2243.

[24] Wei Yu and Raymond Lui. 2006. Dual methods for nonconvex spectrum optimization of multicarrier systems. *IEEE Transactions on Communications* 54, 7 (2006), 1310–1322.

[25] Fuhui Zhou, Xiongjian Zhang, Rose Qingyang Hu, Apostolos Papathanassiou, and Weixiao Meng. 2018. Resource Allocation Based on Deep Neural Networks for Cognitive Radio Networks. In *2018 IEEE/CIC International Conference on Communications in China (ICCC)*. IEEE, 40–45. https://doi.org/10.1109/ICCChina.2018.8641220