MODELLING VARIOUS ALGORITHMS OF ARTIFICIAL INTELLIGENCE IN WIRELESS COMMUNICATION SYSTEM.

Snehasis Dey [a], Dr. Prabodh Khampariya [b], Dr. Manish Jain [c]

[a] Research Scholar, Dept. of Electronics and Communication Engineering ,Sri Satya Sai University of Technology and Medical Sciences,sehore,M.P.India.
[b] Research Guide, Sri Satya Sai University of Technology and Medical Sciences,sehore,M.P.India.
[c]Research Coguide, Dept. of Electronics and Communication Engineering, Mandsaur University,Mandsaur,M.P.India.

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Abstract: 5G wireless communication have been a topic of vast research in recent years.Incidentaly in this covid pandemic period ongoing,the 5G wireless communication is more famous and happening topic altogether.Key technologies like Milimeterwave(mmwave),Massive MIMO,Beamforming,Artificial Intelligence(AI),Block chain adds more specific advantages in 5G wireless communication.The basic five foundations discussed here in 5G have given the communication a new horizon altogether in comparison to the 4G wireless communication. For base stations the major and important problem is to decide the optimal beamforming adjustment because they don't have computationally powerful resources. But on-site optimization processes would take a lot of time framing schedule and power framing which the base stations can't afford. To resolve this major problem, an external inputed data training or trained data can be given and only the prediction process might be left to the base station. Having achieving a pre-built machine learning based algorithm model would drastically reduce the time and power needed for beamforming optimization.

Keywords: 5G,Artificial Intelligence,Beamforming,Machine Learning,mmWave,Massive MIMO.

1. Introduction

Wireless communication has achieved a long run starting from 1G to 4G and now of course the entry of 5G. 3G technologies has shown improved speeds from 200kbps to several megabits per second. 4G technologies are currently offering hundreds of Mbps and even up to gigabit-level speeds. 5G adds some new new aspects to its previous best like: bigger channels to offer faster speeds, lower latency for higher responsiveness, and the ability to connect more devices at once.

Some specifically advanced characteristics in 5G using Massive MIMO technology over others are as follows:

- Up to as higher as 10Gbps data rate
- 10 to 100x speed improvement over 4G and 4.5G networks.
- 1-millisecond latency.
- 1000x bandwidth per unit area.
- Up to 100x number of connected devices per unit area in comparison to 4G.
- 99.999% availability.
- 100% coverage.
- 90% reduction in network energy usage.

From the viewpoint of performance requirements in wireless communication of present day, there are three major requirements for 5G systems: enhanced mobile broadband (eMBB), massive machine-type communications (mMTC), and ultra-reliable low latency communications (URRC). Fundamentally, these are different aspects of requirements. Indeed, as use cases, various independent scenarios are proposed based on these requirements: a rapid download of large data such as movie data of some gigabytes (GB) by satisfying eMBB, management of massive amounts of mobile sensors such as IoT devices by satisfying the mMTC, and telemedicine with extreme low latency wireless network by satisfying URRC.

To satisfy these extreme requirements of 5G communication systems, high-performance devices/equipment are needed in wireless communication systems which can allow management of low-end devices, such as smart IoT. All these requirements and use cases indicate that current and future wireless communication systems are becoming more and more complex and heterogeneous so it is necessity to propose the AI driven and machine learning algorithm based communication networks.

Research challenge to optimize future wireless communication system:

Different studies and research work have been put forward on the optimal decision of wireless communication systems through mathematical and theoretic formulation of wireless channel and transmission power control, modulation and coding, the behavior of MAC protocol or higher layer protocols[1-7]. The common approach of these studies is to define the mathematical model of the function of wireless communication system, to formulate the maximization or minimization problem, and to obtain the optimal solution by solving the problem .An important advantage of these "classical" approaches is that the predetermined theoretical optimal solutions or parameters, or at least their upper- or lower-bounds, can be obtained under the assumption of the continuity of thefunction described.

In prospect of the modeling of wireless communication systems, the classical approach generally focuses on a certain layer performance such as channel capacity(C) in physical layer or through- put in MAC layer, and cannot cover whole system modeling. Indeed, current and future generation complex wireless communication systems are hard to be described mathematically as a whole system. Moreover, the mathematical formulation of wireless systems cannot always be applied and realized to the time-varying situations. Wireless systems such as Wi-Fi or Bluetooth are operated autonomously and interact with each other over time, which is really beyond the description of mathematical modeling and structuring. These indicates that the classical approach faces fundamental difficulty in applying the optimization of current wireless communicationsystems.

Consequently, there are two issues in optimizing the performance of current and future generation complex wirelesscommunication systems.

- Scenario 1. Classical one-way optimal decisions are not suitable for complex time-varying situations.
- Scenario 2. Classical modeling by mathematical formulation cannot be applied to multi-layer andmultiprotocol complex wireless systems.

Cognitive radio technology

Cognitive radio is a basic fundamental concept in wireless systems. It learns the environment and behavior of wireless communication nodes and performs trial-and-error to seek the best action to improve the performance. It can adapt to various changes in the environment, such as sudden increases or decreases in traffic demand, variations in wireless channels, and contention among wireless transmitters. Figure below shows the concept of cognition cycle. The key idea of cognitive radio is the cognitive cycle i.e. learning and action, and their feedback cycle.

The concept of cognitive radio gives insights on facing the issues mentioned above. Important points are feedback cycle and learning. In the next section, we discuss those by applying machine learning technologies.

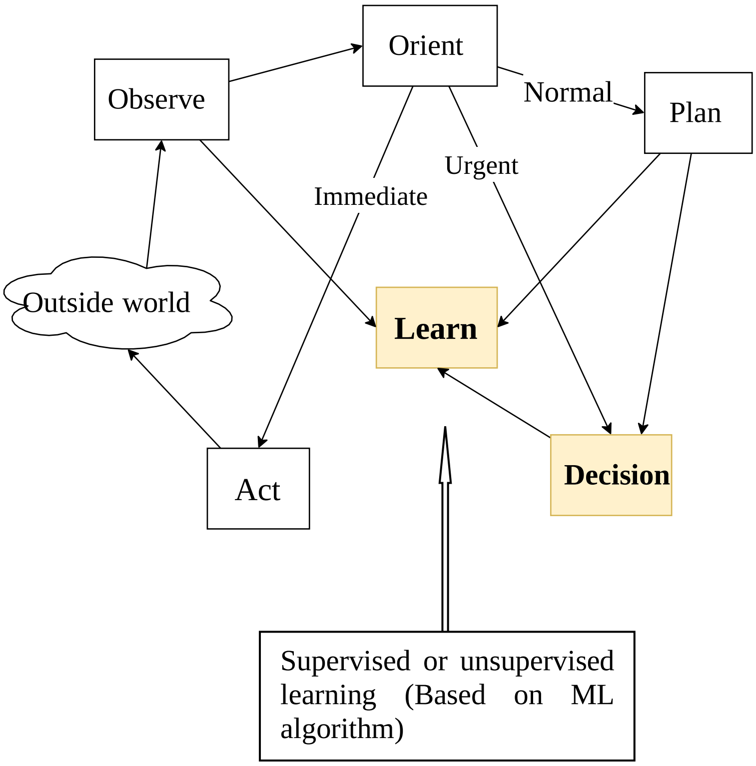


Figure . Concept of cognitive radio with ML algorithm

II. Artificial intelligence / Machine learning for wireless communication system:

AI driven wireless communication solves the tasks that require human intelligence while ML is a subset of artificial intelligence that solves specific tasks by learning from data and making predictions based on that particular communication system.. Several studies indicate that the management of 5G/Beyond5G systems requires machine learning technologies .

AI-enabled intelligent architecture for 5G and above generation is proposed. The proposed architecture is divided into four layers: intelligent sensing layer, data mining and analytics layer, intelligent control layer and smart application layer. Between them, intelligent control layer consists of learning, optimization, and decision-making. They indicate that significantly dynamic and complex network in 6G cannot be optimized through traditional mathematical algorithms. Our research is based on the same viewpoint, and proposes schemes to optimize such complex networks by using machine learning technologies.

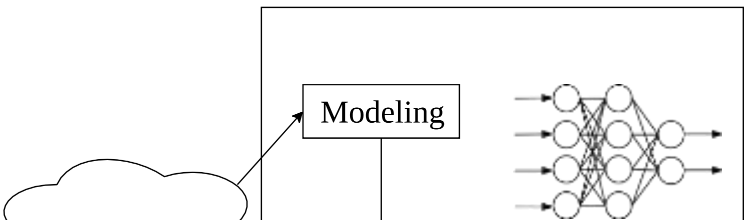
There are two points of view when using machine learning to optimize the decisions and actionsof wireless communication systems. One point is the amount of data. Supervised learning, especially deep learning and its related methods, can deal with a large amount of data to extract the characteristicsof the system from which the data are collected. If the amount of data is limited, the reinforcement learning approach would be more suitable. It allows one to make the optimal decision through the iteration of trial-and-error cycles under the environment of limited information and parameters to be controlled.The relation of these approaches and examples of application of optimizing wireless communication systems is discussed below.

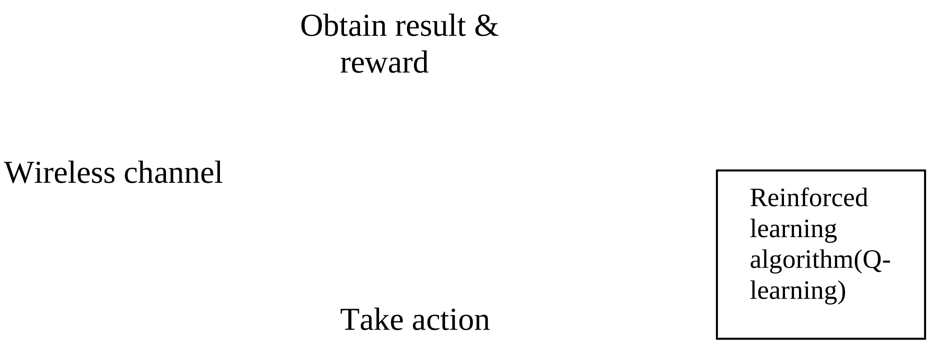
Learning Based decision in wireless communication:

AI/ML based algorithm for learning based decision	**Key area for implementation in wireless communication**
Supervised Learning based Model + Reinforcement Learning based Decision Ex: Deep Reinforcement Learning	Parameter or network selection for UAV, Transmission scheduling for IoT devices, Beamforming for massive MIMO, etc.
Simple Reinforcement Learning based Decision Ex:MAB problem	Contents caching, Frequency hopping, Millimeter wave beam foaming, etc.
Supervised Learning Model + Optimal Decision	Capacity maximization of a multicell wireless network,for seeking better decisions for wireless communication systems

III. Deep Reinforced learning algorithm:

The below figure shows the deep reinforced learning algorithm used in wireless communication system.





DRL is a combination of deep learning and reinforcement learning.It can be seen as an implementation of the cognitive cycle: it learns the relationship among environment, parameter, action, and performance of the wireless communication node through deep learning. Decisioning trial and error: it seeks better actions through reinforcement learning. The major strong point of DRL is to build a performance model by deep learning in an online manner and to utilize it to predict the performance of the systems when certain parameters are deployed. Reinforcement learning, usually
Q-learning based algorithms, are applied to seek better action by evaluating the results, updating its
network, and choosing the predicted parameters better using deep learning. Note that DRL always
requires the information of the state of wireless communication systems, which might be unrealistic in
the real world.

Cross layer modeling of wireless system:

Several studies have attempted to understand the relationships between various variables and performance to optimize wireless networks .These studies generally focused on the performance
of a certain layer, such as channel capacity in the physical layer and throughput in the MAC layer, and do not cover higher layer application throughputs. For an example of the optimization of
wireless network capacity, we refer to the resource allocation problem in . In principle, assuming
ideal link adaptation, the formulation of the sum capacity of a multicell wireless network is expressed
as

$$C(\boldsymbol{U}, \boldsymbol{P}) = \frac{\boldsymbol{1}}{\boldsymbol{N}} \sum_{\boldsymbol{n}=\boldsymbol{1}}^{\boldsymbol{N}} (\log(1 + \Gamma([\boldsymbol{U}]n, \boldsymbol{P})),$$

where N is the total number of cells, Γ is the signal-to-interference and noise ratio (SINR) at the

receiver, $\boldsymbol{U}$ is the set of users simultaneously scheduled across all cells, $[\boldsymbol{U}]n$ is the users in cell n, and
$\boldsymbol{P}$ is the transmit power of the scheduled users. Then, the capacity optimization problem by resource
allocation is formulated as

$$\underset{\boldsymbol{U},\boldsymbol{P}}{\arg\max}\ C(U,P).$$

IV.Cognitive cycle and optimization for complex wireless systems:

Cognitive radio is the concept of an intelligent radio that can learn from its past experience and autonomously decide its actions suitable for radio environments and needs for communication. The
cognitive cycle is a feedback cycle of observation, learning, decision making, and action. Haykin
proposed a more concrete process of cognitive radio from an engineering perspective. He addressed the following fundamental tasks for a cognitive radio: radio-scene analysis, channel-state estimation, transmit-power control, and dynamic spectrum management. Wireless network nodes can change the radio parameters of transmission and reception to avoid interference among users and improve communication quality. In general, wireless communication requires learning to establish wireless links and satisfy communication qualities. For example, a radio frequency (RF) module controls the coding rate based on the received signal strength indicator (RSSI) to reduce the error probability of wireless links. This means that the RF module learns the relationship between the inputs (RSSI, coding rate) and output (link quality). In cognitive radio networks, the cognitive engine should determine and coordinate the actions of the cognitive radio based on the learning of the environment. The relationship between inputs and outputs becomes more complicated in cognitive radio networks owing to its flexibility, such as software-defined radios. Cognitive radio can control various parameters such as frequency, channel, coding rate, and transmission power. The relationship between these parameters and the performance of wireless communication is hardly formulated. Thus, machine learning technologies, which can learn the complex, non-linear relationships among various information, would be the solution. By combining the concept of cognitive cycle and optimal decisioning.

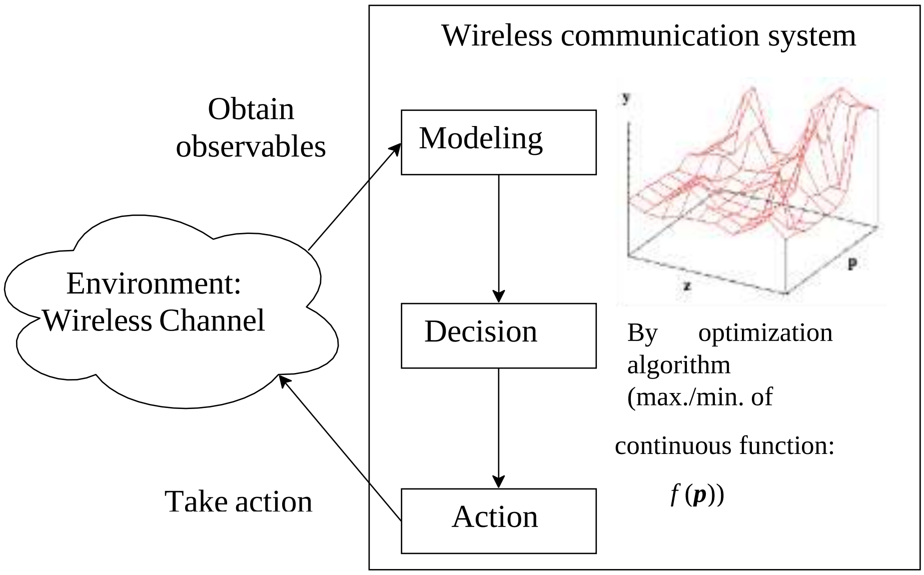
The proposed supervised-learning–based modeling and optimization-based decision making scheme is shown below:

Below figure elaborates the proposed wireless system optimization method using machine learning. The
observables of environment $\boldsymbol{z}$ are collected, which include not only the radio status but also MAC
statistics, or higher layer statistics. For $\boldsymbol{p}$, various parameters of the wireless node or network were
considered. Besides these variables, network performance y is observed. They are a set of samples, S,
for a machine-learning algorithm:

$$S = \{(\boldsymbol{p}1, \boldsymbol{z}1, y1), (\boldsymbol{p}2, \boldsymbol{z}2, y2), ..., (\boldsymbol{pn}, \boldsymbol{zn}, yn)\}.$$

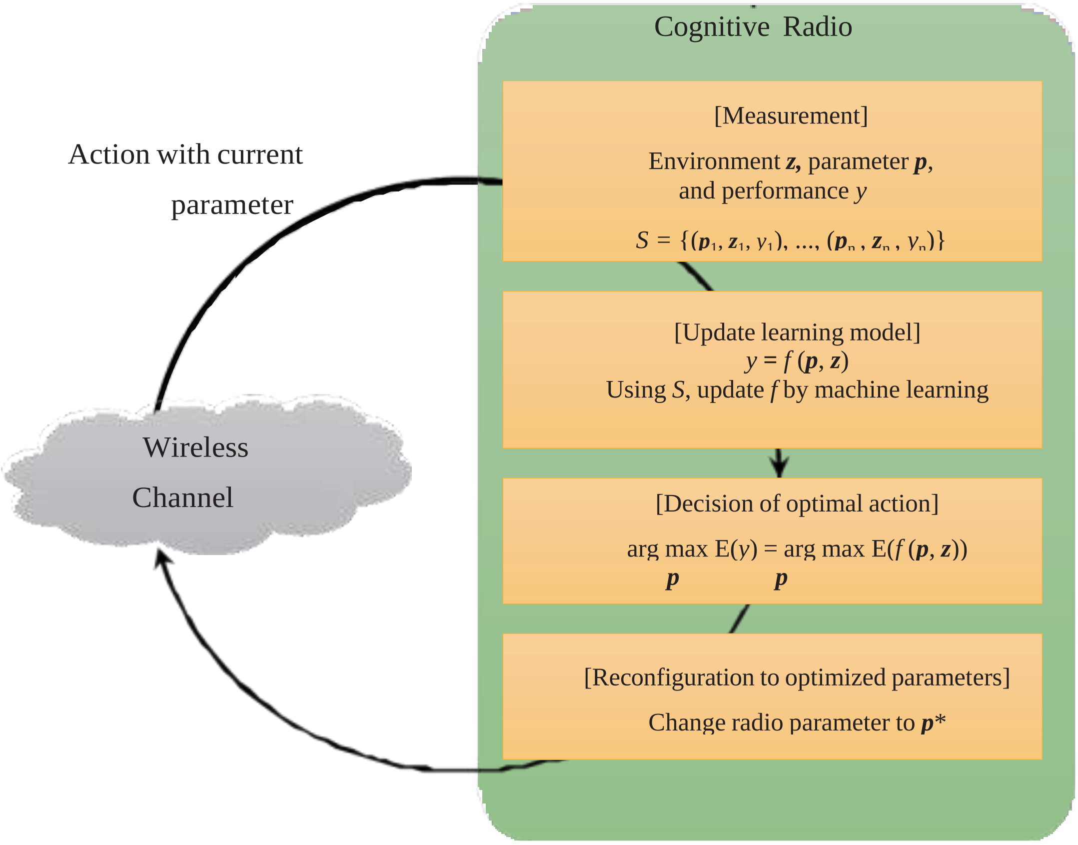
Using S, the cognitive engine builds and updates the model f by machine learning:

$y = f(\boldsymbol{p}, \boldsymbol{z})$.



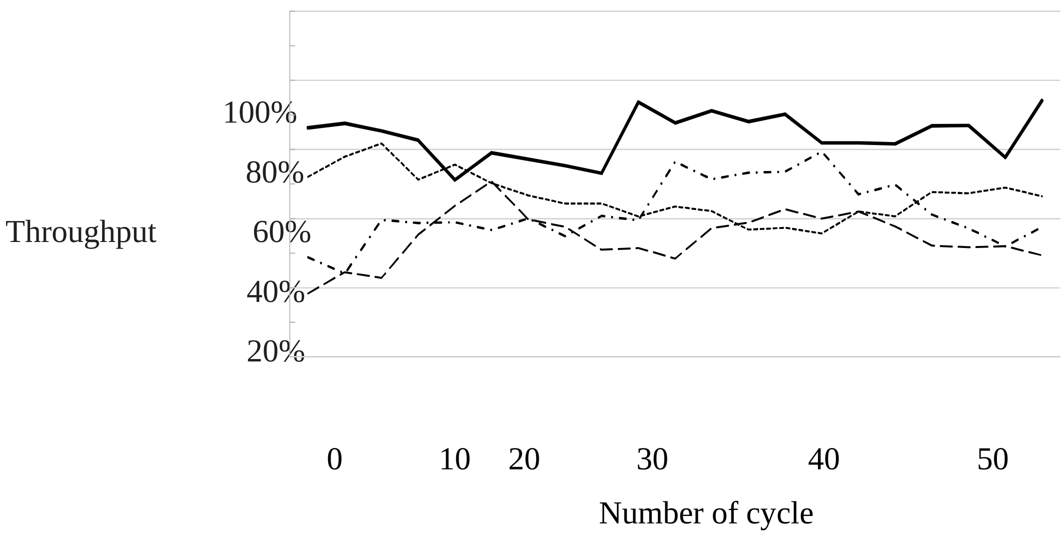
Supervised learning based-modeling and optimization

The updating method depends on the type of algorithm. For supervised learning, it uses S as the training data, and for unsupervised learning, it uses S for clustering or dimension reduction.



cognitive cycle using machine learning method.

Improvement in throughput relative to the received signal strength indicator or RSSI over time for each algorithm is shown here:



V.Wireless system optimization as an MAB problem

The MAB problem is a simple machine learning problem in which a player attempts to obtain the maximum reward from multiple slot machines. The aim of the MAB is to decide which slot machine should be selected to obtain the maximum reward through finite trials. The assumption is that the player does not have any prior information on each slot machine. The player starts to gather information on each slot machine by trying as many slot machines as possible. Then, the player estimates which slot machine has the highest expected reward and selects that slot machine to play. Through this process, the player gets more rewards. There is a trade-off between exploitation and exploration. If the player takes a long time for estimation, the player can estimate the reward more precisely, although the time for playing the selected slot machine becomes short. If the player takes only a short time for estimation, the player can take a long time to play the selected slot machine, although the reward of that slot machine might be low. Figure below shows the concept of the optimal decision making for the MAB problem in wireless communication systems.

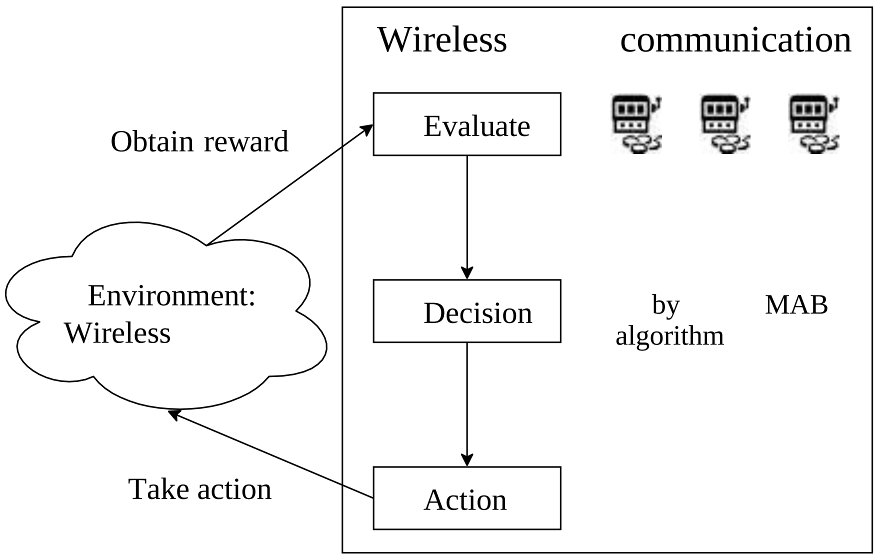
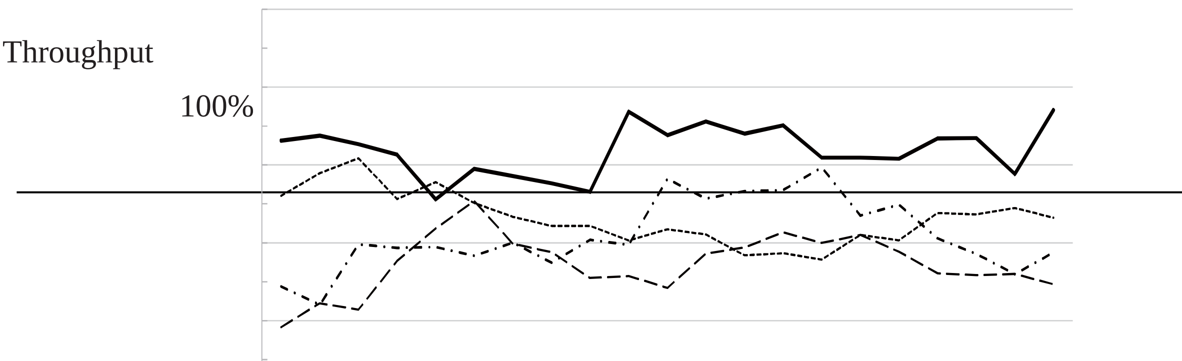


Fig: Simple reinforcement learning(MAB)



80%
60%
40%
20%
0
10 20 30 40 50
No of cycles

Several studies have investigated wireless network selection at the mobile terminal. Most of them require considerable information of networks or computational capacity. However, it is not always possible for mobile devices to gather information from all networks or to spare battery re- sources for complex calculations. It is important for the heterogeneous network selection to seek the best solution as much as and as fast as possible using the limited information about the networks. Simultaneously, it is also important for mobile devices to suppress the complexity of calculations for making decisions. These constraints and requirements are similar to those in the MAB problem. In the MAB problem, a player of slot machines attempts to obtain the maximum reward through finite trials. Therefore, the MAB problem approach can help in heterogeneous network selection.

The major challenges in the selection of wireless networks at mobile terminals in heterogeneous environments are as follows.

- Efficient decisions must be made under the situation in which a small amount of informationregarding each network is available.
- A practical algorithm that can be implemented on resource-constraint mobile devices is required.

VI.CONCLUSION:

Advancements in wireless communication technologies have led to enormous positive changes globally. Along with this, wireless systems have become increasingly complex, not only in a sin- gle communication node, but also as a communication system. From the viewpoint of exploiting its capability, two simple questions rise. One question is how to build models for complex wireless sys- tems of the present and the future. Another is how to decide optimal action using models of wireless communication systems.

A classical mathematical formulation-based optimization scheme cannot be applied to today's com- plex wireless communication systems because the complexity of the systems prevents building math- ematical models. It opens the window for applications of machine learning technologies to optimize the performance of wireless communication systems. Data-driven modelling, by machine learning, is an aid for these issues. Deep reinforcement learning, which combines deep learning-based modelling with reinforcement learning-based decision making for action, is a state-of-the-art scheme in recent research fields. Various studies have applied it in the field of wireless communication. However, there still exist future works to be focused on. One of the proposed schemes is supervised learning based modelling and optimization. It uses a certain amount of information to build a model of the wireless communication system and obtain optimal parameters using an optimization algorithm. This is based on a cognitive cycle using machine learning. It uses a supervised machine learning algorithm to build the performance model of the systems.

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