ARTIFICIAL INTELLIGENCE FOR PLACE-TIME CONVOLVED WIRELESS COMMUNICATION NETWORKS

Ambuj Kumar,
Aarhus University, Herning, Denmark,
ambuj@btech.au.dk

Abstract – Previous works have brought to light that the dynamic and variable motions of potential network users, and other environmental factors, are the eternal threat to present and future wireless communications. One of my earlier works discusses this perennial and perpetual challenge as the place-time dependent functions. The phenomena was coined in my work as place time capacity (PTC), and place time coverage (PTCo), with both collectively known as place time coverage and capacity (PTC^2), are derived as the outcomes of dynamics that can be expressed as the functions of place and time. These phenomena degrade the efficiency of any wireless communication network (WCN) to that lowest point, from where, a network service provider (NSP) may not have any choice but to revamp the network. Artificial intelligence (AI), on the other hand, has been striding profoundly for the past several decades, fanning out its influence in various sectors of scientific and technological developments. However, AI is almost absent in the area of WCN dimensioning and optimization, especially for place–time events. This paper revisits the two place-time functions as WCN phenomena and, with the backdrop of these aspects, shall investigate the inevitable need for AI in WCNs, as well as demonstrating how AI can be part of present and future wireless communications.

Keywords – Artificial intelligence, dynamic path loss, network planning and dimensioning, place time capacity, place time coverage

1. INTRODUCTION

Network planning, dimensioning, and deployment are the processes that assure that any geographical area, where a certain amount of network users is expected, must be catered for in such a way that 'almost' every location in the region has a sufficient level of signal strength with a minimum assured capacity. Such kind of geographical area is defined as the 'Area of Interest' (AoI) in my previous works in [1] and in the PhD dissertation [2]. These processes are accomplished by suitably deciding the proper locations of the network sites[1], and then, installing the necessary equipment with the appropriate configuration (see Fig. 4).

Existing WCNs are very unlike their predecessors. It is expected that there will be more than 5 billion devices [3] by the year 2020, and this estimate greatly differs from what it was 40 years ago. As per ITU's document, about 80% of the youth population in more than 100 countries is online [4]. Modern wireless communication devices fall into the categories of high-power high-data-rate, low-power high-data-rate, and low-power low-data-rate [5]. These mixed characteristics of devices correspond to the type of user that holds them, and the nature of their use. Additionally, these devices can coexist in a single AoI, making things complicated for the NSPs.

It has been observed that, however well planned and deployed the WCNs are, there is always an ongoing demand for new sites, network upgrades, or even network revamps to deal with network users' needs. Many times these network upgrades are not due to any change in communication technology, such as 5th Generation [5] at our doorstep, or to repair equipment, but to accommodate a perpetual and ever-increasing challenge of an "ostentatious nature" [2] of the wireless communication environment, the PTC^2. In section 2, these phenomena will be discussed in detail, where it will be seen why this is most threatening for past, present, and future WCNs. Section 3 relates PTC^2 challenge to the problems in static network planning and dimensioning. Several attempts have been made to cater for this problem [2]. As we know, artificial intelligence (AI) is a technology that involves computational machines in learning a subject and

[1] A physical geographical location where the network base stations, along with necessary equipment, are installed to illuminate the surrounding area with necessary resources.

generating suitable actions for both predicted and unpredicted relevant challenges [6].
This problem has been attempted in this paper, and later, it shall be seen how AI can be an inevitable stairway to attain this seemingly impossible cliff. Section 4 reflects the need (influence) of artificial intelligence (AI) on the place and time events.

2. BACKDROP: OSTENTANEITY OF AN EVENT

Before we get into the broader discussions, let us take a moment to understand the background of why things are not as simple as they seem.

2.1. Unostentatious Events

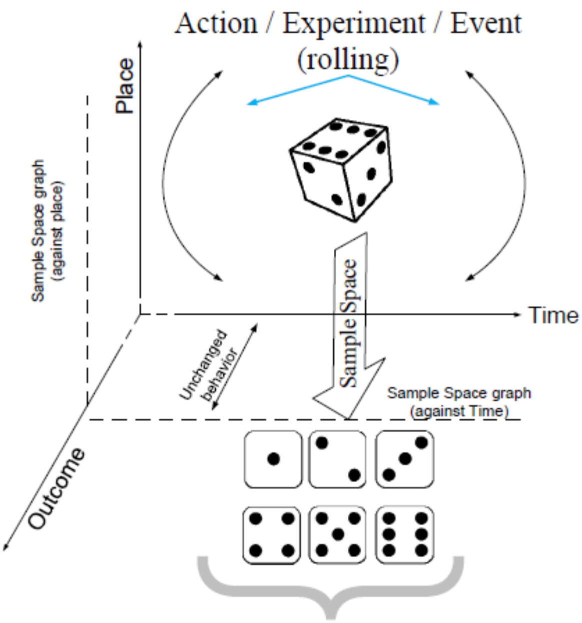


Fig. 1. Unostentatious Event

An 'Event', by definition in mathematics, is an experiment, process, or action that generates some measurable outcome. Fig. 1 shows a conventional die, which produces one of the six results when rolled on a flat surface, and when sample space is plotted against place and time, the graph is linear.
This indicates that no matter how many times we roll a die (on a flat surface), and anywhere across space, we always have a probability of 1/6 for every outcome [7]. Such events, where the behavior remains unchanged with time and place, are defined as an *Unostentatious Event* (UE) in our work in [2]. UEs, as illustrated in [2], are "*Events whose probabilities of all outcomes, or sample space, remain unchanged no matter at what places and at what times the event takes place.*"

Most, but not all, simple events are unostentatious and show the same or similar behavior at different places and/or different times.

2.2. Place-Time Events

In Fig. 2, we revisit the famous Schrodinger's cat example [8], except with a change, where this time the cage is a large walled circular park and nuclear radiation is somewhere within the contour of the park. In this example, as we can imagine, the probability of having the cat alive is not ½ (50%) all the time, and its likelihood is distributed across place and time. The death of the cat is directly proportional to its closeness to the radiation and the time it spends in the park at a particular position.
In our previous work [2], we have defined such events as the *Place-Time Events (PTE)s, whose one or more outcomes depend on at what time and at what position the incidence took place.* This means that an event can have different probabilities of outcomes at various times, while being at the same location. The vice-versa of this, however, is not true, as whenever the position changes, there is always some lapse in time.
By the term 'time', we mean both kinds of time, (i) ***absolute time***, saying the length of time for which the process is ongoing, and (ii) the ***event time***, indicating the time at which the event happened. As an example, I drove a car for 2 hours, is the absolute time, and I parked my car at 10:30 am, is the event time.
Nonetheless, in the present example, the probability of an outcome is definite concerning place and time, meaning that if the position of the cat and the time it spends at that location are known, we can determine the probability of the cat being dead or alive. Hence, this is a *partially unostentatious event*, as we see how the system behaves, and place and time are convolved with each other.

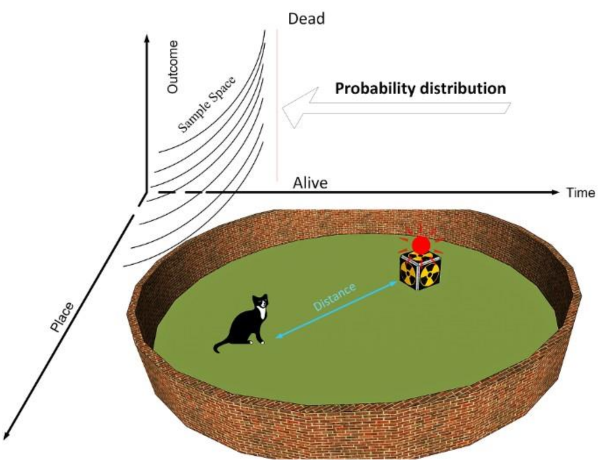


Fig. 2: Example of a place-time event: Schrodinger's thought experiment.

Such probabilities are also defined as the entangled probability in our previous work [2], if the experiment is performed at the same positions, dissipating the same length of time, but at different times, the probabilities of the outcomes are congruent. It is only the *absolute time* that matters and not the *event time*. In subsection 2.3, we discuss a phenomenon, where the probability is almost unpredictable. The discussion shall set a base for further investigations.

2.3. Ostentatious Events

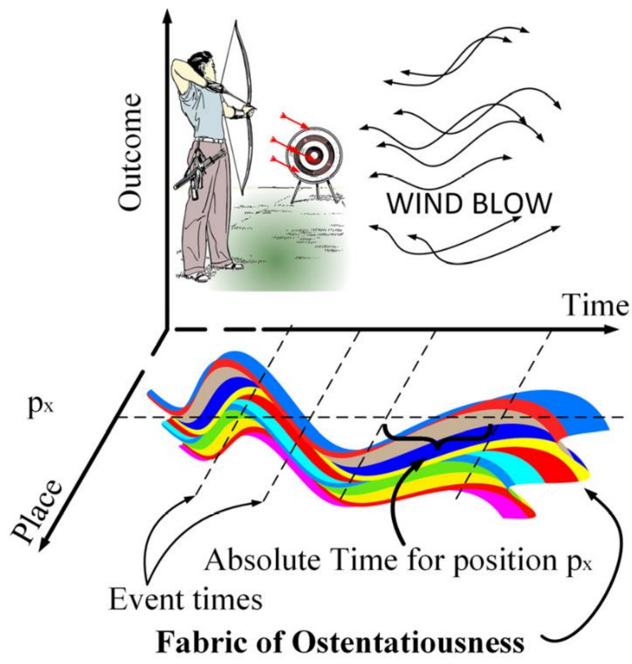


Fig. 3. Ostentatiousness of an event: An archer trying to meet bullseye in a windy field.

Let us examine the situation as illustrated in Fig. 3, where an archer targets a bullseye in an open and windy ground. Since the flow, thrust and direction of the wind are abrupt and unpredictable, the probability of releasing an arrow and the likelihood of hitting the target (bullseye) are not congruent. The situation is purely random and cannot be expressed by any probability distribution function (PDF) and can only be measured when the event occurs. The uncertainty in outcomes is due to varying air pressure hitting an arrow differently at different times, and, at different positions across a 3-dimensional space. This is an example of an **Ostentatious Event**, which we have defined in our work in [2] as "*Those place time events, whose one or more outcomes (sample space) are not interdigitated with either of place or time.*" This means that outcomes shall show different probabilities at the same place and at different times, and therefore depend on both *absolute and event time*.

If we plot the outcomes of an ostentatious event against position and time, we have a graph (see, Fig. 3) that is defined as ***Fabric of Ostentatiousness***. Thus, for an ostentatious event, the probability of an outcome changes with position (place) and time. In Fig. 2, the graph is indicative, to show how the probability of 'the cat is alive' (or 'the cat is dead') varies with the position (distance) and time it spends. The ostentatious events here are defined as the ***Absolute Place Time Events*** (APE).

From the arguments above, it can be made out that the outcomes of an ostentatious event can have different probabilities of outcomes that are completely uncorrelated with each other.

2.4. Appropriateness of APE

The discussions so far might show familiarity with other previous works of probabilities [9], or space-time theories [10], etc. However, there is a big difference, and that is why the word '*Ostentatious*' was used to segregate this perspective from others. While in other cases, the probabilities are continuous/ continuum and may be described by the appropriate probability density functions, in this case, the events have entirely random outcomes.

It is essential to mention the three definitions, especially the ostentatiousness, to understand the challenges that are going to be discussed in the next section of this paper.

3. PLACE TIME COVERAGE AND CAPACITY: NSP's DUO ORDEAL

Can a WCN environment be ostentatious? Moreover, what does it mean by being ostentatious for any WCN? This section elaborates to answer these questions.

3.1. Understanding the network environment

In the previous section, the defined ostentatious events were introduced, the phenomena that have outcomes dependent on place and time. Apropos to which, assume that an area that has a complex morphology of dense urban, urban, rural, vegetation, etc., as shown in Fig. 4. The example in this figure, which is an area, also mentioned earlier as AoI, is a typical example of an NSP, which is trying to cater for this AoI with a certain amount of network sites. It can be seen in Fig. 4, that like any topology, this area also has almost all kinds of environments, namely Dense Urban (DU), Urban (U), Sub-Urban (SU), Rural (RU), Vegetation (VE), and water bodies (WB). Such a scenario can be found in any metropolitan to medium cities across the world; Paris is one of such example, which embraces Dense

Urban surroundings of the Eiffel Tower, River Seine, and vegetation spots like Parc Floral, etc.

What is important here is to see that the density and property of network sites are dependent on their location in AoI. The sites in DU and U are tightly packed, may be of less height, low transmit powers, etc., whereas, those located in SU and RU are taller and have higher transmit power. Some are umbrella sites that just have a purpose of catering for highways and dense vegetation, which have lower carriers and highest transmit power.

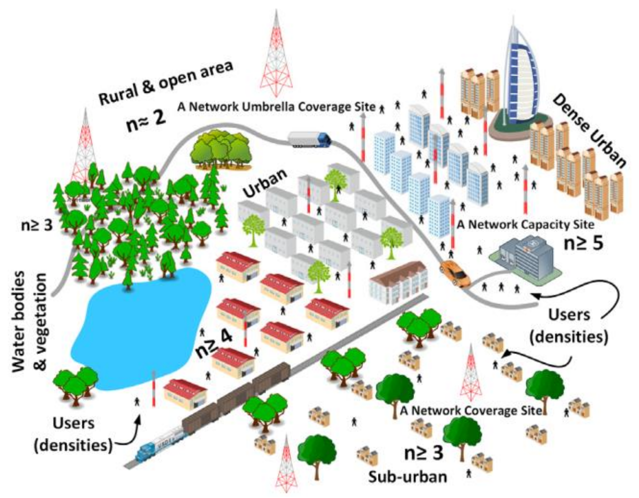


Fig. 4. A complex network environment

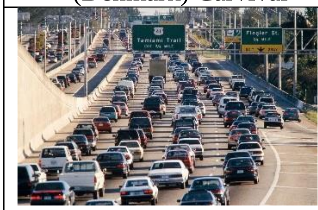
Here, 'n' is the **Path Loss Exponent** (PLE), which is the numerical representation of the 'area type' between Tx and Rx. For example, if the area between Tx and Rx is open, then 'n' takes the value of 2 and similarly, n=3 for urban, n=4 for high dense urban, and likewise. Table 1 in [11] describes characteristics of different physical operating environments that determine the values of 'n' corresponding to the different area types. Therefore, while planning the number of Tx sites required to cover an area (also termed as target area), an NSP can have an estimate of the density of sites by identifying the area type. This means that once the area type is known, how quickly a signal dissipates in the target area while moving away from Tx can be calculated, which eventually, evaluates the site density. The argument behind these different configurations is the way network planning and deployment is approached. Usually, a network is planned based on the probability of finding users in a particular location within AoI. The likelihood of more users, means more resources, thereby, causing higher demand for network sites in a unit area. Another reason for the different site density at various locations in AoI is the ease with which the electromagnetic wave (EMW) propagates through the medium. The EMWs from multiple transmitters around nearby areas have chances of finding a material, in forms of concrete, metals, plastics, glass, trees, rock, water, etc. These may be parts of topology or human-made structures, which may absorb, reflect, and/or diffract the EMW more profoundly than when material was absent. The absorption of signal leads to drop in the signal strength in the following path, and the reflections causes EMWs to divert from its designated path and break down into multiple signals in various other directions, which interacts with other EMWs creating interference at the point of intersection, thereby decreasing the signal strength. In DU and U, these two conjunctures are much more significant than other area types. In vegetation, the absorption is higher than reflections. The configuration, position, and the number of network sites immensely relates with the subscribers' distributions and propagation behavior. As mostly the subscriber densities are proportional to the area type, for example, DU has most users (network subscribers) available at most of the time, and likewise, comes DU, SU, RU, etc., the planning and deployment of network site distribution becomes easier.

Keeping the users distribution and area type, an NSP deploys a WCN; nevertheless, how long an appropriate network deployment can withstand, is the question we take up in next subsection.

3.2. The NSP's nightmare: Ostentations network behavior

(a) Aalborg City (Denmark) Carvival[2]

(b) Greek Open air theatre[3]



(c) Traffic Jam[4]

(d) Heavy Sale during Thanksgiving in Burbank, California[5]

Fig. 5. Unprecedented accumulation of people/ users

[2] Source: https://imgur.com/gallery/WMOMa
[3] Source: https://cbsla.files.wordpress.com
[4] Source: https://www.zmescience.com
[5] Source: https://www.nbcnews.com

In reference to the above discussions, let us assume the following:

- There is a network under consideration,
- there are 'u' users (subscribers) in the network,
- there are 's' sites in the network,
- the 'j^{th}' user is served by 'k^{th}' site,
- the users have instantaneous capacity, demand (or, throughput demand),
- the capacity demand function, in terms of bits per second of j^{th} user, is defined as bj(t),
- all users are dynamic in position and time,
- the velocity and position of jth user at any time 't' is defined as $v_j(t)$ and $p_j(t)$, which is the velocity and position function of user 'j'.

Let it be assumed that the j^{th} user, was the one staying at point 'P', decides to move within the network to reach point 'Q'. In this case, wherever the user j is moving, it is raising an additional demand at the location. Then, all the problems that were once associated with point P are now progressing to point Q. Each time a person or group of people move to a new place, an additional resource demand is created, which keeps on shifting from point to point, as the person or group moves. Thus, the locus of the path that a person or group moves, creates a demand curve in the network area.

Pictures in Fig. 5 show that there can be '**triggers**', such as music concerts, carnivals, market sale, etc., that compel or motivate users to accumulate and move in groups at unprecedented locations and at unforeseen times. The more populated the AoI is the more chances there are of such random wobbles of accumulations.

These uncertainties give rise to dubiousness in capacity and coverage of a network, discussed below.

3.3. Place Time Coverage

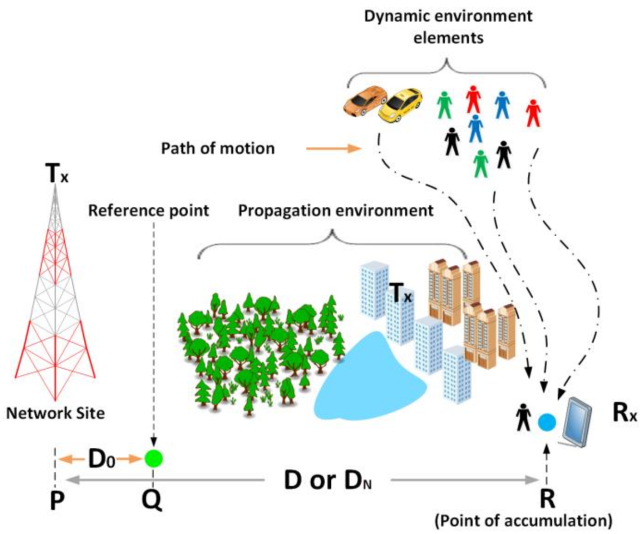


Fig. 6. Place time coverage; dynamic path loss model

As shown in Fig. 6, let us consider a scenario in which, a Transmitter (Tx) at position P and a Receiver (Rx) at position R are separated by a distance 'D', and, there exists a point Q between P and R, such that PQ is a free space. Then, to the Friis Model, the transmit and receive signal power relation can be expressed by [12]:

$$\frac{P_r}{P_t} = G_t G_r \left(\frac{\lambda}{4\pi D_0}\right)^2 \tag{1}$$

Where,

- P_t is the transmit power of the network site,
- P_r is the receive signal power at Q by the receiver,
- G_t is the transmit antenna gain,
- G_r is the receiver antenna gain,
- λ is the wavelength of the carrier in use,
- D_0 is the distance between P and Q,

Considering the antenna gains as unity, that is, $G_t = G_r = 1$, equation 1 yields free space Path Loss Model (PLM), given as [12]:

$$PL_{fs}(D_0) = \frac{P_r}{P_t} = \left(\frac{\lambda}{4\pi D_0}\right)^2 \tag{2}$$

The decibel format of equation 2 can be obtained as:

$$PL_{fsdB}(D_0) = 10\log_{10}(PL_{fs}(D_0)), \text{ or}$$
$$PL_{fsdB}(D_0) = 10log_{10}\left\{\left(\frac{\lambda}{4\pi D_0}\right)^2\right\} \tag{3}$$

The path loss experienced at point R, at a distance D from P, can be obtained in relation to the free space path loss at D_0, using the well-known path loss equation [12], mentioned below as:

$$PL(D) = PL(D_0) + 10log_{10}\left(\frac{D}{D_0}\right)^n . \tag{4}$$

As we can see, from equation 1, the received signal strength at a certain distance 'd' from Tx is primarily influenced by the path loss exponent 'n'.

Now, let us assume that a person from somewhere reaches point P and stands between Tx and Rx path (see, Fig. 6). In such a case, the path loss will not be the same as what is given in equation 1. Likewise, if more people surround Rx, there will be subsequent drops in the receive signal value. If an NSP decides to deploy a mobile WCN using standard path loss models, then the deployed network ought to fail in such conditions.

The new value of PLE can be expressed as:

$$n_{var} = n + N_{AR} \tag{5}$$

Where ‘n_{var}’ is the varying path loss, ‘n’ is the original PLE, and N_{AR} is the ostentatious PLE, which is the place-time factor of the path loss. The PLM in equation 4 can now be modified as:

$$PL_{dyn}(D) = PL(D_0) + 10log_{10}\left(\frac{D}{D_0}\right)^{n_{var}} \quad (6)$$

putting n_{var} in equation (5), we have,

$$PL_{dyn}(D) = PL(D_0) + 10log_{10}\left(\frac{D}{D_0}\right)^{n+N_{AR}} \quad (7)$$

expanding (7) we have,

$$PL_{dyn}(D) = PL(D_0) + 10log_{10}\left(\frac{D}{D_0}\right)^{n} + 10log_{10}\left(\frac{D}{D_0}\right)^{N_{AR}} \ldots\ldots\ldots \quad (8)$$

from (4) and (8), we have,

$$PL_{dyn}(D) = PL(D) + 10log_{10}\left(\frac{D}{D_0}\right)^{N_{AR}} \quad (9)$$

Differentiating both sides with time, we have

$$PL'_{dyn}(D) = PL'(D) + (N'_{AR})10log_{10}\left(\frac{D}{D_0}\right) \quad (10)$$

From previous discussions, we understand that $PL(D)$, and $10log_{10}\left(\frac{D}{D_0}\right)$ are constants; therefore,

$$PL'_{dyn}(D) = (N'_{AR})10log_{10}\left(\frac{D}{D_0}\right) \quad (11)$$

This indicates that with the change in the number of people, the environment’s characteristics have also changed. An environment, which might have been ‘rural’ has now become pseudo suburban, or urban. Hence, the rate of change of PLM is now no more constant and depends on how N_{AR} incorporates user dynamics with time. The same equations can be expressed with the position. This dynamic path loss model is presented as PL_{dyn} which, apart from all previous parameters, considers another factor, N_{AR}, which is defined as ***Augmented Repercussive Exponent*** in [2]. The PL_{dyn} can accommodate any factor that may affect EMW propagation.

From the above discussion, it can be said that Pl_{dyn} can have variable values at the same or different locations. As the PLMs decide the number of sites needed to illuminate an area, the PL_{dyn} changes the paradigm by creating a perpetual variation in demand at different places, at different times. This kind of variable demand in network coverage is defined as the ***Place Time Coverage*** (PTCo) [2].

3.4. Place Time Capacity

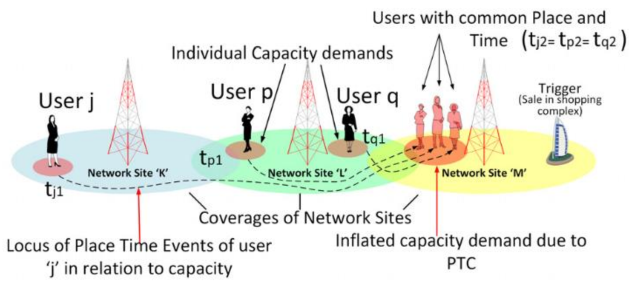


Fig. 7. Place time capacity

Considering Fig. 7, let us assume that j^{th} user, with a throughput demand of b_j, is standing at a position p_j. Then, accordingly, we can define a function that maps throughput with a position at any instant of time as:

$$iPTC(t) = p_j(t)b_j(t) \quad (12)$$

Where iPTC is termed as the “*Instantaneous Place Time Capacity (iPTC)*” in [2].

If we assume that user ‘j’ has traversed a path during the time interval (t_{j1}, t_{j2}), then, integrating (12) with respect to time for the range (t_{j1}, t_{j2}), we have

$$\int_{tj1}^{tj2} iPTC\, dt = \int_{tj1}^{tj2} p_j(t)b_j(t)\, dt \quad (13)$$

Applying integration by parts on RHS, we have,

$$RHS = p_j \int_{tj1}^{tj2} b_j dt - \int_{tj1}^{tj2} \left(\frac{dp_j}{dt} \int b_j dt\right) dt \quad (14)$$

Since, $p_j(t)$ is position function, differentiating it with time will give velocity function for user j, which, as mentioned earlier, is $V_j(t)$. Further, as we know that $b_j(t)$ is data rate in bits per second (bps), integrating it with time will give us the data volume, $D_j(t)$, which is generated during the time interval (t_{j1}, t_{j2}). Therefore, accommodating these points in (14), and equating LHS=RHS in (13) and (14), we have,

$$\int_{tj1}^{tj2} iPTC\, dt = p_j D_j(t)|_{tj1}^{tj2} - \int_{tj1}^{tj2} v_j\, D_j dt \quad (15)$$

iPTC, when integrates over a time interval, yields the place time capacity (PTC) demand generated during the given time interval. Therefore, equation (15) can be rewritten as,

$$PTC|_{tj1}^{tj2} = p_j D_j(t)|_{tj1}^{tj2} - \int_{tj1}^{tj2} v_j\, D_j dt \quad (16)$$

Equation 16 clearly indicates the ostentatiousness of a network with user dynamics. The first term on the RHS of equation 16 shows that user j has raised a demand to cater a volume of data Dj, while being at position p_j and, the second term shows the aggregation of data volumes while in motion. We can extend equation (16) for other individual users and groups (see Fig. 7). We can also see that in Fig. 7 that each user creates its own locus of PTC demand, which is an equivalent to the requirement of additional resources.

3.5. PTC^2: Need of unorthodox approach

There are a variety of ways and complexities to identify and define PTC and PTCo, and the discussions in subsections 3.3 and 3.4 are confined to fewer parameters. Nonetheless, as both PTC and PTCo depend on dynamics within the network area, they usually complement each other. We have combined them with the common definition of place time coverage and capacity, or PTC^2 [2] to indicate their correlation.

From our previous discussions, we can conclude that the PTC^2, being an aggregation of the dynamic behaviors of all users in a network, cannot be handled by conventional network planning and deployment. We need 'intelligence' to understand its behavior. In the next and final section of this paper, how artificial intelligence can handle this challenge is elaborated.

4. DEALING WITH PTC^2 'ARTIFICIAL INTELLIGENTLY'

Despite efficient network planning and volumes of investments in optimization, and revamping of networks, WCNs are not able to get rid of PTC^2, and it is an eternal and perpetual phenomenon. With future demand on more throughput, humongous user mobilities, and many more devices, with the latest being the Internet of things (IoT), the PTC^2 is undoubtedly a significant worry. The increasing user densities and convenient but powerful handheld devices increase the chances of frequent and severe wobbles of accumulations and movements in groups, which is undoubtedly going to hurt more. As WCNs are planned based on some specific user distributions, the cushion for users roaming into a site is very narrow, which often leads to network congestion. If the problem is itinerant and clandestine, the only way out is to handle it 'intelligently'. Involvement of machines to perform intelligent tasks is even better; as then, the system is more robust and accurate. This leads us to propose the percolation of artificial intelligence (AI) in the WCN system. Later sections shall elaborate this scope.

4.1. AI-Assisted Architecture

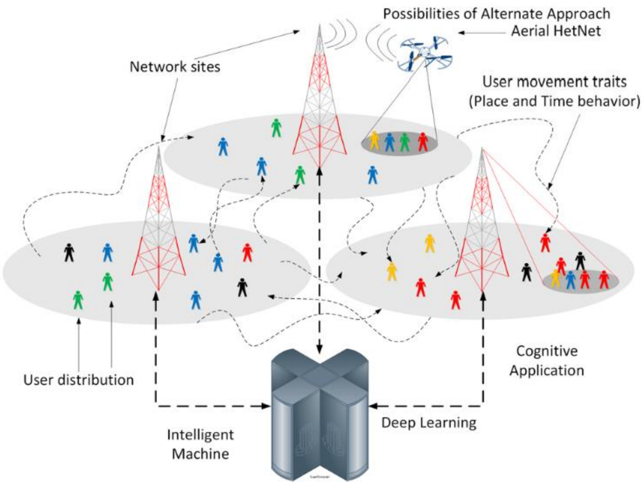


Fig. 8. AI-Assisted Architecture

Fig. 8 shows an AI-Assisted Architecture (AAA) that is found potent to handle the ostentatious network behavior. AAA is expected to have the following components:

- an efficient machine that has sufficient capacity to control large data and functions;
- the set of deep learning and cognitive response algorithms to iteratively configure and drive the network according to the contentiousness of the system;
- an AI-assisted network, means all the network equipment are controlled by the AI machine.

4.2. How should AAA respond to the PTC^2?

The functioning of AAA is discussed below.

4.2.1. Information aggregation

It is expected that both the base stations network and core network be connected with the common AI platform handled by the AI machine. In this way, the change in the environmental characteristics and user wobbles that are sensed by the on-site base stations can be sent to the central computer to learn the environment user behaviors. This is to be noted that environment and user behavior are distinct functions. An environment can be varied by a change in the material composition, which changes the dielectric property of the environment, and therefore, is purely a coverage issue (PTCo). Whereas the accumulation of users is both a coverage (change in material dielectric) and capacity (change in the count of user devices) issue. Both these changes can be sensed by an intelligent antenna system and advanced base stations. We have discussed once such kind of smart network system in our work [2].

4.2.2. Deep Learning

Although the PTC[2] wobbles may seem random, they are not entirely so. If it is observed, most of the severe wobbles are triggered by some periodic events, like carnivals and festivals, and so on. It is proposed that this part is to be done by the deep learning algorithms. Such algorithms can precisely identify the locations and many of wobbles, if not all of them, then at least many of them. Also, with efficient deep learning algorithms, the system can identify where the groups of potential users are heading to. Therefore, we have to involve capable machines that can aggregate all the information and process it in a single time to identify the possibilities of accumulations and the additional resource requirement. The predictions, however, can be modified or regenerated iteratively by continuously processing the network information and learning the network.

4.2.3. Disseminating actions

Once the system knows the probable problematic locations, the AI machine can allocate the new configuration of the network, which can be observed by the connected smart equipment, such as smart antennas, and intelligent BSs.

It is to be noted that a WCN is a closed system. This means that even though things are dynamic in the system, there is a marginal change in the number of users. Hence, the reconfiguration of the network may require the shifting of carrier channel from one base station to another and down-tilting the antennas to confine resources (see Fig. 8). However, many times the accumulation is so severe that even the shifting of resources does not solve the problem. In such cases an AAA system can also use the on-demand basis of spectrum allocation to have the time-based additional spectrum to cater enormous accumulations, as shown in Fig. 5.

4.2.4. Integrating Alternate Solutions

Several research works are being done to cater users through alternative ways. The most promising and looked upon solution is using unmanned aerial vehicles, aka drones, instead of using ground-fixed structures for mounting base stations (BS) [13], Purnima et al. proposed Aerial Hetnet that follows moving crowds.

AI can also play a primary role in integrating such alternate solutions to work in coordination with the prime network to offload the additional resource demand.

A lot of work is required to be done in this regard. Active and smart networks, deep learning, cognitive algorithms, etc., are some of the many areas to be worked on. Nonetheless, it must be said that AI is an inevitable paradigm that is yet, but very soon to, come full-fledged.

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