A Quantum Twin Brain Storm Optimization for Fog Computing in 5G

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Abstract. This paper presents a novel quantum-paired brainstorm-optimized content-driven network-based fog computing in 5G environment. This pesticide detection application driven resource allocator makes a decision based on the center quality parameters obtained instantaneously from the online calculation application network, which in turn depends on the instantaneous mobile speed interaction with the wireless edge service performance parameters. These parameters of the hit rate, packet loss, round trip time, radio signal strength, bandwidth, and data cost and vehicle speed are typically different from location to location. We use a quantum state brain storm optimization to guide the fundamental resource allocator for mode selection within 5G fog networks that are mixed with the normal and super speed optimization of the fog computing in 5G paradise. Simulations are conducted for the proof of the concept.

1 Introduction

Application content driven networking is about management [1] and operation of your network based on the applications actual contents that are utilizing your network. For different application content, the different part of the network resource is waked up to serve the request. It deals with the QoS and almost personalized policies you dictate over the network, to the point a decision has to be made, for example: if the particular end user fluid pesticide application content request can be served by a fixed edge computing network; if not, then trying to get the pesticide detection answer from the mobile edge computing network; if still not, then more on to fixed or mobile cloud computing, finally if all above is not satisfying the end user, we use fog computing in fixed core network or 5G network environment[2].

And the software defined networking is about more flexibility[3] and manageability in your networking, by having software run the underlying hardware and hence abstracting lower level details from the user or a network administrator.[4][5] This allows you to make your network dynamic and adaptable, and hence providing a scope for more automation. It is needed to support the application content driven networking. Here is an example of potential future usage scenario.

A medical company for fast health service usually has to maintain a team of service APP back end on the server, each of which mobile end user is equipped with a mobile scanner that keeps track of the foods quality. The biochemical sensors are on mobile phone, but the phone does not have enough power to complete the complicated calculation, for say, pesticide detection, as such, a nearby fog computing node will be needed to help on do the analysis. The challenges remain to maximize the throughput of the uploading the sensor information, while the user is going through the random route.

There is a security problem when a cheap broken node may allow the attacker to easily obtain information on personal transaction. To minimize this risk; we need a solid and smart algorithm to continuously monitor the overall quality of each network. To handle the economical dilemma, we also need to further improve the performance of the system of sensors by combining the access methods of fixed WiFi or roaming base station. We would like to design a smart mobile algorithm using the latest evolutional computation algorithm to maximize the secured throughput, but with the minimum cost between the 5G networks. To achieve this, we look to the implementation using fog computing with essentially 4 modes: D2D mode [6], which is just device to device, local distributed mode and global center mode, which goes through the modern front haul interface, and the high power mode, which goes through the traditional backhaul interface [7].

Starting as an approach to computer networking [8] a few years ago, fog computing allows network administrators to manage network applications through the abstraction of lower layer functionalities. A communication system in general has two planes and many layers: a control plane that can make decision where traffic is sent, and the data plane that can forward individual user traffic to the selected destination. The fog computing node has to be coupled with the control plane in a system from the data plane in the underlying
systems, due to that the application content may or may not inside the cache server, it will affect which server the user will actually talk to. A cache server is a dedicated network server or service acting as a server that saves Web pages or other Internet content locally. By placing previously requested information in temporary storage, or cache, a cache server both speeds up access to data and reduces demand on an enterprise's bandwidth. However, it will make the control plane more complicated. To simplify the situation, we have divided the locations into three situations, school zone fog, residential zone fog and industry zone fog. Since the school zone users are mainly teachers and students, the application contents will not vary too much from day to day or month to month. However, the residential zone users are from all walks of life, the application contents are varying widely, and may not repeat themselves at all. For the industry zone users, the contents will change but not rapidly, and the user data usually is huge and cannot tolerate the delay, as it is a business. As the contents can be statistical or dynamical, we will use the different optimization method to deal with it. We further employ the paired twin brain storm algorithm to optimize the Fog Computing in 5G solution.

2 A Brain Storm Optimization driven for Fluid Pesticide Calculation Allocation

To minimize the data delay encountered during the pesticide residual detection operation, both the fog system and cloud system have to be seamlessly connected; such that the summation of both providing fast and secure throughput. As the user starts or stops there will be a WiFi connection to the office, as the user moves on the road, there will be 5G services along the road. Note that during the normal driving period, the pre-process or post-process pesticide data is small, while during the start or stop time, where sensor data, picture and certificate signature are collected, the data is relatively large and sensitive; we thus need the fog computing node to switch in between.

Typical wireless performance is determined by looking at the center Going Down (GD) parameter, GD can be a function of a number of measured parameters, such as the hit rate, packet loss, round trip time, radio signal strength, bandwidth, data cost and vehicle speed, etc. Each of these parameters has a relationship to the location environment relative to the base station or access point. Take the most used parameter, Hit Rate, The percentage of accesses that result in cache hits is known as the hit rate or hit ratio of the cache. The alternative situation, when the cache is consulted and found not to contain data with the desired tag, has become known as a cache miss. Radio Signal Strength Indicator (RSSI) is another example, the relationship is not linear with respect to the transmitter to receiver distance; and the typical RSSI value for different 5G bands are also very different, since 5G can run at higher microwave bands that rain or even fog may affect the signals and bandwidth. As such, when we trying to combine all parameters into one decision parameter, it becomes highly complicated nonlinear, and slightly random, as the schedule and route can be deviated depends on which fog node holds which contents; the best way to learn this kind of the function is through a highly local customized application driven network, which we call it cluster fog computing in 5G.

A Quantum Twin Brain Storm Optimized resource allocation structure is proposed instead of one kind for all locations, for the following reason: Each measured parameters has its own underline nonlinear functions, which are stemmed from completely different roots, by using the exact the same brain to optimize them is hard. Note that the switch from 5G to WiFi will be different from switch WiFi to 5G at least. A typical pesticide control operation system is shown in Figure 1. The user A is talking to user B through D2D mode, user C is stamping the pesticide certificate through backhaul on high power mode, the user D is on 5G 2.5GHz to check the certificate, the user E is on WiFi reading the pesticide data base, the user F is on 5G 28GHz to check and compare the pesticide reading from the device through front haul centered and distributed modes at the same time, the user G is remotely flying drone to spray pesticide on the field, so on so forth. We need to optimize the mode optimization in such a way, that the decision is optimum for all the potential users.

It is important to note that the resource allocator makes the decision by using a Brain Storm Optimization (BSO) [9] customized Fog Computing in 5G on the current measured parameters. By monitoring the current parameters, we can automatically balancing the delay with location customized system. The algorithm learns how to increase the secured throughput without causing too much extra delays, based on the collected fields’ data like the hit rate.

Due to the different user behaviour for different zone, there is the need to customize the resource allocation methods for the following reasons:
1) The direct calculation model cannot follow the user daily route variation.
2) The prediction model can deal with random events, but may not be good for fairly regular activities.
3) The original brain storm algorithm can cover one zone with one minimum object, we need more.
The method that can handle the above three considerations is the BSO with a quantum method. The Quantum Brain Storm Optimized approach comes from studying of actual quantum entanglement phenomenon, where a status of particle may affect the other almost instantly.

Brain storm optimization (BSO) algorithm is a new and promising swarm intelligence algorithm, which simulates the human brainstorming process. Through the convergent operation and divergent operation, individuals in BSO are grouped and diverged in the search space/objective space, the group is called cluster. Every individual in the BSO algorithm is not only a solution to the problem to be optimized, but also a data point to reveal the landscape characteristics of the problem, in the sense of the data mining. Swarm intelligence and data mining techniques can be combined to produce benefits above and beyond what either method could achieve alone.

BSO is part of the swarm intelligence algorithm, which has two kinds of ability: capability learning and capacity developing. The capacity developing focuses on moving the algorithm’s search to the area(s) where higher search potential may be obtained, while the capability learning focuses on its actual search from the current solution for single point based optimization algorithms and from the current population for population-based swarm intelligence algorithms. The swarm intelligence algorithms with both capability learning and capacity developing can be called as developmental swarm intelligence algorithms.

To extend the developmental capability, we use a twin brain storming process setting, such that two processes are entangled together, forming a quantum bit status, such that if one BSO process is in a local minimum, the others will be not falling in the same spot. In quantum words, the pair is in both spots at the same time. Fairly much like the Schrödinger’s cat was both live and dead at the same time. In this way, we can move the individual in the search space on different directions of different dimensions, both below the speed of light in normal space or above the speed of light in superspace, as the entanglement does.

The contributions of our work are 1) we are the first to find an important class of the brain network that combines the quantum entanglement concept, and that can mimic the twin experience; 2) the application of the method to 5G fog computing mode control application.

The paper is organized as follows. Section II details the model for the mobile mode resource allocator and Section III mathematical models for the Fog Computing in 5G [10] and then shows the simulation results. The last Section is the conclusion and future work.

3 Modelling the Quantum Entanglement Functions for Fog Computing in 5G

The underlying nonlinearities from the mobile location to the center parameters and from the center parameters to the final decision are complicated. There are interactions among the center parameters of server content hit rate, radio signal strength, packet loss, round trip time, available bandwidth, data cost and user speed. Some examples are
- When the hit rate goes down, the radio signal will go down;
- When the radio signal goes down, available bandwidth will go down;
- When the available bandwidth goes down, the packet loss normally goes up then;
- When the packet loss goes up, typically the round trip time will go high as well;
- When the round trip time goes up, the data cost per unit of information may rise up too.

On the other hand, there are cases
- To keep up with the user speed, the data cost follows up as well;
- When the user velocity speeds up, the signal strength goes down.

In another word, the center parameters are all related to each other through some complicated nonlinear relationships. The only easy way to simplify these relationships is to use the twin brain storm application driven network that is meant to capture the multiple nonlinear relationships, in order for us to make a quick decision from the measured field data. By using this method, we are able to capture both 5G and WiFi characteristics at the same time. The non-linear relationships are first summarized below before we present our Qubit BSO algorithm.

3.1 Mathematical Model of Server Content Hit Rate

The principle of SCHR (Server Cache Hit Rate) can be defined by a simple formula (1):

\[
\text{SCHR} = \frac{\text{CaHits}(t)}{\text{ToHits}(t)} \times 100
\]

(1)

Where \( t \) = time frame of observation

\( \text{CaHits} = \text{recorded Hits during time} \ t \)

\( \text{ToHits} = \text{all requests recorded during time} \ t \)

In the long run, the time period \( t \) becomes irrelevant as it’s cancelled out. Also keep in mind that the rate must be less than or equal to 100 as the total amount of requests must be greater than or equal to Cache Hits. For any site, a cache hit ratio of 99% is possible. This depends, however, on the functionalities and design of the website on the origin server. Websites with a lot of user-generated content or more frequent updates may have a lower cache hit ratio. A cache hit ratio below 15% is either poorly configured or not performing properly; the typical value should be around 80%.

As we can see here, just using one kind of brain to memorize three values in a Fog Computing in 5G mode could be difficult.
3.2 Mathematical Model of Radio Signal Strength

The principle of RSSI (Received Signal Strength Indication) ranging describes the relationship between transmitted power and received power of wireless signals, with respect to the distance among the nodes. This can be expressed in eqn. (2)

$$\log(Pr) = \log(Pt) - n\log(d)$$ (2)

Where $Pr$ is the received power; $Pt$ is the transmitted power; $d$ is the distance between the mobile scanner on the vehicle to the base station or the access point; and $n$ is the transmission path factor depending on the propagation environment. Note that the typical value $n$ for 5G is around 2 and for WiFi is around 3.

As we can see here, just using one kind of brain to memorize both values in a Fog Computing in 5G mode could be difficult.

3.3 Mathematical Model for Available Bandwidth

The available bandwidth is given by the following formula:

$$B = C - O$$ (3)

where $B$ is available bandwidth; $O$ is the overhead consumed by the control and management signals or any non-white noise such as the interference; and $C$ is the total channel capacity limit (measured in bits/second) given by the famous Shannon theory under the strictly white noise assumption. That is

$$C = W \times \log (1 + S/N)$$ (4)

where $W$ is the bandwidth in Hz; $S$ is the signal strength in watts across the bandwidth $W$ and $N$ is the noise power in watts across the bandwidth $W$.

For 5G network, Gallium Nitride is used instead of Gallium Arsenide, and thus the noise level is at least 7dB lower than 4G. [11]

3.4 Mathematical Model of User Speed

The model for user vehicle speed is simple, and given by

$$fd = V/\lambda$$ (5)

Where $fd$ is the Doppler frequency spread; $V$ is the vehicular speed; and $\lambda$ is the wireless wave length. In practice, the mobility model is divided into three categories: a) School area where the normal speed is 15 Miles/Hour; b) Residential area where the typical speed is 30 Miles/Hour; and c) Industry area where the speed is 60 Miles/Hour. One can see that using only one type of brain to memorize all the zone values at different speed for different RF frequency could be difficult.

3.5 Mathematical Model for Packet Loss

We cannot obtain a closed formula to describe the packet loss because the queuing system is nonlinear. We can either use numerical calculation or approximation to calculate the packet loss. One approximation is

$$\log(PL) = \log(PO) + m\log(\rho)$$ (6)

Where $PL$ is the current packet loss; $PO$ is the initial packet loss, when the system has no buffer to queue the packet; $\rho$ is the current system load condition; and $m$ is the equivalent buffer size, i.e. the number of average packets that the buffer can hold. Considering the fractal bursty nature of the data traffic, in practical calculation, it could be the number of the biggest packet that the mobile device can handle within the given time limit from the packet source all the way to the final destination. It is again hard to just use homogeneous brains to capture the buffer sizing situation, typical $m$ for edge network is smaller than those in core network.

For fog computing network, the operators will introduce more complicated pricing models (such as charging by the location, by the transmitting power, by the rush hour, or by the hot spot, small cell etc.) in order to recover the cost of customize the network for different user zones. Since the relationship between the cost and the location is nonlinear; using the nonlinear brain network to guide the mode selection is always beneficial.

4 Brain Storm Optimized Network for Decision on Content Identification

In an user application driven network, simple fog nodes, known as "brains", "processing elements" or "nonlinear units", are connected together to form a network which mimics a center cloud server.

There is no single formal definition of what a user application driven network is. However, a class of edge networks may commonly be called "Application driven" if they possess the following characteristics:

1. Consist of sets of adaptive weighted content cache server, i.e. numerical parameters of hit rate that are tuned by a learning algorithm, such as BSO, and Deep Learning.

2. Capable of approximating cloud functions of their input requests, using server to server content borrowing functions, such as the server confederations.

The adaptive weights are conceptually the dynamic distribution of the contents among fog nodes, which are activated during data mining process, such as BSO.

Brain Storm Optimization (BSO) is a computational method that optimizes a problem by iteratively trying to improve a candidate solution, with regard to a given measure of quality. BSO optimizes a problem by having a population of candidate solutions, here dubbed brains, and changing the solutions representing these brains around in the search-space, according to simple clustering strategy over each brain's score obtained, during every
iteration for each round. Each brain’s updating is influenced by its previous iteration known position, but among each round, they are totally independent, in the search-space, this way, to balance the diversity with convergence. This is expected to move the swarm toward the best solutions. BSO is originally attributed to Shi.

During the course of computer simulation the mobile application parameters are as follows: the fluid pesticide is 24D, the standard detection solution is KMnO4 standard and diluted H2SO4. All the chemicals used were of analytical reagent grade, the other agents for Chlorpyrifos detection are CuCl2·2H2O, FeCl3·6H2O, H2O2, ethanol, Ethylene Glycol (EG), Polyethylene glycol (PEG), NaCH2COOH (NaAc), Acetylcholinesterase (AchE), Cholin Oxidase (CHO), acetylcholine chloride (C7H16ClNO2), 3,3,5,5-Tetramethylbenzidine (TMB), citric acid. Deionized water by a Millipore system was used throughout the study. SU-8 photoresist and polydimethyl siloxane (PDMS) were supplied to us by Wenchang Chip Technology Company (Shanghai, China).

All the sending data parameters are normalized for ease of Matlab simulations, i.e. the trained input and output sample data is normalized to accelerate the convergence of application driven network optimization process.

Both brains adopt either traditional normal speed individual or advanced super speed based mapping function. This application driven network has only one output vector scale, contains the 6 decision weights, corresponding to the success rate of each fog node. For BSO mining, the error between the application driven network output, and the expected value from the field testing with the factional error variation acts as the fitness function. The population size is around a hundred, depending on the adaptation from the quantum entanglement interactions of the twin, new individual probability is 0.2, and the initial positions are of zero, the range is +5 to -5. The velocity of the quantum is 0.01%.

The sum of error cubic root has no bottom limit until the application driven network is trained less than 10 iterations. It is shown that the optimization process is convergent in the course of computer simulation. Thus a BSO trained application driven network module is produced to realize the nonlinear mapping relationship between the measured parameters of mobile in the motion system.[12] Figure 2 shows the flow diagram of the algorithm, note that the maximum iteration should be always set to great than 10, the maximum round can be set to as small as 1, the more calculation better statistical accuracy.

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**Figures 2. Quantum brain storm optimization flow diagram.**

The input channel success rate of the trained application content driven network module is fed with the current center parameters, when the system is in motion. The application driven network output is produced by the final balance of the hit rate optimized, with the computer simulation, by the measured channel field data.

During the training period, twin BSO algorithm searches for the best solution, by making brains moving around the search space, according to the resulted qubit position. But when one brain is weighted as the global best brain continuously, the other brains may still searching for the better global minimum repeatedly, which gets the brain storm out of the local optimization. Here is the pseudo code of the algorithm:

1) Initialization
2) Call the fitness subroutine positive and negative
3) If the error goal is met?
4) No: update the brain position
5) If premature?
6) Yes: change the speed, Go back to to 2)
7) No: go back to step 2).
8) Yes: Optimization ends.

Figures 3 to 8 show the results of computer simulation for 6 fog nodes. The application content driven network output tracks the measured output of the resource allocator model closely. The training error is set to less than 0.2%. The simulation is carried out with three different zones, between different combination of Normal and Super space speed. The final average hit rate is plotted versus the twin brain optimization cycles.
From which, we can see that for any zones, the super brain start with more initial values such that less changes to miss any local minimums than the normal brain, that is to say the super brain is more robust in any cases. This is very important observation for the implementation of the algorithm for a number of zones where we would like to have a robust brain structure that can be customized for all situations.
Table 1 shows the parameters used in the simulation, for different zones.

<table>
<thead>
<tr>
<th>Rates</th>
<th>SCHR</th>
<th>RSSI</th>
<th>PL</th>
<th>BW</th>
<th>SPD</th>
<th>Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Home</td>
<td>0.6</td>
<td>0.81</td>
<td>0.95</td>
<td>0.47</td>
<td>0.81</td>
<td>0.84</td>
</tr>
<tr>
<td>School</td>
<td>0.7</td>
<td>0.86</td>
<td>0.95</td>
<td>0.69</td>
<td>0.86</td>
<td>0.82</td>
</tr>
<tr>
<td>Office</td>
<td>0.5</td>
<td>0.76</td>
<td>0.95</td>
<td>0.39</td>
<td>0.77</td>
<td>0.86</td>
</tr>
</tbody>
</table>

From above results, we see that the Quantum Brain Storm Optimized method offers the additional flexibility to fit the complicated control of different situations. Due to its extra nonlinear decision regions, it allows the search to be carried out in the 5G fog domain over 4 different modes, while single function can only fit either one at a time, not all.

Conclusions

The eight equations of a 5G fog for fast pesticide checking logistical user information system, that is controlled by Quantum Brain Storm Optimized Application Network, is obtained in geographical coordinates system, that takes server hit rate, vehicle speed, route, etc. into considerations. A Fog Computing in 5G trained by brain storm optimization with Quantum entangled algorithm identifies the center going down indicate from hit rate, radio signal strength, packet loss, available bandwidth, data cost, user speed based on simulated testing data. The simulation shows that the proposed approach is a viable engineering solution, towards the low cost high volume and precise controlling of the 5G fog system. New algorithm makes the trained decision more flexible for zone customization; in other words, it minimizes the manufacture cost of each smart scanner goes with pesticide controlling dispatching vehicle.

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References