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Big Data based Self-Optimization Networking: A Novel Approach Beyond Cognition

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ABSTRACT
It is essential to satisfy class-specific QoS constraints to provide broadband services for new generation wireless networks. A self-optimization technique is introduced as the only viable solution for controlling and managing this type of huge data networks. This technique allows control of resources and key performance indicators without human intervention, based solely on the network intelligence. The present study proposes a big data based self optimization networking (BD-SON) model for wireless networks in which the KPI parameters affecting the QoS are assumed to be controlled through a multi-dimensional decision-making process. Also, Resource Management Center (RMC) was used to allocate the required resources to each part of the network based on made decision in SON engine, which can satisfy QoS constraints of a multicast session in which satisfying interference constraints is the main challenge. A load-balanced gradient power allocation (L-GPA) scheme was also applied for the QoS-aware multicast model to accommodate the effect of transmission power level based on link capacity requirements. Experimental results confirm that the proposed power allocation techniques considerably increase the chances of finding an optimal solution. Also, results confirm that proposed model achieves significant gain in terms of quality of service and capacity along with low complexity and load balancing optimality in the network.

KEYWORDS
Wireless multicast; Quality of service (QoS); Power control; Big Data; Load Balanced Gradient power allocation (L-GPA)

1. Introduction

The control and management of various nodes in mobile networks requires self-organization and smart organization to automatically identify the condition and react to it. The complexity of cellular networks has increased with increases in the number of network parameters with complex interrelations and require further assessment and optimization. Self-organization can be used to reach these targets. Self-Organization Networking (SON) has recently become a global method for which the system goal is to find a structure with good functionality through the creation of consistency and it can be categorized as self-configuration, self-optimization and self-healing in wireless systems. In this framework, components, through interaction with all parts of a network and the environment, must be able to behave without requiring planned activity or changes in the structure or functionality. Implementation of these capabilities decreases operational expenses and investment expenses of the operators and increases the scalability, stability and network quality of service (QoS). Ali, Zoha, and Abu-Dayya (2014); Baldo, Giupponi, and Mangues-Bafalluy (2014); Murugeswari et al. (2016).

2. QoS-Aware Coded Multicast

Previous studies for example Guoping, Ni, Liu, Qu, and Tang (2012) have proven that the network coding technique increases the capacities and effectiveness of the network to bring its available capacity closer to maximum theoretical capacity. A proper efficient information exchange using network coding has been presented by Kurihara, Ersin, Jose, and Luna-aceves (2016). Due to the numerous advantages of network coding, mentioned by Ning, Song, Guo, Chen, and Jamalipour (2016), many algorithms, which previously used routings are being modified to incorporate network coding. As an example, Maheshwar, Li, and Li (2012) showed using network coding has made it possible to address the non-deterministic problem of achieving minimum-cost multicast routing to increase network capability. Meanwhile, using this technique maximum network throughput between the source and each receiver based on the max flow-min cut algorithm in a multicast session will be achievable by choosing the optimal sub-graph, Tan, Chen, and Liu (2015).

The optimality of most existing multicast approaches for example introduced approaches by Mohajer, Barari, and Zarrabi (2016); Gabrel, Manouvrier, Moreau, and Murat (2015) based on seeking the optimal sub-graph does not guarantee satisfaction of hard QoS constraints, although they rely on optimization schemes to determine the proper flow sub-graphs to minimize cost functions. So, it appears that using coded-based multicasting optimization the maximum capacity of a network is achievable and a reasonable procedure to finding an optimal sub-graph that guarantees QoS constraints will be possible.

The present study uses the decomposition method to identify potential sub-graphs for a coded multicast session and applies a route-selection mixed integer programming (MIP) method to tackle the path-flow framework, (which is presented by Waller, Fajardo, Duell, and Dixit (2013)) to determine the best sub-graph among all the potential sub-graphs, which can

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satisfy QoS constraints with the minimum cost. However the path-flow algorithm used to find a coded multicast solution has a simple structure. Computational evaluations show that the approach presented in this paper, called Big Data based Self Optimization Networking (BD-SON) is an efficient method for solving the problem of optimal multicast routing in which the primal-dual algorithm considers only trees their QoS level is aligned with user QoS constraints.

Lee et al. (2014a) have already demonstrated that implementation of the model in distributed wireless networks having energy limits, Rician and Rayleigh fading, frequency interference and lack of centralized control over the network entities, faces critical challenges that do not exist in wired networks. In this regard, considering the nature of the wireless environment, numerous studies have been carried out on the use of network coding in dynamic wireless networks such as Jiang, Xu, Li, and Chen (2015); Farooqi, Tabassum, Rehmani, and Saleem (2014) and Aktas, Yilmaz, and Aktas (2013). Jiang et al. (2015) tried to solve a multicast problem based on minimum energy using the advantages of dynamic multicast. Aktas et al. (2013) proposed a distributed protocol supporting multiple unicast flows using the shared nature of interfaces in wireless networks. Also, Xi and Yeh (2010) proposed a method of finding flow sub-graphs so that the minimum transmission rate is satisfied and the utilization function is at an optimum level. From this viewpoint, this scheme is somewhat similar to our proposed approach; however, some aspects of the introduced approach have not been considered in previous articles. The proposed scheme with the aim of guaranteeing the QoS constraints has been extended to distributed wireless networks using novel strategies and considering the dynamic characteristic of the network in dealing with the interference. The present study focuses on dynamic wireless networks in which the flexible capacity of network links can be interpreted as a function of the signal to noise-interference (SINR) in the receiver. Such a wireless network dynamically adjusts link capacities by modifying the power allocated to each link. In fact, in order to increase achievability of the optimal sub-graph, an optimization method is used for coded multicast based on a power control algorithm in the physical layer.

It is important to note that a resource allocation-based optimization should not exert an excessive computational load on the network so that network performance remains optimal. With regards to the points raised, we propose our distributed scheme as an iterative gradient algorithm; in which after receiving the control messages of neighboring nodes, the network flow variables, which emerge as optimization Lagrange coefficients are updated locally by each node in each iteration. After convergence of the algorithm, the optimal power obtained can be allocated to the outgoing links of each node. Clearly, it is evident that the number of iterations required to reach the optimal value relates to the network scale in term of number of nodes and links.

3. The Move towards Distributed Intelligence: Big Data based SON

One of the current challenges in providing high bitrate services in next generation wireless networks is limitation of available resources. Considering the services provided in primary cellular systems, techniques such as frequency reuse were sufficient. However, using these techniques and attributes in next generation mobile networks despite the optimal resource supply, exponentially increase the complexity of optimization. Hence, using self-optimization techniques is the only viable solution for increasing the efficiency in these networks. The goal of proposing a self-optimization model is to maximize the network efficiency and increase the quality of services provided to nodes. To increase the model efficiency, we applied the big data technique for analyzing data and increasing the accuracy of the decision-making process in a way that on the uplink, the sent data by users is to be analyzed in the self-optimization engine. Based on the meaningful extracted information, the SON decision-maker will be able to adjust network parameters and resource allocation factors in a more intelligent manner. Related works in this field either try to propose a scheme for allocating distributed resources, which may not close to the optimal solution, or neglect the effects of the network fluctuations.

As previously reported by Alam et al. (2016), the need to a optimal resource supply in areas covered by the network and ensuring the user QoS require control enormous volume of data and manage the configuration characteristics of new generation wireless networks. This will result in an exponential increase in the functional complexity of the design and optimization for this type of network. Self-optimization techniques are described by Foster, Seiamak, and Tafazolli (2015) as the only viable solution for controlling and managing this type of networks that allows control of resources and key performance indicators (KPI) of the mobile network without human intervention based solely on the intelligence of the network. The main objective behind such a self-optimization model is to maximize network efficiency and increase the quality of service (QoS) provided to macrocell and femtocell users with the limited network resources.

Although some methods such as Learning, Fuzzy Logic, and Convex Optimization approaches have been used to make self-optimization models intelligent but in next-generation networks, these methods do not provide acceptable functionality, because of their restrictions. Also, their computational complexity depends to scale of network and it will increase dramatically with the increasing volume of data exchanged. Lee et al. (2014b) have confirmed that data in this networks require high volume, high speed, and variety, which are the main features of a powerful data management technology called big data so, this study proposes an approach that uses a self-optimization framework based on this technology.

As presented by Murugeswari et al. (2016), in order to satisfy the QoS requirements in multimedia services, resource allocation algorithms must be modified and adjusted to clarify the distinction among services and network conditions. Previous studies such as the scheme conducted by Fadlullah, Duong Minh Quan, Kato, and Stojmenovic (2014) have shown that demand side management increases the efficiency and effectiveness of the network to supply resource demand considering user utility and cost. A proper efficient resource allocation based on peak reduction has been presented by Liu et al. (2014) in which reducing the network operational cost was considered, as well as resource supplier's cost. The optimality of most current distributed optimization schemes are based on achieving a single objective for example; utility of user side does not guarantee satisfaction of hard QoS constraints, although they rely on optimization schemes to apply the proper scheme to minimize cost functions as suggested by De Waegenaere and Wielhouwer (2012); Waller et al. (2013). So, it appears that using multi objective decision-making, the maximum network capacity is achievable and a reasonable procedure to guarantee QoS constraints will be possible while keeping the resource supplier's cost at a relatively lower level.

The continuation of this paper is structured as follows: Section II represents the problem and the formulation of Big Data-based resource allocation during coded multicast session based on SON functionality. Section III, in order to evaluate the functionality of BD-SON under actual conditions, we have introduced a framework to extending the proposed approach to load balanced wireless networks. Also a power allocation algorithms (L-GPA) is proposed and the effectiveness of the scheme is analyzed using power control algorithm. Finally, after evaluation of the numerical results in Section IV, the conclusions and recommendations for future study are presented.

4. Big Data-based Resource Allocation

The present study focuses on a multi-dimensional decision-making framework in which the network resources can be interpreted as a function of the variance of the network load and user requirements based on big data analysis.

Shown in Figure 1, the Big Data register in SON model collects online information of key entities, i.e., node layer, resource provider and access network layer, from uplink and then SON engine makes a decision about resource distribution based on achieved KPIs. Resource Management Center (RMC) allocates the required resource to each part of the network based on made decision in SON engine. Also, this decision will be sent to key entities to adjust their operations. In fact, On the uplink side, user data will be analyzed in a register and the semantic information extracted from this data will allow the resource management center to allocate resources more intelligently.

The data gathered in the analyzer register can be divided into the following categories:

- Control information on network entities such as information related to sessions, resource control, and transmission modes.
- Control information extracted from the OMC, which includes all events and the qualitative state of communication channels and signaling loads. This category also includes user level information, movement direction and population distribution of subscribers.
- Information related to network configuration and the performance level of network entities.
- Information related to the AAA, including the control of connections between entities and the network core i.e., data related to charging.
- Information related to customer complaints about qualitative state and availability of services.

Big data technology has been used to obtain a logical relation between telecommunication parameters and statistical/events parameters can contribute to better decision-making during mobile network optimization in terms of power utilization and frequency resources. The lion's share of this information in current generation of self-organized networks is not used, so decision-making will not have a high level of accuracy. Gathering such information in a register for use in SON engine to make decisions, created a self-optimization approach based on big data (BD-SON) to increase network performance and intelligently allocate resources and maintain the network KPIs in an acceptable range.

Unlike previous schemes, BD-SON acts proactively, which is necessary as real-time feature of 5G networks. The proposed method uses the parameters of network status such as events, fluctuations, etc. recorded in the previous timeframes for predicting network status. Accordingly, it changes the network configurations. The next section of the paper is related to resource allocation in next generation wireless networks. For this purpose, a load balanced gradient power allocation (L-GPA) has been introduced. The performance of the proposed method in more practical scenarios will be assessed by considering the limitations and constraints of real wireless networks.

Our proposed model is composed of two major phases. In the first phase, the optimal transmission power level for each

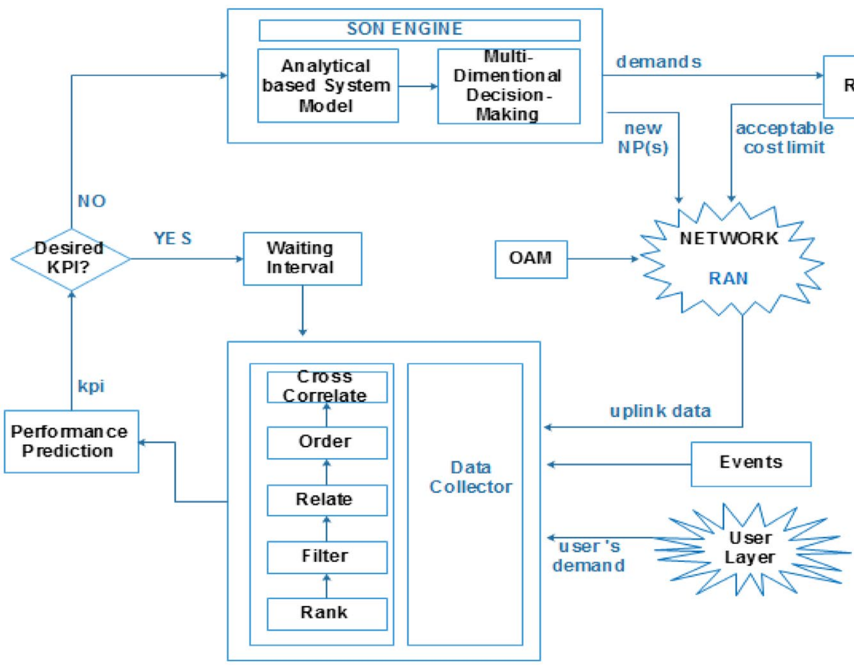

Figure 1. The Proposed BD-SON Architecture.

node that maximize the total network capacity are found. Then, in the second phase, to reduce the number of unavailable links in the sub-graph and satisfy the total constraint for the total aggregated transmission power of all nodes in the network, a power control algorithm is used. The transmitters, which signal-to-interference-plus noise ratio (SINR) of their outgoing links lies below the acceptable threshold are allowed to increase their transmission power so that the SINR of their link satisfies the minimum acceptable threshold for reliable transmission.

5. Load Balanced Gradient Power Allocation: L-GPA

Most literatures in network coding based optimization such as the presented approach by Xi and Yeh (2010) have only focused on acquiring an optimum value for applied utilization function in a cross-layer framework. But, such dynamic optimization algorithms are not effectively possible. The main difference between the proposed approach and such other schemes is its efficiently dynamic properties, which introduced a gradient-based optimization framework in order to optimal power allocation with low computational complexity. Note that in this section, the problem formulation and the coded-based flow algorithm are presented from the perspective of guaranteeing user QoS constraints.

Determining the optimal values in the proposed model is not purely based on local node variables. This method solves optimization Lagrange equations iteratively; each node calculates the updated Lagrange coefficients and uses them for the next iteration of the power allocation algorithm. In the system model, it is assumed that the system has N users, and the K^{th} user has a data rate equal to R_k bits per symbol. $C_k^{(c)}$ is the number of bits allocated to the c^{th} class-carrier for the K^{th} user. In the transmission channels, different class-carriers will experience different channel gains, denoted by $\alpha_k^{(c)}$, the magnitude of the c^{th} class-carrier seen by the K^{th} user. It is assumed that N_0 is white noise and is equal for all class-carriers and the same for all users. The goal of this approach is the best assignment of $C_k^{(c)}$, which besides of satisfying the total power constraint, the capacity of links has been maximized. Note that this problem can be formulated either to minimize the transmission powers besides satisfying the given QoS requirements or to improve the user QoS parameters for a fixed overall transmission power. The formulation for the second approach can be achieved by changing the class-carrier power levels proportionally using the same set of $C_k^{(c)}$. The enhancement in quality can be demonstrated by the increase in total user transmission rate (R) as follows. Ideal resource allocation based on the network load distribution is a main QoS affecting factor. In order to minimize load variance, the proposed self-optimizing model utilizes an intelligent resource allocation pattern. Cost constraints and the upper bound of network power limitation must be considered when distributing resources among entities. In order to allocate power to users over time intervals $t = [1, 2, \ldots, T]$, information related to flexibility $\omega_i(\mathrm{t})$ and cost component $c(t)$ must be determined by the big data processing engine through analysis of the received data. $P_i(t)$ denotes the power consumption by user i at moment t and P denotes the restriction on network total power. The problem of real time resource assignment can be formulated as follows:

$$maximize \ \sum_{k=1}^{K} \alpha_k R_k \qquad subject\ to{:}\ R_k = \sum_{c=1}^{M} C_k^{(c)} \tag{1}$$

Replacing $C_k^{(c)}$ with its equivalent in Equation (1) results in the formulation of the goal function in Equation (2). The goal of this formula is to maximize the weighted aggregation rate of the network users considering total power constraints. In addition, U and f indicate Utility and Cost functions respectively, which are calculated based on network condition and flexibility factor. Also, to achieve optimal solution, variance of allocated resources should be at the minimum possible value.

$$\begin{aligned} maximize \quad & \textstyle\sum_{k=1}^{K}\sum_{c=1}^{M}\Big[\alpha_k\rho_k^{(c)} log\Big(1+\frac{p_k^{(c)}|h_k^{(c)}|^2}{\Gamma.n_k^{(c)}}\Big) + \varphi U(P_i(t),\omega_i(\mathrm{t})) \\ & -\psi f(\textstyle\sum_{i\in N}P_i(t))P_i(t)\Big] - \phi\frac{\alpha T}{2}Var\Big(\textstyle\sum_{k\in K}\vec{P}_k\Big) \end{aligned} \tag{2}$$

$$subject\ to{:}\ \sum_{k=1}^{K}\sum_{c=1}^{M}\alpha_k p_k^{(c)} \le P_{tot}\ \&\ \omega_i(\mathrm{t}), \rho_k^{(c)} \ge 0$$

In this model the mentioned coefficients i.e., $\omega$and α are determined based on current user status, service type and network condition through uplink data analysis. Using this method for resource allocation, the self-optimization model satisfies QoS constraints with the minimum cost and low computational load where each user is allowed to transmit at a rate associated with $\alpha_{k,}$ which is related user priority and $\rho_k^{(c)}$ a coefficient with values within the interval 0 and 1 associated with the c^{th} class-carrier for c = 1,2,..,M. The Lagrange equation in Equation (3) is used to take the problem constraints into account.

The channel coefficient for the K^{th} transmitter node on the c^{th} class is denoted by $h_k^{(c)}$ and includes the path loss, Rayleigh fading factor, and constant coefficients for the transmitter and receiver antenna. Moreover, Γ indicates the SINR-gap, which is function of coding and modulation and the bit error ratio (BER). For example, for the modulation of non-coded QAM, the SINR-gap Γ will be shown as $\Gamma = -\ln(5.BER)/1.5$ and $n_k^{(c)}$ denotes the noise of class c for the node k.

$$\begin{aligned} L(P,\lambda) = \quad & \sum_{k=1}^{K}\sum_{c=1}^{M}\Bigg[\alpha_k\rho_k^{(c)} log\Bigg(1+\frac{p_k^{(c)}|h_k^{(c)}|^2}{\Gamma.n_k^{(c)}}\Bigg) \\ & +\varphi U\big(P_i(t),\omega_i(\mathrm{t})\big) - \psi f\Bigg(\sum_{i\in N}P_i(t)\Bigg)P_i(t)\Bigg] \\ & -\phi\frac{\alpha T}{2}Var\Bigg(\sum_{k\in K}\vec{P}_k\Bigg) - \lambda\Bigg(\sum_{k=1}^{K}\sum_{c=1}^{M}\rho_k^{(c)}p_k^{(c)} - P_{tot}\Bigg) \end{aligned} \tag{3}$$

Assuming that the derivation of Equation (3) is equal to zero, the optimal power allocated to each class-carrier can be obtained by Equation (4). For each iteration of the power assignment algorithm, a current power of the class-carrier that does not satisfy the reliability will be modified and the Lagrange coefficient will be updated accordingly. After R iterations, the algorithm provides an optimal transmission power for each class-carrier as demonstrated by $P_k^{(c)*}$.

$$p_k^{(c)*} = \rho_k^{(c)}\left[\frac{\theta_k}{\lambda} - \frac{\Gamma.n_k^{(c)}}{\left|h_k^{(c)}\right|^2}\right]^+ - \nu - \frac{\alpha T}{2}(\nabla P) \tag{4}$$

Where λ is a Lagrange coefficient associated with transmission power constraints. Equation (4) can be solved by defining auxiliary variable g as:

$$g_k^{(c)} = \frac{\left|h_k^{(c)}\right|^2}{n_k^{(c)}}$$

$$P_k^{(c)*} = \rho_k^{(c)} \left[\frac{\theta_k}{\lambda} - \frac{\Gamma}{g_k^{(c)}} \right]^+ - \nu - \frac{\alpha T}{2} (\nabla P) \tag{5}$$

The optimal power allocation formulation in Equation (5) is very similar to the common waterfilling problem. In this formulation, power is assigned to nodes based on the difference in their weighting coefficients. Each class-carrier of user k is assigned to a flow level equal to $\frac{\alpha_k}{\lambda}$. After waterfilling, the different users have flow levels that are proportional to their weighting coefficients. The users with the higher weighting factors have higher flow levels and can allocate more power to their class-carriers. Equation (6) can be used to convert a single level waterfilling to a multilevel.

$$\frac{P_k^{(c)*}}{a_k} = \rho_k^{(c)} \left[\frac{1}{\lambda} - \frac{\Gamma}{\theta_k . g_k^{(c)}} \right]^+ - a_k \nu - (\nabla P) \frac{\alpha . a_k T}{2} \tag{6}$$

Pkc*ak=ρk(c)[1λ-Γak.gk(c)]+(8). Starting with small values for initial Lagrange coefficients, the coefficients are modified in each iteration so that the data rate constraints of different users are satisfied in each node. Each node is treated in turn using the new allocated power until the SINR in the output of the links with temporary failure reach at a minimum level of sensitivity. When the link is recovered, the possibility of obtaining a solution sub-graph in the BD-SON algorithm will increase. In this way, the data rate constraint and dedicated power constraint for all nodes are satisfied and the algorithm will converge.

$$g(\lambda) = maximize_{\,P_k^{(c)}} L(P, \lambda) \approx minimize\, g(\lambda); \;\; \lambda \geq 0 \tag{7}$$

The solution to Equation (7) leads to optimal values for maximizing $L(P, \lambda)$. The gradient method can be used to solve the problem to obtain a distributed solution. According to the steepest descent lemma, we have Equation (8):

$$\lambda(t+1) = \left[\lambda(t) - \gamma . \nabla g(\lambda(t)) \right]^+ \tag{8}$$

Where $g > 0$ is the step size and $[Z]^+ = \max\{Z, 0\}$. Using Equation (8) and according to dual function derivation, we will have Equation (9).

$$\nabla g(\lambda(t)) = \sum_{k=1}^{K} \sum_{c=1}^{M} \rho_k^{(c)} P_k^{(c)*} - P_{tot} (\nabla P) \frac{\alpha T}{2} J \tag{9}$$

Using the Lagrange coefficient (λ), the class-carrier powers in the next iteration can be calculated as in Equation (10):

$$P_k^{(c)*} = \rho_k^{(c)} \left[\frac{\theta_k}{\lambda(t)} - \frac{\Gamma}{g_k^{(c)}} \right]^+ - \nu - (\nabla P) \frac{\alpha T}{2} = P_k^{(c)}(\lambda(t)) \tag{10}$$

The Lagrange coefficient λ can be updated for the next step in Equation (11) during successive iterations.

$$\lambda(t+1) = \left[\lambda(t) - \gamma \left(\sum_{k=1}^{K} \sum_{c=1}^{M} \rho_k^{(c)} p_k^{(c)}(\lambda(t) - P_{tot} \frac{\alpha T}{2} Var\left(\sum_{k \in K} \vec{P}_k \right) \right) \right]^+ \tag{11}$$

Based on the algorithm performance, the SINR can be calculated as the reliability of the transmission in the output of each link. By calculating the value of this parameter, the status of the link becomes clear and the temporary failures can be determined with greater confidence. The new SINR can be used to calculate their new capacities as $C_{ij} = C\left(SINR_{ij} \right)$.

To achieve transmission reliability, the SINR value at the end point of each link is compared with the minimum SINR required for reliable transmission. In fact, the acceptable SINR threshold is the sensitivity level of the node. If the calculated SINR value is lower than the sensitivity, temporary failure is considered to have occurred for that link and the link will be removed from the set of potential sub-graphs. It is evident that; frequent link failure decreases the possibility of finding a solution sub-graph, which satisfies the QoS requirements and increases the cost. To prevent link failure, the power control algorithm is used to gradually increase the transmission power of the node located at the beginning point of the failure links. It should be noted that during all the steps of power control, the total power allocated to all nodes must not exceed a pre-determined value.

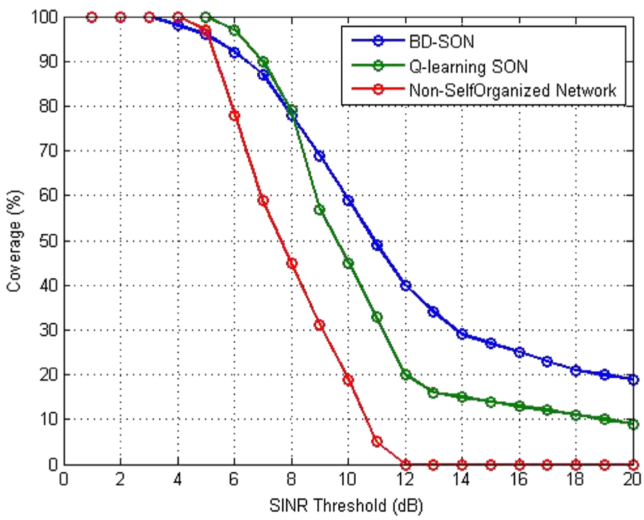

Figure 2. Coverage Probability of Q-Learning SON, BD-SON and Non-Self Organized Network based on Needed SINR.

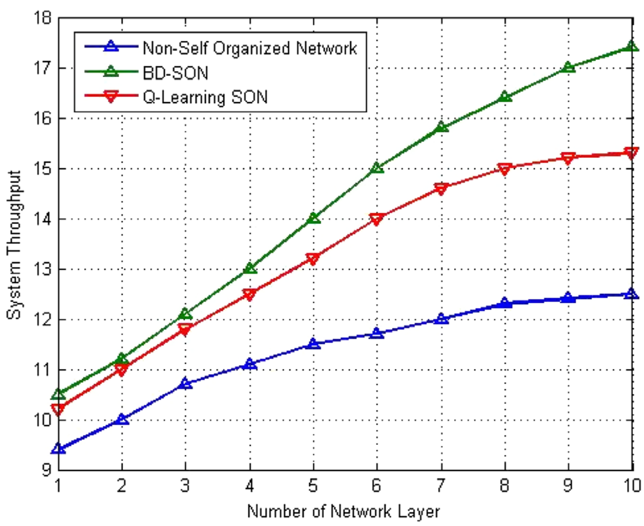

Figure 3. Increasing Throughput by Increasing the Number of Layers in BD-SON in Comparison with Q-Learning.

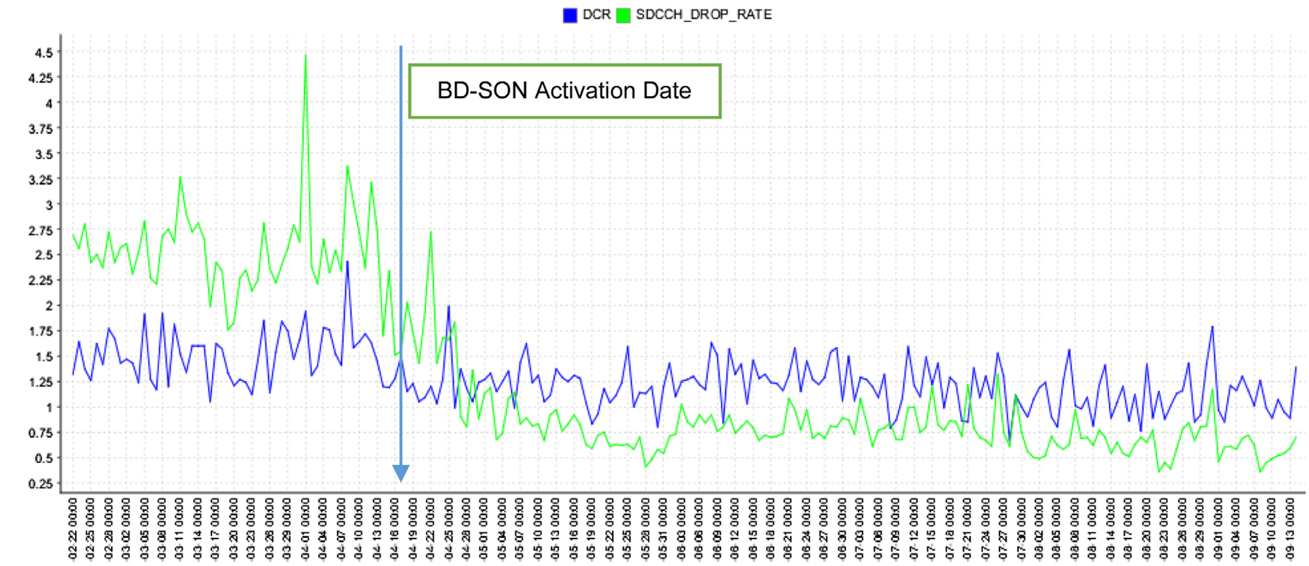

Figure 4. Decreasing the Drop Rate by Enabling the Self-optimization Model.

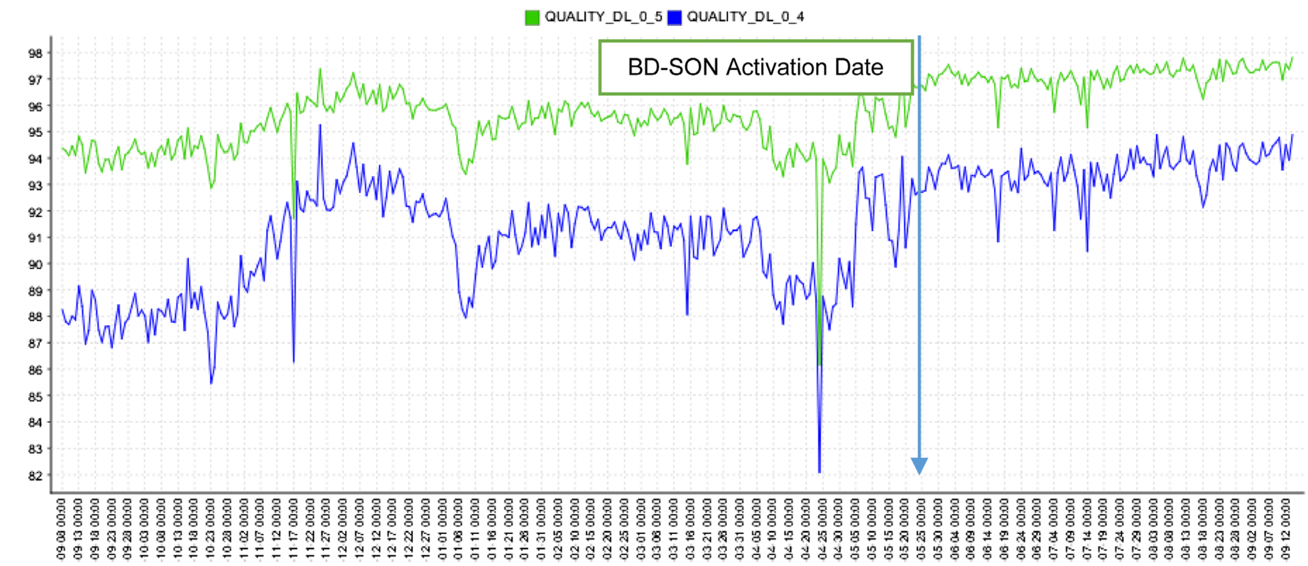

Figure 5. Stable Downlink Quality by Enabling the Self-optimization Model.

6. Experimental Results

The performance of our proposed algorithm BD-SON was evaluated under different scenarios. When all the algorithms arrived at a solution, the optimality of solutions found by the BD-SON algorithm in combination with L-GPA was much better than that of the solution found by the basic BD-SON algorithm, although the iterations required to achieve a solution was much higher than those required by the BD-SON individual.

Our introduced approach not only reduces the interference of its specified cell, but also increases the network functionality by alleviating interference to adjacent cell areas. Figure 2 demonstrates the coverage probability considering SINR values based on BD-SON functionality in comparison with Q-Learning SON scheme presented by Galindo and Serrano (2012) and the SOTA schemes with the non-self-organization feature.

Figure 3 shows the effects of the proposed model on throughput based on number of layers defined for the network. As expected, the self-optimization model using big data increased the throughput. Also, the network capacity has been approached to the maximum theoretical capacity. Using this model, the SINR indicator for macro users was maintained at an ideal level and the throughput of each cell was improved by increasing the number of layers.

We have evaluated the performance of the network in a cluster having 15 sites in the presence and the absence of the SON engine. As shown in Figure 4, the level of DCR and the signaling drop rate (SD_Drop_Rate) have significantly degradation after self-optimization model activation.

Downlink quality will also increase when the SON model is enabled. As shown in Figure 5, when the self-optimization scheme was applied in the BSS layer, the user quality of service is stable without any considerable fluctuation.

The complexity of the L-GPA is higher than for the RPA; however, in environments with high interference, the L-GPA can better satisfy strict QoS requirements of multicast sessions.

7. Conclusion and Future Works

This study introduced a self optimization technique as a powerful tool for distributed network management, consistent with next-generation wireless networks. In the proposed method, coded flow multicasting has been utilized for guaranteeing the QoS constraints by finding an optimal sub-graph in a flow-based optimization framework. The load balanced gradient power allocation (L-GPA) algorithm was also applied for the QoS-aware multicast model to accommodate the effect of transmission power level based on load distribution to increase link resistance to temporal failure caused by interference and noise. In comparison to other schemes, the proposed method can better satisfy the QoS requirements of multicast sessions. The simulation results prove that using the introduced approach considerably increases the chance of finding an optimal sub-graph. Also, Experimental results show that the proposed method can improve the throughput and quality of service in next-generation wireless networks. A further study with more focus on other requirements of next generation wireless networks are therefore recommended. Also, further research might investigate determining the self-healing intelligently based on environmental conditions.

Disclosure statement

No potential conflict of interest was reported by the authors.

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