A Wireless Traffic QoS Optimization Algorithm Based on Fuzzy Measurement

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Abstract —A cross-layer based QoS optimization algorithm for wireless traffic networking is presented in this paper. In terms of the fuzzy measure theory, we propose a nonlinear wireless traffic networking optimization model based on the Choquet integral. The model can characterize not only the protocol parameters' significance but also the interdependency among those parameters on the QoS of data transmission by a non-additive function. The distinct characteristic of the proposed model lies in that the contribution of interaction among the system parameters to the network performance can be evaluated quantitatively by a general nonlinear and non-additive integral. Once the network condition cannot satisfy the user's QoS requirement, the most significant networking parameters can be adjusted to improve the data transmission performance and further achieve the user's QoS demand. Finally, simulation results are given to verify the effectiveness and efficiency of the proposed method over the WLAN network.

Index Terms—Choquet integral, interdependency, QoS, protocol parameter

I. Introduction

With the rapid development of broadband wireless communication technology, the wireless network tends to support more complicated traffic gradually. In order to improve the user experience, different traffics should satisfy different QoS (Quality of Service) requirements. For instance, for the best-effort delivery traffic, it should be provided with high throughput and low data packet loss ratio. While for the real-time traffic, it should satisfy the low latency and low jitter QoS demand. However, due to the intricacy of wireless network and the complicated relationship among the network parameters, how to guarantee the user's QoS based on the internet technology becomes an intractable issue. Recently, cross-layer design has attracted a lot research interests because of its particular advantage in improving the system performance, such as decreasing interference and reducing the power consumption.

A plethora of research has been done in cross-layer design and wireless network QoS optimization in terms of the network latency and throughput. The research in [1, 2] has explored the end-to-end delay problem. Cheng *et al.* [1] emphasized on the impact incurred by the route length and path interference on the latency in the multi-hop wireless network. And they designed the loose coupling and tight coupling cross-layer optimization scheme aiming at the route path searching and link layer scheduling. Wang *et al.* [2] studied the cross-layer design in wireless sensor network. The authors proposed a theoretical framework based on the stochastic queuing model and then analyzed the end-to-end delay to provide the user's QoS requirement. Yang *et al.* [3] presented a picture transmission optimization model, which minimizes the picture transmission energy through adjusting the transmission power and data packet size while satisfying the user's assigned quality constraint. Chen *et al.* [4] concentrated on improving the TCP data transfer throughput with considering the master user's QoS in the cognitive radio network. Rodriguez *et al.* [5] applied cross-layer design in the dynamic spectrum allocation under the cognitive radio network, in order to reduce the overhead and minimize the interference caused by the users' spectrum switching. Jaramillo *et al.* [6] proposed an optimization algorithm aiming at the congestion control and traffic scheduling in the ad-hoc wireless network. The scheme makes the optimal resource allocation strategy based on the dual mode function assuring the network stability and traffic QoS restraint. Cheng *et al.* [7] proposed an efficient framework to jointly optimize spectrum and power efficiencies of wireless networks, supporting the statistical QoS provisioning for real-time traffic.

In recent years, the interaction among the protocol parameters has gained the researchers' attention [8]-[11]. Lin *et al.* [8] studied the cross-layer design and optimization for delay QoS provisioning in two-way relay systems. Their goal is to find the optimal transmission policy to maximize the weighted sum throughput of the two users in the physical layer while guaranteeing the individual statistical delay-QoS requirement for each user in the datalink layer. Xue *et al.* [9] proposed a cross-layer

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scheduling algorithm that achieves a throughput "ε-close" to the optimal throughput in multi-hop wireless networks with a tradeoff of O([1/(ε)]) in average end-to-end delay guarantees. Barrett *et al.* [10] focused on exploring the effect on the system latency and throughput, which is caused by the interdependency among the parameters between the MAC protocol and routing protocol. And they demonstrated the interaction's importance on the network performance by simulations. Kliazovich *et al.* [11] quantitatively described the parameters' impact on the throughput and delay for the link layer. Further, they presented a scheme which improves the user's QoS by adjusting the parameters according to the real-time network condition.

The main principle of cross-layer design is to fully utilize the interaction among the design variables on different network layers to achieve the transmission performance optimization for the time-varying wireless network. However, most of the current researches analyze this problem qualitatively and they do not evaluate the network parameters' effect on the user's QoS quantitatively. Besides, the interdependency among the parameters should be taken into account to achieve system performance enhancement.

This paper formulates the mathematic model based on the configurable parameters of different network layers and various traffic QoS requirements. The Choquet non-additive integral has been adopted to analyze the significance of various parameters and their interactions on the system performance quantitatively. By adjusting the most significant parameter, the network performance can be optimized to guarantee the user's QoS requirement.

The rest of the paper is organized as follows. Section II describes the preliminary knowledge of the fuzzy measurement and Choquet integral. Section III formulates the transmission optimization model. The performance evaluation and results analysis are given in Section IV. Finally, we conclude the paper in Section V.

II. Fuzzy Measurement and Choquet Integral

The measurement generally means the dimension of the measuring field, which extends the concept of figure area, the volume of vessel and so on. The classical measurement is linear additive. For example, the volume of two vessels which do not have overlapping space is the same as that the sum of each vessel's volume. However, many practical cases can not satisfy the linear additivity, which might cause the so-called *Ellsberg Paradox*, where each individual system parameter makes "good" decisions for maximizing the objective function respectively, but the overall performance goes against the traditional expected utility function [12]. For instance, in the wireless network, the profit brought by adjusting two protocol parameters simultaneously may not just equal the sum of the profit brought by adjusting each protocol parameter. Therefore, we need to comprehensively understand the network behavior and model parameters' interaction to achieve the global performance optimization. Based on the non-additive measurement theory, the fuzzy measurement is proposed to replace the additivity by the weak monotonicity property [13].

To clearly depict the measurements' significance corresponding to each system parameter and the interdependency among these parameters, the non-additive regression model on the basis of the Choquet integral has been applied in many practical areas,such as the multi-criterion decision [14], the picture and pattern recognition [15], and data mining [16]. Choquet integral fuses the contribution of each predictive attribute toward the objective attribute. The fuzzy measurement of the integral is a non-additive set function, which reflects the contribution of each parameter and the interaction among each parameter into a non-additive measurement set using the Choquet integral.

Definition 1: Let f be a real-valued function on X and μ be a signed efficiency measurement on $P(X)$. The Choquet integral of f with respect to μ is defined by

$$\int_c f d\mu = \int_{-\infty}^{0} [\mu(F_\alpha) - \mu(X)] d\alpha + \int_0^\infty \mu(F_\alpha) d\alpha \tag{1}$$

where $F_\alpha = \{x \mid f(x) \geq \alpha\}, \forall \alpha \in (-\infty, \infty)$, if not both Riemann's integrals in the right hand are infinite.

Generally, when f and μ are determined, the Choquet integral can be written as

$$\int_c f d\mu = \sum_{i=1}^{n} [f(x_i^{'}) - f(x_{i-1}^{'})] \cdot \mu(\{x_i^{'}, x_{i+1}^{'}, \ldots, x_n^{'}\}) \tag{2}$$

where $f(x_0^{'}) = 0$ and $(x_1^{'}, x_2^{'}, ..., x_n^{'})$ is a permutation of $(x_1, x_2, ..., x_n)$ such that $f(x_1^{'}) \leq f(x_2^{'}) \leq .... \leq f(x_3^{'})$. To avoid the sorting process, Guo *et al.* [17, 18] proposed a new genetic algorithm to calculate the Choquet integral, which is expressed by the following expression

$$\int_c f d\mu = \sum_{j=1}^{2^n - 1} (z_j \cdot \mu_j) \tag{3}$$

where

$$z_j = \begin{cases} \min_{i:\mathrm{frc}\left(\frac{j}{2^i}\right) \in \left[\frac{1}{2}, 1\right)} f(x_i) - \max_{i:\mathrm{frc}\left(\frac{j}{2^i}\right) \in \left[0, \frac{1}{2}\right)} f(x_i) & \text{if } > 0 \text{ or } j = 2^n - 1 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

in which $frc(\frac{j}{2^i})$ is the fractional part of $\frac{j}{2^i}$ and the maximum operation on the empty set is zero.

III. Wireless Network Traffic Transmission Optimization Model based on The Choquet Integral

A. Measurement of Protocl Parameters

According to the OSI (Open Systems Interconnection) TCP/IP reference model [19], the Internet network architecture is classified into four layers: the application layer, the transport layer, the internet layer and the network interface layer.

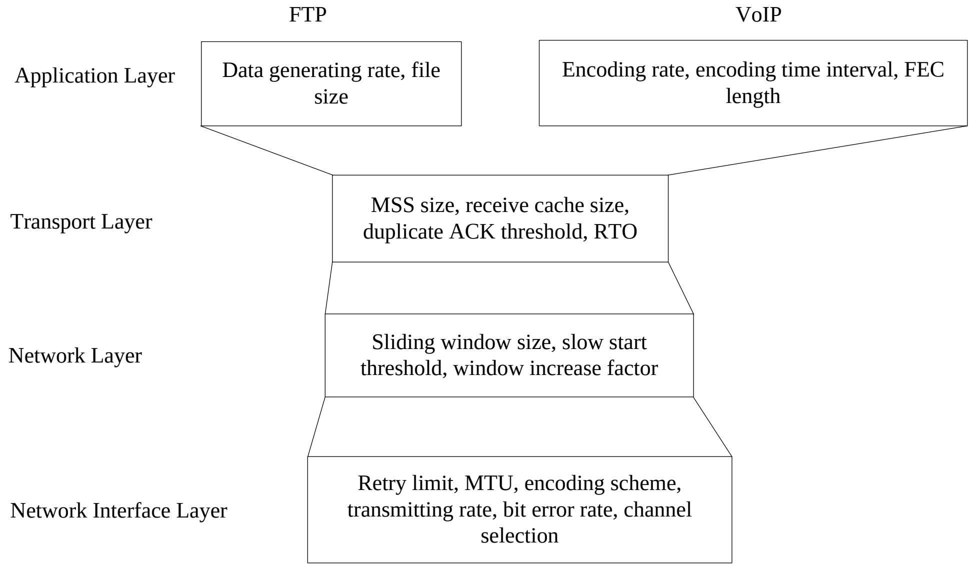


Fig 1. Configurable parameters included in different network layers

Different layers of this model include different protocol parameters. For example, the application layer includes the request time interval, request file size, etc; the transport layer includes the sliding window size, the slow start threshold, etc. Fig. 1 illustrates the dominating configurable parameter included in different protocol layers where the IEEE 802.11 protocol is adopted as the access technology.

As for the measurement of a specific protocol parameter r, the EWMA (Exponential Weighted Moving Average) [20] method is adopted to acquire the value, in order to ameliorate the vibration caused by the network burst, which is written as

$$r'_n = r_{n-1}(1-s) + r_n s \tag{5}$$

where r_n means the measured value of r at time n and s represents the degree of weighting decrease, a constant smoothing factor between 0 and 1. It is not hard to conclude that a higher s represents the current measured value is given a greater weight and discounts older observations faster, leading more sensitive to the network variation. On the other hand, r is conservative to the network variation and emphasizes on the past accumulation, which could mitigate the network burst.

Suppose the collected data consists of l observations of the predictive attributes $(x_1, x_2, ..., x_n)$ and the objective attribute y. Then the data can be formed as

x_1	x_2	...	x_n	y
f_{11}	f_{12}	...	f_{1n}	y_1
f_{21}	f_{22}	...	f_{2n}	y_2
...	...	...	...	...
f_{l1}	f_{l2}	...	f_{ln}	y_l
f_{j1}	f_{j2}	...	f_{jn}	y_j

Each row is the observation of attributes $(x_1, x_2, ..., x_n)$ and y, j = 1, 2, …, l. The predictive attributes' observation can be regarded as a function f: $X \rightarrow (-\infty, \infty)$ and thus, the i-th attribute's j-th observation can be expressed as $f_{ji} = f_j(x_i)$, $1 \le i \le n$, $1 \le j \le l$. The observed data is regularized as the following formula

$$f'_{ji} = \frac{f_{ji} - \min(f_i)}{\max(f_i) - \min(f_i)}, 1 \le i \le n, \le j \le l \tag{6}$$

where f_i represents all the observation values of i-th attribute, f'_{ji} means the normalized observation value of f_{ji}, indicating the relative size among the observations. Note that here y might be a comprehensive value which synthesizes many objective attributes. For example, the user's QoS might be sensitive to the network throughput and packet loss ratio, while blunt to the delay for FTP traffic. Suppose y_1 denotes the network throughput, y_2 denotes the network packet loss ratio and y_3 denotes the delay, then we can describe y as the following

$$y = y_1\omega_1 + y_2\omega_2 + y_3\omega_3 \tag{7}$$

where $\omega_1, \omega_2, \omega_3$ represent different weights corresponding to each objective attribute and satisfy the following constraint [21]:

$$\begin{cases} 0 \le \omega_1, \omega_2, \omega_3 \le 1 \\ \omega_1 + \omega_2 + \omega_3 = 1 \end{cases} \tag{8}$$

B. Analysis of Protocl Parameters' Nonlinear Regression

According to the parameters' value obtained in the measurement phase (subsection 3.1), the nonlinear multiregression can be regarded as a multi-input single-output system shown in Fig. 2,

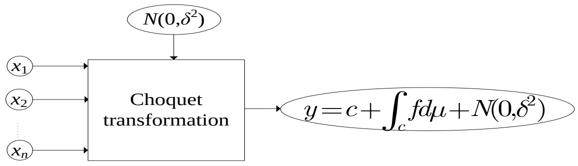


Fig 2. Regarding the nonlinear multi-regression as a multi-input single-output system

where x_1, x_2,..., x_n represent the system input parameters, c is the regression constant, $N(0,\delta^2)$ is a normally distributed interference with mean 0 and variance δ^2 and y is the system output. The set function μ describes the importance of each individual attribute and the combination of these attributes, which indicates the convergence condition on the global set X. Such as μ: $P(X)\rightarrow(-\infty,\infty)$, $\mu(\theta)=0$. Thus, the non-additive regression model can be described as

$$y = \mathrm{c} + \int_c fd\mu + N(0,\delta^2) \tag{9}$$

Based on the observation data of x_1, x_2,..., x_n and y, the $l\cdot(2^n)$ augmented matrix $Z = [z_{jk}]$ can be constructed, where k=1, 2, ..., 2^n, j=1,2,...,l. And z_{jk} is determined by Equation (4) with $z_{(j2^n)}=y_j$. The linear regression problem can be modeled by mapping the data on set X into $P(X)$. Here, the non-additive measurement is the regression coefficient set and furthermore, the least square method can be adopted to solve the linear regression equation which is constructed by Z. The regression residual error δ^2 of this equation can be obtained in the following way

$$\delta^2 = \frac{1}{l}\sum_{j=1}^{l}(y_j - c - \sum_{k=1}^{2^n-1} z_{jk}\mu_k)^2 \tag{10}$$

In conclusion, given the set of observation data, the fuzzy measurement coefficient can be obtained by solving the nonlinear integral equation. Then the interdependency relationship among the parameters can be ascertained by evaluating the design variables' fuzzy measurement. Through this way, the single variables and their combinations' contribution to the objective function can be calculated quantitatively.

C. Adaptive Adjustment of Protocol Parameters

By comparing the non-additive measurements' significance derived by the analysis phase (subsection 3.2), the system parameter corresponding to the most significant measurement is selected to be adjusted. For different applications, different thresholds can be set. For example, to the voice application, which is sensitive to the delay, the threshold can be set as the delay that the users can accept. Once the system detects that the network delay exceeds the presumed threshold, the corresponding adjustment is enabled to achieve the user's QoS requirement.

The nonlinear regression analysis is the core of the system in the proposed transmission model, which includes the measurement of the single parameters and their interactions' contribution on the system performance. From the above discussion, our significance evaluating algorithm only depends on the system operation data or simulation data, which can easily be obtained from the equipment driver or the network management protocol. Therefore, our proposed algorithm is effectively in computational complexity and hardware storage.

IV. Simulationo Results

In this section, we present the numerical results to validate our developed analytical model and investigate the performance improvement using NS2 software. The CLL (Cognitive Link Layer) algorithm [8] has been compared with our algorithm. Fig. 3 shows the network topology and the simulation parameters are shown in Table I.

The users join the core network through the AP (Access Point) and FTP service is configured on the server. Combined with the simulation environment, we first embody the formulas in the above proposed model. We select the data packet generating ratio (α) of the application layer, the sliding window size (β) of the network layer and the data transmitting rate (γ) of the physical layer as our experimental predictive attributes.

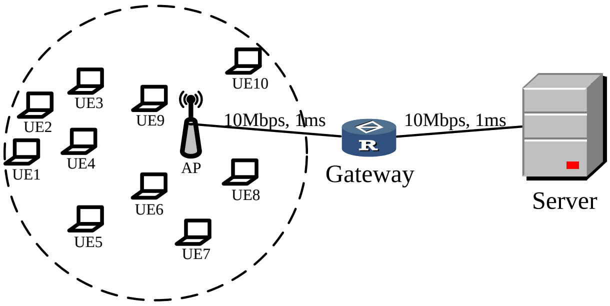


Fig 3. Illustration of the network topology

TABLE I: A GLOSSARY OF CONFIGURATIONS IN THE SIMULATION SCENARIO

User number	10
Wireless AP coverage	250*m*
Data link layer protocol	IEEE 802.11
Data packet size	512*Byte*
Link delay	1*ms*
Link bandwidth	10*Mbps*
Simulation time	300*s*
Traffic	FTP

Next, $\mu(\{\alpha\})$, $\mu(\{\beta\})$, $\mu(\{\gamma\})$, $\mu(\{\alpha, \beta\})$, $\mu(\{\beta, \gamma\})$, $\mu(\{\alpha, \gamma\})$, $\mu(\{\alpha, \beta, \gamma\})$ are denoted as the corresponding fuzzy measurement, respectively. The user's QoS indexes include throughput, packet loss ratio (loss) and delay. We assign a higher weight on throughput and loss ($\omega_1 = \omega_2 = 0.4$) and lower weight on delay ($\omega_3 = 0.2$) as the FTP traffic is sensitive to the throughput and packet l-oss ratio compared with the network delay. Notice that delay and loss are inverse proportional to the QoS. In other words, while the delay or data packet loss ratio increases, the user's QoS performance decreases. Thus, the two objective attributes have been reciprocally transformed before they are applied in our model. Table II lists part of the collected data used in our simulations.

TABLE II: THE COLLECTED OBSERVATION DATA IN THE SIMULATIONS

Network protocol parameters			Traffic performance index		
data packet generating ratio (α)	sliding window size (β)	data transmitting ratio (γ)	delay	loss	throughput
10	20	1	0.079091	0.00122	398.909
10	20	2	0.047583	0.00031	398.716
10	20	5.5	0.02964	0.00011	398.733
...	...	...	...	...	...
...	...	...	...	...	...
20	20	1	0.079091	0.00122	398.909
20	20	2	0.047583	0.00031	398.716
...	...	...	...	...	...
...	...	...	...	...	...
40	50	2	0.11	0.01322	1003.707
...	...	...	...	...	...
50	100	1	0.51814	0.08459	655.687
50	100	2	0.320264	0.07965	1058.964
50	100	5.5	0.197457	0.08044	1751.699

By collecting the different performance indexes of the FTP traffic transferred with different values of α, β, γ, the significance analysis has been done for the integrated QoS, where α={20, 50, 80, 100, 200}, β={10, 20, 30, 40, 50}, γ={1, 2, 5.5, 11}. Fig. 4 shows different input parameters' contributions to the three performance indexes, respectively. It can be observed that the three input predictive attributes have different impact on the system performance. Fig. 4(a) shows that while $\alpha < 50$ *Kbps*, it has obvious effect on the system output. And while $\alpha > 50$ *Kbps*, the network performance tends to be stable. Figure 4(b) shows that under the current network condition, the sliding window size has a relative high influence on the network delay. Fig. 4(c) indicates that the WLAN data transmitting ratio has a high contribution to the throughput and delay. Also, with the increment of WLAN data transmitting ratio, the network delay increases much more than throughput and data packet loss ratio.

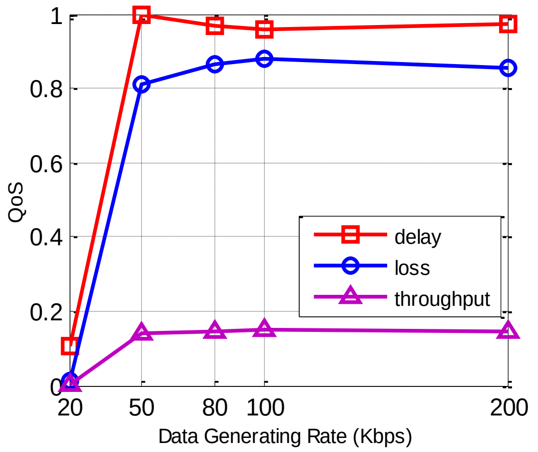
Next, we adopt the nonlinear regression model proposed in Section 3 to obtain the fuzzy measurement comprised of the three input parameters and their interactions quantitatively. After the significance measur-ement analysis, $\mu(\{\alpha\})$ and $\mu(\{\alpha, \gamma\})$ have been deleted and the remaining five fuzzy measurements have been conserved, which have been given in Table III. Here, the positive sign means user's QoS can be improved by increasing the corresponding measurement and vice versa. It can be observed that $\mu(\{\beta, \gamma\})$=0.742 is the most significant measurement under the current network condition. In other words, the user QoS can be improved by adjusting the sliding window size and the data transmission rate.

TABLE III: SIGNIFICANCE MEASUREMENT OF THE OBSERVATION DATA

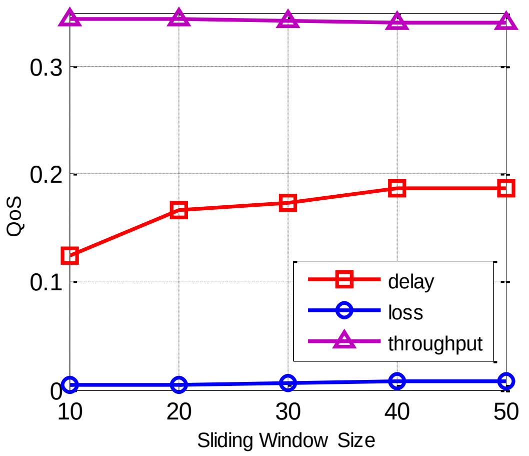
$\mu(\{\beta\})$	$\mu(\{\alpha,\beta\})$	$\mu(\{\gamma\})$	$\mu(\{\beta,\gamma\})$	$\mu(\{\alpha,\beta,\gamma\})$
-0.034	-0.09	0.368	0.742	0.379

Then, the measurements shown in Table III have been adjusted to validate the effectiveness of our proposed model. Table 4 shows the results of the user's QoS after adjusting the corresponding fuzzy measurement. We do not present the result of adjusting the measurement $\mu(\{\beta\})$ due to its relative small significance measurement. The CLL algorithm operates in the same way as adjusting $\mu(\{\alpha, \beta, \gamma\})$, which means that the network performance is improved by adjusting the data packet generating ratio α, sliding window size β, data transmitting rate γ

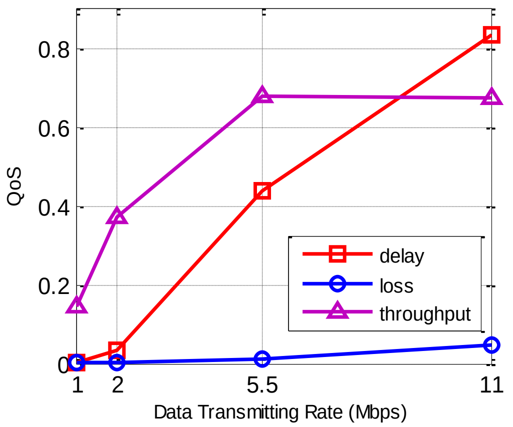
simultaneously. From Table IV, we conclude that user's QoS achieves the maximum value after adjusting the most significant measurement $\mu(\{\beta, \gamma\})$. And adjusting $\mu(\{\alpha, \beta, \gamma\})$ brings more QoS performance enhancement compared with the results derived by adjusting $\mu(\{\gamma\})$, which is in accordance with the analysis shown in Table III.



(a) α vs QoS



(b) β vs QoS



(c) γ vs QoS

Fig 4. Different predictive attributes' contributions to the network performance.

It can also be seen that the user's QoS decreases after adjusting $\mu(\{\alpha, \beta\})$ because of the negativeness of measurement $\mu(\{\alpha, \beta\})$. As the CLL algorithm does not quantitatively depict the significance of the parameters and their interactions, our proposed algorithm behaves better than CLL algorithm.

Specifically, we compare the concrete values of each performance index before and after the parameter adjustments in Fig. 5. It can be observed that by adjusting the most significant measurement $\mu(\{\beta, \gamma\})$, the user's QoS has much improvement on delay, packet loss ratio and throughput. Although not all the performance indexes achieve their optimal values, the integrated QoS value achieves the optimal value (for example, the throughput after adjusting $\mu(\{\beta, \gamma\}$ is less than the results derived by adjusting $\mu(\{\gamma\})$). More specifically, adjusting $\mu(\{\alpha, \beta, \gamma\})$ means adjusting the sliding window size on the basis of $\mu(\{\beta, \gamma\})$, which indicates that the network is in a slight congested state. While the sliding window size is increased, the network throughput decreases and the data packet loss ratio increases. In the beginning, the network resource has not been utilized fully, which can be concluded by the fact that the QoS increases by adjusting $\mu(\{\alpha\})$ (the data generating ratio) and $\mu(\{\gamma\})$ (the data transmitting rate). The network condition tends to be congested with the increment of data generating rate. Under the condition that the sliding window size still grows, the network QoS would declines, which agrees well with the experimental results.

TABLE IV: THE USER'S QOS AFTER ADJUSTING THE CORRESPONDING MEASUREMENT

Initial value	$\mu(\{\alpha,\beta\})$	$\mu(\{\gamma\})$	$\mu(\{\beta,\gamma\})$	CLL
0.071	0.025	0.83	0.99	0.84

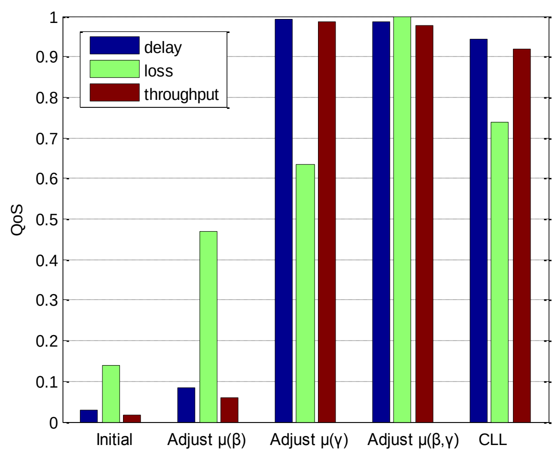


Fig 5. Performance comparison between the initial value and the values obtained by adjusting each fuzzy measurement

V. CONCLUSIONS

With the rapid development of wireless network and the increment of wireless applications, user' requirement tends to show diversified characteristics, leading the situation that the service QoS provided by the current network is hard to be satisfied. From the perspective of cross-layer optimization, this paper considers the contributions brought by the different protocol parameters and their interactions on the wireless networking QoS performance. Based on the fuzzy measurement theory, the self-adjusting model in terms of the protocol parameters is proposed to optimize the wireless network performance. The protocols' parameters are analyzed based on the nonlinear Choquet integral and the significance measurement is concluded. According to the measurements' significance analysis, the most significant measurement is adjusted to improve the network performance and achieve the user's QoS. The simulation results have validated our proposed model's effectiveness and feasibility.

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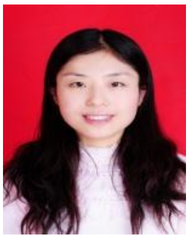

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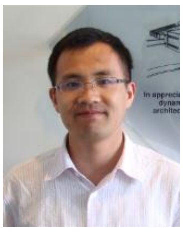

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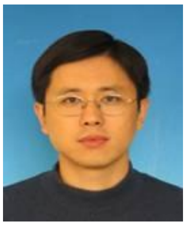

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