Service recommendation for a group of users on the Internet of things using the most popular service

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***Abstract*— With the emergence of the Internet of Things (IoT), advanced technologies like fog and cloud computing have been harnessed to create dynamic, real-time platforms addressing the needs of modern decision-makers. Crucial to this process is the recommendation of services tailored to each user's requirements in IoT settings, with the potential for improved Quality of Service (QoS) and Quality of Experience (QoE). The presented method in this paper leverages sensors, services, and fog computing within IoT systems to enhance QoS and adapt to user feedback. The approach involves ranking QoS of services based on Reliability, Availability, and Cost (RAC), and identifying the Most Popular Service (MPS) previously selected by the user. Comparison with Co-Scheduling System for Fog-node Recommendation and Load Management (CoS_FRLM) and User Characteristics-Collaborative Filtering (UCCF) demonstrates our method's effectiveness in maximizing recall, precision, and f-measure, as tested with the Network Simulator (NS3).**

Keywords—Internet of things, Service recommendation, Quality of Service, Most popular service (MPS)

I. Introduction

The Internet of Things (IoT) proves to be the most efficient network in wireless communication from an economic point of view. Through IoT, data can be transferred with low delay and high reliability to users [1]. IoT is a group of perceptible, intelligent sub-systems with computing and communication capabilities that can gather and store data from hard-to-reach natural environments or dangerous places [2]. IoT uses communication protocols to connect objects to the Internet with unique identifiers and addresses [3]. Examples of such objects can be smartphones, heart rate monitors, smart farming devices, transportation, and various sensors. Thus, new applications, like the internet of everything (IoE), the internet of flying things (IoFT), the internet of nano things (IoNT), the internet of medical things (IoMT), and many other technologies are used nowadays. Therefore, IoT systems should find suitable services and combine them to complete a task or create new applications [4]. IoT is regarded as the Internet of the future and will change the current mode of communication from person-to-person, person-to-gadget, and gadget-to-gadget [5].

There are many new IoT services and products operating throughout the world. To propose the most appropriate service to consumers, recommended services analyze data about objects, users, and their interactions [6]. Also, in IoT and Wireless Sensor Networks (WSN), the service management module is named the service recommender. This module aims to evaluate the most suitable services that can provide an increased Quality of Service (QoS) to all users [7]. The four-step filtering, scoring, ranking, and assessing process is used to implement the recommender service in the IoT network. First, services that do not fit the users' needs are excluded through filtering. Each service is given a numerical value through scoring. Finally, ranking delivers a list of services in a particular order based on filtering and scoring outcomes. Both issues will be resolved by a hybrid recommender system based on fog and cloud computing [8]. Pre-filtering useless data and processing data locally to the extent possible will be done using a fog-based recommender system. As a result, the solution will drastically reduce the demand for cloud servers and Internet connectivity.

In decentralized computing, data processing, computing, storage, and applications are distributed between the source and the fog [9]. Due to the importance of system accuracy from users' perspectives, this research focuses on service recommendations for IoT systems utilizing cloud and fog computing. To ensure the best services in IoT with improved accuracy, this paper employs a technique called Most Popular Service (MPS). In the proposed method, the MPS is determined by the user selection from the first round, and the main QoS is defined based on Reliability, Availability, and Cost (RAC). After obtaining the RAC, the services are categorized in each round. Since the services have different QoS in each round, their QoS must be sorted. The primary objectives of the current study are:

- To increase the precision of the MPS and RAC methods based on service recommendations in given IoT systems and compare the results obtained with other methods from existing literature.
- To increase the recall and f-measure of the service recommendations based on the MPS and RAC.

II. Related work

To support the users in IoT system to reach the highest QoS, recommendations services are presented in the early 2010s. Several works and research aim to meet the users' best needs based on agent techniques. Most investigators used collaborative, knowledge-based, and metaheuristic algorithms to solve this issue. However, this topic is an Np-hard problem [10], thus a global best answer cannot be reached. In this section, we examine some recently published papers in journals and conferences in this area.

Aji, Nurhasan [11] proposed a recommendation system based on CRoss-Industry Standard Process for Data Mining (CRISP-DM) for smart farming based on IoT. In this paper, the authors tried to use data mining and a planning strategy for users. Here data modelling is defined as a potential decision and divided it into three steps: in the first step, recommendation is performed; in the second step, they proceed with data preparation, and in the third one the decision variables analyses are used to recommend the best services. This paper has a low complexity compared with other methods in this area.

Munoz-Organero, Ramírez-González [12] proposed a context-aware service recommendations in an IoT environment based on 75 sensors tagged with readable RFID.

In this paper, they created a proof-of-concept system to evaluate the performance of collaborative recommender techniques based on user ratings with similarity operations. Their method proved to achieve a good efficiency in recall and f-measurements.

Tu, Aznoli [10] proposed a service recommendation based on a metaheuristic algorithm called Artificial Bee Colony (ABC) and Genetic Algorithm (GA). This paper proposed a smart farming system based on fog computing using the highest recommender services. The ABC algorithm and GA algorithm used collaborative filtering to operators the effective scheme in service discovery. Compared with other well-known methods, this proposed method has a good performance in Mean Absolute Error (MAE) and Hamming distance.

Bouazza, Said [13] proposed a recommender service based on Social IoT (SIoT) using different IoT sensors. This research suggested hybrid techniques that use users' collaborative filtering and personalized services. This topology incorporates social relations between processes alongside ratings and produces recommendations. This paper demonstrate a good accuracy and recall performance compared with Graph-based recommender (GBR) and Collaborative Filtering (CF).

Zhang, Zhu [14] proposed a neural network for service recommendation in SIoT. This proposal used a model to obtain a vector for smart sensors related to Bidirectional long-short-term memory (BI-LSTM) with mechanisms to extract a representation of the intelligent sensors. Also, the proposed method is divided into two parts Self-Attention (SA) layer and Global-Attention (GA) layer. The SA can predicate the QoS of each services to users, and the GA can measure the relationship between service and user requests. This proposed method has a good performance in mean absolute error and high reliability.

Chen, Tao [15] proposed a time-aware recommendation based on the client's performance over time and social activity. In the first step, the system learns the user's usage in specific times, while in the second one they can evaluate the similarity of the intelligence of the object's by introducing their heterogenous relationships into lower dimensional space. Finally, they generate the recommendation list using the collaborative filtering. The proposed method shows that, all evaluations in terms of MAE and Root Mean-Square Error (RMSE) achieved a good performance.

Xiong, Wang [16] proposed a recommendation service based on an artificial intelligence algorithm. This paper focused on security collaboration for Mashup and web services. They used 2 model for a recommendation; at first, a deep neural network for accuracy, and secondly they used a predicted rating mashup service. The proposed method has good performance in recall and precision.

III. Network Architecture

The (n) number of services' and the (U) number of users have been determined. The intended user's service recommendation is modeled mathematically using an all-or-nothing model, as described in (1) and (2). If the IoT system can find the best QoS, the recommendation (Y_{ik}) is set to one, else it is zero. Service i can not service in parallel to K users.

$$Y_{ik} = \begin{cases} 1 \text{ when the } i\text{-th service is recommended to the } k\text{-th user} \\ 0 \text{ otherwise} \end{cases} \quad (1)$$

$$\sum_{k=1}^{U} Y_{ik} = 1 \qquad i = 1, \ldots, n \quad (2)$$

Another criterion in service recommendation is the capacity offered by the services, since every service has a limited number of capabilities that can be offered to the users. Thus, in equation (3) for each user will be offered the maximum capacity of services, it can serve the user.

$$\sum_{i=1}^{U} \beta_i Y_{ik} \le M_k \qquad k = 1, \ldots, n \quad (3)$$

where M_k is the highest number of requirements from k user and β_i is the amount of demands or transmission that one service can offer per unit of time.

A. The proposed method

Identifying the best QoS for a user with certain requirements is a critical challenge for quality management. Some QoS parameters are independent of the user and have the same value for different users (such as cost, availability, and reliability). In contrast, other parameters depend on the user, having different threshold values depending on the users demands (such as response time and usability). In this paper, we considered the RAC values for recommending services. The reliability and availability are determined based on the failure time and the repair of the service when certain issues are detected. Denoting by λ is the failure probability during small interval ($t, t+\Delta t$). To estimate the value of λ, can use the method of maximum likelihood estimation (MLE), which seeks to find the value of the parameter that maximizes the likelihood of observing the given data. Equation (4-7) shows the reliability and availability formula and function is:

$$f(t) = \frac{1}{(a-1)!} (\lambda t)^{a-1} e^{-\lambda t} \quad (4)$$

The failure time probability distribution function (i.e., the probability that the system will fail between 0 and t) is:

$$F(t) = \int_0^t f(x)\, dx, \; t > 0 \quad (5)$$

And the reliability distribution function (i.e. the probability that the system will not fail between 0 and t) is:

$$R(t) = 1 - F(t) \quad (6)$$

From this, we can calculate the average time until failure as follows:

$$E = \int_0^\infty t f(t) dt \quad (7)$$

The cost is the amount of funds spent to satisfy an user (for example an IoT node) demands, based on the amount of memory, number of operations, and bandwidth required. We can determine the costs based on:

$$\text{Cost} = \sum_{i=1}^{N} (C_i \cdot T_i) \quad (8)$$

where N is the size of the concrete service requested by an IoT node, C_i is the number of nodes necessary to fulfill the users' requests, and T_i is the time interval in which the user has access to the nodes.

The RAC parameters are analyzed according to these formulas and sent to Fog computing to start the second phase.

To consider the relative and uncertain information, in this research a triangular membership function has been used for each service quality parameter, as shown in figure 1. The triangular membership function divides the domain into 4 categories (poor, moderate, good, and excellent). If these 3 parameters (cost, reliability, and availability) have a performance higher than 0.45 the service considers a suitable one. Since these three parameters results should be between 0 and 1, according to this experiment, the threshold of the services is calculated. For example, if one service has the Reliability of 0.5, the Availability of 0.55, and the Cost of 0.7 are considered as suitable services in IoT..

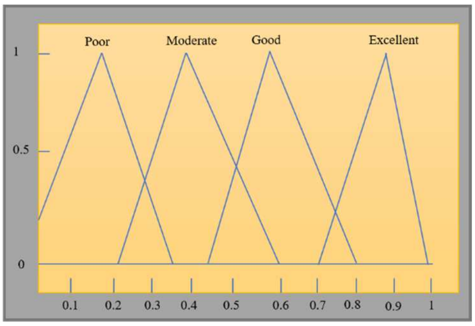

Figure 1: Triangular function of each QoS parameter

In the second step we must find the MPS of these services, in order to obtain the best combination of services based on users' demands. In most IoT scenarios, the system selects a specific service according to users demands and this selection is called MPS. The MPS usually determine an increase of the QoS and based on the user's behavior. MPS can be one single service or a set of multiple services that fits the best to user's requests. In MPS the similarity between the behavior of the users that have selected at least one service. MPS seeks to identify common patterns in user behavior by analyzing the services chosen by different users. By discovering similarities in the preferences of users who have selected at least one service, the MPS approach can better comprehend the popularity of specific services and potentially enhance recommendations for users with similar preferences. In this paper, the MPS is used as a similarity function, so it has been used for the similarity computation. It basically computes the statistical correlation between two nonfunctional attributes values to determine their similarity. Equation (9) and (10) defines the MPS selected by users. Counting the number of services, a particular person has subscribed to MPS [17].

$$S(U,O) = (\beta \mid Y_{S,U} \mid + (1-\beta) \mid Y_{S,O} \mid) \tag{9}$$

where S shows the service, U is the user and O is an object or service, β is a parameter that shows the balance of the influence of components between the user and the object, and Y is a set of services weighted in all service subscriptions.

$$Sim(i,j) = \frac{\sum_{u \in U} (r_{u,i} - r_i)(r_{u.j} - r_j)}{\sqrt{\sum_{u \in U} (r_{u,i} - r_i)^2} \sqrt{\sum_{u \in U} (r_{u,j} - r_j)^2}} \tag{10}$$

where $Sim(i,j)$ indicates the degree of similarity between services i and j and. Here U shows the users that offers the service items i and j, $r_{u,i}$ and $r_{u,j}$ indicate the QoS value which was produced when the user used both service i and j , while r_i and r_j shows the average QoS value of services i and j.

IV. Results

The method proposed in this paper has been simulated in Network Simulator (NS3) and compared with Co-Scheduling System for Fog-node Recommendation and Load Management in Cloud-fog Environment (CoS_FRLM) [18], and Association rule, and User Characteristics-Collaborative Filtering (UCCF) [10] in the same dataset. The Dataset is used on large scale and considered as critical for IoT systems. This dataset offered by companies like Telus, Libelium, and BlueRover that provide customer IoT services. A total of 90 services and 110 IoT objects are explored to offer them to customers to find out which one is beneficial from customer's viewpoint. The data set is used in a real environment and the simulation parameters are summarized in table I.

Table I. Simulation settings / parameters

Parameters	Value
Number of users	500
Number services	90
Objects (servers)	110
Service collected	Libelium, Telus, Bluerover

On order to evaluate the performance of the proposed method in this paper, we compared it with well-known metrics as follows.

Recall(R): Recall is the number of recommended services that are correctly suggested to the user. Figure 2 shows that our proposed method achieves a higher recall than other two algorithms taken as reference.

$$R = \frac{1}{|U|} \sum_{u \in U} \left(\frac{|S_u^k \cap S_u|}{|S_u|} \right) \tag{11}$$

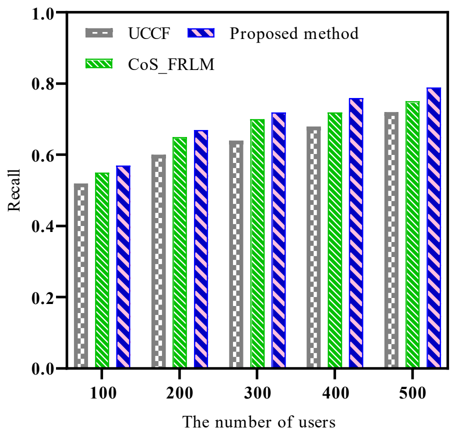

Figure 2: Comparing recall among the number of users

where S_u^k indicates the highest k recommended services and S_u the set of services that are relevant for user $u \in U$. For all users between 100-500, CoS-FLRM method achieves results closed to the ones obtained by the proposed method, while UCCF has the lowest recall results.

Precision (P): The precision indicates the suitability of the recommendation and determined as the total number of services that have been correctly recommended over the total number of recommended services.

$$R = \frac{1}{|U|}\sum_{u\in U}\left(\frac{|S_u^k \cap S_u|}{|S_u^k|}\right) \tag{12}$$

Figure 3 shows that our proposed method achieves a higher precision for the users.

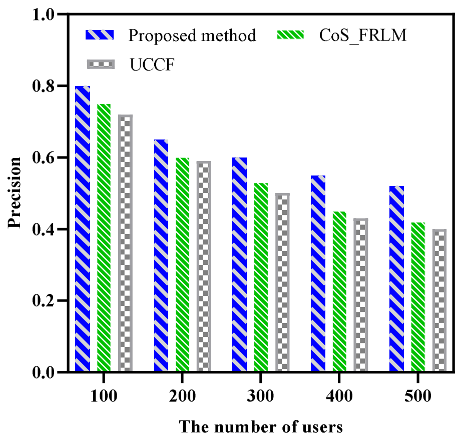

Figure 3: Comparing precision among the number of users

For 100 users, the CoS_FLRM achieves results closed to the ones obtained by our algorithm, but when the number of users increase, the efficiency of the CoS_FRLM decreases. For a large scalability setup, the COS_FLRM and UCCF obtain approximately similar results.

V. Conclusion and Future Work

Recent advances in fog computing have revolutionized applications such as Internet of Vehicles IoT, sensor networks, and smart grids. Its combination with available networks offers numerous benefits, but service recommendation within fog-based IoT systems remains a challenge due to its NP-hard nature. Our paper presents a novel recommendation algorithm for IoT that uses a Quality of Service (QoS) and Most Popular service (MPS) for service selection, factoring in previous user choices. The QoS first step calculates, normalizes, and sorts each service's reliability, availability, and cost, followed by MPS calculation. The resultant recommended service, based on these parameters, outperforms the Co-Scheduling System for Fog-node Recommendation and Load Management (CoS_FRLM), and User Characteristics-Collaborative Filtering (UCCF) on recall, precision, and f-measure metrics according to NS3 simulations. Looking forward, integrating service recommendations into a composition approach may be beneficial, albeit with more complex selection criteria. Additionally, merging metaheuristic algorithms with machine learning could offer promising results for Ultra reliability and Low latency (URLLC) applications.

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