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Eliciting and Considering Underlay User Preferences for Data-Forwarding in Multihop Wireless Networks

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ABSTRACT Until now, user preferences remained widely unconsidered in the design process of underlay wireless networks. Yet, with new technologies, such as device-to-device (D2D) communications being contingent upon user acceptance and their participation, user preferences are the key ingredient for designing successful products and services. Following this notion, we provide a general framework which elicits users' preferences for underlay networks (UUP) and active roles in multihop networks. Furthermore, we define an interface which translates the technical jargon related to the topic into non-technical terminology and introduce a virtual scenario which is also understandable for users with no technical background. Subsequently, based on a choice-based conjoint study, we derive the corresponding UUPs, translate them back into technical relationships, and assess the system's performance and the user participation by incorporating the elicited UUPs into a suitable D2D scenario.

INDEX TERMS Communications technology, conjoint analysis, consumer electronics, device to device communication, mobile ad hoc networks, user centered design, user preferences, willingness to forward, wireless communication, wireless multihop networks, wireless networks.

I. INTRODUCTION

Traditionally, user preferences are considered during the development of new solutions in the upper layers of the network protocol stack, e.g., when developing a new internet service. This is reasonable as users have direct interaction with these solutions which are designed explicitly to satisfy their needs, for example, considering user preferences to model user quality of experience (QoE) in video streaming services. On the contrary, users have no direct interaction with the lower three layers, and thus, user preferences are usually not considered in the development of new solutions in the lower layers such as new transmission, scheduling or routing techniques. Instead, the lower layers are designed to meet the requirements posed by the upper layers.

In the last decade, wireless networks have significantly evolved and user roles have extended from being passive only, where a user has demands and the network is designed to meet these demands, to an active role such as forwarding, caching or computing for others [1], [2]. This means that users become part of the network and their preferences may affect the network performance. In other words, assigning users an active role shows technically a significant enhancement in the overall performance of the network [3]–[6]. Nevertheless, users may not be satisfied with such a role because of battery depletion or privacy concerns, and thus, the developed underlay techniques based on the assumption that users certainly will accept an active role may be inappropriate. Hence, the impact of user preferences on the performance of multihop networks needs to be understood first, and then new multihop techniques aware of user preferences should be developed. For instance, device to device (D2D) communication technology has been extensively investigated in the last few years and showed technically a significant performance gain over other conventional technologies [2]. However, this technology strongly relies on the acceptance of users who are asked to act as forwarders.

To the best of our knowledge, this paper is the first attempt to elicit and consider underlay user preferences (UUP) in

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multihop networks. In particular, we propose a general UUP eliciting framework which can be applied to any user's active role in multihop networks. To elaborate our investigations, we focus on data forwarding as an example of an active role while our framework can be adapted to other user active role cases. Due to differences in users' concerns about battery level reduction, slow functioning of the device or diverse privacy issues, users have different preferences on their forwarding role. Accordingly, some users may not be willing to act as forwarders which prevents the technology from being widely accepted. Therefore, incorporating UUP in the underlay models of future wireless networks leads to more realistic models and ensures that the technology, when it is realized, will be most probably accepted by the targeted users.

Acting as a forwarder has different consequences on the experience of the user and the functioning of the user's device because forwarding will use parts of the limited resources such as energy, memory, processing and communication resources. Among these employed limited resources, we select the consumed energy to be the main cost of the forwarding since studies show that mobile users are mostly concerned about their battery [7] because mobile devices are always equipped with limited battery. As a reward for forwarding, the user receives a free internet service with assured requirements in terms of throughput and latency. The main question addressed in this paper is what the UUP are in terms of: 1) the amount of energy consumed for forwarding to others, 2) the minimum throughput and maximum latency tolerable for the internet service delivered as a reward to the user.

To get access to an unbiased sample of users which represents the whole population of mobile users, we prepared an online survey and launched it with the help of a market research firm that offers data collection field services. In general, online surveys have the advantage of being able to gather user data with considerably less time, effort and cost as compared to other conventional approaches such as interviewing users personally or implementing a prototype of the technology and examining the UUP in realtime based on user perception or behavior. Moreover, people feel anonymous when answering a survey on the internet. There are several challenges facing the survey preparation process when aiming at collecting high quality reliable data. First, users do not have, in general, technical background, so they cannot understand technical underlay terms like throughput, energy, and latency. Thus, they cannot state their UUP. Secondly, users do not have experience with the proposed technology, i.e., multihop transmission and acting as a forwarder. Thirdly, users may have different assumptions when being asked about the amount of energy that they are willing to spend for forwarding to others and the characteristics of the rewarded services. For instance, they may think of different scenarios and situations in terms of place, time, battery level or charging possibility when being asked about their UUP. In this case, their answers will be based on their different assumptions rather than their UUP. To tackle these three challenges, we propose a framework for eliciting UUP from users. In particular, our framework employs a method from market research called choice-based conjoint analysis (CBC) [8]. CBC is a well-recognized method in the community of information systems and marketing [9] and is widely applied in studies which deal with choice, respectively trade-off decisions among products. They provide insights into user preferences, even when the product or service of interest does not exist on the market yet or was just recently launched [10]–[13]. Furthermore, we analyze the collected data to find the UUP and incorporate them in a D2D scenario in which we optimize the transmission and assess the performance from the overall network perspective and individual users perspectives.

The rest of the paper is organized as follows: Section II discusses related work and lists the contributions of this paper. In Section III, we summarize the proposed framework of eliciting the UUP. Then, the approach is explained in details in the following sections IV – VI. We show and analyze the empirical results in Section VII. In Section VIII, we incorporate our findings of UUP in a D2D communication model. In Section IX, we draw our conclusions.

II. STATE OF THE ART AND CONTRIBUTIONS

In general, finding user preferences in underlay networks for developing UUP-aware underlay schemes is not well investigated. Nevertheless, it becomes essential to consider UUP when designing underlay schemes for future communication systems in order to raise user acceptance. In particular, emerging technologies such as fifth generation communication systems (5G) and the internet of things (IoT) set challenging system requirements such as high throughput, low latency, high energy efficiency and spectral efficiency. To tackle these challenges, several research directions have been investigated. For instance, new underlay communication resources such as new frequency bands and additional spatial dimensions are exploited, e.g., millimeter wave (mmWave) communication and massive multiple input multiple output (massive MIMO) [14]. A second direction focuses on designing the underlay to meet the service requirements posed by the application layer [15]–[17]. Finally, some researchers investigate the possibility of exploiting user contexts, such as user location, activity, and demographic information, when designing the underlay [18]. Accordingly, UUP can be estimated from user contexts and data traffic history using big data analysis [19], [20]. This can however only be done when the technology is already on the market. However, we are interested in finding UUP on the upcoming technologies before we develop systems based on uninformed assumptions.

In underlay, several algorithms are proposed in which UUP are assumed to be given and previous research mainly investigated how UUP affect the network performance. For instance, Liu *et al.* [21] proposed that both, content popularity and user preferences in terms of content type are essential for determining the optimum cached content at base stations. In [22], a distributed machine learning based algorithm for content forwarding was proposed. The proposed algorithm assumes that users have UUP on the forwarding energy budget and it uses virtual tokens to incentivize or punish users if they forward content or not, respectively. The authors showed that user density and forwarding energy budget have a strong impact on network performance. Furthermore, the distributed video multihop broadcasting algorithm proposed in [23] considers two classes of users w.r.t. UUP: users with high willingness to forward and users with low willingness to forward. The proposed algorithm rewards users with high willingness to forward with a high-quality video while the other users receive the video with basic quality only. The authors showed that incentivizing users to invest more energy in forwarding improves the overall network efficiency in terms of number of bits per Joule. Reference [24] proposed an energy efficient distributed algorithm for video dissemination in multihop broadcast scenario. The algorithm considers user preferences on perceived video quality and forwarding energy. The distributed algorithm employs an incentive mechanism which ensures that users receives the video with their preferred quality while minimizing the total forwarding energy in the network. The algorithms in [22]–[24] assume that users have different preferences in terms of forwarding energy and/or video quality. However, the considered preference models are artificial and not based on actual user studies.

On the contrary, user studies are conducted for finding user preferences with respect to existing and new services. For instance, Singhal and De [25] proposed a user preference based adaptive scalable video coding (SVC) scheme in a downlink broadcast scenario which aims at saving energy at the receiving mobile devices. The proposed scheme employs analytical models of average user preferences on the video quality as a function of the energy saving at the mobiles. The analytical model of user preferences is approximated from empirical data collected from 25 respondents using a subjective test questionnaire in which respondents watch a video in different qualities and rank their preferences between 1 for 'not preferred' and 5 for 'most preferred'. However, the user preferences cover only video quality and not consumed energy at mobile devices. Also, the data is collected using standard procedures from International Telecommunication Union (ITU), see [26]. The results are not generalizable because user preferences are highly dependent on the chosen video and its quality profile. In [27], a conjoint analysis was performed to determine whether users are willing to adopt new advanced and secure services such as smart address book, group communication and seamless switching between devices and media types, rather than using the conventional services, e.g., Skype, Whatsapp, Google+, etc. The design of the survey is well motivated and detailed. However, the respondents were only university students and faculty members which is rather a homogeneous set and not a proper sample in terms of the target population of mobile service users.

Based on the previously mentioned works, it can be clearly seen that there is a research gap on finding and considering the UUP when designing underlay techniques, and hence, the contributions of this paper can be summarized as follows:

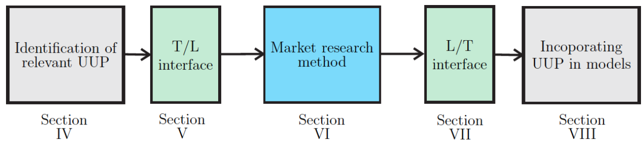


FIGURE 1. An illustration of the process of eliciting UUP and incorporating them in underlay models.

- We propose a general framework for eliciting UUP on active roles in multihop networks. The framework finds the trade-off between UUP on the cost and rewards for performing an active role.
- Since users are unfamiliar with the underlay problems and technical terms, we define an interface which basically translates the technical problem into layman terminology understandable by the users. We term this interface as technical to layman terminology (T/L) interface which represents the underlay problem and its respectively needed UUP as a prospective technology with different adaptable features in which users assume that this technology will be realized and their preferences on different features of this technology are needed.
- We introduce a virtual scenario and detailed assumptions such that users imagine the same situation when being asked about their preferences.
- Since users may have no experience with the prospective technology, we employ the CBC method to help users to create an imaginary experience with the prospective technology and be able to express their preferences.
- The survey is launched through a market research firm which is professional in reaching the right respondents and querying high-quality data. For a reproducible research, the collected data will be made available online after publishing the paper.
- We analyze the collected data and estimate user participation rates based on the derived user preferences.
- From the user preferences on the prospective technology, we also define a layman to technical terminology (L/T) interface which translates from the users' answers based on layman language back to technical meaning and, accordingly, it deduces the UUP of the underlay problem.
- We incorporate our findings into a D2D scenario and assess the system performance and user satisfaction.

III. OVERVIEW OF THE FRAMEWORK

In this section, the proposed UUP eliciting framework will be explained in general for any active role in multihop networks. We illustrate the framework in Fig. 1. In technical terms, the first step aims at identifying the underlay parameters in which the UUP are needed for a considered problem. For instance, in the case of users taking the active role of caching for others, the UUP on the amount of cached data, forwarding energy and/or the quality of service (QoS) of rewarded

TABLE 1. The identified underlay parameters for data forwarding in a multihop network.

	technical underlay parameters
reward	minimum throughput maximum latency amount of transferred data
cost	forwarding energy

service may be considered. Since users are unfamiliar with active roles and they may not understand technical terms, a T/L interface needs to be defined. In this T/L interface, a prospective technology is presented to users. The prospective technology is carefully selected and explained in layman terminology such that user preferences on the properties of this technology can be simply transferred to the original underlay parameters identified in the first step. In the third step, a market research method, e.g., conjoint analysis, which finds how users value different aspects of the prospective technology is employed. Then, we define a L/T interface in which user preferences on the prospective technology are translated to the identified UUP in technical terms. In other words, the fourth step aims at analyzing and deducing UUP in technical terms from user answers. In the last step, we incorporate the deduced UUP in underlay models. For the rest of the paper, each of these steps is explained in terms of data forwarding as an active role.

IV. IDENTIFICATION OF RELEVANT UUP

In the first step, the scenario, system model and problem statement need to be well understood. Accordingly, the technical parameters to measure the cost and reward of a user should be identified for a particular scenario. Based on this information, the needed UUP and their domains can be determined. For instance in the multihop broadcast scenario [23], [24], the authors focused on the problem of finding the best topology for data dissemination in a multihop transmission. In this problem, a forwarder spends energy for forwarding the data to its neighbors. As a reward, the forwarder receives a video with a certain quality level which depends on the amount of energy the user spends for forwarding. Different video qualities require different throughput and latency levels. Accordingly, the identified underlay parameters in this problem are the forwarding energy, the minimum throughput and the maximum latency and the amount of transferred data for the internet service provided as the reward, see Table 1.

V. T/L INTERFACE

The *T/L interface* aims at representing the multihop network and the identified underlay parameters, e.g., see Table 1, as a prospective technology understandable by potential users. In this prospective technology, a potential user is asked about his/her preferences on different technology features and characteristics of interest in layman terminology. However, considering a new technology such as a multihop network, using market research methods, one has to predict under which circumstances users are willing to adopt this new technology. As van de Wijngaert and Bouwman [28] pointed out, it is challenging to assess user preferences for a technology which is known to the public and even more challenging when the technology is unknown or when prospective users are unfamiliar with it. Basically, the reason is that market research methods always assume that respondents are familiar with the technology, well informed about its characteristics and capable to answer questions regarding the technology of interest. To introduce a prospective technology to potential users, two steps have to be done. First, a virtual scenario has to be explained in which users will imagine the same situation when they participate in the survey. Second, the identified underlay parameters need to be translated into understandable terms represented as different features of the prospective technology. In the following, the two steps are explained in details.

A. VIRTUAL SCENARIO

In general, one cannot ask the potential users directly to state their preferences on a new technology by simply explaining its features because this may bias the impression of the potential users and therefore may lead to unreliable preference data. For instance, potential users may show high acceptance of a new technology if they are asked directly about their preferences. Klopfenstein in [29] stated that potential users tend to be optimistic when being asked directly about their preferences on a technology with which they are unfamiliar. However, later, when the technology is realized, they become cautious, conservative, and thus, may show different preferences than previously stated. This implies that only within a scenario which is close to a real life situation, potential users will be able to answer questions or make decisions according to their actual preferences [28].

In general, the concept of data forwarding to nearby mobile devices is not familiar to many potential users. Hence, we introduced to the respondents that there is a new technology called *ad hoc network* which will be installed in public areas. This new technology is based on multihop communication and shall provide free internet services to its subscribers. However, subscribers have to forward data to other users in their vicinity which costs part of their devices' batteries. On the one hand, the survey implies that users are answering questions of whether the *ad hoc network*, the percentage of battery-level potentially spent for the network and the type of rewarded internet services are acceptable. On the other hand, our goal is to deduce UUP on the amount of forwarding energy as well as the throughput, latency and amount of data demanded as an incentive for forwarding.

To avoid ambiguities on the *ad hoc network*, we described a specific scenario to the respondents so that everybody imagines the same situation. This step is necessary because different assumptions about the context can highly influence user preferences. van de Wijngaert and Bouwman [28] pointed out that understanding the user adoption of a new technology is not a trivial task and it involves an interplay of several factors such as characteristics of the technology, the situation, and the user's personality. Therefore, the data collection process for assessing user preferences on a new technology is non-trivial and it needs careful preparation in terms of all the relevant factors, e.g., technical, psychological, economical, linguistic, legislative and social factors.

The evaluation of our pretests with different initial battery-levels shows that respondents do not have a significant concern about their device battery-level if it is relatively high, e.g., more than 70%. Moreover, our pretests show that with 50% initial battery-level and a 20% drop of the battery-level for personal usage, a respondent is forced to decide on the amount of energy to spend for forwarding out of the 30% remaining battery-level. Putting a respondent in pressure for deciding among different profiles is necessary because people typically try to avoid making such judgments by searching for unambiguous solutions involving dominance or following a relatively clear heuristic [30]. We therefore chose a 50% initial battery-level in our scenario. Furthermore, even though the percentage of battery-level which drops during the waiting time strongly depends on the potential user, the device, and the type of used services, it is assumed that exactly 20% of the full battery-level will be consumed. This assumption is necessary to remove any dependency between the consumed energy for forwarding to others and the consumed energy for using the awarded services. In other words, decoupling the preference dependency between these two types of energy consumption is essential for better preference estimation which will be described in Section VI. Also, the scenario considers that the *ad hoc network* has to compete against the existing cellular network and therefore, respondents can always decide not to subscribe to the *ad hoc network*. Accordingly, this assumption will not only show that there are potential users unwilling to invest part of their battery energy in forwarding, but also gives insights on the acceptance of the multihop technology itself. Therefore, the scenario is described to respondents as follows:

Scenario: Suppose that you are in a train station waiting for a train for one hour and your train journey takes one hour as well. Assume that you do not have the possibility to charge your device for the whole two-hour duration. Moreover, your initial battery level is 50% *and it will drain by exactly* 20% *during the one hour waiting time for your personal use. The ad hoc network is supported in this train station and can give its subscribers free internet services if they are willing to forward to other subscribers in their vicinity. This forwarding process is totally secure and will affect neither your privacy, device functionality nor the data plans.*

B. ATTRIBUTES AND ATTRIBUTE LEVELS

In this section, the attributes and attribute levels of the prospective technology, i.e., *ad hoc network*, are explained. To ensure that respondents understand and are familiar with the attributes, we translated our underlay parameters to non-technical attributes. Before explaining our design of translated attributes and their levels, we explain the basic rules that we followed to find the attributes and their levels.

TABLE 2. The underlay parameters for data forwarding in a multihop network and the translated non-technical attributes.

	technical underlay parameters	translated non-technical attributes
reward	minimum throughput maximum latency	service type
	amount of transferred data	service duration
cost	forwarding energy	remaining battery level

In general, a technology can be characterized by several features and only a few of them, called attributes, can be selected for a user preferences study based on the following properties [31]:

- Relevant: Only the technology features which are relevant to users and the overall network performance should be selected.
- Adjustable: It should be technically possible and economically beneficial to adjust a selected feature value and discretize the feature values into different finite levels.
- Unrestricted: The selected features have to be relevant to the whole target population and not only to a specific group.
- Independent: The selected features have to be independent of each other such that changing the level of one feature will not accordingly change the level of another feature.
- Compensatory: The design of the attributes and their levels should be compensatory such that decreasing the level of a feature can be compensated by increasing the level of another feature, i.e., such that the offered technology is still interesting for potential users.

The number of attributes has to be carefully chosen because a too small number of attributes can bias the respondent decisions by directing their attention to some attributes that they may not focus on during the actual realization of the technology [32]. Moreover, a too large number of attributes results in long and complex surveys where respondents cannot accurately answer, see [32], [33], and references therein.

It is advisable to choose the same number of levels per attribute [34]. If an attribute has significantly more levels than other attributes, it may be perceived as being more important. Green and Srinivasan [35] show that respondents usually give more attention to the attribute with more levels.

Using the above properties of selecting attributes and attribute levels, we translated our underlay parameters to non-technical attributes as shown in Table 2. In the following, each attribute and its levels are explained highlighting the technical challenges of increasing different attribute levels from underlay perspective.

1) SERVICE TYPE

The first attribute is the service type which a potential user receives as a reward for forwarding. Basically, this attribute

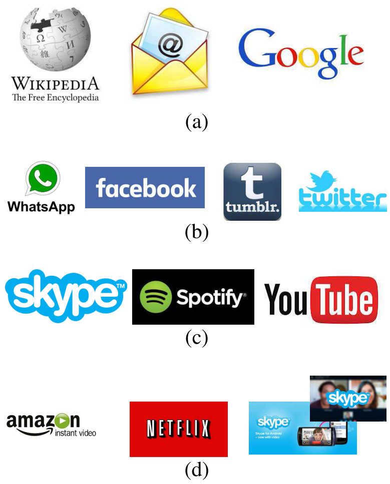


FIGURE 2. Example of applications represented as a reward in every service type level. (a) Level A. (b) Level B. (c) Level C. (d) Level D.

reflects the required minimum throughput and maximum latency needed for serving this potential user. Obviously, different internet services are characterized with multiple underlay requirements such as packet loss, jitter, and packet size. However, all these parameters can be abstractly described using throughput and latency. From underlay perspective, communication resources can be optimized in different ways to satisfy the internet service requirements in terms of throughput and latency. For instance, video streaming in Youtube requires relatively high throughput between 2.25 Mbps and 6 Mbps, but it is tolerant in terms of latency of up to 5 s, while voice over IP (VoIP) telephony in Skype requires relatively short latency of around 150 ms, but it accepts small throughput of at least 100 kbps [36], [37]. Hence, the communication resources will be optimized for maximizing the throughput in video streaming scenarios while they are optimized for minimizing the latency in VoIP telephony.

For different combinations of minimum throughput and maximum latency requirements, four service type levels can be distinguished which are termed levels A, B, C and D, as shown in Table 3. It can be noted that the higher the service type level, the higher the underlay requirements in terms of minimum throughput and maximum latency. This increases financial costs and technical challenges to the multihop network. A potential user who is granted a certain service type level has access to all lower levels. Table 3 shows the service type levels with the corresponding throughput and latency requirements [38]. Since respondents are familiar with smartphone applications rather than service types, we selected some of the most popular applications in Europe [39] and place them in these four service type levels based on their throughput and latency requirements [36], [37], [40]. Since there are applications supporting multiple services belonging to different service type levels such as Facebook, we tried to place these applications according to their basic or dominant service type, see Fig. 2.

2) SERVICE DURATION

We design the second attribute to be the service duration which indicates how long a certain service type level with its applications shall be supported. This attribute reflects the amount of data needed to be transferred to the potential user as a reward for forwarding. However, this raises several technical challenges in the underlay because the required minimum throughput and maximum latency need to be maintained at the forwarding device for a certain time duration irrespective of the position of the potential users and their movement pattern. This means that the longer the service duration, the more attractive the service will be to the potential users, but the more technically challenging problems will appear in the underlay. For this attribute, we select four levels: 15, 30, 45 and 60 minutes.

3) FRACTION OF BATTERY ENERGY USED FOR FORWARDING

We select the last attribute to be the percentage of the battery-level spent for forwarding which is the cost that a potential user needs to pay for getting the services. Note that the maximum percentage which can be spent for forwarding is 30% which is the difference between the 50% initial battery-level and the 20% of the battery-level drained for personal use. To avoid confusion that respondents have to calculate how much battery-level percentage remains after forwarding, we represent this attribute in the survey using the percentage of the remaining battery-level instead. Accordingly, the percentage of the remaining battery-level after forwarding is calculated as

$$e_{\text{remain}} = 30\% - e_{\text{forward}}, \tag{1}$$

where e_{forward} represents the percentage of battery-level used for forwarding. For this attribute, four levels are defined: $e_{\text{forward}} = 5\%$, 10%, 15% and 20% for the percentage of the battery-level used for forwarding. Using (1), the percentage of the remaining battery levels are $e_{\text{remain}} = 25\%$, 20%, 15% and 10%. The attributes and their levels are summarized in Table 5.

Based on the attributes and their levels, there is a tradeoff between the cost, i.e., forwarding energy, and the reward, i.e., service type and duration, and thus, potential users need to find their own preferences in this tradeoff.

VI. CHOICE-BASED CONJOINT ANALYSIS

A. MOTIVATION

Before explaining the applied market research method, i.e., CBC, it is essential to introduce the conventional conjoint analysis method. Conjoint analysis was developed and applied to the field of psychology in 1964 by Luce and Tukey [41]. Later in 1971, Green and Rao [42] introduced this method to the field of marketing. Basically, conjoint analysis is a method which reliably determines user preferences on different attributes of a product or technology based on the idea that a technology is characterized by different attributes, each of which has different benefits or costs for the users.

TABLE 3. Overview of the service type levels and their underlay requirements.

Level	Included levels	Service types	Min. throughput (kbps)	Max. latency (ms)
A	-	Web Browsing, Mail, File Transfer	10	5000
B	A	Instant Messaging	16	1000
C	A, B	Music Streaming, Voice over IP	96	150
D	A, B, C	Video Streaming, Video Telephony	2000	150

TABLE 4. Overview of the attributes and attribute levels.

	Service type	Service duration	Remaining battery-level
Level 1	A	15 minutes	25%
Level 2	B	30 minutes	20%
Level 3	C	45 minutes	15%
Level 4	D	60 minutes	10%

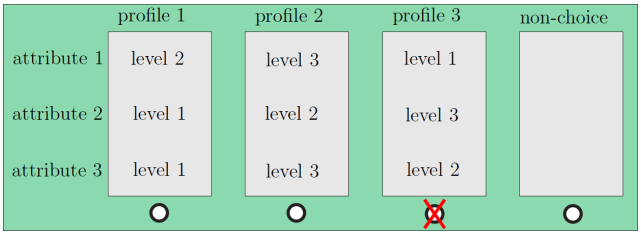


FIGURE 3. Illustration of choice-set in CBC.

For instance, using conjoint analysis, respondents are asked to rank attributes of a technology based on their preferences. Out of this ranking process, user preferences in terms of each technology attribute can be derived, analyzed and the best technology, i.e., the best combination of attribute levels in terms of boosting the participation rate, can be found. However, this classical conjoint analysis method has two major drawbacks. First, it is usually applied to technologies with a small number of attributes because when the number of technology attributes grows, it becomes complicated for the respondents to rank the attributes precisely [32]. Second, it does not explicitly indicate after all whether the technology is accepted by the respondent or not.

In a CBC on the contrary, which is a more recent approach, respondents are offered different variations of a technology and are asked to choose one of them or to decline all displayed options [8]. As an example, Fig. 3 shows a choice-set in which a respondent needs to either choose among different profiles or reject all of them and therefore selecting the non-choice option. In a typical survey, there are several choice-sets, and thus, the information of how respondents value the product attributes is derived from their choice decisions. Hoeffler and Ariely [43] pointed out that making repeated choices leads to an increase in preference stability.

B. CBC DESIGN

In a CBC, respondents are repeatedly challenged to make hypothetical choices between a set of profiles, which are described by their attributes and the corresponding attribute levels. Thereby, respondents make trade-off decisions between the attractiveness of those profiles, which provide valuable insights about the contribution of each attribute to form a choice. In our survey, respondents had to choose between three technology options and a non-choice option in each choice-set as shown in Fig. 3. It is recommended to have between three to six profiles in a choice-set [44] because it becomes difficult for a respondent to make a choice properly for a larger number of profiles [45]. Moreover, a minimum number of profiles are needed to represent a proper choice situation. The number of choice-sets in a CBC should be selected neither too small to avoid preference estimation errors nor too large to ensure that the respondents will not lose their focus, i.e., typical surveys should take between 15 minutes and 20 minutes. Therefore, in our design, we decided to have 12 choice-sets and three technology profiles per choice-set which is a typical design for a CBC. Within each choice-set, different combinations of the attribute levels are randomly selected in the three profiles with a minimum overlap. Since we have four levels in every attribute in our design, the three profiles in every choice-set have almost likely no overlap on levels so that we can ensure that these profiles are independent which in turn improves the preference estimation of each attribute level. Furthermore, the respondents should face a trade-off situation when choosing between the different profiles in a choice-set so that there is no dominant or trivial choice. This trade-off helps to understand the user preferences by putting him/her in a choice pressure in that degrading a level in an attribute can be compensated by upgrading a level in another attribute. Hence, it is assumed that respondents choose the technology option which they perceive as most attractive and thus, would adopt it. If none of the technology profiles provides sufficient utility to justify an adoption of this technology, the respondents can choose the non-choice option. Given the similarity of these decisions to real-world purchase or adoption decisions, discrete choice experiments like CBC are able to explain actual behavior quite well. The non-choice option can be used to determine how competitive the prospective technology profiles are. If the non-choice option is often selected, it implies that the technology is not attractive or too expensive. Accordingly, CBC needs to be designed such that the profiles are at the threshold of the respondent's acceptance. In our design, respondents can choose among different profiles of battery costs and service rewards in the *ad hoc network* or the non-choice option which means they will use their own data plans from their cellular network operators. Moreover, we ran multiple pretests for selecting an appropriate attribute levels to ensure that our profiles are at the threshold of the respondent's acceptance.

The pretests thus gave a rough impression on market needs, while the main study helps to find detailed UUP. Fig. 4 shows a sample of the choice-set based on our CBC design.

C. PREFERENCE ESTIMATION

In our survey, we collected data from 267 respondents. In particular, we employed a market research firm for finding the right sample of potential users for our study. The sample is heterogeneous and representative for the whole population of mobile users in a large western European country. As described in Section VI-B, the collected raw data represents how much a respondent prefers a profile over other profiles in every choice-set. However, the goal is to find individual preferences for each attribute level. This means that the collected raw data is correlated and incomplete because different respondents answer different subsets of choice-sets and each subset has fewer choice-sets than a complete design, i.e., all possible choice-sets with all possible combinations of profiles.

Let the term partworth utility $z_{i,l}$ be a measure which quantifies the preference of respondent i on an attribute level l. Then, the utility $u_{i,j}$ of respondent i on a profile j can be defined as the sum of the partworth utilities of the included attribute levels in this particular profile, i.e.,

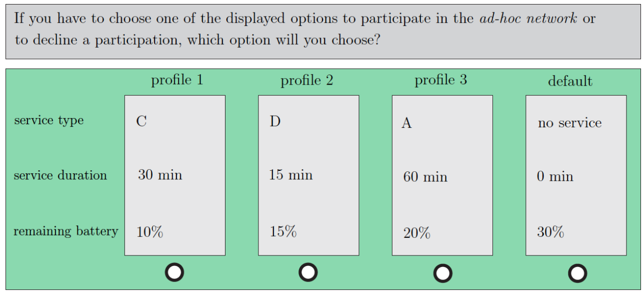
$$u_{i,j} = \sum_{l \in \psi_j} z_{i,l}, \tag{2}$$

where ψ_j is a set of indices of attribute levels in profile j. Given the number of respondents, attributes and levels per attribute, the accuracy of estimating a partworth utility of every individual attribute level depends on the number of profiles per choice-set, the number of choice-sets per respondent and the total number of choice-sets in the study. The higher the number of presented choice-sets and profiles, the more accurate the estimation will be, but the response quality of the respondents tends to decrease with increasing amount of choices because respondents suffer in concentration when answering long surveys [32]. Therefore, CBC uses an estimation algorithm called Hierarchical Bayes (HB) [32] which can, with a significantly high accuracy, estimate the partworth utilities of the individual attribute levels using a small number of profiles and choice-sets per respondent and a small number of choice-sets in total. The HB algorithm is based on the assumption that people stay almost constant during decision making. We explain how the HB algorithm estimates the partworth utilities of every attribute level from the respondent's profile selections in each choice-set in the appendix.

D. FURTHER QUESTIONS

Besides the set of choice-sets, the survey includes additional questions:

- Screening questions: To ensure that the respondent is qualified to participate in our survey, we included two screening questions at the beginning of the survey. The first question filters all respondents out of the sample who do not own a smartphone while the second question excludes all respondents from our study who do not use any of the applications shown in Fig. 2 on a regular basis.
- Validation questions: To ensure that a respondent answers the survey carefully and does not make random selections, we included two additional fixed choice-sets with a clearly dominant choice each. Furthermore, we added manipulation checks. If a respondent fails to answer these validation questions correctly, the corresponding data will not be considered.
- Additional questions: We added more questions at the end of the survey for statistical classifications and analyses. These questions elicit information on the gender, age, occupation of the respondent, and the usual cellular connection speed such as 3G, H+ or LTE. Moreover, to get more information particularly on the respondent's interest in free internet services and his/her concerns on the battery energy, we asked respondents about the number of monthly data plans and the brand of smart-phones, respectively. We also selected a set of applications as shown in Fig. 2 and asked the respondents on how often they usually use these applications.


If you have to choose one of the displayed options to participate in the *ad-hoc network* or to decline a participation, which option will you choose?

	profile 1	profile 2	profile 3	default
service type	C	D	A	no service
service duration	30 min	15 min	60 min	0 min
remaining battery	10%	15%	20%	30%

FIGURE 4. Example of choice-set in the survey.

Based on the answers to the screening and validation questions, we deleted 20 respondents from our sample because they did not pass the screening questions or their answers were not reasonable in terms of the validation questions. We therefore only used 247 respondents from our database for further analysis.

VII. EMPIRICAL RESULTS AND ANALYSIS

A. VALIDITY, UTILITY VALUES AND IMPORTANCE WEIGHTS

The face validity of our estimation model is high since all signs and magnitudes are reasonable and plausible. For further evaluation of the validity of our results, we consult the share of correctly predicted choice decisions based on the first-choice-model. Our model provides a hit rate of 77% which clearly outperforms the 25%-level in case of random choice decisions. This indicates an adequate pattern quality and high validity of our results.

When looking at the utility values which we display in Table 5, we can see the ranking of the attribute levels according to the stated preferences gained in the survey. According to our used evaluation method, the sum of all

TABLE 5. Utility values and average importance weights.

Attribute	Attribute Level	Average Utility	Standard Deviation	Average Importance Weight	Standard Deviation
Service type	Level A	−29.67	31.00	15.07%	17.34%
	Level B	3.49	14.32		
	Level C	10.63	12.99		
	Level D	15.55	23.68		
Service duration	15 minutes	−55.93	43.70	41.06%	20.62%
	30 minutes	−4.78	31.20		
	45 minutes	26.06	28.48		
	60 minutes	34.65	49.54		
Remaining battery-level	25%	39.40	60.99	43.86%	21.25%
	20%	28.03	29.09		
	15%	−22.36	33.18		
	10%	−45.07	52.39		

utility values of one attribute always adds up to zero. Thus, the distance between the levels offers information about the user preferences. Negative utility values, therefore, do not necessarily indicate that respondents perceive a negative utility with those attribute values. It rather illustrates lower preferences for attribute levels with lower utility values. Even the attribute level with the lowest utility value may still offer a benefit to the users. Taking a look at the attribute *Service type*, the difference of 33.16 between Level A and Level B is sticking out compared to the differences of 7.14 between Level B and Level C and 4.92 between Level C and Level D. Therefore, the perceived utility gain for a user when improving the service level from A to B is much higher than the additional utility when a user is offered Level C instead of B or Level D instead of C. The utility still increases from B to C and further to D, but to a smaller extent. Since ad-hoc networks only work if a certain amount of users participate, Level B should at least be offered in order to provide a reasonable level of attraction and user acceptance. We get similar results for the attribute *Service duration*. There is an increase in utility of 51.15 between 15 minutes and 30 minutes, 30.84 between 30 minutes and 45 minutes and 8.59 between 45 minutes and 60 minutes. Again, the service should at least be offered for 30 minutes or even better for 45 minutes to reach a reasonable participation rate. In terms of battery, users prefer a remaining battery-level of 25%. The utility value decreases by 11.37 between 25% and 20% and drops dramatically by 50.39 between 20% and 15%. If the battery-level is further decreased to 10%, the utility value declines by 22.71. Presumably, there is a threshold of 20% as an accepted remaining battery-level. If the battery-level drops further, the willingness of the users to participate in the technology collapses dramatically. On average, the remaining battery-level is the most important attribute to the users, closely followed by service duration. With an average importance weight of 15.07%, the service type of an offered technology option is the least important attribute considered while making the decision whether to participate in the technology or not. In general, the respondents of our study are rather heterogeneous in terms of their preferences which can be seen in the rather high levels of standard deviations of the average utility as well as the average importance weights, see Table 5.

TABLE 6. Overview of participation.

Number of offered technologies	Number of participants	Participation rate
Single-product solution	196	79.35%
Two-product solution	200	81%
Individual solution	202	81.78%

B. THE BEST SINGLE-PRODUCT SOLUTION

We would like to maximize the participation rate because multihop networks with D2D communication only become beneficial if a certain number of users participate. We, therefore, calculated the utility for each technology option on an individual level to forecast whether a respondent will act as a forwarder in the technology or not. We make the standard assumption that users will participate in the technology as soon as the perceived utility overruns the utility value for the non-choice option. With 3 attributes and 4 attribute levels each, there are 64 different technology option combinations possible. Moreover, there are 34 respondents who chose the non-choice option in each choice set. Even if we offer the solution which they perceive as the best, they will not participate because they always value the non-choice option as more beneficial. Nevertheless, our ambition is to make as many users as possible participate in the technology. Thus, we focus on the remaining 213 users. If we only offer one single technology option, we have the highest participation rate for the technology option with the attribute levels *Service type: Level C, service duration: 45 minutes, Remaining battery-level: 25%*. In this case where we offer only the best single-product solution, 196 out of the 247 survey respondents would participate which leads us to a participation rate of 79.35%, see Table 6.

C. THE BEST MULTIPLE-PRODUCT SOLUTION

To further increase the participation rate, it is also conceivable to offer multiple technology options which differ in the composition of the attribute levels. With this variety, more users might be attracted to participate who would otherwise have a higher preference for the non-choice option compared to the single-product solution. We start with the examination of the two-technology solution case, in which two different technology options are offered to the users. In case a respondent would participate in both technologies, we assume that he or she would select the option which provides a higher utility. We calculated the participation rate for all possible combinations. If two different technology options are offered, technology 1 should be *Service type: Level B, service duration: 45 minutes, Remaining battery-level: 25%* and the second technology should be *Service type: Level C, service duration: 45 minutes, Remaining battery-level: 15%*. In this case, 129 respondents would participate in technology 1 and 71 respondents would choose to act as forwarders in technology 2. The number of participants, therefore, increased to 200, so that we can increase the participation rate to 81%, see Table 6. We have one segment of users who are rather sensitive regarding their battery. They, therefore, accept a lower service level if they can keep a higher remaining battery-level instead. The other group who chooses option 2 is willing to sacrifice a certain amount of the battery-level in favor of a higher service level. If we offer two different technology options instead of one, the participation rate increases by 1.65% which is only a very small gain. We therefore estimate the expected number of participants if we offer individual solutions. But even if users are offered his or her most preferred technology option, only 202 respondents would participate. The remaining 45 respondents would even then prefer not to participate in the technology. Thus, the highest achievable participation rate is 81.78%, see Table 6.

D. USER STUDY RESULTS

Summing up, we are able to increase the number of participants if two technology options are offered instead of only one or if we even offer individual technology options for each user. But the gain in participation rate if multiple technology options are offered is very small. In the real world, each enhancement of the product range will cause a certain amount of extra costs for the provider. We will experience the highest costs if we offer individual solutions. Since the benefit of increasing the participation rate from 79.35% (single-product solution) to 81% (two-product solution) or accordingly to 81.78% (individual solution for each user) is very small, we expect that the costs will overrun these benefits. We therefore recommend to offer only one single technology option, namely *Service type: Level C, service duration: 45 minutes, Remaining battery-level: 25%*. According to the results based on our survey, developers should first of all create a technology which is battery-saving since potential users accept a non-perfect service level, but are really sensitive to their battery. Moreover, users demand a certain minimum of the service level if they participate. In addition to that, the majority of users prefer a rather long duration of the service which makes a low energy consumption the most important challenge.

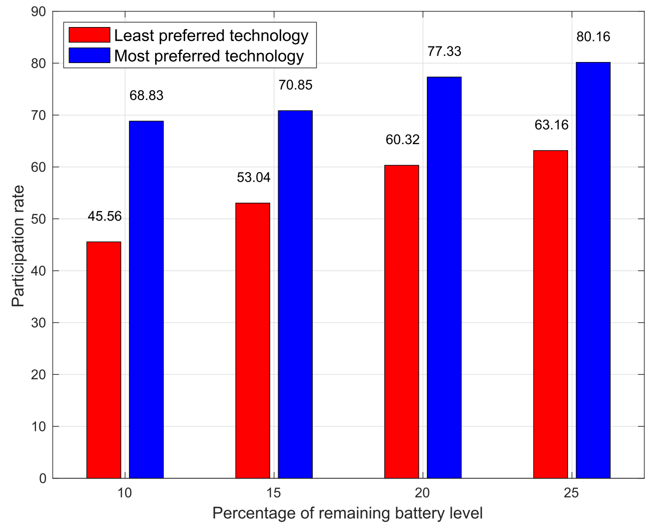


FIGURE 5. Participation rates.

Fig. 5 shows the participation rates for the least preferred technology and the most preferred technology depending on the remaining battery-level. The presented technology seems to interest a lot of people. 46.56% of the users would participate in the technology even if the least preferred option is offered, see Fig. 5. The increase in participation rate due to the increase in the remaining battery-level from 10% to 25% is about 11.33% for the most preferred option and 16.6% for the least preferred option showing the importance of the battery attribute level. Nevertheless, our results further show that although remaining battery-level is perceived as the most important attribute, see Table 5), it is not the only factor influencing the decision whether to participate in the forwarding technology or not. For example, offering the most preferred technology option in terms of service duration and service type with a remaining battery-level of 10% leads to a participation rate of 68.83%, see Fig. 5. On the other hand, increasing the remaining battery-level to 25% and meanwhile offering the worst service duration and service type results in a participation rate of only 63.16%. Taking a closer look at the difference the other two attributes service type and service duration make, we see that the delta between "least preferred technology option" and "most preferred technology option" is increasing from 17% (remaining battery-level of 25%) to 22.27% (remaining battery-level of 10%). On average, these attributes with a summarized importance weight of 56.13% make a difference in participation rate of 18.52%.

VIII. INCORPORATING UUP INTO UNDERLAY MODELS

In this section, a D2D communication scenario will serve as an example of how the UUP can be incorporated into underlay models. First, a snapshot based system model is explained. Then, a problem formulation is introduced. The L/T interface for this system model is explained. Finally, numerical results showing the performance gain when involving users in an active role of forwarding in the network will be discussed.

A. SYSTEM MODEL

A single cell downlink scenario is considered. The cell contains a central base station (BS) and two categories of mobile users as shown in Fig. 6. First, M receiving mobile users (RMUs) which are located at the cell edge. Second, K forwarding mobile users (FMUs) which are located close to the cell center. It is assumed that the BS serves the RMUs simultaneously, but through different orthogonal frequency division multiple access (OFDMA) radio resource blocks (RRBs). Also, it is assumed that the FMUs have half duplex transceivers, i.e., transmission and reception of a node takes place in different time slots. Furthermore, different FMUs transmit simultaneously using different RRBs, i.e., it is assumed that resource allocation is done a priori at the BS. Hence, there is no intra-cell interference. Let W be the bandwidth of an RRB and g_m be channel gain between BS and the m-th RMU. The channel within an RRB is assumed to be frequency non-selective and modeled using a single slope pathloss model. The receive noise is modeled as additive white Gaussian noise with zero mean and same variance σ^2. The target throughput at the RMU m is R_m. Accordingly, the required transmit power p_m for serving the m-th RMU using direct communications is calculated as

$$p_m = \frac{\sigma^2}{g_m}\left(2^{\frac{R_m}{W}} - 1\right). \tag{3}$$

However, BS can serve a RMU m through one the FMUs using D2D communication. In this case, the transmit power of the FMU k is

$$p_k^{\text{fwd}} = \frac{\sigma^2}{g_{m,k}}\left(2^{\frac{R_m}{W}} - 1\right), \tag{4}$$

where $g_{m,k}$ is the channel gain of the link between the FMU k and RMU m. It is assumed that the transmit powers at the BS and FMUs are constrained as $p_m \leq p_{\max}$ and $p_k^{\text{fwd}} \leq p_{max}^{\text{fwd}}$, respectively. If a FMU k is willing to forward the data to the RMU m, BS needs to transmit the data to be forwarded together with a reward. To this end, a total throughput of $R_m + R_k^{\text{re}}$ has to be maintained between BS and the FMU k and hence, the required transmit power at the BS to transmit to the FMU k is calculated as

$$p_k = \frac{\sigma^2}{g_k}\left(2^{\frac{R_m + R_k^{\text{re}}}{W}} - 1\right), \tag{5}$$

where g_k is the channel gain between the BS and the FMU k.

B. PROBLEM FORMULATION

The main objective is that all RMUs are served with the minimum total transmit power at BS. Based on this, BS can serve an RMU either directly (direct communication) or through an FMU (D2D communication). Because FMUs have different UUP on the forwarding powers p_k^{fwd}, $\forall\, k$ and rewarded throughput R_k^{re}, $\forall\, k$, an optimization problem which finds the optimum direct and D2D communications can be formulated

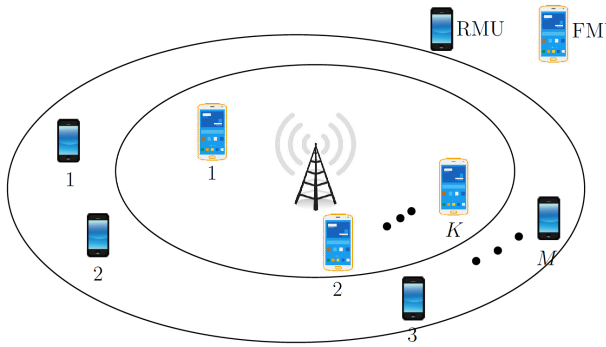


FIGURE 6. A single cell scenario with M RMUs and K FMUs.

as:

$$\underset{\{x_{k,m}\}_{\forall k,m}}{\text{argmin}} \left\{\sum_{k=1}^{K}\sum_{m=1}^{M}\left(x_{k,m}p_k + \left(1 - x_{k,m}\right)p_m\right)\right\} \tag{6}$$

$$\text{subject to } x_{k,m}W log_2\left(1 + \frac{p_k^{\text{fwd}} g_{m,k}}{\sigma^2}\right) + \left(1 - x_{k,m}\right) \tag{7}$$

$$W log_2\left(1 + \frac{p_m g_m}{\sigma^2}\right) \geq R_m, \quad \forall x_{k,m},$$

$$x_{k,m} W log_2\left(1 + \frac{p_k g_k}{\sigma^2}\right) \geq x_{k,m}\left(R_m + R_k^{\text{re}}\right), \quad \forall x_{k,m}, \tag{8}$$

$$\sum_{k=1}^{K} x_{k,m} \leq 1, \quad \forall m, \tag{9}$$

$$\sum_{m=1}^{M} x_{k,m} \leq 1, \quad \forall k, \tag{10}$$

and

$$x_{k,m} \in \{0, 1\}. \tag{11}$$

In this problem, the optimization variables are $x_{k,m}$, $\forall k, m$. The value of $x_{k,m}$ equals 0 for direct communication in serving the m-th RMU and 1 for hiring the FMU k to serve RMU m using D2D communication. Constraint (7) guarantees that the RMU m is served with throughput R_m either directly, i.e., $x_{k,m} = 0$, or with D2D communication, i.e., $x_{k,m} = 1$. The constraint in (8) is a vanishing constraint [46] which states that the total throughput at the FMU k has to be $R_k^{\text{re}} + R_m$ if the FMU k shall forward the data to RMU m, i.e., if $x_{k,m} = 1$. Constraints (9) and (10) express that only a single FMU can forward to RMU m and only a single RMU can be served through a FMU k, respectively.

C. L/T INTERFACE

In this section, the design of the L/T interface will be discussed. Based on the above system model, UUP of two technical parameters need to be deduced from the results, namely rewarded throughput R_k^{re} and forwarding power p_k^{fwd}, see Table 7. Based on the survey design, four forwarding powers are considered to map the four remaining energies, see Table 5. By dividing the forwarding powers over the noise

TABLE 7. The translated attributes and corresponding underlay parameters based on the system model.

	attribute	underlay parameter
reward	service type service duration	rewarded throughput R_k^{re}, $\forall k$
cost	remaining battery-level	forwarding power p_k^{fwd}, $\forall k$

power, the normalized forwarding powers, i.e., the pseudo signal to noise ratios, of the four levels are -5.2 dB, -3 dB, -1 dB and 0.8 dB. Concerning the rewarded throughput in our snapshot based system model, it is mapped from both service type and service duration. Based on the requirements of each of the service levels shown in Table 3, the ratio of minimum throughput over maximum latency will be considered. Then, this ratio will be normalized by the target throughput. On the other hand, the service duration levels are normalized by the minimum level 15 minutes. This way, the rewarded throughput is the ratio of minimum throughput over maximum latency normalized by the target throughput and multiplied by the normalized service duration level. For instance, considering 15 minutes service duration, the normalized rewarded throughput is 0.2×10^{-3} for delivering service level A, 1.6×10^{-3} for delivering service level B, 64×10^{-3} for delivering service level C and 1300×10^{-3} for delivering service level D. Note that these rates are normalized by the target throughput which is equal to 10 Mbps.

D. SIMULATION RESULTS

In this section, simulation results showing the performance of the network considering the UUP is investigated. We consider a circular cell with a radius of 150 m. The $M = 8$ RMUs are uniformly distributed at the cell edge with distances [90, 150] m from the BS whereas the $K = 1, \ldots, 100$ FMUs are uniformly distributed at the cell center with distances [10, 90] m from the BS. The channel gain between a transmitter k and a receiver m is calculated based on the single slope pathloss model

$$g_{m,k} = \left(\frac{r_0}{r_{m,k}}\right)^{\alpha}, \tag{12}$$

where r_0, $r_{m,k}$ and α are the reference distance, the distance between transmitter k and receiver m and the pathloss exponent, respectively. In the following simulation results, we set $r_0 = 75$ m and $\alpha = 4$.

In the following, we considered that the BS serves the RMUs either directly, named direct transmission, or through an FMU. In the latter case and based on our study results, there are two options. First, an FMU will participate with a probability of 0.79, the pseudo SNR of -5.2 dB and normalized rewarded throughput of 192×10^{-3}. In the second option, two classes of FMUs are considered: 1) FMUs which will participate with a probability of 0.52, the pseudo SNR of -5.2 dB and normalized rewarded throughput of 4.8×10^{-3}. 2) FMUs which will participate with a probability

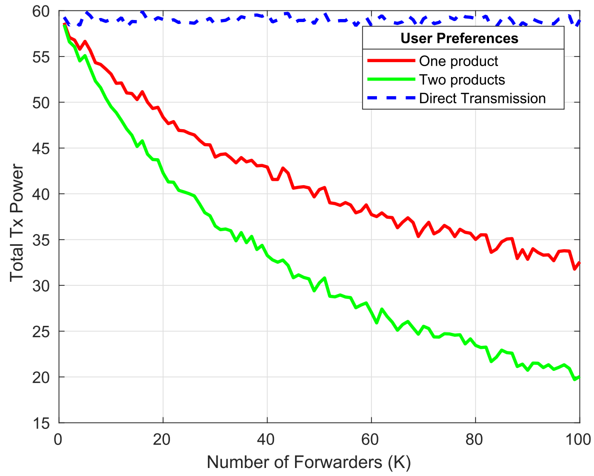


FIGURE 7. Total Tx power at BS normalized over thermal noise for different number of FMUs.

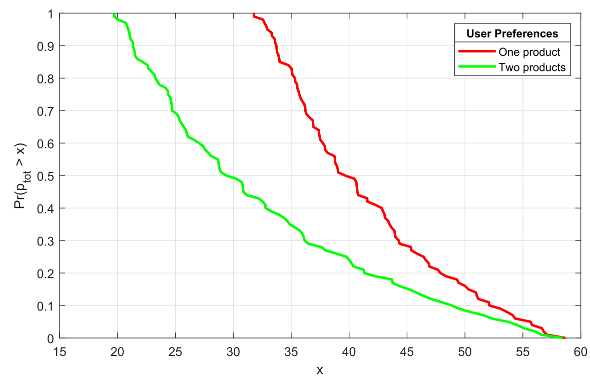


FIGURE 8. CCDF of the total Tx power at BS normalized over thermal noise for $K = 100$ FMUs.

of 0.29, the pseudo SNR of -1 dB and normalized rewarded throughput of 129×10^{-3}.

We ran Monte Carlo simulations of 1000 snapshots with different channel realizations and mobile positions. Fig. 7 shows the total Tx power consumed at the BS as a function of the number K of FMUs. Basically, the direct transmission is independent of the number of FMUs and it consumes a high power because the receivers are at the cell edge. As the number of FMUs increases, the chances to find an FMU which reduces the total Tx power at the BS increases. By comparing the two options of user preferences, having two products contributes to the network better with lower Tx power at the BS. This is because in this case, there are FMUs willing to spend more power on forwarding. This shows that even by offering two products with only few more users participating, e.g., only 1.65 % increase in participation rate, we can decrease the network resources, i.e., transmit power at the BS, by around 10 dB if we considered 40 FMUs.

Fig. 8 shows the CCDF of the total Tx power for the case of $K = 100$ FMUs. It shows even if we considered 10 % of the cases, a 13 dB reduction in Tx power is achieved.

IX. CONCLUSION

Focusing on user preferences and taking them into account becomes more and more important, especially in the field of information and communication systems. New technologies like D2D communication and multihop networks are reliant on the participation of users and therefore on the user acceptance. Thus, the consideration of underlay user preferences during the development of underlay schemes becomes indispensable. Until now, previous research either assumed given preferences and focused on the effect of UUP on the network performance or they derived user preferences for existing technologies and services. Thus the underlay design of communication systems is an open field up to now. In this paper, we show for a general framework how underlay user preferences in multihop networks can be elicited and considered for technical improvements during the design of underlay techniques. In particular, we take data forwarding as a showcase for a user active role which goes along with battery-concerns from the user perspective. In a first step, we propose a general framework for eliciting UUP on active roles in multihop networks. We then identified *maximum throughput, maximum latency, amount of transferred data* on the reward side and *forwarding energy* on the cost side as the relevant technical underlay parameters for our forwarding scenario. Afterwards, we define the T/L interface with the aim of translating the technical problem into layman terminology. We therefore use the non-technical attributes service type, service duration, and remaining battery level in the scenario description of our user study which are on par with the previously named technical underlay parameters, with the important difference that respondents with low technical background can understand these terms. Within the user study, we employ the CBC method which enables us to derive user preferences for the single attribute levels on an individual basis, although the respondents are faced with a new technology and without any experience with that technology. After an evaluation and analysis of the user preferences, we translate back from layman to technical terminology within the L/T interface and finally, we incorporate these UUP findings into a D2D scenario. The results show that we already reach a participation rate of 79.35% if we offer our best single-product solution. Offering more products to forwarding users will not increase the participation substantially, i.e., around 2% increase. However, offering multiple products to forwarders significantly decreases the total transmit power at the BS by around 12 dB.

APPENDIX

The appendix describes the HB algorithm. Basically, the HB algorithm estimates the partworth utilities of each attribute level for every attribute given the profile selections of the respondents. Let I, T and J denote number of respondents, number of choice-sets and number of profiles in a choice-set including the non-choice option, respectively. Aiming at maximizing his/her utility, respondent i selects profile j in choice-set t. Accordingly, using the random utility model [47], the utility of this selection can be written as

$$u_{i,t,j} = v_{i,t,j} + \epsilon_{i,t,j}, \tag{13}$$

where the utility consists of two terms: a deterministic term $v_{i,t,j}$ which is common to all potential users and an error term $\epsilon_{i,t,j}$ which varies randomly and independently across all users and choice-sets and it is usually modeled as Gumbel distribution [48]. Using Logit model [47], the probability that respondent i will select profile j in choice-set t is calculated as

$$\Pr\left(y_{i,t} = j\right) = \frac{e^{v_{i,t,j}}}{\sum_{n=1}^{J} e^{v_{i,t,n}}}, \tag{14}$$

where $y_{i,t}$ denotes the index of the selected profile in choice-set t by respondent i.

Let $\mathbf{z}_i \in \mathbb{R}^{L\times 1}$ denote the partworth utility vector of respondent i where L is the total number of levels of all attributes. Also, let $\mathbf{D}_{i,t} \in \mathbb{R}^{J\times L}$ be the design matrix of choice-set t for respondent i. $\mathbf{D}_{i,t}$ is of binary entries where each row corresponds to a profile with ones at the chosen level of every attribute in this profile. A zero row in the design matrix $\mathbf{D}_{i,t}$ corresponds to the non-choice option. Accordingly, the utility vector $\mathbf{u}_{i,t} = \left(u_{i,t,1}, \ldots, u_{i,t,J}\right)^{\mathrm{T}}$ of all profiles in choice-set t for respondent i is calculated as

$$\mathbf{u}_{i,t} = \mathbf{D}_{i,t}\mathbf{z}_i + \boldsymbol{\epsilon}_{i,t}, \tag{15}$$

where $\boldsymbol{\epsilon}_{i,t} = \left(\epsilon_{i,t,1}, \ldots, \epsilon_{i,t,J}\right)^{\mathrm{T}}$ is the error vector with entries $\epsilon_{i,t,j}$, $\forall j$ drawn independently from Gumbel distribution [48]. Using (15), (14) can be rewritten as

$$\Pr\left(y_{i,t} = j\right) = \frac{e^{\mathbf{d}_{i,t,j}\mathbf{z}_i}}{\sum_{n=1}^{J} e^{\mathbf{d}_{i,t,n}\mathbf{z}_i}}, \tag{16}$$

where $\mathbf{d}_{i,t,j}$ is the j-th column of design matrix $\mathbf{D}_{i,t}$ which corresponds the j-th profile in choice-set t. Assuming that the partworth utilities $\mathbf{z}_i$, $\forall i$ are given, the conditional probability that respondent i will select profile j in choice-set t is

$$\Pr\left(y_{i,t} = j|\mathbf{z}_i\right) = \frac{e^{\mathbf{d}_{i,t,j}\mathbf{z}_i}}{\sum_{n=1}^{J} e^{\mathbf{d}_{i,t,n}\mathbf{z}_i}}, \tag{17}$$

where the sum of the conditional probabilities of all profiles in choice-set t given the partworth utilities is

$$\sum_{j=1}^{J} \Pr\left(y_{i,t} = j|\mathbf{z}_i\right) = 1, \quad \forall i. \tag{18}$$

Since the profiles in different choice-sets are drawn randomly and independently from a probability distribution, the conditional probability of selecting profile j by respondent i across all choice-sets is calculated as

$$\Pr\left(y_i = j|\mathbf{z}_i\right) = \prod_{t\in\mathcal{T}_{i,j}} \Pr\left(y_{i,t} = j|\mathbf{z}_i\right), \tag{19}$$

where $\mathcal{T}_{i,j}$ is the set of all choice-sets which include the j-th profile and were shown to respondent i. Also, y_i denotes the index of the selected profile by respondent i over all choice-sets. Using (19), $\Pr(\mathbf{y}_i|\mathbf{z}_i)$ is a vector of conditional probabilities of each profile shown to respondent i given his/her partworth utilities $\mathbf{z}_i$. However, we want to calculate the partworth utilities $\mathbf{z}_i$ given the profile selections $\mathbf{y}_i$, i.e., we need to estimate $\Pr(\mathbf{z}_i|\mathbf{y}_i)$ rather than $\Pr(\mathbf{y}_i|\mathbf{z}_i)$. Therefore, Bayes rule needs to be employed:

$$\Pr(\mathbf{z}_i|\mathbf{y}_i) \propto \Pr(\mathbf{y}_i|\mathbf{z}_i)\Pr(\mathbf{z}_i), \tag{20}$$

or in words, the posterior $\Pr(\mathbf{z}_i|\mathbf{y}_i)$ is proportional to the product of likelihood $\Pr(\mathbf{y}_i|\mathbf{z}_i)$ and the prior $\Pr(\mathbf{z}_i)$ [49]. In HB algorithm, it is assumed that the partworth utilities $\mathbf{z}_i$, $\forall i$ are drawn from a multivariate normal distribution with mean vector $\boldsymbol{\beta}$ and covariance matrix $\boldsymbol{\Psi}$, i.e., $\mathbf{z}_i \in \mathcal{N}\{\boldsymbol{\beta}, \boldsymbol{\Psi}\}$ [50]. However, the mean vector $\boldsymbol{\beta}$ and covariance matrix $\boldsymbol{\Psi}$ are not a priori known and both needed to be estimated from the collected data. Therefore, the HB algorithm estimates the partworth utilities, mean vector and covariance matrix in a two level hierarchy [32], [51]. In the upper level, both mean vector and covariance matrix are estimated given the partworth utilities of all respondents, i.e., $\Pr(\boldsymbol{\beta}|\mathbf{z}_1, \ldots, \mathbf{z}_I, \boldsymbol{\Psi})$ and $\Pr(\boldsymbol{\Psi}|\mathbf{z}_1, \ldots, \mathbf{z}_I, \boldsymbol{\beta})$. In the lower level, the parthworth utility vector of each respondent individually is estimated given the mean vector and covariance matrix $\Pr(\mathbf{z}_i|\boldsymbol{\Psi}, \boldsymbol{\beta})$, $\forall i$. This means that the estimation in the upper level is among respondents, i.e., it represents the heterogeneity among respondents whereas the lower level estimation is within each respondent, i.e., it represents the heterogeneity among attribute levels of each respondent [49]. The process of estimating partworth utilities, mean vector and covariance matrix is done iteratively based on Markov Chain Monte Carlo method [52]. So, the mean vector and covariance matrix are updated in every iteration to fit the collected data into the multivariate normal distribution and hence, the corresponding priors $\Pr(\mathbf{z}_i)$, $\forall i$ are found. Then, both the prior $\Pr(\mathbf{z}_i)$ and the likelihood $\Pr(\mathbf{y}_i|\mathbf{z}_i)$ are used to estimate the partworth utilities using Bayes rule in (20).

This process of hierarchical estimation is done iteratively in two phases. First, the convergence phase in which the algorithm runs for hundreds to few thousands of iterations till convergence or till the estimation of a partworth utility does not change significantly. In the second phase, the estimated partworth utilities $\mathbf{z}_i$, $\forall i$ can be considered. Because the algorithm does not necessarily converge, the average of estimated partworth utilities of the several thousands of iterations in the second phase will be considered as the estimated partworth utility [49].

REFERENCES

[1] M. Chen, Y. Hao, M. Qiu, J. Song, D. Wu, and I. Humar, "Mobility-aware caching and computation offloading in 5G ultra-dense cellular networks," *Sensors*, vol. 16, no. 7, pp. 1–13, Jun. 2016.

[2] J. Liu, N. Kato, J. Ma, and N. Kadowaki, "Device-to-device communication in LTE-advanced networks: A survey," *IEEE Commun. Survey Tuts.*, vol. 17, no. 4, pp. 1923–1940, 4th Quart., 2015.

[3] D. Datla *et al.*, "Wireless distributed computing: A survey of research challenges," *IEEE Commun. Mag.*, vol. 50, no. 1, pp. 144–152, Jan. 2012.

[4] E. Bastug, M. Bennis, and M. Debbah, "Living on the edge: The role of proactive caching in 5G wireless networks," *IEEE Commun. Mag.*, vol. 52, no. 8, pp. 82–89, Aug. 2014.

[5] J. Jiang, S. Zhang, B. Li, and B. Li, "Maximized cellular traffic offloading via device-to-device content sharing," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 1, pp. 82–91, Jan. 2016.

[6] M. Ji, G. Caire, and A. F. Molisch, "Wireless device-to-device caching networks: Basic principles and system performance," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 1, pp. 176–189, Jan. 2016.

[7] M. DeHart, "Top 10 smartphone purchase drivers," IDC's ConsumerScape 360, 2014.

[8] J. J. Louviere and G. Woodworth, "Design and analysis of simulated consumer choice or allocation experiments: An approach based on aggregate data," *J. Marketing Res.*, vol. 20, pp. 350–367, Nov. 1983.

[9] D. Naous and C. Legner, "Leveraging market research techniques in is—A review of conjoint analysis in is research," in *Proc. 38th Int. Conf. Inf. Syst.*, 2017, pp. 1–19.

[10] D. S. Bunch, M. Bradley, T. F. Golob, R. Kitamura, and G. P. Occhiuzzo, "Demand for clean-fuel vehicles in california: A discrete-choice stated preference pilot project," *Transp. Res. A, Policy Pract.*, vol. 27, no. 3, pp. 237–253, 1993.

[11] G. Ewing and E. Sarigöllü, "Assessing consumer preferences for clean-fuel vehicles: A discrete choice experiment," *J. Public Policy Marketing*, vol. 19, no. 1, pp. 106–118, 2000.

[12] M. Fritz, C. Schlereth, and S. Figge, "Empirical evaluation of fair use flat rate strategies for mobile Internet," *Bus. Inf. Syst. Eng.*, vol. 3, no. 5, p. 269, 2011.

[13] D. A. Hensher, P. O. Barnard, and T. P. Truong, "The role of stated preference methods in studies of travel choice," *J. Transp. Econ. Policy*, vol. 22, no. 1, pp. 45–58, 1988.

[14] T. E. Bogale and L. B. Le, "Massive MIMO and mmWave for 5G wireless HetNet: Potential benefits and challenges," *IEEE Veh. Technol. Mag.*, vol. 11, no. 1, pp. 64–75, Mar. 2016.

[15] M. Fasil, H. Al-Shatri, S. Wilk, and A. Klein, "Application-aware cross-layer framework: Video content distribution in wireless multihop networks," in *Proc. IEEE 26th Annu. Int. Symp. Pers., Indoor, Mobile Radio Commun.*, Hong Kong, Aug. 2015, pp. 1088–1093.

[16] M. Fasil, H. Al-Shatri, S. Wilk, and A. Klein, "A network-centric view on DASH in wireless multihop networks," in *Proc. IEEE 84th Veh. Technol. Conf.*, Montreal, QC, Canada, Sep. 2016, pp. 1–6.

[17] H. Zhang, N. Liu, X. Chu, K. Long, A.-H. Aghvami, and V. C. M. Leung, "Network slicing based 5G and future mobile networks: Mobility, resource management, and challenges," *IEEE Commun. Mag.*, vol. 55, no. 8, pp. 138–145, Aug. 2017.

[18] B. Bangerter, S. Talwar, R. Arefi, and K. Stewart, "Networks and devices for the 5G Era," *IEEE Commun. Mag.*, vol. 52, no. 2, pp. 90–96, Feb. 2014.

[19] S. Bi, R. Zhang, Z. Ding, and S. Cui, "Wireless communications in the era of big data," *IEEE Commun. Mag.*, vol. 53, no. 10, pp. 190–199, Oct. 2015.

[20] P. Felka, A. Sterz, K. Keller, B. Freisleben, and O. Hinz, "The context matters: Predicting the number of in-game actions using traces of mobile augmented reality games," in *Proc. 17th Int. Conf. Mobile Ubiquitous Multimedia*, 2018, pp. 25–35.

[21] D. Liu, B. Chen, C. Yang, and A. F. Molisch, "Caching at the wireless edge: Design aspects, challenges, and future directions," *IEEE Commun. Mag.*, vol. 54, no. 9, pp. 22–28, Sep. 2016.

[22] N. Mastronarde, V. Patel, J. Xu, L. Liu, and M. van der Schaar, "To relay or not to relay: Learning device-to-device relaying strategies in cellular networks," *IEEE Trans. Mobile Comput.*, vol. 15, no. 6, pp. 1569–1585, Jun. 2016.

[23] M. Mousavi, H. Al-Shatri, O. Hinz, and A. Klein, "Incorporating user willingness for message forwarding in multi-hop content distribution scenarios," in *Proc. 20th Int. ITG Workshop Smart Antennas*, Munich, Germany, Mar. 2016, pp. 1–6.

[24] M. Mousavi, H. Al-Shatri, W. R. KhudaBukhsh, H. Koeppl, and A. Klein, "Cross-layer QoE-based incentive mechanism for video streaming in multi-hop wireless networks," in *Proc. IEEE 86th Veh. Technol. Conf.*, Toronto, ON, Canada, Sep. 2017, pp. 1–6.

[25] C. Singhal and S. De, "ePAB: Energy-efficient, user-preference based adaptive multimedia broadcast," in *Proc. 20th Nat. Conf. Commun.*, Kanpur, India, Mar. 2014, pp. 1–6.

[26] *Subjective Video Quality Assessment Methods for Multimedia Applications*, document ITU-T Rec. P.910, 2008.

[27] S. Nikou, H. Bouwman, and M. de Reuver, "The potential of converged mobile telecommunication services: A conjoint analysis," *Info*, vol. 14, no. 5, pp. 21–35, 2012.

[28] L. van de Wijngaert and H. Bouwman, "Would you share? Predicting the potential use of a new technology," *Telematics Inform.*, vol. 26, no. 1, pp. 85–102, Feb. 2009.

[29] B. Klopfenstein, "Problems and potential of forecasting the adoption of new media," *Media Use in the Information Age: Emerging Patterns of Adoption and Consumer Use*. Hillsdale, NJ, USA: Lawrence Erlbaum Associates, 1989, pp. 21–41.

[30] J. Huber, "Conjoint analysis: how we got here and where we are (An Update)," in *Proc. Sawtooth Softw. Conf.*, vol. 98382, 2005, p. 360.

[31] B. Orme, "Formulating attributes and levels in conjoint analysis," Sawtooth Softw., Provo, UT, USA, Tech. Rep., 2002. [Online]. Available: https://www.sawtoothsoftware.com/download/techpap/formatt.pdf

[32] P. J. Lenk, W. S. DeSarbo, P. E. Green, and M. R. Young, "Hierarchical Bayes conjoint analysis: Recovery of partworth heterogeneity from reduced experimental designs," *Marketing Sci.*, vol. 15, no. 2, pp. 173–191, 1996.

[33] R. Weiber and D. Mühlhaus, "Auswahl von eigenschaften und ausprägungen bei der conjointanalyse," in *Conjointanalyse*, D. Baier and M. Brusch, Eds. Berlin, Germany: Springer, 2009, pp. 43–58.

[34] D. R. Wittink, J. Huber, P. Zandan, and R. M. Johnson, "The number of levels effect in conjoint: Where does it come from, and can it be eliminated," in *Proc. Sawtooth Softw. Conf.*, 1992, pp. 355–364.

[35] P. E. Green and V. Srinivasan, "Conjoint analysis in marketing: new developments with implications for research and practice," *J. Marketing*, vol. 54, no. 4, pp. 3–19, 1990.

[36] *Live Encoder Settings, Bitrates, and Resolutions*. Accessed: Sep. 21, 2017. [Online]. Available: https://support.google.com/youtube/answer/2853702?hl=en

[37] *How Much Bandwidth Does Skype Need?*. Accessed: Sep. 21, 2017. [Online]. Available: https://support.skype.com/en/faq/FA1417/how-much-bandwidth-does-skype-need

[38] Y. Chen, T. Farley, and N. Ye, "QoS requirements of network applications on the Internet," *Inf. Knowl. Syst. Manage.*, vol. 4, no. 1, pp. 55–76, Mar. 2004.

[39] *Ranking der beliebtesten Social Networks und Messenger nach dem Anteil der Nutzer an den Internetnutzern in Deutschland im Jahr 2018*. Accessed: Sep. 30, 2018. [Online]. Available: https://de.statista.com/statistik/daten/studie/505947/umfrage/reichweite-von-social-networks-in-deutschland/

[40] J. Schneider. (Nov. 2015). *Wie Viel MB Datenvolumen Braucht WhatsApp?*. Accessed: Feb. 21, 2019. [Online]. Available: https://praxistipps.chip.de/wie-viel-mb-datenvolumen-braucht-whatsapp_43483

[41] R. D. Luce and J. W. Tukey, "Simultaneous conjoint measurement: A new type of fundamental measurement," *J. Math. Psychol.*, vol. 1, no. 1, pp. 1–27, 1964.

[42] P. E. Green and V. R. Rao, "Conjoint measurement for quantifying judgmental data," *J. Marketing Res.*, vol. 8, no. 3, pp. 355–363, 1971.

[43] S. Hoeffler and D. Ariely, "Constructing stable preferences: A look into dimensions of experience and their impact on preference stability," *J. Consum. Psychol.*, vol. 8, no. 2, pp. 113–139, 1999.

[44] *Sawtooth Software Lighthouse Studio Help*. Accessed: Sep. 21, 2017. [Online]. Available: https://www.sawtoothsoftware.com/help/lighthouse-studio/manual/hid_web_cbc_designs_4.html

[45] R. Dhar, "The effect of decision strategy on deciding to defer choice," *J. Behav. Decis. Making*, vol. 9, no. 4, pp. 265–281, 1996.

[46] W. Achtziger and C. Kanzow, "Mathematical programs with vanishing constraints: Optimality conditions and constraint qualifications," *Math. Program.*, vol. 114, no. 1, pp. 69–99, Jul. 2008.

[47] D. Raghavarao, J. Wiley, and P. Chitturi, *Choice-Based Conjoint Analysis: Models and Designs*. Boca Raton, FL, USA: CRC Press, 2011.

[48] A. L. M. Antonio, "The good, the bad and the fitting: A Bayesian hierarchical model for patient preferences elicited through discrete choice experiments," Ph.D. dissertation, Univ. California, Los Angeles, Los Angeles, CA, USA, Jan. 2017.

[49] *CBC/HB V5 Software for Hierarchical Bayes Estimation for CBC Data*, Sawtooth Softw., Sequim, WA, USA, Aug. 2009.

[50] R. Johnson, "Understanding HB: An intuitive approach," Sawtooth Softw., Provo, UT, USA, Tech. Rep., Mar. 2000. [Online]. Available: http://www.sawtoothsoftware.com/download/techpap/2000Proceedings.pdf#page=209

[51] J. Kruschke and W. Vanpaemel, "Bayesian estimation in hierarchical models," in *The Oxford Handbook of Computational and Mathematical Psychology*. London, U.K.: Oxford Univ. Press, 2015, ch. 13, pp. 279–299.

[52] S. Chib and E. Greenberg, "Understanding the metropolis-Hastings algorithm," *Amer. Stat.*, vol. 49, no. 4, pp. 327–335, 1995.

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