Social-Feature Enabled Communications Among Devices Toward the Smart IoT Community

Qinghe Du, Houbing Song, and Xuejie Zhu

Motivated by the tendency of socialization over IoT, the authors present an overview and discussion of social features affecting connections among IoT devices. They propose studies to characterize highly-varying social features by using the queuing model and asymptotic analysis framework.

Abstract

Future IoT is expected to achieve ubiquitous access and information exchange on a global scale. Facing the massive IoT access and spectrum shortage problems, centralized control becomes prohibitively complicated. But with the increasing capability of IoT devices in communications and computing, IoT will gradually evolve to be highly autonomous, yield social features in IoT networking, and eventually form the smart IoT community. Motivated by the tendency of socialization over IoT, this article first presents an overview and discussions on social features affecting connections among IoT devices. Then, we propose studies to characterize the highly-varying social features by using the queuing model and asymptotic analysis framework. With emphases on social features including credit and reputation, we show how to fit transmissions between IoT devices to the framework for socially-aware optimization. Finally, this article shares opinions about open problems and future topics on socially-aware design toward the smart IoT community.

Introduction

The future Internet of Things (IoT) is expected to achieve ubiquitous connection and access on a global scale [1], such that fast and convenient information exchange can contribute to implementing diverse smart-city applications [1–3]. With the empowered wireless communications capability for IoT devices/nodes, IoT communications will no longer be only labeled with low-rate services and location-fixed devices. In contrast, IoT connections will carry services with diversified data rates and IoT devices can also have mobility [1, 2, 4].

Nowadays, IoT has not yet been deployed in a globally-connected fashion, which is mainly caused by the following issues. First, existing IoT deployments lack infrastructure support, making it hard for IoT across large area to get connected via wireless systems. Moreover, the future IoT aims at accommodating the drastically-increasing population of devices [1, 5], and therefore complete control of wireless IoT communications would be prohibitively complicated. In addition, wireless resources such as frequency spectrum have been ultra scarce compared with the massive scale of IoT access.

These issues would naturally motivate studies on direct wireless connection between IoT devices in a distributed or semi-distributed fashion, which requires autonomous rules abided by all IoT devices. Correspondingly, the autonomous feature along with the large device population will evolve to generate social features in communications and information exchange over IoT. It is no doubt that social features of IoT devices are one of the core factors to establish the smart IoT community [2–7].

The fifth generation (5G) of mobile communications systems and networks is now the central focus in the area of wireless communications and networking [8, 9], which promises to provide the infrastructure support for massive IoT access control. In the meantime, direct communications between cellular terminal devices, termed device-to-device (D2D) communications, have been considered to be supported by the 5G system [8]. Although D2D communications are developed for devices like smart phones, they can shed light on the design for direct connections between IoT devices. On one hand, D2D users in proximity are allowed to reuse the licensed cellular spectrum in an underlaying fashion [8]. Such communications take advantage of the short propagation distance to enable low-power transmissions and cause low cross-interferences, thus offering a solution for IoT to significantly relieve the spectrum shortage problem. On the other hand, the 5G architecture decouples the data plane and control plane [9], providing powerful functions for further coordination and interference management. In addition, many socialized communications designs for D2D networks [10–14] brought reference and guidance for design in smart IoT. Benefiting from these advantages and the 5G architecture, we can expect that the direct communications between IoT devices are ready to be applied to practical networks. Such a communications approach has already been suggested as a potential future mode for machine-to-machine (M2M) communications in cellular networks [1], which addressed self-initiated machine-type communications (MTC) in contrast to human-to-human (H2H) communications. In the meantime, devices like smart phones can also connect to IoT and function as an IoT device in many cases. It can be expected that with the continuously increasing capability

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Role of IoT nodes	Type of direct communications between IoT devices			
	Data sharing		Data forwarding	
	Node type	Social incentives	Node type	Social incentives
Source node	IoT device (offering services)	• Payment by destination • Common data • Social bond of devices	Access controller or IoT device (offering or requesting services)	• Operator's duty • Payment by destination • Payment to forwarding device
Forwarding node	N/A	N/A	IoT device as a router (offering services)	• Operator's compensation • Payment by destination • Payment by source device • Social bond of devices • Common data
Destination node	IoT device (requesting services)	• Payment to source • Common data • Social bond of devices	Access controller or IoT devices (requesting services)	• Payment to forwarding device • Payment to source • Social bond of devices

Table 1. Functions of direct device communications and the associated social incentives for IoT community.

of IoT devices, direct connection between IoT devices and D2D communications can follow the same connection procedures and standards in the near future. In other words, it is desired to unify the two communications types as they are essentially alike. However, it is worth noting that the most challenging factors to do so include how to encourage cellular devices' participation in assisting their peers and IoT nodes and how to benefit the infrastructure such as increasing the income or decreasing the expenditure.

The above discussions imply that in order to form the smart IoT community, integrating socialization features to IoT communications under infrastructure support, such as the 5G system, is urgently desired. Consequently, there are the urgent needs to understand the essential social features and how they impact IoT communications. Specifically, the typical IoT communications involving socialization features include forwarding data to and/or share data with other IoT devices [1, 2, 6, 7]. While the assistance among devices will enhance the connectivity and efficiency for IoT, it consumes the helpers' battery energy and cost for bandwidth usage. Therefore, how to encourage IoT devices to participate in socialized communications benefiting the entire work via reasonable incentive mechanisms/rules would be the top-priority task [6, 7].

There are existing designs for socialization mechanisms [2–7]. However, effectively incorporating the stochastic social features and wireless environments' characteristics still calls for persistent research efforts. First, a fine-grained yet efficient framework is desired to characterize the highly-varying dynamics of a spectrum of widely-used social-feature metrics, such as credit, reputation, and so on. Second, how to integrate the features of wireless networks and socially-aware framework still faces many challenges. Third, geographic information would also be critically important to deal with the mobility of IoT devices.

Motivated by these issues, this article starts with an overview of scenarios for direct communications between IoT devices that are impacted by typical social features. We then propose to use the queuing model to characterize the statistical social features and present an asymptotic queuing analysis framework. How to apply the proposed framework and approach to analyze IoT social features including credit and reputation is further studied. Future research directions and open problems toward the smart IoT community are also presented, followed by the conclusions of this article.

Social Features Impacting Device Communications for the Smart IoT Community

We start with an overview of the types of communications between IoT devices and the associated social incentives. We further discuss these social features and then categorize them from a network perspective and a user interest perspective.

Types of Direct Connection between IoT Devices and Associated Social Incentives

According to Table 1, direct communications between IoT device nodes can be mainly categorized into two different types: data sharing and data forwarding. Data sharing typically occurs between two adjacent devices. For this scenario, the incentives driving the source device to share data include payment by the destination device, a social bond between the two devices, or the common content they are both interested in. Among all these incentives, the social bond often reflects the device owner's prior strategies and preferences; the common content usually depends on the owner's interests. Thus, these two social features do not vary drastically within a short time period. In contrast, the payment by devices that request data sharing introduces many more dynamics to the network. In particular, the payment, regardless of its specific forms, can be treated as the currency circulated in the business market, and therefore it has great impact on the network's capacity and performance. In this article, we will use the term credit to represent the general payment and show how to model it toward the optimization of the devices' strategies. There are also other similar yet different metrics such as reputation, which will be discussed later.

Table 1 also lists the incentives for data forwarding in IoT. This type of communications occurs when the source is geographically far away

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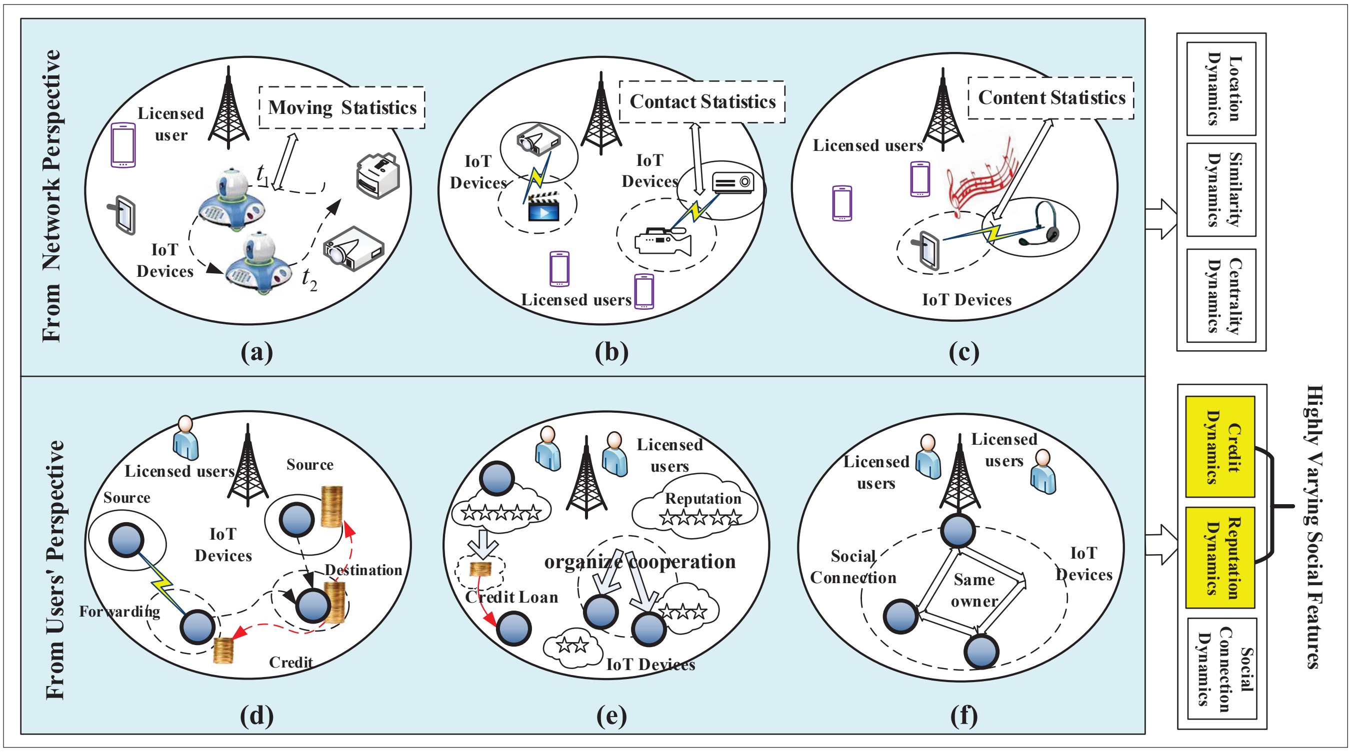

Figure 1. Categorization of social features for communications over IoT devices.

from the destination device or there are no line-of-sight channels between the source and destination nodes. In such a case, multi-hop transmission is then enabled. The source node here could be either a peer IoT device or the centralized access controller, such as the base station in cellular networks and the access point in WiFi networks. The characteristics of social bonds would be similar to that in the data sharing case, but the payment for data forwarding services involves more IoT nodes. Specifically, the payment for forwarding services can be provided by either the source (access controller or IoT device) or the destination node, as both of them might request transmission services. Moreover, the operator of the network might also pay for forwarding services because it has the responsibility to enhance the connectivity of the entire network. In addition, if the data falls into the interests of the forwarding node without security/encryption constraints, it can also offer the service as the cost to keep the data. Evidently, how to accurately yet effectively model the payment would contribute significantly to networking optimization.

Categorization of Social Features

Social Features from the Network Perspective: From the network perspective, the beneficial social features need to able to assist in establishing robust, flexible, fully connected networks. Figures 1a–1c summarize a number of representative social features, including moving statistics, contact statistics, and content statistics. We will elaborate on them and analyze their statistical and dynamic properties affecting network performance. Figure 1 also addresses the coexistence of IoT devices and licensed users, where the IoT devices reuse the licensed users' spectrum in an underlaying mode.

Moving Statistics: Many IoT devices, such as smart home robots, are already equipped with mobility, as depicted in Fig. 1a. Two key properties of mobility are temporal and spatial statistics. Leveraging the two statistical characteristics to predict the moving trajectory can provide important information for dynamic IoT connections. Moreover, it is worth noting that the mobility of the majority of IoT devices is often limited within a local range and moving speed is not high, which implies its variation does not affect the network connection in a small time scale.

Contact Statistics and Centrality: The infrastructure network can record the history of direct contact between devices, and extract the social feature termed *contact statistic* of each device (Fig. 1b), which is extremely useful to build robust topology for data dissemination over IoT. With contact statistics, the infrastructure network can identify the *centrality* metric of devices within a local area. Centrality was introduced to characterize the devices' frequency of forwarding data, stableness of contact time [11], and the transmission rate [12] in D2D networking, which can also be readily applied to direct communications between IoT devices. Centrality represents the importance of a device node in maintaining connectivity, where the node with high centrality can help improve throughput [11], coverage, robustness, and peer discovery [12] of the network.

Content Statistics: Aside from the devices' networking behavior, content statistics also offer valuable social information as illustrated in Fig. 1c. Common interests or data can initiate tight social ties between IoT devices [3]. However, in realistic networks, the similarity of content interests often results from the initial setup based on the owner's preferences and specific targets. Thus, the content statistics may not bring much impact on the dynamic optimization over fast-varying network status.

Social Features from the IoT User Perspective: From the IoT user perspective, the social features of interests must reflect their own benefits, as users are typically selfish. We next discuss three such social features tightly associated with IoT devices, namely credit, reputation, and social connections, as depicted in Fig. 1d–f.

Credit: For data forwarding, the requesting device needs to pay for the service. The payment can be measured by the operator-issued and operator-supervised credit. Accordingly, the paid credit will be deposited to the forwarding node's account, as illustrated by Fig. 1. Thus, the devices' social relation is built based on credit trade for data service. Also, the credit-data trade can be applied to the data sharing scenario. It is evident that this mechanism can enable global social-feature recognition and the corresponding socially-aware strategy design. The credit metric can be defined in many ways. One convenient yet reasonable metric to measure credit is the amount of data forwarded. A device cannot request data sharing and forwarding aided by other devices without credit, if there is no social bond or common content interests. Therefore, devices need to help other devices occasionally such that they can save a certain amount of credits, which is beneficial to the robustness of the entire network. Moreover, it is undesirable to directly use true financial currency to replace credit, which might blur the boundary between network optimization and real financial markets and actually degrade the efficiency of running the network.

Reputation: Reputation is the other widely employed social metric in social networks. To some extent reputation is similar to credit, but plays different roles in IoT. Both credit and reputation reflect the willingness and history of assisting other devices. But reputation addresses more the quality of forwarding or sharing services. The device with high reputation shall be rewarded with networking benefits. As illustrated in Fig. 1e, even without credit, the device with high reputation can loan credit to support its own service. The reputation metric can also be defined in diverse ways. As it reflects service quality, the successful transmission, low delay, and high reliability can all be counted in a cumulative fashion, but governing mechanisms are also needed to determine how reputation is gained and how it is consumed.

Social Connections: Social connections among IoT devices, shown in Fig. 1f, typically reflect ownership. For example, IoT devices in one smart home can be clearly closely tied to each other with full trust. Therefore, social connections are also very stable as they are often determined by the ownership or the owner's prior setup, thus mainly affecting the long-term network performance.

Queuing Analysis Model for Varying Social Features

Social features often change drastically due to the highly-varying wireless channels and frequent data dissemination, implying that statistical characteristics as well as the instantaneous status of social features shall be jointly taken into consideration to optimize IoT transmissions. For the social features given in Fig. 1, we are particularly interested in the statistical characteristics of credit and reputation, which vary more significantly than others.

There are some commonly-recognized characteristics for credit, reputation, and even centrality, regardless of the specific metric definitions. On one hand, they can all be accumulated increasingly by forwarding or sharing data with the peer devices. On the other hand, the accumulation will be consumed when a device requests sharing or forwarding services. Inspired by these facts, we can use the queuing system to model the variation and dynamics of these social features. The queue length can then be used to characterize the IoT device's social feature status. The accumulation and consumption processes then naturally represent the arrival and departure processes, respectively. The other reason why we would like to apply a queuing model is that there are powerful queuing analysis tools in the literature.

Among numerous results on queuing systems, the theory of asymptotic queuing analysis based on the large deviation principle offers a very useful result [15]. For a stable queuing system with independent random arrival and/or departure processes, under sufficient conditions the complementary cumulative distribution function (CCDF) of the queue length exponentially decays with a growing queue length. That is, the distribution of queue length can be roughly approximated by exponential distribution, which turns out to be suitable for a wide spectrum of arrival and departure processes such as Poisson process, Markovian process, auto-regression process, and so on. This result was initially developed for asynchronous transfer mode (ATM) networks and later was well applied in wireless communications.

This principle is further detailed in Fig. 2, which illustrates the CCDF, that is, the probability of queue length Q exceeding a given value q. Following the asymptotic analysis result mentioned above, the probability asymptotically decays with an exponential rate θ, suggesting that in logarithm scale, the CCDF curve appears as a straight line. Figure 2 draws three such straight lines with slopes θ equal to $-\theta_1$, $-\theta_2$, and $-\theta_3$, respectively, representing exponential distributions with different parameters.

For a stable queuing system, the parameter θ is determined by both arrival and departure processes. When θ gets larger, the decaying speed also becomes higher, suggesting a statistically higher departure rate, and vice versa. Moreover, given the arrival process $A[t]$ and departure process $R[t]$, the parameter θ can be obtained by solving the equation $E_B(\theta, A[t]) = E_C(\theta, R[t])$ [15]. In the above equation, $E_B(\theta, A[t])$ is termed *effective bandwidth*, which defines the minimum constant departure rate required to control the CCDF decay rate equal to q under arrival process A[t]; EC(θ, $R[t]$) is called *effective capacity*, as the dual of effective bandwidth, which defines the maximum supportable constant arrival rate with CCDF decay rate θ under departure process $R[t]$. For more details, please refer to [15] and related references.

Social connections among IoT devices, shown in Fig. 1f, typically reflect ownership. For example, IoT devices in one smart home can be clearly closely tied to each other with full trust. Therefore, social connections are also very stable as they are often determined by the ownership or the owner's prior setup, thus mainly affecting the long-term network performance.

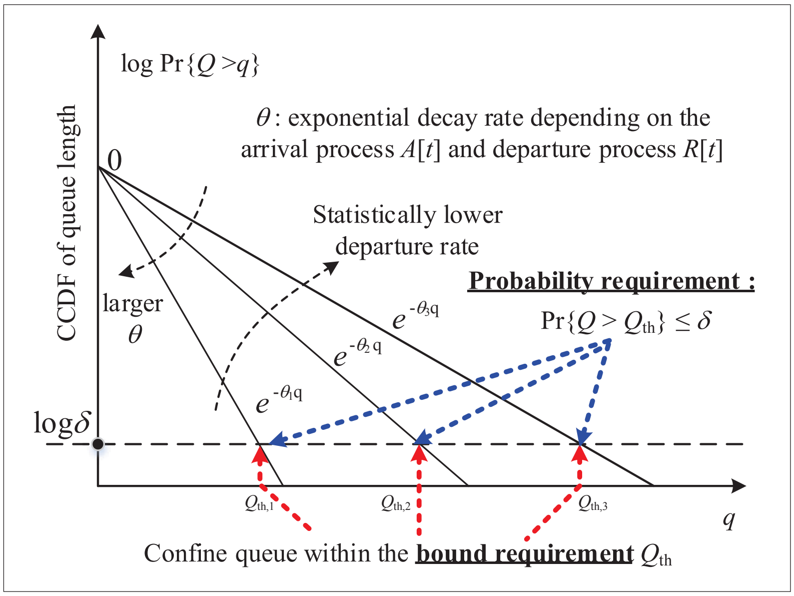

Figure 2. Exponential queue-distribution characterization for social features in IoT communications.

Using this theory, we can effectively describe and control the distribution of the social features by adapting the arrival and/or departure processes to network environments. For example, if a device does not hope to accumulate too much credit, that is, avoiding the case with more services offered but much less services requested, it can confine the credit queue within a specified bound Q_{th} with a small probability δ. Following the exponential distribution, we can then calculate the decay rate q through the pair of parameters (Q_{th}, d), which will drive the design of transmission control. As depicted in Fig. 2, the three decaying rates θ_1, θ_2, and θ_3 are determined by parameter pairs ($Q_{th,1}$, δ), ($Q_{th,2}$, δ), ($Q_{th,3}$, δ), respectively. For the case that the device wants to avoid using up credit, it will be elaborated on later. Evidently, the queuing model associated asymptotic analysis presents a fine-grained network for socially-aware networking, which can be flexibly regulated by adjusting the parameter pair (Q_{th}, δ). Further note that this approach addresses statistical control rather than the deterministic control. The hard queue-bound control is typically inefficient for drastically-varying systems.

Applying Queuing Model to Social Features

Credit Awareness Model and Statistical Credit Driven Transmissions

The section describes how to integrate the credit queuing model to direct communications between IoT devices. Figure 3 illustrates the credit-aware IoT communications scenario including behavior from both the social domain and transmission domain. In particular, we consider three IoT devices denoted by A, B, and C, respectively. Device C requests data from device B, and thus in the social domain (see the upper part of Fig.

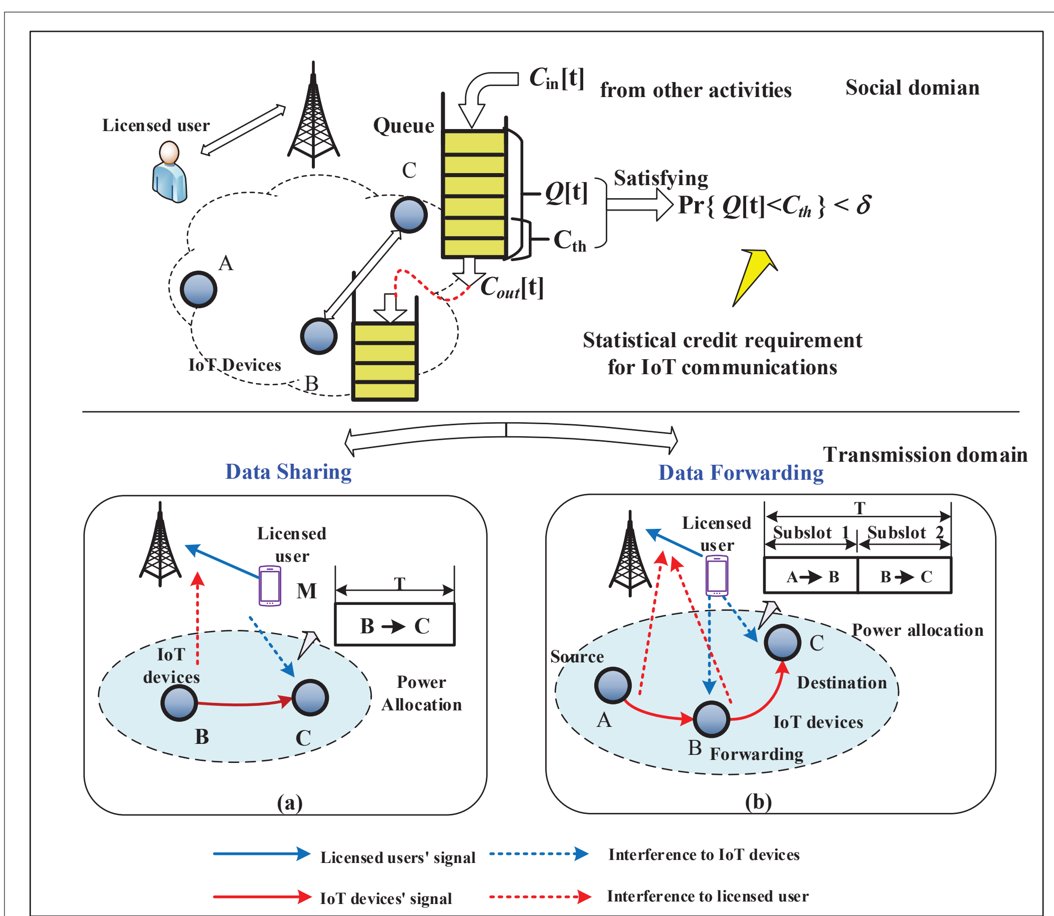

Figure 3. Modeling for credit-aware communications between IoT devices.

3), C is required to pay some credits to B. This is the data sharing case in the transmission domain. If B does not have the data, it might be able to obtain data from adjacent device A. In this case, B functions as the forwarding node, and then we have the data-forwarding case. Clearly, B needs to pay credits to A in this case, yet here we mainly address the interaction between B and C. Moreover, for the data-forwarding case, each transmission will be split into two phases to complete the two-hop transmissions as shown in case (b). While the social domain described here can lead to different data-dissemination scenarios, we next focus on data sharing to grasp the spirit of queuing modeling and credit control for transmission optimization. As aforementioned, all IoT communications reuse the licensed spectrum of the infrastructure network (e.g., cellular network) in an underlaying fashion. Thus, cross-interferences exist between the IoT link and the licensed link. The interference from IoT devices to the licensed user needs to be confined within a certain threshold. As previously discussed, this framework accords with the principles of D2D communications.

Device C's credit variation is modeled by a dynamic queuing system shown in Fig. 3, where the queue length $Q[t]$ is the amount of credit currently owned by C and $[t]$ represents the index of time-slotted transmissions. Device C needs to pay credit to B for data forwarding, where $C_{out}[t]$ is the credit payment process (departure process). In the meantime, device C can gain credit $C_{in}[t]$ from other service activities. It is reasonable to measure credit by the normalized amount of data transmitted. In light of the highly-varying network environments and wireless channels, $C_{in}[t]$ and $C_{out}[t]$ can be viewed as independent processes, thus enabling the application of asymptotic queuing results. Here, the statistical feature of $C_{in}[t]$ is assumed to follow the on-off process and we can concentrate on the control of $C_{out}[t]$, as it directly regulates the transmission process. The operator set a device's maximum allowed credit amount to C_{max}. This setup is to protect the connectivity of the network by avoiding the case that some devices hoard credits and then refuse to help their peers for a long time.

As aforementioned, C wants to avoid credit outage, which is defined as an event with credit queue length Q lower than a threshold C_{th}. Moreover, the credit outage probability cannot exceed the other threshold δ, as illustrated in Fig. 3. However, this requirement brings a very challenging problem, because in order to preserve credits beyond a certain level to deal with bursty transmissions, the credit arrival process often needs to be statistically higher than the credit payment process, which in fact leads to the queuing system being unstable and violating the fundamental condition on queuing analysis.

To solve this problem, we can introduce the *inversely-queuing technique* [13]. In particular, we exchange the roles of $C_{in}[t]$ and $C_{out}[t]$. The credit consumption $C_{out}[t]$ then functions as the arrival process instead, which can be interpreted as the credit budget; similarly, we treat $C_{in}[t]$ as the departure process, which can be explained as the credit income to support the budget. As a result, we get a new *stable* queuing system with queue length $\tilde{Q}[t]$ representing the credit budget, which

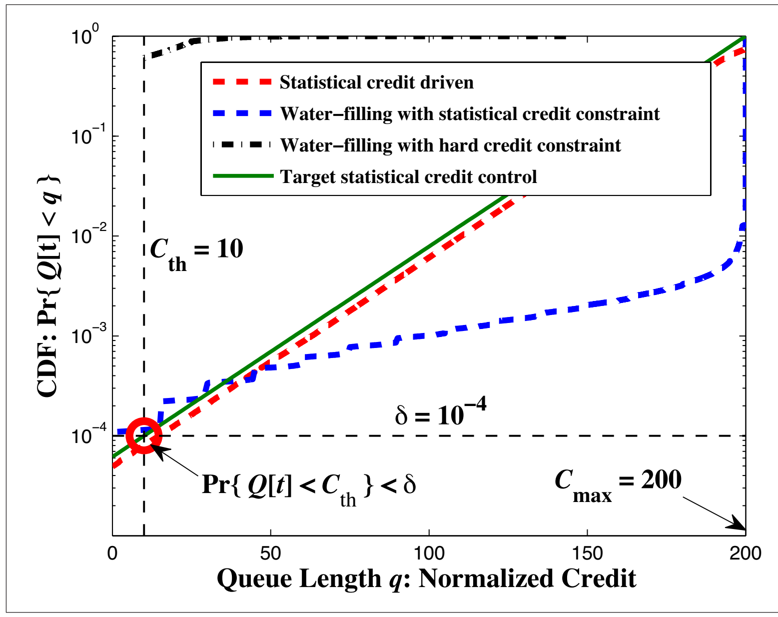

Figure 4. Simulation evaluations for credit-aware communications between IoT devices, where $\delta = 10^{-4}$.

is $C_{max} - Q[t]$. Accordingly, the statistical credit constraint equivalently becomes: the probability of $\tilde{Q}[t]$ exceeding $(C_{max} - C_{th})$ needs to be smaller than δ, where the powerful asymptotic queuing analyse can be well applied. Next, device C's target is to maximize the average throughput under the constraints on average power, statistical credit, and interferences to licensed users, by adapting transmit power to the channel and interference variation (Fig. 3). Preliminary results have been obtained [13] and we term the optimal solution to this problem as the statistical credit driven scheme.

Figure 4 shows simulation experiments on credit distribution for certain networking environments. Note that since the inversely-queuing techniques are applied, here we need to depict the cumulative distribution function (CDF), instead of CCDF, against the device's normalized credit (b/s/Hz). The comparative schemes include water-filling schemes (WF) under statistical credit constraint and hard credit constraints. In particular, the WF under hard credit constraint applies water-filling power control as long as the credit level is higher than C_{th}, and does not transmit if the credit level degrades to C_{th}. The WF under statistical credit constraint simply lowers the average transmit power and rate to avoid credit outage. We can see from Fig. 4 that the statistical credit driven scheme well matches the exponential function predicted earlier, while the probability of the credit beneath C_{th} is controlled lower than $\delta = 10^{-4}$. In contrast, the credit distribution of WF under hard credit constraint typically lies around the outage threshold, because it does not reserve credits for bursty transmissions. The WF under statistical credit constraint is clearly too conservative for transmissions, thus always accumulating credits to the maximum allowed level, which causes severely inefficient use of resources. Based on simulation statistics, the normalized average throughput for the statistical credit driven scheme is 1.84 bit/s/Hz, significantly outperforming the WF scheme's normalized average throughput

The gradually-enhanced mobility of IoT devices may cause the drastic variation of network topology and connectivity. The evident deficiency of these IoT social features is that they become ineffective when the location changes significantly. Therefore, identifying global social metrics for devices is urgently needed to expand IoT coverage and enhance the ubiquitous information exchange.

under hard and statistical credit constraints, which are 1.60 and 0.012 bit/s/Hz, respectively. This demonstrates the advantages of the statistical credit driven scheme in terms of avoiding credit outage to combat bursty transmissions and utilizing resources efficiently.

Modeling Reputation for IoT Communications

Reputation shares similar social functions and properties with credit, but they have essential differences. In particular, credit substantializes the currency to buy services, where reputation reflects the typical nature of a device's behavior, such as a device's typical willingness to help other peers. It is clear that reputation will involve an accumulation process and can fade away over time. In this sense, reputation can also be modeled by a queuing system, yet there are also other approaches modeling the variation of reputation. The reputation update can be modeled by an auto-regression process, where the current reputation is the weighted sum over previously and newly gained reputations. This approach describes the dynamic reputation process as an output of a linear invariant filter. The weight can be explained as the expiring speed of reputation over time. The filter aims at extracting the average reputation and filtering out the varying components. This might not be able to accurately reflect the reputation accumulation process, but the filter model leads to simple analysis of the statistics of reputation and thus is still often employed.

To more accurately characterize the device's behavior in socially-aware IoT, we can consider enjoying the joint usage of credit and reputation via loans, as depicted in Fig. 1e. Given a device's reputation, it is allowed to overdraft or loan some credits from the infrastructure network to support its service requests. The maximum amount of a loan will be determined by the reputation. Matching this to the credit queuing model, we can view the credit loan as the dominating factor to set a queue-bound requirement, making the queuing model control more comprehensive and flexible and formulating a very interesting topic.

Future Research Directions

There have been many unsolved open issues for socially-aware IoT communications. Some research efforts are anxiously expected in the following areas.

Global Social Metric for the Smart IoT Community: Many social features, such as centrality and community, are confined within a local area. The gradually-enhanced mobility of IoT devices may cause the drastic variation of network topology and connectivity. The evident deficiency of these IoT social features is that they become ineffective when the location changes significantly. Therefore, identifying global social metrics for devices is urgently needed to expand IoT coverage and enhance the ubiquitous information exchange.

Socially-Aware Security Assurance for the Smart IoT Community: One of the major concerns for ubiquitous information exchange over IoT is security. IoT peers might not be trustworthy when forwarding/sharing secrecy data. Also, the trust level between different device peers will directly reflect their social bonds and connections. How to incorporate other social features in security guarantees will motivate many new approaches in socially-aware IoT transmissions.

Centrality Modeling for Drastically-Varying Topology: In future IoT with enhanced mobility and massive information exchange, the centrality of IoT devices will vary much faster. How to characterize its dynamics becomes a critical issue. As centrality can reflect the frequency of a device to assist its peers within the neighboring area, to some extent centrality has properties similar to reputation. Thus, we might also apply the power queuing model and asymptotic analysis to characterize centrality, but encountering many new challenges. For example, the centrality feature plays an ultra important role in harmonizing distributed and centralized network control, which will significantly impact social-feature modeling techniques and need further research efforts.

Conclusions

Toward the smart IoT community, this article surveyed and discussed the social features that impact optimization and control for communications among IoT devices. We showed that highly-varying social features like credit and reputation can be modeled by the queuing system. Asymptotic queuing analysis results enabled the unified characterization for the queue-length distribution, which bridges fine-grained social-feature requirements and adaptive transmissions between IoT devices. Moreover, future research topics in socially-aware IoT communications toward the smart IoT community were highlighted, where global social metrics, socially-aware security assurances, and modeling techniques for more social features call for wide research attention.

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