Human-in-the-Loop Mobile Networks: A Survey of Recent Advancements

Lingjie Duan, *Member, IEEE*, Longbo Huang, *Senior Member, IEEE*, Cedric Langbort, *Member, IEEE*, Alexey Pozdnukhov, *Member, IEEE*, Jean Walrand, *Life Fellow, IEEE*, and Lin Zhang, *Senior Member, IEEE*

***Abstract*— Recent developments of smart devices and mobile applications have significantly increased the level at which human users interact with mobile systems. As a result, human activities, usage behavior, and perceived experience of users weigh increasingly on the performance of mobile networks, which has created new challenges for system operation in various aspects, such as increasing uncertainty, selfishness in operations, and complicated performance evaluation. On the other hand, the strong engagement of a large population of human users makes it possible to take advantage of the unique features of human behavior and to leverage the computing powers owned by users. Due to these emerging features of mobile networks, their design and evaluation require a hybrid view of human factor and information technology, and a paradigm shift is required for designing a new human-in-the-loop architecture by actively learning, adapting, and steering user behavior, so as to exploit the human factor in future ubiquitous mobile systems, and to greatly enhance system efficiency and provide superior quality-of-experience to users. The goal of this survey is to summarize recent results that focus on understanding and exploiting the human factor in mobile networks. In the tutorial, we summarize and discuss novelties of these formulations, adopted methodologies, and interesting results. We also point out some future research directions.**

***Index Terms*— Human-in-the-loop, mobile networks, optimal control, prediction, online learning, crowdsensing, game theory.**

I. INTRODUCTION

THE recent developments of smart devices and mobile applications have significantly increased the level at which human users interact with mobile systems and the penetration of mobile subscribers exceeded 97% in 2015. The popularity of smart mobile devices and social networks such as Facebook stimulates a surge of mobile data traffic. It is estimated that the monthly global mobile data traffic will reach 49 exabytes by 2021 and represent 20 percents of total IP traffic [1]. As a result, human activities, usage behavior, and user perceived experience weigh increasingly on the performance of mobile networks.

This fast growing data traffic presents great challenges to mobile network design, e.g., in spectrum efficiency, energy efficiency, and computing capacity. On the other hand, unique features of human behavior, e.g., repeating or semi-stationary behavior, and the human computing power from the network edge, make it possible to learn and predict user preferences and needs, and to improve user experience by performing human-aware system control through behaviorial data, as well as to exploit human capacity for resolving large-scale distributed computing problems.

Indeed, during the past decade, growing attentions have been paid to monitoring, analyzing, and steering human behavior in various human-in-the-loop systems, including cellular networks, haptic communication systems, and E-commerce sites. New techniques such as machine learning algorithms are being developed and implemented to learn user preferences and to exploit the discovered behavior properties, with the objective of enhancing system performance and improving user experience. For instance, content providers such as Youtube pre-fetch video clips onto terminal devices, e.g., small cells and smartphones, based on the learned user preferences. Amazon pre-ships desired products to the closest distribution center of customers based on predicted customer purchase patterns. A haptic system can also deploy predictive intelligent modules to provide quick response actions while the actual actions are still in delivery. These examples show how human behavior patterns can be exploited for performance improvement. Another way to exploit the human factor is demonstrated by Amazon Mechanical Turk, which efficiently gathers human user intelligence, and facilitates solving hard technical problems for machines by human workers. All these techniques have been proven effective in practice in improving system performance and enhancing user experience.

Despite such a strong industry effort and continuing success, the human factor has not yet been fully understood and taken into consideration in the current generation's design of mobile communication networks. As a result, we still do not have a good understanding about the fundamental benefits of the human factor to system performance. For instance, what are the benefits of learning and predicting user behavior? How to exploit human user behavior patterns in system control to achieve performance gains and improve quality-of-experience? How can we best incentivize human users to supplement a computing infrastructure by changing their usage behavior?

Manuscript received October 22, 2016; revised January 04, 2017; accepted April 04, 2017. Date of publication April 25, 2017; date of current version May 22, 2017. *(Corresponding author: Longbo Huang.)*

L. Duan is with the Singapore University of Technology and Design, Singapore (e-mail: lingjie_duan@sutd.edu.sg).

L. Huang and L. Zhang are with Tsinghua University, Beijing 100084, China (e-mail: longbohuang@tsinghua.edu.cn; linzhang@tsinghua.edu.cn).

C. Langbort is with the University of Illinois at Urbana–Champaign, Urbana, IL 61801 USA (e-mail: langbort@illinois.edu).

A. Pozdnukhov and J. Walrand are with the University of California at Berkeley, Berkeley, CA 94720 USA (e-mail: alexeip@berkeley.edu; walrand@berkeley.edu).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/JSAC.2017.2695738

TABLE I
TOPICS AND CATEGORY

Category	HULA Topic
Human intelligence	Sec.II: Crowdsensing applications and data assembly Sec.III: Mechanism design for human-collaboration
Exploring human factor	Sec.IV: Human-system interaction for network management Sec.V: Network control with user demand prediction Sec.VI: Learning-aided dynamic system control
Human data	Sec.VII: Privacy of human-related data

Moreover, technology challenges regarding understanding human behavior and human-aware system implementation also call for new research efforts. For example, how to best identify human behavior patterns? What are the most effective ways to gather human user data? What are the key distinct features of behaviorial data, and how to best protect privacy?

Addressing these questions in human-intense mobile networks requires an in-depth joint investigation from both theory and systems, and a paradigm shift is required for designing a new **HUman-in-the-Loop Architecture** (HULA) that explicitly takes into account and explores the human factor in such systems, by actively learning, adapting, and steering user behavior. In this new architecture, we are able to exploit the human factor in future ubiquitous mobile systems, e.g., 5G, and to greatly enhance system efficiency and provide superior quality-of-experience (QoE) to users.

In this tutorial, our objective is to provide a timely survey of recent results on understanding and exploiting the human factor in various contexts of mobile networks. We do not intend to cover all related topics on human-in-the-loop mobile networks. Instead, we narrow down our focus to the following topics, and try to discuss related recent developments, with an emphasis on novelties of the frameworks and new techniques/methodologies adopted in the studies. The topics are summarized in Table I.

These topics are chosen to demonstrate the collaborative efforts undertaken in three key categories in the HULA architecture, namely, collecting human intelligence, exploring the human factor for performance improvement, and handling human data, where the first two concern the fundamental benefits of exploring human-in-the-loop characteristics and the last concerns the technology aspect. In our presentation, we also selectively present some results in more details based on relevance and ease of elaboration.

The organization of this paper is as follows. In Section II, we discuss crowdsensing and its applications. In Section III, we discuss incentive mechanism design for mobile networks. We then discuss network management with human users in Section IV. After that, we consider network control with prediction in Section V, followed by Section VI about joint learning and optimization. Finally we discuss data privacy in Section VII. We then provide an editorial for the accepted papers in this special issue in Section VIII. We conclude the paper and discuss possible future directions in Section IX.

II. CROWDSENSING APPLICATIONS AND DATA ASSEMBLY

Mobile personal devices with embedded sensors are becoming increasingly popular. Nowadays, almost all smartphones have built-in sensors including accelerometer, gyroscope and magnetometer. High-end products also embed proximity sensors, light sensors, barometers and humidity sensors. Besides these built-in sensors, other components in smartphones can also provide sensing capacity. For example, WiFi modules can be treated as a signal strength sensor, and microphone as a noise level sensor. Some manufacturers also tailor products to specific needs of users. For instance, a Japanese manufacturer provided a smartphone with radiation sensor after the Fukushima tragedy in 2011 [2]. Connected vehicles compose another category of mobile sensing devices that enjoy more stable power supplies and variety of sensors. Compared to mobile personal devices, vehicles traverse the city and provide larger and better coverage for the urban areas.

This wide availability of high performance sensors makes it profitable to elicit the power of the crowd to accomplish tasks that will otherwise be hard to accomplish. Indeed, over the past few years, crowdsensing has received much attention due to its wide applicability. Below, we first introduce various applications of crowdsensing. Then, we explain how to assemble the crowdsourced data from multiple sources, and ensure the most trustworthy information.

A. Crowdsensing Applications

There have been many applications for crowdsensing, e.g., environmental sensing and social sensing. In the following, we mainly focus on three applications: environment, transportation and people.

1) Environment Sensing Applications: Citizens sharing environment awareness and health concerns has been a very popular application of crowdsensing. CommonSense [3] relies on specialized hand-held air quality sensing devices that communicate with smartphones to measure various air pollutants, e.g., CO_2 or NO_x. These devices, when deployed across a large population, collectively measure the air quality of a community or a large area. PiMi air community [4] makes a progress on understanding influential factors to environment with crowdsensing. Specifically, PiMi measures the indoor PM2.5 concentration through a portable device connected to volunteers' smartphones, and asks users to label building information and activities. With hundreds of hours indoor air quality information labeled, it is capable to analyze the impact factors for indoor air quality. Personal Environmental Impact Report (PEIR) [5] is a system that allows users to leverage their smartphones to determine their exposure to environmental pollutants. A sensing module installed on the phone determines the current location of the user as well as information about the mode of transportation, e.g., bus or car, and transmits this information to a central server. In return, the server provides users with useful information about the ambient impact of their traveling in terms of carbon and particle emissions. Additionally, the server estimates participants' exposure to particle emissions generated by other vehicles and fast food restaurants when commuting. A more recent work, Gotcha [6], crowdsources air quality monitoring to electric-taxi fleets, which enables fine-grained pollution mapping and source identification in urban areas.

Besides air quality, other environmental factors such as noise, floods, water quality are also interesting crowdsensing objectives. Ear-Phone [7] and NoiseTube [8] leverage microphones of smartphones to record ambient acoustic levels, and infer noise levels in communities. CreekWatch [9] monitors water levels and quality in creeks by aggregating reports from individuals, such as pictures taken at various locations along the creek or text messages about the amount of trash. These information can be used by water control boards for tracking pollution levels in water resources.

2) Transportation Applications: Transportation centric crowdsensing applications focus on measuring traffic congestion, road conditions, parking availability, etc. Pan *et al.* [10] use crowdsensing for collecting two types of data, human mobility and social media, to address the problem of detecting and describing traffic anomalies. MIT's Car-Tel [11] exploits specialized devices installed in cars to measure the location and speed of cars, and transmits measured values using public WiFi hotspots to a central server, which can then provides information such as the least-delay routes or traffic hotspots to users via queries. Microsoft Research's Nericell [12] utilizes individuals' smartphones to not only determine the average speed or traffic delay, but also to detect honking levels and potholes on roads. The pothole patrol in [13] uses the inherent mobility of the participating vehicles, opportunistically gathered data from vibration and GPS sensors, and data processing to assess road surface conditions.

VTrack [14] is a system for travel time estimation using the collected sensor data from drivers. It leverages less energy-hungry but noisier sensors such as WiFi to estimate user's trajectory and travel time along the route, and then leverages a hidden Markov model based map matching scheme and travel time estimation method, to identify the most probable road segments driven by the user and to attribute travel times to those segments. This work addresses energy consumption and sensor unreliability issues well. ParkNet [15] system collects parking space occupancy information through distributed sensing from passing-by vehicles. PocketParker [16] is also a crowdsensing system using smartphones to predict parking lot availability. Unlike ParkNet [15], PocketParker does not require new vehicle capabilities. MetroEye [17] uses volunteers' efforts and plural sensors on their smartphones to track transfer and riding activities in subway system, and analyzes the efficiency of the transportation system.

3) Health Application: CenceMe [18] integrates virtual representations of participants' current state and context in social networks and virtual worlds. Based on multimodal information, e.g., acceleration, audio samples, pictures, neighboring devices, and location, captured by the smartphone, context information is inferred in various dimensions, including user mood, habit, and information about current activity and environment. The inferred information is then posted as status message in social networks or translated into irtual representation of the participants in virtual worlds.

BikeNet [19] proposes a system for monitoring bicycling experiences of participants. It draws a fine-grained portrait of a cyclist by measuring his current location, speed, burnt calories, and galvanic skin responses. The collected data from the crowd can be used to develop live maps for the cycling community. DietSense [20] assists participants who wish to lose weight by documenting their dietary choices through images and sound samples. Participants take pictures of what they eat and share within a community to compare their eating habits. A typical use scenario for this is for a community of diabetics to watch what other diabetics eat and control their diet and to provide suggestions to others.

B. Data Assembly

As most participants in crowdsensing tasks are non-experts, errors are inevitable. As a result, conflicting information may be given to the same task. To obtain the final results from these potentially inconsistent data, one important issue is how to assemble the crowdsourced data from multiple sources, and obtain the most trustworthy information. We now discuss different methods that have been proposed in the literature.

The most intuitive approach of data assembling is majority voting [21], which selects the majority answers from all sources as the final output. However, this approach fails to take the reliability levels of different sources into consideration, which may lead to poor performance when the number of low quality sources is large. To solve this problem, numerous techniques for multi-source aggregation have been proposed to derive true answers from a collection of sources by considering source reliability. One classic approach is named D&S [22], which leverages a confusion matrix for each user and a class prior to model user expertise. ZenCrowd [23] instead uses expectation-maximization (EM) to simultaneously estimate true labels and user reliability. It assumes that users act independently and simplifies the estimation of the full confusion matrix per user.

Snow et al. [24] adopt the D&S approach but consider the fully-supervised case of maximum likelihood estimation with Laplacian smoothing to test the source reliability. Venanzi et al. [25] introduce community-based Bayesian aggregation model to estimate each user's reliability and true labels by using the community's confusion matrices and employing ground truth to improve accuracy. Raykar et al. [26] propose a Bayesian approach to add work specific priors for each class for binary labeling tasks. Similarly, Welinder et al. [27] also added priors to each parameter used in Bayesian approach. Zhou et al. [28] defined a separate probabilistic distribution for each user-item pair and adopted a minimax entropy principle to estimate true labels and user reliability jointly. These methods are able to handle multiple-choice question aggregation.

Pasternack and Roth [29] introduce a framework in which sources invest their reliability uniformly on the observations they provide, and collect credits back from the confidence of those observations. In turn, the confidence of observations grows according to a non-linear function based on the sum of invested reliability from their providers. Li et al. [30] propose an optimization framework to model different data types jointly, and estimate source reliability and truth simultaneously. They also propose a different method in [31] to automatically estimate truth from conflicting data with long-tail phenomenon. FaitCrowd [32] proposes a novel probabilistic Bayesian model to address the challenge of inferring fine-grained source reliability. By jointly modeling question contents and collected answers, the proposed model learns the topics of questions, topic-specific expertise of sources, and true answers simultaneously.

III. Mechanism Design for Human Collaboration

To prepare for future 5G mobile networks, there are new wireless access structures such as heterogeneous networks [33], networked MIMO [34], and cloud-based radio access networks [35] to improve system performance in many aspects (e.g., spectrum, energy, and computing efficiency). A large number of cooperative wireless access points will be deployed close to users to serve their traffic in the vicinity, which also helps monitor their activities and collect data. However, this dedicated network for data sensing and processing is costly to deploy and operate, making it not scalable to continued growth of real-time data traffic in the new era of big data [36]. Moreover, it can only respond to existing data and cannot actively interact with users to obtain useful data beforehand.

To efficiently monitor users' behavior and collect useful data in a proactive way, mobile crowdsensing is proposed as a promising approach on the network edge. It employs human-centric mobile sensing and computing devices (such as smartphones, smartwatches, and in-vehicle sensors) as well as human intelligence to sense and transmit back the selected data collectively to the mobile system's central office. Given millions of smartphones sold every year, mobile systems recently started to utilize the power of crowd at the network edge. For example, the mobile system can track users' GPS locations via their smartphones to obtain user mobility pattern and predict traffic in spatial and temporal domains for proactive resource allocation. Besides, the mobile system can employ a large number of smartphones to build up a real-time database to provide location-based services (e.g., ambient environment monitoring, public recommendation, smart transportation, and indoor localization) whose global revenue increased from US$2.8 billions to US$10.3 billions between 2010 and 2015. For example, each smartphone can transmit back the name, location, signal strength and congestion level of any nearby WiFi networks, helping build a live map of commercial WiFi networks. Another service can be live map of auto traffic, where dynamics of users' GPS location data on a highway tell whether there is a traffic jam.

We also note that human intelligence is a good supplement to machines and mobile devices in many tasks. In complex tasks such as public recommendation (e.g. of spectrum channel, traffic, news and popular video files), image tagging and natural language processing, solely developing or improving algorithms is unable to ensure high accuracy, while human participation efficiently covers the shortfall in current technologies [37], [38]. We can roughly categorize mobile crowdsensing tasks into device- and human-oriented tasks.

Such edge devices and human activities are expected to lead to the evolution of mobile IoT [39], yet there are two main challenges that hinder the development of mobile crowdsensing:

Incentive for Smartphone Collaboration: To handle sensing and computing tasks, users concern about the potential privacy loss, inconvenience and energy consumption. As some sensed data (e.g., GPS location coordinates) are personal and sensitive, a user may psychologically worry about privacy loss or even property loss due to disclosure of bank account information in data reporting [40]. He may also face discomfort due to frequency annoyance from unwanted advertising in using location-based services (e.g., [39], [41], [42]). Besides privacy loss, users also concern about the resource consumption (e.g., energy) and the resulting inconvenience to own usage. Periodically sensing and transmitting data to the system's central office consume a user's smartphone battery energy. According to experiments and measurements done by [43] and [44], the consumed energy depends on the detailed specifications of data sensing tasks, involving the interaction efficiency across different layers (e.g., user interaction layer, application layer, transport layer, and radio channel state).

Human users are rational and take the potential privacy loss or energy consumption in smartphones into account when deciding whether to join the tasks. To understand and estimate their behavior, we model them using the classical expected utility or cost model to tell the effect of incentive design. Depending on the assigned tasks, users are risk averse when reporting sensitive data and are more risk neutral when handling the other tasks like computing. Compared with risk neutral users, risk averse users dislike average-preserving spreads in the distribution of their final collaboration benefit [45]. It is natural to model their utility as a concave function while risk neutral users' utility is linear. Using game theory, human users' collaboration behaviors can be analyzed at the equilibrium, and then it is feasible to design efficient incentive mechanisms in the first place to stimulate desirable user behavior.

Ho et al. [46] study the use of financial incentives to encourage high quality crowdwork on Amazon Mechanical Turk. Specifically, they focus on the use of performance based payments (PBPs), bonus payments awarded to workers for producing high quality work. Horton and Chilton [47] design a labor supply model to estimate a worker's reservation wage, which is for balancing a company's production cost and its workers' reservation wage. In CrowdSearch [48], crowd sourcing and micro-payments are adopted to incentivize people to improve automated image search. The human-in-the-loop stages are added to the process of image search with tasks distributed to the user population. Zhao et al. [49] focus on online incentive mechanisms for mobile crowdsensing. The authors have designed two online mechanisms under different assumptions and proven that the mechanisms satisfy the computational efficiency, individual rationality, budget feasibility, truthfulness, consumer sovereignty and constant competitiveness. Zhang et al. [50] propose online incentive mechanism design for crowdsensing applications with Smartphones. They have designed three computationally efficient, individual rational, profitable and highly competitive mechanisms. Koutsopoulos [51] propose an incentive mechanism to minimize the total cost of compensating participants, given the quality constraint of sensing tasks.

Quality of Information: To successfully build up a database and keep it updated, the mobile system requires reliable data sources from users. When employing the public crowd equipped with various smartphones for large-scale sensing, the quality of sensory data/information varies significantly among individuals. An individual's quality of information (QoI) is affected by various factors in handling a specific task, e.g., the sensor quality, noise, and human intelligence. Critical QoI metrics should be determined for different tasks and the general goal is to obtain high quality data at the minimum cost through system-human interaction [52]. In the online process of learning massive datasets' quality, we should differentiate low and high quality labelers over time and select the best set with performance guarantee [53]–[55]. Today's mobile devices are similarly good in standard sensing (e.g. GPS and WiFi signals), whereas human users' performances vary significantly in education and skill levels as well as efforts to make. We expect more QoI diversity in human-oriented tasks than device-oriented ones.

To incentivize enough collaborators and ensure high QoI, there are increasingly more works for modelling of device/human diversity (e.g., in collaboration cost and QoI), and they aim to address the collaboration incentive and quality management problems via mechanism design and learning. We will introduce the detailed learning approach in Sections V and VI, and now focus on incentive mechanism design in this section. To model the relationship between the mobile system and human users for the QoI-aware incentive design, principal-agent models under information asymmetry are widely used, and mechanisms like economic pricing, contract and auction are proposed to motivate users' collaboration despite lack of information (see [52], [54], [56]–[58]). To provide readers with more background knowledge, we introduce some simple but typical mechanisms in [58] for both device- and human-oriented tasks in the following.

1) Incentive Design for Device-Oriented Crowdsensing Tasks: In these tasks, mobile devices are employed to sense and report target data (e.g., GPS location and WiFi signal) without continuous human intervention, and their owners/users simply decide whether to collaborate at the beginning of a sensing period (e.g., a month or a year), by comparing the long-term collaboration benefit and cost. As the mobile devices periodically sense and contribute similar amounts of data, we consider a threshold-based model for the QoI control.[1] Given a large number N of users in mobile networks, if the mobile system attracts at least n_0 users as collaborators for sensing, it will successfully build the database with guaranteed QoI and receive a revenue of V. Otherwise, it does not receive any revenue. We assume a fixed collaboration cost for each user (e.g., cost C_i for user i) which is a private information unknown to the system or the other users. The interaction between the system and devices under asymmetric information is modeled as a Stackelberg game:

- In Stage I, the system simply announces a total reward R to be fairly shared among collaborators and the required collaborator number n_0 to all users.
- In Stage II, each user decides to join the crowdsensing or not by predicting its shared reward and the other users' costs and decisions.

Assume there are randomly n out of N users willing to collaborate in Stage II, there are two models for determining a collaborator's payoff:

- *Reward model for collaboration effort:* By joining the collaboration, user i's expected payoff is[2]
$$\mathbb{E}\left(\left(\frac{R}{n} - C_i\right)\mathbf{1}_{\{n \geq n_0\}}\right),$$
where $\mathbf{1}_{\{X\}}$ is the indicator function and equals 1 when the event X happens, and the expectation is taken over all $N-1$ users' cost and decision distributions. The crowdsensing starts only when there are sufficiently many collaborators to meet the QoI requirement, and the user of cost C_i obtains the equally allocated reward R/n by sharing with the other $n-1$ collaborators.
- *Reward model for successful collaboration:* A collaborator i's expected payoff is
$$\mathbb{E}\left(\left(\frac{R}{n}\right)\mathbf{1}_{\{n \geq n_0\}} - C_i\right),$$
where the crowdsensing does not wait for enough users to start. Here users take the risk for not being awarded.

In the two reward models above, the system receives an expected profit of
$$f(R) = \mathbb{E}((V-R)\mathbf{1}_{\{n \geq n_0\}}),$$
where the expectation is taken over random variable n by considering all users' possible binary responses.

This dynamic game can be analyzed by backward induction. We start analysis with users' equilibrium decisions in Stage II and then end up with the system's reward decision in Stage I. Though the second reward model (for successful collaboration) seems easier to implement by the system, [58] shows that the first reward model (for collaboration effort) outperforms in motivating users' collaboration and save the system's budget for compensating users' costs. Now we focus on the first model to explain the detailed analysis. Without much loss of generality, we assume that users' collaboration costs are independent and identically distributed with a cumulative probability distribution function $F(\cdot)$.

Starting with Stage II, we can show that there is an identical decision threshold γ such that a user i will collaborate if and only if $C_i \leq \gamma$. For the user with the cost equal to γ, he is indifferent to collaborate or not and has zero payoff. That is,
$$\mathbb{E}\left(\left(\frac{R}{m+1} - \gamma\right)\mathbf{1}_{\{m+1 \geq n_0\}}\right) = 0,$$
and the expectation is taken over m which follows a binomial distribution $B(N-1, F(\gamma))$. Note that m tells the collaborator number among the other $N-1$ users. The above equation helps

[1]Through rigorous probabilistic analysis, this threshold-based model is validated by [37] to provide certain QoI guarantee.

[2]The linear utility in this payoff function tells the user's risk neutrality. We can extend to a risk-averse version by formulating a concave utility function.

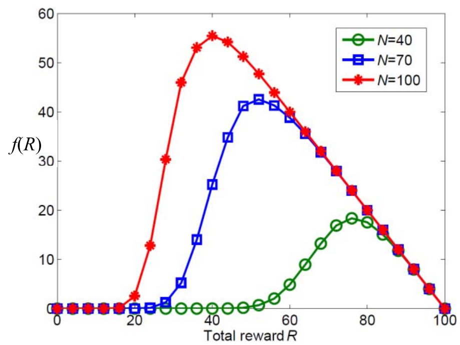


Fig. 1. System's expected crowdsensing profit $f(R)$ as a function of total reward R and total user number N in [58].

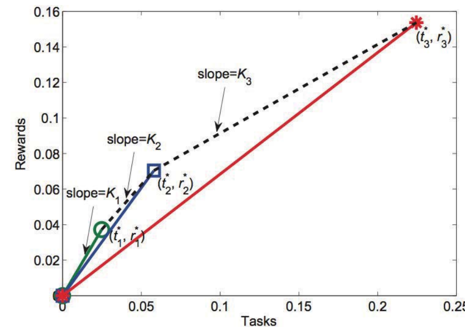


Fig. 2. Optimal contract $\{(r_i, t_i), \forall i \in \mathcal{I}\}$ for three types of users under asymmetric information in [58].

determine the value of γ and the equilibrium γ increases with reward R to include more users.

Finally back to Stage I, there is a trade-off to decide the optimal reward R: a larger R leads to a smaller net value $V - R$ for the system, but increases the collaboration success probability $\mathbb{E}_n\ (\mathbf{1}_{\{n \geq n_0\}})$ to meet QoI requirement. Note that random variable n follows a binomial distribution $B(N, F(\gamma))$. To illustrate such a trade-off, Figure 1 shows the expected profit $f(R)$ is first increasing and then decreasing in R, and the optimal R^* yields the maximum profit. As the total user number N increases and more users are realized to have small collaboration costs, the optimal reward R^* decreases and the optimal expected profit $f(R^*)$ increases.

2) Incentive Design for Human-Oriented Crowdsensing Tasks: In many device-oriented crowdsensing tasks, users report fixed and periodic data over time, and each contributes similarly in the large scale network. Differently, users in human-oriented tasks can flexibly decide how many efforts to make. For example, an individual can decide how much time to learn required skills via self-training or consulting friends and how much time to directly contribute to handle the tasks [37], [38]. Still, users are different in cost efficiency to handle sensing tasks and we categorize N users into I types in set $\mathcal{I} = \{1, \cdots, I\}$. Each type includes N_i users and we have $\sum_{i \in \mathcal{I}} N_i = N$. A user of type-$i$ perceives a unit cost K_i in handling t amounts of tasks and expects to receive a reward r. Its payoff function is thus $u_i(r, t) = r - K_i t$.

Under asymmetric information about users' types, contract theory is widely used to study how the system decides contractual arrangements with users. The contract can be written as $\{(r_i, t_i), \forall i \in \mathcal{I}\}$ by designing specific reward r_i and task t_i for type-i users. To ensure users' participation and their truthful identity revelation, two properties should be satisfied for the optimal mechanism design:

- *Individual rationality (IR):* A contract satisfies the individual rationality or participation constraints if each type-i user receives a non-negative payoff by accepting its own contract item (r_i, t_i), i.e.,

$$u_i(r_i, t_i) = r_i - K_i t_i \geq 0, \quad \forall i \in \mathcal{I}.$$

- *Incentive compatibility (IC):* A contract satisfies the incentive compatibility constraints if each type-i user will truthfully choose the contract item for its own type, i.e.,

$$u_i(r_i, t_i) \geq u_i(r_j, t_j), \quad \forall i, j \in \mathcal{I}.$$

Subject to these IR and IC constraints, the system aims to maximize its profit in expected sense, i.e.,

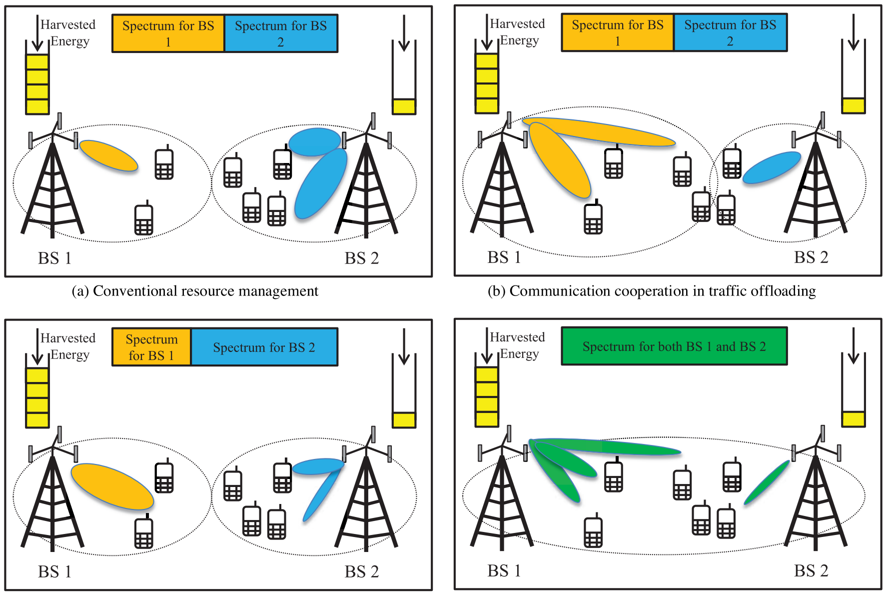
$$\max_{\{(r_i, t_i), \forall i \in \mathcal{I}\}} \mathbb{E}_{\{N_i, \forall i \in \mathcal{I}\}}(f(\{N_i t_i, \forall i \in \mathcal{I}\}) - \sum_{i \in \mathcal{I}} N_i r_i),$$

where function $f(\cdot)$ combines all user types' efforts and may follow a sigmoid or threshold-based structure to reflect the QoI requirement.

Without loss of generality, we assume user types are reordered according to increasing cost efficiency or decreasing unit cost: $K_1 > K_2 > \cdots > K_I$. Reference [58] shows that the optimal contract $\{(r_i^*, t_i^*), \forall i \in \mathcal{I}\}$ should assign more tasks to a user with higher type (better cost efficiency) and reward it more. Fig. 2 shows the relationship between different contract items in a three-type example to satisfy both IR and IC constraints. A type-1 user's tight IR constraint $r_1^* - K_1 t_1^* = 0$ is sufficient to ensure IC constraints, as this type of users cannot afford the higher cost when choosing a higher contract type ($u_1(r_2^*, t_2^*) < 0$ and $u_1(r_3^*, t_3^*) < 0$). Similarly, a type-2 user cannot afford the higher cost when choosing (r_3^*, t_3^*) and does not want to choose type-1 contract to get less reward.

We should note that the above crowdsensing contract in [58] and some other works (e.g., [54], [57]) is in general a screening contract with observable sensing efforts and the system can perfectly pay according to users' efforts. There are also other contracts like moral-hazard with unobservable efforts (see [59]), where the system cannot directly observe users' efforts or infer their sensing efficiencies from the noisy crowdsensing outcomes. Such contract design may fit some other crowdsensing tasks under the difficulty to tell sensing quality of users or even determine the ground truth [38], [60].

Besides modelling the interaction between the system and users as principal-agent problems and solving by contract or other pricing mechanisms, there are some ways other than economic rewards/payments to stimulate users' crowdsensing efforts. For example, more and more users are subscribing to the location-based services supported by mobile crowdsensing and they act as both information contributors and consumers in the market or social community [61]. The benefit of accessing the information database or the



(a) Conventional resource management (b) Communication cooperation in traffic offloading

(c) Communication cooperation in spectrum sharing (d) Communication cooperation in CoMP

Fig. 3. An illustrative example of conventional resource management and three new communication cooperation schemes for two neighboring base stations (BSs) [63].

supported services help motivate users especially those with high information/service valuations to contribute to crowdsensing. Despite the help from this social effect, [62] shows that incentive mechanisms like side-payment are still needed to ensure heterogeneous users' high participation.[3] Instead of using complicated economic payment, [62] also designs novel content-restriction mechanisms to restrict information content to be accessed by the low contributors as potential penalty and incentivize users even with low valuations to contribute in the first place.

IV. Human-System Interaction for Network Management

Provided with massive useful data obtained via mobile crowdsensing, how to best use such information for preparing for and improving network management is a question. Users' ever-increasing demands in high-throughput or low-delay traffic services challenge the limited capacity of wireless networks. In the following, we show to leverage such information to improve the system efficiency.

A. Traffic-Aware Dynamic Communication Cooperation

With knowledge of users' data traffic distribution in time and space domains, we can proactively reshape their demands to better fit the regional resource distribution in the limited-capacity networks. We seek dynamic communication cooperation between users and mobile networks and between different mobile networks for proactive operation.

In the time domain, a traditional cellular network needs to over-provision capacity for traffic demand at peak times of the day. After sensing and learning users' traffic behavior over time, [64] presented a price-based feedback control loop between the cellular network and users to smooth out temporal demand fluctuation. In such cooperation, users are willing to reschedule their demands to less congested periods to save money. Reference [65] studies how to learn users' social activities to estimate and control network congestion. To further reduce severe traffic overloads in cellular networks, delayed traffic offloading is proposed by exploiting user mobility data and opportunistically offloading cellular data through WiFi or small-cell [66]–[68]. Users inside or close to WiFi or small-cell coverage are provided with economic benefits to roam and connect to the under-utilized access points, by taking their limited-capacity backhaul into account.

In the space domain, the mobile networks continuously sense users' locations and applications' QoS, and estimate varying wireless traffic over cellular networks. Given unevenly distributed traffic, it is desirable for neighboring base stations (BSs) of the same or different cellular networks to cooperate [63].[4] As shown in Fig. 3, there are three new cooperation schemes on the demand side that exploit the broadcast nature of wireless channels and employ resource sharing to reshape BSs' load and reduce energy consumption [63]. Before the cooperation, the two BSs exchange with each other the communication information (e.g., traffic types and user locations) and energy information (e.g., renewable harvesting rates). According to their load, spectrum and energy information, they apply one out of three cooperation schemes, namely, traffic offloading, spectrum sharing, and coordinated multi-point (CoMP). The first scheme shifts traffic of the heavily loaded BS to the lightly loaded one [71], [72],

[3] Besides IR and IC properties, when applying side-payments on users, some other property like budget balance should be ensured for the mechanism design.

[4] In practice, according to [69] and [70], three major mobile networks (i.e., China Mobile, China Unicom and China Telecom) in China have agreed to jointly deploy shared tower infrastructures and share resources to enable the co-location of individually deployed BSs by different networks.

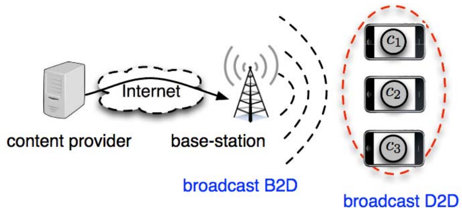


Fig. 4. Co-existence of broadcast BS-to-device (B2D) and broadcast device-to-device (D2D) communications in [76]. Here, all users c_1, c_2 and c_3 are interested in the same video streaming.

the second scheme reallocates idle spectrum resource from lightly loaded BS to heavily loaded one [73], and the last scheme implements coordinated baseband signal processing to jointly serve multiple mobile terminals over the same time-frequency resource [74]. If the two BSs belong to different selfish entities, fairness (e.g. in proportional or symmetric sense) in sharing cooperation benefits should be ensured to make their cooperation feasible and sustainable [71], [73].

B. Content-Aware Cognitive File Delivery

Given a transmission protocol, each BS in the cellular networks can further improve its transmission efficiency by examining and comparing the content of users' requested files. For example, a traditional BS communicates with users via their cellular links independently, though a number of users within the cell are interested in the same Internet content (e.g., news, football matches and popular movies) at the same time. Such content interests overlap more and more frequently due to growing attentions of mobile social networks [75]. Aware of users' common interests, Hsu and Duan [76] proposes the content-aware BS to leverage such common interests by broadcasting files over BS-to-device medium (see Fig. 4). Due to the unreliable wireless channels, users may not receive target files simultaneously. Reference [76] investigates the efficiency of B2D broadcast and further employs D2D broadcast for the physically neighboring users to locally repair files. Online scheduling algorithms are proposed to cope with the case of dynamic content arrivals.

Awareness of users' requested content, mobile networks can also identify popular files and proactively download such files to BSs' caches [77]. This saves the download time from content providers' remote servers and achieves high throughput via the last-mile B2D delivery only. As popular files are downloaded in off-peak hours, the BS-caching helps alleviate the traffic congestion during the peak hours. With further knowledge of users' locations, multiple BSs can cooperatively serve users to achieve diversity gain, and a user can also choose BSs dynamically to adaptively adjust transmission quality (e.g., [78]–[80]). Besides local caching at BSs, popular files are also cached on the user side. Mobile users exploit their mobility profile to share files via D2D communications during peak hours. Reference [81] derives the power scaling law of network capacity by considering the range of D2D communications and [82] further investigates the resulting outage in file sharing. To motivate selfish users to cache and share files useful to the whole system, [83] investigates their diverse caching preferences and the impact of selfish behavior on system performance (e.g., average delay of file delivery).

As the mobile networks become more heterogeneous and decentralized, we note that human users are playing more active roles in shaping the HULA architecture. There are more and more user-initiated or controlled networks (e.g., D2D, WiFi offloading, and small cells) and the involved network-edge devices are more powerful.

and this will be strengthened in the future considering the

C. Human-Human Interaction for Resource Sharing

The file caching and D2D sharing among users on the network edge leverage their mutual interaction in mobile networks. More generally, it is desirable for the mobile networks to motivate and manage the human-human interaction to establish a new sharing economy among users in a societal scale. To reach a win-win situation, users can cooperate with each other in cooperative communications or pooling personal resources. As users are selfish and they are sensitive to their resource consumption, how to provide sufficient incentives to users for motivating sharing is a question.

1) User-Initiated Cooperative Communications in Short Term: Most users report only two days of battery life during smartphone active use and they have to charge smartphones more frequently due to the heavy data usage and limited battery capacity [84], [85]. This is one of the biggest customer complaints for smartphones. As such, it is important to resolve phones' energy shortage problem and improve the connectivity of the whole wireless network. User-initiated cooperative communications provide an efficient way for smartphones' energy saving [86], where a user short of energy in the uplink can first forward data to another in the vicinity via short-range communications (e.g., D2D) and the latter user will transmit to the BS. However, most work overlook the fact that users are selfish and are only willing to help when they can benefit from the cooperation [87]. By modelling the transmission energy consumption and battery storage of smartphones, [88] exploits the diversity of smartphones' battery levels and channel conditions to propose a pricing scheme to incentivize the cooperative communications. Optimal traffic-dependent pricing is designed for source users to submit to helping users (if any) without knowing the latter party's battery levels, channel conditions and even stay time in D2D range. After a data transmission, a smartphone stays in high-power state in cellular interface and [89] further proposes the traffic aggregation of multiple smartphones for energy saving.

User-initiated cooperative communications not only address energy issue for users but also help serve users in poor signal coverage. For example, in a cognitive radio network, primary users in poor coverage can opportunistically discover neighboring secondary users to relay traffics, while secondary users also gain dedicated spectrum access time for transmitting their own traffic. Reference [90] motivates dynamic spectrum sharing between a primary user and multiple secondary users, and [91] further extends the cooperation mechanism to a large-scale network including multiple primary users.

2) User-Initiated Service Networking in Long Term: Other than cooperative communications for short-term energy saving and signal coverage, users can further collaborate with each other in long term to share networked services. Differently, here users share upper-layer WiFi or wireless data services with each other instead of physical-layer relay helps. Users own and operate devices like the femtocell/WiFi access points at home and personal hotspots in their smartphones, yet they are unwilling to share with other people even if such devices are not used. The development of user-initiated device sharing and resource trading for enabling such a new sharing economy of user-provided networks is still at its infancy, and recently there are some preliminary work to promote this research direction. Reference [92] and [93] encourage host users to share home-deployed femtocell/WiFi access points to guest users, by providing host users with economic return or roaming benefit to access the other users' access points.

As all the shared access points are fixed and only cover a small area, it is difficult for such a static network to serve many moving users in the future mobile networks. Differently, [94] proposes a personal hotspot market by motivating users with data-plan surplus to form a mobile WiFi network for serving the others in data deficit. Under the existing two-part tariff data plans (each including a lump-sum fee and a per-unit price charge), some users use up monthly data quota easily and pay for expensive data over-usage, while some other users cannot use up all the data quota. By setting up the personal hotspot in its smartphones, a user with data surplus can share the cellular connection to another user with data deficit or a foreign tourist in the vicinity. By taking users' diverse data usage behavior and random mobility into account, [94] develops a market-clearing price for opportunistic data-plan trading between data sellers and buyers to realize a win-win situation.[5] Given this user-initiated secondary service provision, the traditional data services face direct competition as traditional over-usage charge or roaming fee is lost. The operators' counter-measures are also investigated in [94].

V. Network Control With User Demand Prediction

In this section, we consider another important aspect about how the human-in-the-loop feature can be exploited for improving system performance, namely, predictive service. This is a unique opportunity enabled by the human factor for providing superior quality-of-service to customers by proactive service, an opportunity not present in causal systems, i.e., system only reacts to user demand after they enter the system.

Let us start with a few examples. The first example is streaming online videos. In this case, an online video site, e.g., Youtube, serves users' video demand. Instead of taking a passive approach and waiting for a user to click on video clips before transmission, in which case the user may need to wait for the video to load and suffer significant delay, the server can "guess" what the user may want based on observed user ativities, and pre-load part of the videos to the user's device beforehand to reduce delay. The second example scenario is prefetching in computing systems, e.g., [96], [97]. Here, data or instructions are preloaded into memory before they are actually requested. Doing so enables faster access or execution of the commands and enhances system performance. Indeed, this unique potential extends to general computing systems, where each user can represent a software application and the server represents a workload management unit. Then, according to application needs, the managing unit pre-computes certain information in case some later applications request them, e.g., branch prediction in computer architecture [98], [99].

In order to provide high level quality-of-service and efficiently utilize future information, it is critical to understand human behavior features and to utilize such information to guide system control algorithm design. Therefore, various studies have been conducted to learn and predict human behavior patterns, e.g., online social networking [100], online searching behavior [101], and online browsing [102]. It is important to note that problems in systems where prediction is possible are significantly different from those in causal systems, for instance, [103]–[108], in that prediction provides additional information for decision making, and should intuitively bring performance gain. Incorporating user behavior prediction into network control is non-trivial. The main challenges include (i) uncertainty in prediction, (ii) efficient incorporation of prediction into algorithm design, and (iii) rigorous analysis of predictive control algorithms. These challenges pose new requirements on both system modeling and analytical method. Below, we survey several recent results that try to develop deeper understanding about predictive control. These results provide us with new insights on the fundamental benefits of predicting user behavior and how to design efficient predictive control algorithms. Notice that in these formulations, user behavior prediction is often abstracted as demand prediction. This is an important step that facilitates analysis and understanding without losing generality.

A. Proactive Service for Delay-Intolerant Service

The general setting in this thread is as follows. Consider a system operator providing delay-intolerant service to a set of users. The system operates in slotted time. In every time, users generate requests that must be fulfilled in the same timeslot. The operator get access to a demand prediction module that outputs the demand distribution in future slots, often assumed to be cyclostationary. Then, at every time, the system can decide whether to proactively serve demand in future timeslots, so as to minimize the overall cost incurred serving user requests. Under this formulation, recent works [109]–[111] characterize the benefits of prediction for both asymptotic and finite user cases.

B. Predictive Scheduling in Queueing Systems

In the second research thrust, the impact of prediction on queueing system is investigated. The general setting in this direction is as follows. Consider a single-server queueing system. Arrivals enter the system according to certain

[5] Note that there are some system-coordinated secondary data-plan trading work (e.g., [95]), yet the market is still operated by the network operators without using personal hotspots.

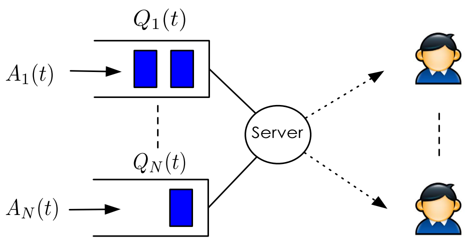


Fig. 5. A single-server multi-queue system where a server is serving workloads for different users/applications.

stochastic process. The system is assumed to have prediction power, in the form of a prediction window that contains future arrival information. In this formulation, the queueing aspect is explicitly modeled.

There are two settings considered under this formulation. Work [112] considers the power of prediction in delay reduction based on a continuous-time $M/M/1$ queue. They show that with future prediction, the system delay under a diversion rate constraint can be made bounded from the unbounded case without prediction, given that the prediction window size is $\Theta(-\ln(1-\lambda))$, where λ is the arrival rate of the queue. Reference [113] further shows that the required prediction power is also the lower bound.

In the discrete time setting, [114] considers a general single-server multi-user system as shown in Fig.5. In this system, the operator gets access to information about future arrival $\{A(t), \ldots, A(t+w)\}$, where w is the prediction window size. In addition, the operator can also try to *pre-serve* future demand requests, with the objective of minimizing the average power usage for stabling the queues. This is a challenging problem. Firstly, the network state changes over time. Secondly, the prediction, though perfect, evolves according to a sliding window process. Existing results with prediction typically only handle frame-based prediction.

To tackle this problem, [114] first shows a result that, under general fully-efficient scheduling policies (equivalent to work-conserving in non-predictive systems), we have:

$$\pi_{n,0}^{(D_n)} = \sum_{k=0}^{D_n} \hat{\pi}_{n,k} \quad \text{and} \quad \pi_{n,k}^{(D_n)} = \hat{\pi}_{n,k+D_n}, \quad k \geq 1. \tag{1}$$

Here $\hat{\pi}_{n,k}$ denotes the probability for packets in queue n to experience delay k and $\pi_{n,k}^{(D_n)}$ denotes the counterpart in the non-predictive system. That is, the delay distribution is "shifted-to-the-left." Then, based on a novel notion of prediction queue, [114] develops a predictive backpressure (PBP) algorithm, which at every time, chooses a scheduling action to solve the following problem:

$$\min: \frac{1}{\epsilon} f(\boldsymbol{S}(t), \boldsymbol{P}(t)) - \sum_n Q_n^{\text{sum}}(t) \mu_n(\boldsymbol{S}(t), \boldsymbol{P}(t)) \tag{2}$$

$$\text{s.t. } \boldsymbol{P}(t) \in \mathcal{P}^{(\boldsymbol{S}(t))}. \tag{3}$$

Here $f(\boldsymbol{S}(t), \boldsymbol{P}(t))$ is the resource cost with $\boldsymbol{S}(t)$ being the vector of service link condition and $\boldsymbol{P}(t)$ is the vector of power allocation, $Q_n^{\text{sum}}(t)$ denotes the sum of the actual queue size and the predicted arrivals, and $\mu_n(\boldsymbol{S}(t), \boldsymbol{P}(t))$ is the service

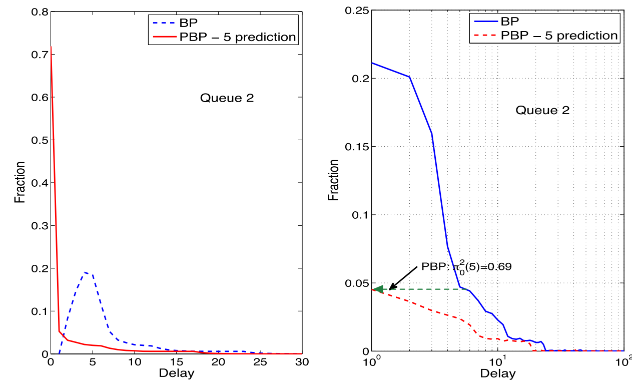


Fig. 6. Packet Delay distribution under PBP with FIFO and LIFO scheduling ($1/\epsilon = 100$ and $D_n = 5$ for all n). The arrows show the shift-to-the-left phenomenon. In the LIFO case, a large fraction of the packets now experience zero delay under PBP and this fraction is shown with the number $\pi_0^n(D_n)$.

rate queue n obtains under channel condition $\boldsymbol{S}(t)$ and $\boldsymbol{P}(t)$. It is shown that PBP achieves an $O(1/\epsilon)$ close-to-optimal utility performance (compared to offline optimal). Moreover, for first-in-first-out (FIFO) scheduling, delay reduction is linear in the window size, whereas the reduction can be exponential in the last-in-first-out (LIFO) case. The key idea to overcome the aforementioned challenges is to incorporate the sliding-window prediction in a proper way into the queue values for decision making. Doing so enables one to design low-complexity algorithm based on the Backpressure controller for dynamic networks. Fig. 6 shows the delay reduction performance of PBP with FIFO and LIFO scheduling. From the results, we see that if as the prediction power increases, system delay can be pushed arbitrarily close to zero while keeping the utility performance. The PBP methodology is also applied in the follow-up work [115] to study the power-delay tradeoff in cellular networks.

While the above works in predictive control assume exact prediction, the recent work [116] quantifies the impact of predictive scheduling on delay reduction with prediction error. In particular, there now two types of errors, mis-detection and false-alarm. Based on an $M/M/1$ queueing model and an i.i.d. prediction error model, it shows that queueing delay decays exponential in the prediction power, i.e., the length of the window within which the operator can see the future arrivals and serve them, to a lower bound (can be nonzero) that is determined by the mis-detection rate. The intuition is that when the mis-detection rate is non-zero, the system will not be able to preserve the subset of arrivals that are not predicted, resulting in a delay lower bound.

C. Online Algorithm With Filter-Based Prediction

Another interesting framework in this thrust is online algorithm design. Problems in this category does not assume any statistical model of the underlying dynamics. Instead, control algorithms must be designed to be robust for *any* condition that can show up during algorithm implementation.

In the perfect prediction regime, works [117] and [118] have also shown that prediction necessarily reduces the competitive ratios of the proposed algorithms, which are defined to be the ratio between the algorithm performance over the optimal cost in the offline setting, i.e., complete future conditions are known. In the imperfect prediction region, [119] and [120] propose a general filter-based prediction model for studying algorithm performance. Specifically, in this formulation, no stochastic model is assumed. Instead, arbitrary input can happen and the question we face is how to design our algorithm so that it performs well on arbitrary input (compared to an offline optimal algorithm that knows the entire future system conditions). However, it is assumed that a filter-based prediction model predicts the future states with error being charactered by a convolution of errors over time, i.e.,

$$Error_t(t+s) \triangleq y_t(t+s) - \hat{y}_t(t+s) = \sum_{k=t+1}^{t+s} f(t+s-k)e(s). \qquad (4)$$

Here $y_t(t+s)$ is a vector in an Euclidean space and specifies the state the system will be in. $Error_t(t+s)$ is the prediction error when predicting the state for time $t+s$ at time t, $f(t)$ is the impulse function that characterizes the predictor and $e(s)$ are i.i.d. random variables. This predictor model is general and includes the widely used Kalman filter and Wiener filter [119].

Under this general prediction model, the papers [119] and [120] analyze the performance of an onlie algorithm called average fixed horizon control (AFHC) proposed in [121] and [122], and show that with prediction, it is possible to simultaneously achieve good performance in regret and competitive ratio.

VI. Learning-Aided Dynamic System Control

The previous sections have discussed the settings where prediction or other relevant information are given a-priori. In this section, we turn to the case where such information may not be available beforehand. As a result, an explicit learning phase is required and the system has to go through a "transient" period before reaching an optimal state. Note that this learning requirement is recently made possible by rapid developments in sensing and data analytical tools. Hence, real-time monitoring and learning have now been enabled and implemented in various information systems, for instance, drivers observing real-time road congestion on map applications, operator tracking web server traffic in data centers, and system monitoring user usage in power grid. The objective of this thrust is to efficiently utilize these capabilities in learning important statistics about the system, and incorporate the learned information into network control. Results in this section will help provide a deeper understanding about the benefits of learning system dynamics.

Below, we present several recent developments. Note that the human behavior learning component is also abstracted into learning the environment and can be made explicit in learning human behavior.

A. Online-Learning Based Control

In the first thread in this topic, stochastic models are assumed and online-learning based algorithms were developed.

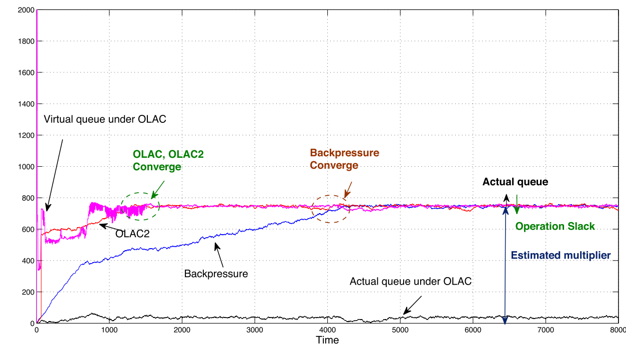


Fig. 7. Convergence behavior of queue sizes under three algorithms, Backpressure, OLAC and OLAC2. It can be seen clearly that the virtual queue under OLAC and the actual queue under OLAC2 converge much faster to γ^* compared to the queue size under Backpressure. This clearly demonstrates the power of dual learning.

Specifically, the following general formulation is considered in these works. Consider a general discrete-time stochastic network with r queues. In every timeslot, the network condition changes (called state), and the operator observes the network state and chooses a control action. The control action incurs a cost, generates traffic into network queues and serves workload from them. The objective is to find an optimal policy to minimize the time average cost subject to queue stability.

This is a classic setting that has been studied in the network control literature, e.g., [123]–[126]. However, most prior results try either to develop approaches based on given statistics, or to rely on techniques such as stochastic approximation and waive the requirement of statistics. Both approaches do not investigate the potential impact learning can make to control. Recent works [127]–[130] instead explicitly consider the impact of online learning in control.

The work [127] proposes an online learning method by combining the Backpressure method [125] and online learning. It develops two algorithms called online learning-aided control (OLAC) and OLAC2, which work by (i) first accumulating state statistics, and then (ii) solving an empirical optimization problem to learn an approximate Lagrange multiplier, and finally (iii) incorporating the multiplier into the Backpressure algorithm for realtime control. OLAC and OLAC2 remain greedy control algorithms and do not require any a-priori network statistics for implementation. In addition, the authors show that both algorithms achieve an $O(\epsilon), O(\log(1/\epsilon)^2)$ utility-delay tradeoff, and a provable faster $O(\epsilon^{-2/3})$ convergence time that is strictly better than the existing $\Theta(1/\epsilon)$ bounds. Fig. 7 shows the performance of OLAC and OLAC2 compared to the well-known Backpressure algorithm.

This framework was later applied to provide efficient resource allocation in virtual mobile operator network [131]. A more recent work [130] also explicitly applies the technique in learning human behavior patterns and tries to understand factors that affect the intelligence level perceived by human users in human-in-the-loop information systems. The methodology was also extended in [129] to resolve underflow problems in matching in stochastic queues, a setting that models various human-intense scenarios including ride-sharing platform matching and crowdsourcing. Reference [128] and [132] further extend the results to handle non-stationary network state distributions, by incorporating a change-detection module and carefully integrating the detection and learning components.

B. Machine Learning Aided Network Control

Another very interesting line of work is on improving network control with machine learning. Recent results include [133]–[135]. Specifically, [133] develops a resource allocation problem based on logistic regression. Here the training instances are first used to obtain a classifier. Then, the classifier is then combined with a network optimization framework to guiding network resource allocation. Based on real-world data set, it is shown that this learning-aided approach achieves a significant performance improvement compared to baseline algorithms.

Reference [134] further proposes a closed-loop control approach, where a neural network is applied to learning user preference as a function of the resource allocation decisions, and a dual decomposition based scheme for deciding resource allocation. Reference [135] adopts a similar methodology for mobile systems. The work first analyzes user usage patterns of an android system. Then, personal context classification is done with unsupervised learning methods. With these learned information, the paper then proposes a context-aware scheduling algorithm for unloading and preloading background applications.

With the fast growing advances in machine learning and deep learning tools, it is expected that more efficient learning-based control schemes will be developed.

VII. Privacy for Human-Related Data

In this section, we discuss an important technology aspect in designing the HULA architecture related to handling human-related data, and focuses on data privacy. As we know, many applications in mobile networks require possession of large amount of user-generated data for user experience improvement. For instance, in order to build an accurate human behavior model, it is important to acquire enough user activity records. In crowdsensing, it is critical to have enough reported data to enable reliable aggregation. Hence, large amount of user behavior data is the foundation for designing "intelligent" system control to meet the increasingly stringent quality-of-experience requirements of human users in mobile networks. The strong need for privacy thus naturally arises from the fact that data can reveal much information about human users. Indeed, it has been observed that even a slight leakage of location information will enable identifying users from data [136]. Moreover, any disclosure of data to malicious users or misuse will immediately ruin users' trust in the system, resulting in poor long-term performance.

The privacy issue has received increasing attentions in recent years, and various aspects of privacy have been investigated. We divide them as follows according to their focuses.

The first set of results try to identify key factors that affect user privacy. In [137]–[139], Christin et al. identified the privacy threats in sensing applications, and outlined how privacy aspects were addressed in existing sensing applications. Typical countermeasures, such as anonymous task distribution, spatial cloaking, and access control, were also discussed. Note that applications such as crowdsensing can often be regarded as a type of data mining applications. Hence, solutions proposed for privacy issues in data mining can also be applied to crowdsensing applications, e.g., [140], [141]. In [140], Xu et al. identify four different types of parties involved in data mining applications, namely, data provider, data collector, data miner, and decision maker. For each type of parties, the authors discussed the privacy concerns and the methods that can be adopted to protect sensitive information.

The second set of results focus on anonymization-based schemes, which is a popular approach to preserve privacy by removing any identifying information from the sensor data before sharing it with a third party. Several different anonymization schemes are proposed. Works [142], [143] hide the participant locations by specific router/relay organization instead of directly anonymizing their names. For instance, the TOR-based routing scheme applied in [144] anonymizes the connections to the tasking server by multiple relays and onion routing to hide the IP address. The participating devices receive broadcast beacons including the sensing tasks without having to register or authenticate themselves to a central entity. For example, users in AnonySense system, e.g., [144], [145] periodically download all available tasks from a Tasking Service when they are in public locations. The Tasking Service only learns that some users in some public location downloaded tasks. Krontiris and Dimitriou [146] propose a mechanism to protect the privacy of the mobile users by the cloud-based agents, which obfuscates user location and enforces the sharing practices of their owners. Shin et al. [144] show that the high density of people at such locations makes the identification of the participants by the server difficult, and hence conceals their identities. Secure multiparty computation [147] is another approach for preserving privacy. This method leverages cryptographic techniques to transform the data and preserve privacy.

The third set of results focus on designing incentive mechanisms discussed in Section III for privacy protection. These studies consider privacy as a factor that may prevent individuals from participating and address the privacy and incentive issues in a separate manner. Recent works [148]–[151] propose several privacy-aware incentive mechanisms. In [150], Xu et al. assumed that the data collector sign contracts with individuals who may provide private data. The privacy protection level is explicitly formulated as a contract item, so that the derived optimal contract can assist the data collector to make a wise decision on privacy protection. In their later work [151], Xu et al. studied how to pay individuals where the data collector sequentially buys data from individuals. The sequential decision-making problem of the collector was formulated as a multi-armed bandit problem, and several learning policies were proposed to assist the collector to make optimal decisions. How individuals value their privacy also plays an important role in aforementioned studies [152]. Finding an appropriate way to determine the value of privacy is also an important question that needs further investigation.

VIII. Editorial

In this section, we provide an editorial for the papers that are accepted to the JSAC Special Issue on "Human-in-the-loop Mobile Networks." Specifically, we first group the papers into four main categories, including crowdsensing and crowdsourcing, game and mechanism design, mobile system optimization, and mobile technologies. Then, within each category, we provide a brief summary for each accepted paper. Notice that the papers in this special issue are published in two separate issues. Papers in the first two categories are contained in the first issue, and the other papers are in the second issue.

A. Mobile Crowdsensing and Crowdsourcing

The paper *On Designing Data Quality-Aware Truth Estimation and Surplus Sharing Method for Mobile Crowdsensing* considers the problem of crowdsensing and designs an unsupervised learning approach for data quality and reputation quantification. The user surplus sharing is formulated as a cooperative game and a Shapley value-based scheme is adopted for computing user payments. Experiments are conducted and the results demonstrate the effectiveness of the proposed solution.

The paper *Crowd Foraging: A QoS-oriented Self-organized Mobile Crowdsourcing Framework over Opportunistic Networks* proposes the crowd foraging framework for opportunistic crowdsourcing. Under this framework, the worker recruitment problem is formulated as an online multiple stopping problem and an optimal recruitment policy is designed based on dynamic programming. Data-driven case studies are also conducted to demonstrate the superior performance of the algorithm.

The paper *Tack: Learning Towards Contextual and Ephemeral Indoor Localization With Crowdsourcing* designs a mobile application framework called Tack for identifying contexts during events. Tack combines a set of signals for estimating user locations. Its performance is extensively evaluated with real-world experiments with iOS and is proven efficient.

In the paper *Incentive Mechanism for Mobile Crowdsourcing Using an Optimized Tournament Model*, the authors investigates the problem of designing crowdsourcing tournament for maximizing principle's utility. A mathematical formulation is first proposed, with the constraint that each user optimizes its own utility by choosing the effort in the crowdsourcing competition. Numerical experiments are conducted to evaluate the impact of parameters. It is shown that the tournament scheme optimizes principal's utility and incentives user participation.

The paper *Incentivize Multi-class Crowd Labeling under Budget Constraint* considers the problem of incentivizing crowd workers for multi-class labeling, subject to budget constraints. It formulates the problem with a sequential Bayesian approach. The paper then shows that the platform utility maximization objective can be intractable, and a polynomial time algorithm is developed. Through analysis and extensive simulation, the paper shows that the mechanism achieves high platform utility.

The paper *Privacy Management and Optimal Pricing in People-Centric Sensing* studies the privacy issue in people-centric services. A metric is proposed to quantify the correlation between service quality and privacy level, based on which closed-form solutions are derived. Several interesting properties of interrelated people-centric services are derived and carefully studied.

The paper *An Exchange Market Approach to Mobile Crowdsensing: Pricing, Task Allocation and Walrasian Equilibrium* looks at the problem of mobile crowdsensing from the exchange economy standpoint. The paper first characterizes the supply-demand pattern for given price vectors. Walrasian equilibrium existence is then established. The paper also develops a polynomial-time algorithm for finding the equilibrium for an interesting practical setting, and an efficient search algorithm for the general settings.

B. Game and Mechanism Design for Mobile Networks

In the paper *Spectrum Allocation and Bitrate Adjustment for Mobile Social Video Sharing: A Potential Game With Online QoS Learning Approach*, the authors present a general framework for modeling video diffusion among mobile users and user QoS. The problem is decomposed into two subproblems, for which a decentralized algorithm is proposed to find the Nash equilibrium. Both analysis and trace-driven simulations are conducted to demonstrate the good performance of the algorithm.

The paper *Customized Data Plans for Mobile Users: Feasibility and Benefits of Data Trading* examines the secondary data market where users can trade leftover data caps from others. It derives users' optimal behavior and develops an algorithm for ISPs to match buyers and sellers. Conditions under which the secondary market performs better for the ISP are derived. The results are also validated via usage data from mobile users.

The authors of the paper *Coexistence Between Wi-Fi and LTE on Unlicensed Spectrum: A Human-Centric Approach* propose a human-centric approach for understanding the coexistence between WiFi and LTE. It is shown that static partitioning of unlicensed spectrum between the two does not provide any advantage for user satisfaction maximization, while adaptive partitioning does bring benefits. A semi-adaptive algorithm is proposed in the paper and shown to achieve good performance.

In the paper *On Consideration of Content Preference and Sharing Willingness in D2D Assisted Offloading*, the authors consider the optimal content pushing scheme for D2D networks. The problem is formulated into an optimization with the objective of maximizing the offloading gain. Despite the non-convexity, the optimal closed-form solution is derived and a group optimization algorithm is proposed for solving the general problem. Simulation results are presented to demonstrate the efficiency of the scheme.

The paper *Mobile Data Trading: Behavioral Economics Analysis and Algorithm Design* presents a brokerage-based market for trading mobile data, based on prospect theory. It then designs an algorithm to estimate user's risk preference and to give recommendations for trading. Then, the paper derives several useful results on understanding how risk preference affects the market via simulations.

C. Mobile System Optimization and Control

The paper *CAS: Context-aware Background Application Scheduling in Interactive Mobile Systems* tries to design context-aware scheduler for mobile systems. It first discovers several interesting patterns from Android experiments. Then, the paper proposes a scheduling framework, CAS, to adaptively load background applications. Through trace-driven simulations and practical implementation, the paper shows that CAS outperforms existing algorithms.

The paper *Small Cell Transmit Power Assignment Based on Correlated Bandit Learning* investigates base station transmit power setting in ultra dense network. The problem is addressed with the stochastic bandit theory, taking advantage of human user behavior. An algorithm is proposed to exploit the correlation structure and to consider power switching penalties. Through comprehensive system-level simulations, the algorithm is shown to achieve significant gains.

The authors of the paper *Caching in the Sky: Proactive Deployment of Cache-Enabled Unmanned Aerial Vehicles for Optimized Quality-of-Experience* consider the problem of proactive deployment of cache-enabled UAVs for QoE optimization. A machine learning algorithm is proposed based on conceptor-based echo state networks. Simulations results with real mobility patterns and actual content transmission data show that the algorithm achieves significant QoE improvement compared to benchmark algorithms.

The paper *From Prediction to Action: Improving User Experience with Data-Driven Resource Allocation* develops a data-driven resource allocation framework to perform prediction and guide resource allocation. A case study is conducted to reduce the number of complains in cellular networks, and a DualHet algorithm is developed to tackle the problem. Numerical results show that the algorithm can achieve up to 2x performance improvement compared to existing solutions.

The authors of the paper *Understanding Performance of Edge Content Caching for Mobile Video Streaming* use real-world datasets to understand request patterns and user behavior in mobile video streaming. Then, several strategies of edge content caching are compared. It is discovered that content, location and mobility factors all affect caching performance. An efficient strategy is proposed and shown to improve hit rate by 30%.

D. New Technology Development

The paper *R-TTWD:Robust Device-Free Through-The-Wall Detection of Moving Human with WiFi* tries to design through-the-wall human detection with commodity devices. The scheme takes advantage of subcarrier correlations. It first performs a PCA-based filtering and fuses the detection results for accuracy improvement. The scheme is prototyped on commodity WiFi devices and evaluation results show that it accurately detects moving human and human absence.

The paper *Stride-in-the-Loop Relative Positioning Between Users and Dummy Acoustic Speakers* proposes and implements a position system called WalkieLokie. The scheme relies on computing the relative position from a smart device to a target and only requires simply devices. An algorithm is designed to enable accurate positioning. Experimental results over noisy environment validate the robustness of the scheme.

The paper *Device-Free Human Activity Recognition Using Commercial WiFi Devices* designs CARM, a channel state information based human activity monitoring system. The scheme is based on the CSI-speed model and the CSI-activity model. It is then implemented on commercial WiFi devices and shown to achieve high recognition accuracy.

The paper *Pervasive Floorplan Generation Based on Only Inertial Sensing: Feasibility, Design, and Implementation* conducts study on addressing the low quality problem of crowdsourced data for floorplan generation. A scheme called SenseWit is proposed and implemented. Real-world experiments in different spaces show its efficiency for obtaining high-quality structure from low-quality data.

The authors of the paper *Peer-to-Peer Indoor Navigation using Smartphones* design a P2P navigation system, ppNav, to enable fast-to-deploy navigation services. The scheme utilizes WiFi fingerprints, and tracks user mobility and alerts potential deviations. The authors implement ppNav on commodity mobile devices and validate the performance in real environments. Results show that the scheme achieves good performance.

The paper *Martian: Message Broadcast via LED Lights to Heterogeneous Smartphones* designs a modulation scheme and a link-layer protocol, Martian, for improving visible light communication data rate. Through implementation, the paper shows that Martian can achieve a data rate of about 1.6kbps even with NLOS-light. Moreover, Martian is able to achieve a stable and small delay for broadcasting to random receivers.

In the paper *Device-Free Counting via Wideband Signals*, the authors propose a mathematical framework for designing device-free counting systems. An MAP algorithm is first developed for counting based on model order selection. Then, a method is designed to lower computational complexity. Sample-level simulations are conducted to compare its performance with existing solutions.

The problem of keystroke recognition is studied in the paper *Recognizing Keystrokes Using WiFi Devices*. It is shown that WiFi signal can also be exploited to recognize keystrokes. In particular, a WiFi based recognition system called WiKey is proposed, which consists of two commercial WiFi devices. The system is implemented and shown to achieve a detection rate higher than 97.5%. In real-world experiments, it is also shown to recognize 93.5% keystrokes in continuously typed sentences and 85% words in a sentence.

IX. Conclusion and Discussion

In this paper, we survey recent results that investigate three key aspects in human-in-the-loop information systems, i.e., collecting human intelligence, exploring the human factor for improving performance, and handling human data, where the first two concern fundamental benefits of exploring the human-in-the-loop characteristics and the last concerns the technology aspect. The topics range from human data privacy and assembly (the data aspect), crowdsensing, network management and sharing (the game-theoretic aspect), prediction and learning-aided network control (the control aspect).

We can see from the results that the human factor in mobile networks has brought more challenges for system operators, but at the same time provided unique features that can be exploited for performance improvement and user experience enhancement.

Note that there are many important open problems that remain to be understood and solved, both in theory and systems. Here we highlight three directions that are important and still require further investigations. (i) Understanding the fundamental benefits of learning and prediction. Although the current results have provide new insights on how learning and prediction can benefit the system, they provide only upper bounds in terms of what improvements can be achieved. However, it is not clear whether these bounds are tight. Obtaining tight lower bounds can help provide a better performance evaluation criteria for prediction-based and learning-based schemes. (ii) Optimal control with strategic users in repeated settings. The strategic aspect of users is often considered and tackled in a one-shot setting with game-theoretic formulations. Though being insightful, the results do not capture the common scenario where users interact with the system repeatedly and the system can learn about users over time. The challenge here is that the learning component will now be affected by user behavior, which can itself be strategic. How to jointly design good mechanisms that allow both efficient learning and optimization of the system in this case remains an important open problem. (iii) Developing a secure and efficient system infrastructure for human data. As discussed in the paper, one key ingredient for exploiting the human factor is the collection of human data, either learned behavior data or collected responses for crowdsensing tasks. While efficiently utilizing these data is important, the privacy aspect is also critical when it comes to human users. Thus, a computing infrastructure that is both efficient in data collecting and process, and secure in privacy preserving is an important building block for better exploiting the benefits of the human factor.

Resolving these challenging questions requires investigations from various directions including stochastic modeling, network control, machine learning, human behavior study, to systems. Indeed, an increasing attention has been paid to solving human-in-the-loop system control questions by combining network control techniques and machine learning tools. It is expected that we will see more such results.

Finally, the interdisciplinary nature of the human-in-the-loop theme brings new formulations into various fields, and results developed for solving these problems will likely also facilitate further developments in existing methodology and tools, in particular, queueing theory, game theory, learning and optimization.

References

[1] "Cisco visual networking index: Global mobile data traffic forecast update, 2016–2021," White Paper, Cisco, San Jose, CA, USA, Feb. 2017. [Online]. Available: http://www.cisco.com/c/en/us/solutions/collateral/serviceprovider/visualnetworkingindexvni/mobilewhitepaperc11520862.html

[2] DailyMail. (2012). *Japanese Smartphone Manufacturer Builds Phone With Radiation Detector Following Last Year's Fukushima Plant Meltdown*. [Online]. Available: http://www.dailymail.co.uk/sciencetech/article-2151725/Japanese-smartphone-manufacturer-builds-phone-radiation-detector-following-years-Fukushima-plant-meltdown.html#ixzz4YGRhhSkt

[3] P. Dutta *et al.*, "Common sense: Participatory urban sensing using a network of handheld air quality monitors," in *Proc. 7th ACM Conf. Embedded Netw. Sensor Syst.*, 2009, pp. 349–350.

[4] Y. Zheng, L. Li, and L. Zhang, "PiMi air community: Getting fresher indoor air by sharing data and know-hows," in *Proc. 13th Int. Symp. Inf. Process. Sensor Netw.*, 2014, pp. 283–284.

[5] M. Mun *et al.*, "PEIR, the personal environmental impact report, as a platform for participatory sensing systems research," in *Proc. 7th Int. Conf. Mobile Syst., Appl., Services*, 2009, pp. 55–68.

[6] X. Xu, P. Zhang, and L. Zhang, "Gotcha: A mobile urban sensing system," in *Proc. 12th ACM Conf. Embedded Netw. Sensor Syst.*, 2014, pp. 316–317.

[7] R. K. Rana, C. T. Chou, S. S. Kanhere, N. Bulusu, and W. Hu, "Ear-phone: An end-to-end participatory urban noise mapping system," in *Proc. 9th ACM/IEEE Int. Conf. Inf. Process. Sensor Netw.*, Apr. 2010, pp. 105–116.

[8] N. Maisonneuve, M. Stevens, M. E. Niessen, and L. Steels, "NoiseTube: Measuring and mapping noise pollution with mobile phones," in *Information Technologies in Environmental Engineering*. Berlin, Germany: Springer, 2009, pp. 215–228.

[9] S. Kim, C. Robson, T. Zimmerman, J. Pierce, and E. M. Haber, "Creek watch: Pairing usefulness and usability for successful citizen science," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, 2011, pp. 2125–2134.

[10] B. Pan, Y. Zheng, D. Wilkie, and C. Shahabi, "Crowd sensing of traffic anomalies based on human mobility and social media," in *Proc. 21st ACM SIGSPATIAL Int. Conf. Adv. Geograph. Inf. Syst.*, 2013, pp. 344–353.

[11] B. Hull *et al.*, "CarTel: A distributed mobile sensor computing system," in *Proc. 4th Int. Conf. Embedded Netw. Sensor Syst.*, 2006, pp. 125–138.

[12] P. Mohan, V. N. Padmanabhan, and R. Ramjee, "Nericell: Rich monitoring of road and traffic conditions using mobile smartphones," in *Proc. 6th ACM Conf. Embedded Netw. Sensor Syst.*, 2008, pp. 323–336.

[13] J. Eriksson, L. Girod, B. Hull, R. Newton, S. Madden, and H. Balakrishnan, "The pothole patrol: Using a mobile sensor network for road surface monitoring," in *Proc. 6th Int. Conf. Mobile Syst., Appl., Services*, 2008, pp. 29–39.

[14] A. Thiagarajan *et al.*, "VTrack: Accurate, energy-aware road traffic delay estimation using mobile phones," in *Proc. 7th ACM Conf. Embedded Netw. Sensor Syst.*, 2009, pp. 85–98.

[15] S. Nawaz, C. Efstratiou, and C. Mascolo, "ParkSense: A smartphone based sensing system for on-street parking," in *Proc. 19th Annu. Int. Conf. Mobile Comput. Netw.*, 2013, pp. 75–86.

[16] A. Nandugudi, T. Ki, C. Nuessle, and G. Challen, "PocketParker: Pocketsourcing parking lot availability," in *Proc. ACM Int. Joint Conf. Pervas. Ubiquitous Comput.*, 2014, pp. 963–973.

[17] W. Gu, M. Jin, Z. Zhou, C. J. Spanos, and L. Zhang, "Metro-Eye: Towards fine-grained passenger tracking underground," in *Proc. ACM Int. Joint Conf. Pervas. Ubiquitous Comput., Adjunct*, 2016, pp. 77–80.

[18] E. Miluzzo *et al.*, "Sensing meets mobile social networks: The design, implementation and evaluation of the CenceMe application," in *Proc. 6th ACM Conf. Embedded Netw. Sensor Syst.*, 2008, pp. 337–350.

[19] S. B. Eisenman, E. Miluzzo, N. D. Lane, R. A. Peterson, G.-S. Ahn, and A. T. Campbell, "BikeNet: A mobile sensing system for cyclist experience mapping," *ACM Trans. Sensor Netw.*, vol. 6, no. 1, 2009, Art. no. 6.

[20] S. Reddy, A. Parker, J. Hyman, J. Burke, D. Estrin, and M. Hansen, "Image browsing, processing, and clustering for participatory sensing: Lessons from a dietsense prototype," in *Proc. 4th Workshop Embedded Netw. Sensors*, 2007, pp. 13–17.

[21] L. S. Penrose, "The elementary statistics of majority voting," *J. Roy. Statist. Soc.*, vol. 109, no. 1, pp. 53–57, 1946.

[22] A. P. Dawid and A. M. Skene, "Maximum likelihood estimation of observer error-rates using the EM algorithm," *Appl. Statist.*, vol. 28, no. 1, pp. 20–28, 1979.

[23] G. Demartini, D. E. Difallah, and P. Cudré-Mauroux, "ZenCrowd: Leveraging probabilistic reasoning and crowdsourcing techniques for large-scale entity linking," in *Proc. 21st Int. Conf. World Wide Web*, 2012, pp. 469–478.

[24] R. Snow, B. O'Connor, D. Jurafsky, and A. Y. Ng, "Cheap and fast—But is it good? Evaluating non-expert annotations for natural language tasks," in *Proc. Conf. Empirical Methods Natural Lang. Process.*, 2008, pp. 254–263.

[25] M. Venanzi, J. Guiver, G. Kazai, P. Kohli, and M. Shokouhi, "Community-based Bayesian aggregation models for crowdsourcing," in *Proc. 23rd Int. Conf. World Wide Web*, 2014, pp. 155–164.

[26] V. C. Raykar *et al.*, "Learning from crowds," *J. Mach. Learn. Res.*, vol. 11, pp. 1297–1322, Apr. 2010.

[27] P. Welinder, S. Branson, P. Perona, and S. J. Belongie, "The multidimensional wisdom of crowds," in *Proc. Adv. Neural Inf. Process. Syst.*, 2010, pp. 2424–2432.

[28] D. Zhou, S. Basu, Y. Mao, and J. C. Platt, "Learning from the wisdom of crowds by minimax entropy," in *Proc. Adv. Neural Inf. Process. Syst.*, 2012, pp. 2195–2203.

[29] J. Pasternack and D. Roth, "Knowing what to believe (when you already know something)," in *Proc. 23rd Int. Conf. Comput. Linguistics*, 2010, pp. 877–885.

[30] Q. Li, Y. Li, J. Gao, B. Zhao, W. Fan, and J. Han, "Resolving conflicts in heterogeneous data by truth discovery and source reliability estimation," in *Proc. ACM SIGMOD Int. Conf. Manage. Data*, 2014, pp. 1187–1198.

[31] Q. Li *et al.*, "A confidence-aware approach for truth discovery on long-tail data," *Proc. VLDB Endowment*, vol. 8, no. 4, pp. 425–436, 2014.

[32] F. Ma *et al.*, "FaitCrowd: Fine grained truth discovery for crowdsourced data aggregation," in *Proc. 21st ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, 2015, pp. 745–754.

[33] J. G. Andrews, "Seven ways that HetNets are a cellular paradigm shift," *IEEE Commun. Mag.*, vol. 51, no. 3, pp. 136–144, Mar. 2013.

[34] R. Irmer *et al.*, "Coordinated multipoint: Concepts, performance, and field trial results," *IEEE Commun. Mag.*, vol. 49, no. 2, pp. 102–111, Feb. 2011.

[35] S.-H. Park, O. Simeone, O. Sahin, and S. Shamai (Shitz), "Joint precoding and multivariate backhaul compression for the downlink of cloud radio access networks," *IEEE Trans. Signal Process.*, vol. 61, no. 22, pp. 5646–5658, Nov. 2013.

[36] 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.

[37] X. Liu, M. Lu, B. C. Ooi, Y. Shen, S. Wu, and M. Zhang, "CDAS: A crowdsourcing data analytics system," *Proc. VLDB Endowment*, vol. 5, no. 10, pp. 1040–1051, 2012.

[38] B. C. Ooi *et al.*, "Contextual crowd intelligence," *ACM SIGKDD Explorations Newslett.*, vol. 16, no. 1, pp. 39–46, 2014.

[39] R. K. Ganti, F. Ye, and H. Lei, "Mobile crowdsensing: Current state and future challenges," *IEEE Commun. Mag.*, vol. 49, no. 11, pp. 32–39, Nov. 2011.

[40] Y. Gong, L. Wei, Y. Guo, C. Zhang, and Y. Fang, "Optimal task recommendation for mobile crowdsourcing with privacy control," *IEEE Internet Things J.*, vol. 3, no. 5, pp. 745–756, Oct. 2016.

[41] M. Langheinrich, "Privacy by design—Principles of privacy-aware ubiquitous systems," in *Proc. Int. Conf. Ubiquitous Comput.*, 2001, pp. 273–291.

[42] R. Want, A. Hopper, V. Falcao, and J. Gibbons, "The active badge location system," *ACM Trans. Inf. Syst.*, vol. 10, no. 1, pp. 91–102, 1992.

[43] F. Qian, Z. Wang, A. Gerber, Z. Mao, S. Sen, and O. Spatscheck, "Profiling resource usage for mobile applications: A cross-layer approach," in *Proc. 9th Int. Conf. Mobile Syst., Appl., Services*, 2011, pp. 321–334.

[44] A. Pathak, Y. C. Hu, and M. Zhang, "Where is the energy spent inside my app? Fine grained energy accounting on smartphones with eprof," in *Proc. 7th ACM Eur. Conf. Comput. Syst.*, 2012, pp. 29–42.

[45] M. Lelarge and J. Bolot, "Economic incentives to increase security in the Internet: The case for insurance," in *Proc. INFOCOM*, 2009, pp. 1494–1502.

[46] C.-J. Ho, A. Slivkins, S. Suri, and J. W. Vaughan, "Incentivizing high quality crowdwork," in *Proc. 24th Int. Conf. World Wide Web*, 2015, pp. 419–429.

[47] J. J. Horton and L. B. Chilton, "The labor economics of paid crowdsourcing," in *Proc. 11th ACM Conf. Electron. Commerce*, 2010, pp. 209–218.

[48] T. Yan, V. Kumar, and D. Ganesan, "CrowdSearch: Exploiting crowds for accurate real-time image search on mobile phones," in *Proc. 8th Int. Conf. Mobile Syst., Appl., Services*, 2010, pp. 77–90.

[49] D. Zhao, X.-Y. Li, and H. Ma, "How to crowdsource tasks truthfully without sacrificing utility: Online incentive mechanisms with budget constraint," in *Proc. IEEE INFOCOM-IEEE Conf. Comput. Commun.*, Apr./May 2014, pp. 1213–1221.

[50] X. Zhang, Z. Yang, Z. Zhou, H. Cai, L. Chen, and X. Li, "Free market of crowdsourcing: Incentive mechanism design for mobile sensing," *IEEE Trans. Parallel Distrib. Syst.*, vol. 25, no. 12, pp. 3190–3200, Dec. 2014.

[51] I. Koutsopoulos, "Optimal incentive-driven design of participatory sensing systems," in *Proc. IEEE INFOCOM*, Apr. 2013, pp. 1402–1410.

[52] H. Jin, L. Su, D. Chen, K. Nahrstedt, and J. Xu, "Quality of information aware incentive mechanisms for mobile crowd sensing systems," in *Proc. 16th ACM Int. Symp. Mobile Ad Hoc Netw. Comput.*, 2015, pp. 167–176.

[53] Y. Liu and M. Liu, "An online learning approach to improving the quality of crowd-sourcing," *ACM SIGMETRICS Perform. Eval. Rev.*, vol. 43, no. 1, pp. 217–230, 2015.

[54] D. Peng, F. Wu, and G. Chen, "Pay as how well you do: A quality based incentive mechanism for crowdsensing," in *Proc. 16th ACM Int. Symp. Mobile Ad Hoc Netw. Comput.*, 2015, pp. 177–186.

[55] K. Han, C. Zhang, and J. Luo, "Taming the uncertainty: Budget limited robust crowdsensing through online learning," *IEEE/ACM Trans. Netw.*, vol. 24, no. 3, pp. 1462–1475, Jun. 2016

[56] L. G. Jaimes, I. J. Vergara-Laurens, and A. Raij, "A survey of incentive techniques for mobile crowd sensing," *IEEE Internet Things J.*, vol. 2, no. 5, pp. 370–380, Oct. 2015.

[57] D. Yang, G. Xue, X. Fang, and J. Tang, "Crowdsourcing to smartphones: Incentive mechanism design for mobile phone sensing," in *Proc. 18th Annu. Int. Conf. Mobile Comput. Netw.*, 2012, pp. 173–184.

[58] L. Duan, T. Kubo, K. Sugiyama, J. Huang, T. Hasegawa, and J. Walrand, "Motivating smartphone collaboration in data acquisition and distributed computing," *IEEE Trans. Mobile Comput.*, vol. 13, no. 10, pp. 2320–2333, Oct. 2014.

[59] P. Bolton and M. Dewatripont, *Contract Theory*. Cambridge, MA, USA: MIT Press, 2005.

[60] H. Park and J. Widom, "CrowdFill: Collecting structured data from the crowd," in *Proc. ACM SIGMOD Int. Conf. Manage. Data*, 2014, pp. 577–588.

[61] D. Niyato, X. Lu, P. Wang, D. I. Kim, and Z. Han, "Economics of Internet of Things: An information market approach," *IEEE Wireless Commun.*, vol. 23, no. 4, pp. 136–145, Apr. 2016.

[62] Y. Li, C. A. Courcoubetis, and L. Duan, "Dynamic routing for social information sharing," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 3, pp. 571–585, Mar. 2017. [Online]. Available: https://arxiv.org/abs/1608.03397

[63] J. Xu, L. Duan, and R. Zhang, "Cost-aware green cellular networks with energy and communication cooperation," *IEEE Commun. Mag.*, vol. 53, no. 5, pp. 257–263, May 2015.

[64] S. Ha, S. Sen, C. Joe-Wong, Y. Im, and M. Chiang, "Tube: Time-dependent pricing for mobile data," *ACM SIGCOMM Comput. Commun. Rev.*, vol. 42, no. 4, pp. 247–258, 2012.

[65] X. Gong, L. Duan, and X. Chen, "When network effect meets congestion effect: Leveraging social services for wireless services," in *Proc. 16th ACM Int. Symp. Mobile Ad Hoc Netw. Comput.*, 2015, pp. 147–156.

[66] J. Lee, Y. Yi, S. Chong, and Y. Jin, "Economics of WiFi offloading: Trading delay for cellular capacity," *IEEE Trans. Wireless Commun.*, vol. 13, no. 3, pp. 1540–1554, Mar. 2014.

[67] M. H. Cheung and J. Huang, "Optimal delayed Wi-Fi offloading," in *Proc. 11th Int. Symp. Modeling Optim. Mobile, Ad Hoc Wireless Netw. (WiOpt)*, May 2013, pp. 564–571.

[68] Y. Yang, T. Q. Quek, and L. Duan, "Backhaul-constrained small cell networks: Refunding and QoS provisioning," *IEEE Trans. Wireless Commun.*, vol. 13, no. 9, pp. 5148–5161, Sep. 2014.

[69] (2014). Cisco. *China's Three State-Owned Carriers Form Telecoms Tower Firm*. [Online]. Available: http://www.reuters.com/article/2014/07/11/us-china-telecomunications-idUSKBN0FG11X20140711

[70] D.-E. Meddour, T. Rasheed, and Y. Gourhant, "On the role of infrastructure sharing for mobile network operators in emerging markets," *Comput. Netw.*, vol. 55, no. 7, pp. 1576–1591, 2011.

[71] J. Xu, L. Duan, and R. Zhang, "Energy group buying with loading sharing for green cellular networks," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 4, pp. 786–799, Apr. 2016.

[72] S. Cai, Y. Che, L. Duan, J. Wang, S. Zhou, and R. Zhang, "Green 5G heterogeneous networks through dynamic small-cell operation," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 5, pp. 1103–1115, May 2016.

[73] Y. Guo, J. Xu, L. Duan, and R. Zhang, "Joint energy and spectrum cooperation for cellular communication systems," *IEEE Trans. Commun.*, vol. 62, no. 10, pp. 3678–3691, Oct. 2014.

[74] D. Gesbert, S. Hanly, H. Huang, S. S. Shitz, O. Simeone, and W. Yu, "Multi-cell MIMO cooperative networks: A new look at interference," *IEEE J. Sel. Areas Commun.*, vol. 28, no. 9, pp. 1380–1408, Dec. 2010.

[75] Y. Li, T. Wu, P. Hui, D. Jin, and S. Chen, "Social-aware D2D communications: Qualitative insights and quantitative analysis," *IEEE Commun. Mag.*, vol. 52, no. 6, pp. 150–158, Jun. 2014.

[76] Y.-P. Hsu and L. Duan, "To motivate social grouping in wireless networks," *IEEE Trans. Wireless Commun.*, [Online]. Available: https://arxiv.org/abs/1511.01795

[77] N. Golrezaei, A. F. Molisch, A. G. Dimakis, and G. Caire, "Femtocaching and device-to-device collaboration: A new architecture for wireless video distribution," *IEEE Commun. Mag.*, vol. 51, no. 4, pp. 142–149, Apr. 2013.

[78] K. Shanmugam, N. Golrezaei, A. G. Dimakis, A. F. Molisch, and G. Caire, "FemtoCaching: Wireless content delivery through distributed caching helpers," *IEEE Trans. Inf. Theory*, vol. 59, no. 12, pp. 8402–8413, Dec. 2013.

[79] D. Bethanabhotla, G. Caire, and M. J. Neely, "Adaptive video streaming for wireless networks with multiple users and helpers," *IEEE Trans. Commun.*, vol. 63, no. 1, pp. 268–285, Jan. 2015.

[80] M. Tao, E. Chen, H. Zhou, and W. Yu, "Content-centric sparse multicast beamforming for cache-enabled cloud ran," *IEEE Trans. Wireless Commun.*, vol. 15, no. 9, pp. 6118–6131, Sep. 2016

[81] N. Golrezaei, A. G. Dimakis, and A. F. Molisch, "Scaling behavior for device-to-device communications with distributed caching," *IEEE Trans. Inf. Theory*, vol. 60, no. 7, pp. 4286–4298, Jul. 2014.

[82] M. Ji, G. Caire, and A. F. Molisch, "The throughput-outage tradeoff of wireless one-hop caching networks," *IEEE Trans. Inf. Theory*, vol. 61, no. 12, pp. 6833–6859, Dec. 2015.

[83] Y. Guo, L. Duan, and R. Zhang, "Cooperative local caching under heterogeneous file preferences," *IEEE Trans. Commun.*, vol. 65, no. 1, pp. 444–457, Jan. 2017. [Online]. Available: https://arxiv.org/abs/1510.04516

[84] (2005). C. Technology. *Battery Life Concerns Mobile Users*. [Online]. Available: http://edition.cnn.com/2005/TECH/ptech/09/22/phone.study/

[85] D. Ferreira, A. K. Dey, and V. Kostakos, "Battery life concerns mobile users," in *Proc. Int. Conf. Pervasive Comput.*, 2011, pp. 19–33.

[86] G. Kramer, I. Maric, and R. Yates, "Cooperative communications," in *Foundations and Trends in Networking*, vol. 1. Boston, MA, USA: Delft, 2007, pp. 271–425.

[87] S. Kandeepan, S. K. Jayaweera, and R. Fedrizzi, "Power-trading in wireless communications: A cooperative networking business model," *IEEE Trans. Wireless Commun.*, vol. 11, no. 5, pp. 1872–1880, May 2012.

[88] Y. Guo, L. Duan, and R. Zhang, "Optimal pricing and load sharing for energy saving with cooperative communications," *IEEE Trans. Wireless Commun.*, vol. 15, no. 2, pp. 951–964, Feb. 2016.

[89] W. Hu and G. Cao, "Energy optimization through traffic aggregation in wireless networks," in *Proc. IEEE Conf. Comput. Commun. (INFOCOM)*, Sep. 2014, pp. 916–924.

[90] L. Duan, L. Gao, and J. Huang, "Cooperative spectrum sharing: A contract-based approach," *IEEE Trans. Mobile Comput.*, vol. 13, no. 1, pp. 174–187, Jan. 2014.

[91] L. Gao, L. Duan, and J. Huang, "Two-sided matching based cooperative spectrum sharing," *IEEE Trans. Mobile Comput.*, vol. 16, no. 2, pp. 538–551, Feb. 2017.

[92] S. Yun, Y. Yi, D.-H. Cho, and J. Mo, "Open or close: On the sharing of femtocells," in *Proc. IEEE INFOCOM*, Apr. 2011, pp. 116–120.

[93] G. Iosifidis, L. Gao, J. Huang, and L. Tassiulas, "Incentive mechanisms for user-provided networks," *IEEE Commun. Mag.*, vol. 52, no. 9, pp. 20–27, Sep. 2014.

[94] X. Wang, L. Duan, and R. Zhang, "User-initiated data plan trading via a personal hotspot market," *IEEE Trans. Wireless Commun.*, vol. 15, no. 11, pp. 7885–7898, Nov. 2016.

[95] L. Zheng, C. Joe-Wong, C. W. Tan, S. Ha, and M. Chiang, "Secondary markets for mobile data: Feasibility and benefits of traded data plans," in *Proc. IEEE Conf. Comput. Commun. (INFOCOM)*, Apr. 2015, pp. 1580–1588.

[96] V. N. Padmanabhan and J. C. Mogul, "Using predictive prefetching to improve world wide Web latency," *ACM SIGCOMM Comput. Commun. Rev.*, vol. 26, no. 3, pp. 22–36, Jul. 1996.

[97] J. Lee, H. Kim, and R. Vuduc, "When prefetching works, when it doesn't, and why," *ACM Trans. Archit. Code Optim.*, vol. 9, no. 1, pp. 1–29, Mar. 2012.

[98] T. Ball and J. R. Larus, "Branch prediction for free," in *Proc. Conf. Programm. Lang. Design Implement., ACM SIGPLAN Notices*, vol. 28, no. 6, pp. 300–313, 1993.

[99] M. U. Farooq, Khubaib, and L. K. John, "Store-load-branch (SLB) predictor: A compiler assisted branch prediction for data dependent branches," in *Proc. 19th IEEE Int. Symp. High-Perform. Comput. Archit. (HPCA)*, Feb. 2013, pp. 59–70. [Online]. Available: http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=6522307

[100] M. Maia, J. Almeida, and V. Almeida, "Identifying user behavior in online social networks," in *Proc. 1st Workshop Social Netw. Syst.*, 2008, pp. 1–6.

[101] I. Weber and A. Jaimes, "Who uses Web search for what: And how," in *Proc. Web Search Data Mining (WSDM)*, 2011, pp. 21–30.

[102] R. Kumar and A. Tomkins, "A characterization of online browsing behavior," in *Proc. 19th Int. Conf. World Wide Web*, 2010, pp. 561–570.

[103] R. A. Berry and R. G. Gallager, "Communication over fading channels with delay constraints," *IEEE Trans. Inf. Theory*, vol. 48, no. 5, pp. 1135–1149, May 2002.

[104] M. J. Neely, "Optimal energy and delay tradeoffs for multiuser wireless downlinks," *IEEE Trans. Inf. Theory*, vol. 53, no. 9, pp. 3095–3113, Sep. 2007.

[105] M. J. Neely, "Energy optimal control for time-varying wireless networks," *IEEE Trans. Inf. Theory*, vol. 52, no. 7, pp. 2915–2934, Jul. 2006.

[106] M. A. Zafer and E. Modiano, "A calculus approach to energy-efficient data transmission with quality-of-service constraints," *IEEE/ACM Trans. Netw.*, vol. 17, no. 3, pp. 898–911, Jun. 2009.

[107] C. W. Tan, D. P. Palomar, and M. Chiang, "Energy–robustness tradeoff in cellular network power control," *IEEE/ACM Trans. Netw.*, vol. 17, no. 3, pp. 912–925, Jun. 2009.

[108] L. Huang and M. J. Neely, "Delay reduction via Lagrange multipliers in stochastic network optimization," *IEEE Trans. Autom. Control*, vol. 56, no. 4, pp. 842–857, Apr. 2011.

[109] J. Tadrous, A. Eryilmaz, and H. El Gamal, "Proactive resource allocation: Harnessing the diversity and multicast gains," *IEEE Trans. Inf. Theory*, vol. 59, no. 8, pp. 4833–4854, Aug. 2013.

[110] J. Tadrous, A. Eryilmaz, and H. El Gamal, "Proactive content download and user demand shaping for data networks," *IEEE/ACM Trans. Netw.*, vol. 23, no. 6, pp. 1917–1930, Dec. 2015.

[111] J. Tadrous, A. Eryilmaz, and H. El Gamal, "Joint smart pricing and proactive content caching for mobile services," in *Proc. 2nd IEEE Int. Workshop Smart Data Pricing (SDP) INFOCOM*, 2013. [Online]. Available: http://ieeexplore.ieee.org/document/7182787/

[112] J. Spencer, M. Sudan, and K. Xu, "Queueing with future information," *Ann. Appl. Probab.*, vol. 24, no. 5, pp. 2091–2142, 2014.

[113] K. Xu, "Necessity of future information in admission control," *Oper. Res.*, vol. 63, no. 5, pp. 1213–1226, 2015.

[114] L. Huang, S. Zhang, M. Chen, and X. Liu, "When backpressure meets predictive scheduling," *IEEE/ACM Trans. Netw.*, vol. 24, no. 4, pp. 2237–2250, Aug. 2016.

[115] H. Yu, M. H. Cheung, L. Huang, and J. Huang, "Power-delay tradeoff with predictive scheduling in integrated cellular and Wi-Fi networks," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 4, pp. 735–742, Apr. 2016.

[116] S. Zhang, L. Huang, M. Chen, and X. Liu, "Effect of proactive serving on user delay reduction in service systems," *IEEE/ACM Trans. Netw.*, vol. 25, no. 2, Apr. 2017

[117] C. M. L. Chau Chen Lu, J. Tu, and X. Lin, "Online energy generation scheduling for microgrids with intermittent energy sources and co-generation," in *Proc. ACM SIGMETRICS*, 2013, pp. 53–66.

[118] M. H. Hajiesmaili, C. K. Chau, M. Chen, and L. Huang, "Online microgrid energy generation scheduling revisited: The benefits of randomization and interval prediction," in *Proc. ACM e-Energy*, 2016.

[119] N. Chen, A. Agarwal, A. Wierman, S. Barman, and L. Andrew, "Online convex optimization using predictions," *ACM SIGMETRICS*, vol. 43, no. 1, pp. 191–204, 2015.

[120] N. Chen, J. Comden, Z. Liu, A. Gandhi, and A. Wierman, "Using predictions in online optimization: Looking forward with an eye on the past," in *Proc. ACM SIGMETRICS*, 2016, pp. 193–206.

[121] M. Lin, Z. Liu, A. Wierman, and L. L. H. Andrew, "Online algorithms for geographical load balancing," in *Proc. Int. Green Comput. Conf. (IGCC)*, Jun. 2012, pp. 1–10.

[122] M. Lin, A. Wierman, L. L. H. Andrew, and E. Thereska, "Dynamic right-sizing for power-proportional data centers," in *Proc. IEEE INFOCOM*, Apr. 2011, pp. 1098–1106.

[123] L. Jiang and J. Walrand, "A distributed CSMA algorithm for throughput and utility maximization in wireless networks," *IEEE/ACM Trans. Netw.*, vol. 18, no. 3, pp. 960–972, Jun. 2010.

[124] L. Jiang and J. Walrand, "Stable and utility-maximizing scheduling for stochastic processing networks," in *Proc. Allerton Conf. Commun., Control, Comput.*, 2009, pp. 1111–1119.

[125] M. J. Neely, E. Modiano, and C. E. Rohrs, "Dynamic power allocation and routing for time-varying wireless networks," *IEEE J. Sel. Areas Commun.*, vol. 23, no. 1, pp. 89–103, Jan. 2005.

[126] A. Eryilmaz and R. Srikant, "Fair resource allocation in wireless networks using queue-length-based scheduling and congestion control," *IEEE/ACM Trans. Netw.*, vol. 15, no. 6, pp. 1333–1344, Dec. 2007.

[127] L. Huang, X. Liu, and X. Hao, "The power of online learning in stochastic network optimization," *ACM Sigmetrics*, vol. 42, no. 1, pp. 153–166, 2014.

[128] L. Huang, "Receding learning-aided control in stochastic networks," *Perform. Eval.*, vol. 91, pp. 150–169, Sep. 2015.

[129] L. Huang, "The value-of-information in matching with queues," *IEEE/ACM Trans. Netw.*, vol. 25, no. 1, pp. 29–42, Feb. 2017.

[130] L. Huang, "System intelligence: Model, bounds and algorithms," in *Proc. ACM MobiHoc*, 2016.

[131] T. Zhang, H. Wu, X. Liu, and L. Huang, "Learning-aided scheduling for mobile virtual network operators with QoS constraints," in *Proc. IEEE WiOpt*, May 2016, pp. 1–8.

[132] L. Huang, M. Chen, and Y. Liu, "Learning-aided stochastic network optimization with imperfect state prediction," in *Proc. ACM MobiHoc*, 2017.

[133] Y. Bao, X. Liu, and A. Pande, "Data-guided approach for learning and improving user experience in computer networks," in *Proc. 7th Asian Conf. Mach. Learn. (ACML)*, 2015, pp. 127–142.

[134] Y. Bao, H. Wu, and X. Liu, "From prediction to action: A closed-loop approach for data-guided network resource allocation," in *Proc. 22nd ACM SIGKDD Conf. Knowl. Discovery Data Mining (KDD)*, 2016, pp. 1425–1434.

[135] J. Lee, K. Lee, E. Jeong, J. Jo, and N. B. Shroff, "Context-aware application scheduling in mobile systems: What will users do and not do next?" in *Proc. ACM UbiComp*, Sep. 2016, pp. 1235–1246.

[136] Y. L. T. Cheng Huang Hao, J. Zhou, and H. Wu, "User identification in cyber-physical space: A case study on mobile query logs and trajectories," in *Proc. ACM SigSpatial (Short Paper)*, Nov. 2016, p. 71.

[137] D. Christin, A. Reinhardt, S. S. Kanhere, and M. Hollick, "A survey on privacy in mobile participatory sensing applications," *J. Syst. Softw.*, vol. 84, no. 11, p. 1928– 1946, 2011.

[138] L. Pournajaf, L. Xiong, D. A. Garcia-Ulloa, and V. Sunderam, "A survey on privacy in mobile crowd sensing task management," Dept. Math. Comput. Sci., Emory Univ., Atlanta, GA, USA, Tech. Rep. TR-2014-002, , 2014.

[139] D. Christin, "Privacy in mobile participatory sensing: Current trends and future challenges," *J. Syst. Softw.*, vol. 116, pp. 57–68, Jun. 2016.

[140] L. Xu, C. Jiang, J. Wang, J. Yuan, and Y. Ren, "Information security in big data: Privacy and data mining," *IEEE Access*, vol. 2, pp. 1149–1176, Oct. 2014.

[141] L. Xu, C. Jiang, Y. Chen, J. Wang, and Y. Ren, "A framework for categorizing and applying privacy-preservation techniques in big data mining," *Computer*, vol. 49, no. 2, pp. 54–62, Feb. 2016.

[142] J. Al-Muhtadi, R. Campbell, A. Kapadia, M. D. Mickunas, and S. Yi, "Routing through the mist: Privacy preserving communication in ubiquitous computing environments," in *Proc. 22nd Int. Conf. Distrib. Comput. Syst.*, Jul. 2002, pp. 74–83.

[143] R. Dingledine, N. Mathewson, and P. Syverson, "TOR: The second-generation onion router," Defense Tech. Inf. Center, Fort Belvoir, VA, USA, Tech. Rep., 2004. [Online]. Available: http://oai.dtic.mil/oai/oai?verb=getRecord&metadataPrefix=html&identifier=ADA465464

[144] M. Shin, C. Cornelius, D. Peebles, A. Kapadia, D. Kotz, and N. Triandopoulos, "AnonySense: A system for anonymous opportunistic sensing," *Pervasive Mobile Comput.*, vol. 7, no. 1, pp. 16–30, Feb. 2011.

[145] C. Cornelius, A. Kapadia, D. Kotz, D. Peebles, M. Shin, and N. Triandopoulos, "AnonySense: Privacy-aware people-centric sensing," in *Proc. 6th Int. Conf. Mobile Syst., Appl., Services*, 2008, pp. 211–224.

[146] I. Krontiris and T. Dimitriou, "Privacy-respecting discovery of data providers in crowd-sensing applications," in *Proc. IEEE Int. Conf. Distrib. Comput. Sensor Syst.*, May 2013, pp. 249–257.

[147] A. C. Yao, "Protocols for secure computations," in *Proc. 23rd Annu. Symp. Found. Comput. Sci. (SFCS)*, Nov. 1982, pp. 160–164.

[148] Q. Li and G. Cao, "Providing efficient privacy-aware incentives for mobile sensing," in *Proc. IEEE 34th Int. Conf. Distrib. Comput. Syst. (ICDCS)*, Jun. 2014, pp. 208–217.

[149] J. Son, D. Kim, R. Hussain, A. Tokuta, S.-S. Kwon, and J.-T. Seo, "Privacy aware incentive mechanism to collect mobile data while preventing duplication," in *Proc. IEEE Military Commun. Conf. (MILCOM)*, Oct. 2015, pp. 1242–1247.

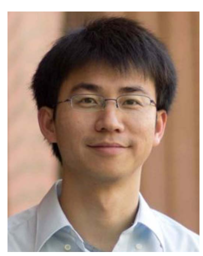
[150] L. Xu, C. Jiang, Y. Chen, Y. Ren, and K. J. R. Liu, "Privacy or utility in data collection? A contract theoretic approach," *J. Sel. Topics Signal Process.*, vol. 9, no. 7, pp. 1256–1269, Oct. 2015.

[151] L. Xu, C. Jiang, Y. Qian, Y. Ren, Y. Zhao, and J. Li, "Dynamic privacy pricing: A multi-armed bandit approach with time-variant rewards," *IEEE Trans. Inf. Forensics Security*, vol. 12, no. 2, pp. 271–285, Feb. 2017.

[152] D. Christin, C. Buchner, and N. Leibecke, "What's the value of your privacy? Exploring factors that influence privacy-sensitive contributions to participatory sensing applications," in *Proc. IEEE 38th Conf. Local Comput. Netw. Workshops (LCN Workshops)*, Oct. 2013, pp. 918–923.

Lingjie Duan received the B.Eng. degree (Hons.) from the Harbin Institute of Technology in 2008, and the Ph.D. degree in information engineering from The Chinese University of Hong Kong in 2012. He was a Visiting Scholar with the University of California at Berkeley in 2011. He is currently an Assistant Professor of Engineering Systems and Design Pillar with the Singapore University of Technology and Design.

His research focuses on nonlinear optimization and game theoretic analysis of communication networks, especially in network economics, spectrum- and energy-efficient communications, and mobile crowdsourcing. He has been awarded prestigious research awards, including the 2016 SUTD Awards - Excellence in Research, the 10th Asia-Pacific Outstanding Young Researcher Award from the IEEE Communications Society in 2015, and the Hong Kong Young Scientist Award (finalist in engineering science track) in 2014. He is currently an Editor of the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS and the IEEE COMMUNICATIONS SURVEYS AND TUTORIALS. He is also a Guest Editor of the IEEE WIRELESS COMMUNICATIONS Special Issue on Green Networking and Computing for 5G Systems in 2016. He has served as a Program Co-Chair at the IEEE GCNC 2016 Green Communications and Networking Symposium, the IEEE ICCC 2015 Wireless Communications System Symposium, and the INFOCOM 2014 GCCCN Workshop. He is a technical program committee member of top conferences, including INFOCOM, MobiHoc, and WiOPT.



Longbo Huang received the Ph.D. degree in electrical engineering from the University of Southern California in 2011. He was a Post-Doctoral Researcher with the Department of Electrical Engineering and Computer Sciences, University of California at Berkeley (UC Berkeley), Berkeley, CA, USA, from 2011 to 2012.

He has been a Visiting Scholar with the Laboratory for Information and Decision Systems, Massachusetts Institute of Technology and at the Department of Electrical Engineering and Computer Sciences, UC Berkeley, and a Visiting Professor with The Chinese University of Hong Kong, Bell-labs France, and Microsoft Research Asia. He was a Visiting Scientist with the Simons Institute for the Theory of Computing, UC Berkeley, in 2016. His current research interests are in the areas of online learning, network optimization, online algorithm design, and sharing economy. He is currently an Assistant Professor with the Institute for Interdisciplinary Information Sciences, Tsinghua University, Beijing, China. He was selected into China's Youth 1000-Talent Program in 2013 and received the Outstanding Teaching Award from Tsinghua University in 2014. He has served as a TPC member for top-tier IEEE and ACM conferences, and as the TPC Vice Chair for Submissions for the IEEE WiOpt 2016 and the Publicity Chair for ACM e-Energy 2017. He was the Lead Guest Editor of the IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS Special Issue on Human-In-The-Loop Mobile Networks and has served as an Associate Editor of *ACM Transactions on Modeling and Performance Evaluation of Computing Systems* since 2017.

Cedric Langbort received the degrees from the Ecole Nationale Superieure de l'Aeronautique et de l'Espace-Supaero, Toulouse, France, the Institut Non-Lineaire, Nice, France, and the Ph.D. degree from Cornell University, in 2005. He is currently an Associate Professor of aerospace engineering with the University of Illinois at Urbana–Champaign, Urbana, IL, USA, where he is also affiliated with the Decision and Control Group at CSL. He also spent a year and a half as a Post-Doctoral Scholar with the Center for the Mathematics of Information, Caltech. He focuses on applications of control, game, and optimization theory to a variety of fields; most recently to smart infrastructures problems within the Center for People and Infrastructures which he co-founded and co-directs at CSL. He was a recipient of the NSF CAREER Award, advisor to the IEEE CDC Best Student Paper Award recipient, as well as a former subject editor for OCAM, the *Journal of Optimal Control Applications and Methods*. He also was the Student Activity Chair for the 2014 IEEE Conference on Decision and Control.

Alexey Pozdnukhov received the degree in mathematical physics from the Physics Department, Moscow State University, in 2003, and the Ph.D. degree in computer science from EPFL, Switzerland, in 2006, following his research in machine learning methods and computer vision that he carried out at IDIAP Research Institute in Martigny, Switzerland. He was with the Institute of Geomatics and Analysis of Risk, University of Lausanne, where he was involved in developing approaches to apply machine learning techniques for geospatial data analysis. In 2008, he joined the National Centre for Geocomputation, National University of Ireland Maynooth as a recipient of a Stokes Lectureship from the Science Foundation Ireland. He led a group engaged in several research projects, including the strands of Irish Strategic Research Cluster in Advanced Geotechnologies, and several national and European projects. He is a co-author of one book and an author of over 20 peer- reviewed journal and full conference papers. He has developed methodologies to apply machine learning methods in computational environmental modeling, integrate prior knowledge and efficiently process geo-referenced data streams from sensor networks. He was a recipient of the Google Research Award in 2011, an Innovation Award and a fellowship from the IBM Smarter Cities Technology Centre. His current research at CEE, University of California at Berkeley, Berkeley, CA, USA, is in the area of complex data analysis in the domain of smart cities, including applications of streaming data analytics in urban mobility, location-based social networks, and computational social science.

Jean Walrand (S'71–M'74–SM'90–F'93–LF'17) received the Ph.D. degree from the Electrical Engineering and Computer Sciences Department (EECS), University of California at Berkeley (UC Berkeley). He has been on the faculty of EECS, UC Berkeley, since 1982, where he is currently a Professor. He is the author of *An Introduction to Queueing Networks* (Prentice Hall, 1988) and the *Communication Networks: A First Course* (2nd ed. McGraw-Hill, 1998) and co-author of *High-Performance Communication Networks* (2nd ed, Morgan Kaufman, 2000), *Communication Networks: A Concise Introduction* (Morgan & Claypool, 2010), and *Scheduling and Congestion Control for Communication and Processing Networks* (Morgan & Claypool, 2010). His current research interests include stochastic processes, queuing theory, communication networks, game theory, and the economics of the Internet.

He has received numerous awards for his work over the years. He is a Fellow of the Belgian American Education Foundation. Additionally, he is a recipient of the Lanchester Prize, the Stephen O. Rice Prize, the IEEE Kobayashi Award, and the ACM SIGMETRICS Achievement Award.

Lin Zhang (S'05–M'06–SM'13) received the B.Sc., M.Sc., and Ph.D. degrees from Tsinghua University, Beijing, in 1998, 2001, and 2006, respectively. He was a Visiting Professor with the University of California at Berkeley, Berkeley, CA, USA, from 2011 to 2013. He is currently an Associate Professor with the Electronic Engineering Department, Tsinghua University. He is a co-author of over 60 peer-reviewed technical papers and five U.S. or Chinese patents applications. His current research interests include sensor networks, sensory data processing, and societal cyber physical systems. He is a Committee Member of the Chinese Information Theory Society. He was also the winner of the IEEE/ACM SenSys 2010 Best Demo Awards, the IEEE/ACM IPSN 2014 Best Demo Awards, and the IEEE CASE 2013 Best Paper Awards.

In 2006, he led a 2008 Beijing Olympic Stadium (the "Bird's Nest") structural security surveillance project, which deployed over 400 wireless temperature and tension sensors across the stadium's steel support structure and dome. The system adopted a flexible spectrum sensing and adaptive multihop routing algorithm to overcome strong radio interference and long-distance transmission channel fading, and played a critical role in the construction of the stadium. Since then, he has implemented wireless sensor networks in a wide range of application scenarios, including underground mine security, precision agriculture, and industrial monitoring. Since 2008, he has been in close association with CISCO to develop a Metropolitan Area Sensing and Operating Network (MASON). MASON utilizes moving vehicles as carriers of the sensor platform so as to gain good sensing coverage and low cost at the same time. Shenzhen has adopted the technology and is deploying the MASON system in the urban area to monitor the microclimate environment, as an important part of the information service to its citizens. At Tsinghua University, he has been teaching the courses Selected Topics in Communication Networks and Information Theory to senior undergraduate and graduate students. In 2004 and 2010, he received the Excellent Teacher Awards from Tsinghua University.