Real-Time Energy Trading and Future Planning for Fifth Generation Wireless Communications

Xiaojing Chen, Wei Ni, Tianyi Chen, Iain B. Collings, Xin Wang, and Georgios B. Giannakis

Abstract

Future 5G cellular networks, equipped with energy harvesting devices, are uniquely positioned to interoperate with smart grid, due to their resemblance in scale and ubiquity. New interoperable functionalities, such as real-time energy trading and future planning, are of particular interest to improve productivity, but extremely challenging due to the physical characteristics of wireless channels and renewable energy sources, as well as time-varying energy prices. Particularly, a priori knowledge on future wireless channels, energy harvesting, and pricing is unavailable in practice. In this scenario, simple but efficient Lyapunov control theory can be applied to stochastically optimize energy trading and planning. Simulations demonstrate that Lyapunov control can approach the offline optimum which is obtained under the ideal assumption of full a priori knowledge, leading to 65 percent reduction of the operational expenditure of 5G on energy over existing alternatives.

Xiaojing Chen is with Fudan University and Macquarie University

Xin Wang is with Fudan University and Florida Atlantic University.

Wei Ni is with CSIRO.

Tianyi Chen and Georgios B. Giannakis are with the University of Minnesota.

Iain B. Collings is with Macquarie University.

Work in this article was supported by the National Natural Science Foundation of China grants 61671154; the Innovation Program of Shanghai Municipal Education Commission; and U.S. NSF grants 1509005, 1508993, 1423316, and 1442686.

Digital Object Identifier: 10.1109/MWC.2017.1600344

Introduction

Fifth generation (5G) cellular networks are anticipated to be densely deployed with a significantly reduced coverage area per cell. Along with its reduced per-cell size, the number of cells will dramatically increase due to the explosively increasing mobile traffic and the limited availability of high-frequency spectrum [1]. Consequently, the total energy consumption of all base stations (BSs) would be high. It would contribute overwhelmingly to the operational expenditure of cellular networks, and adversely to the global carbon footprint. For economic and ecological purposes, an increasing number of BSs are now equipped with energy harvesting devices such as solar panels or wind turbines. Renewable energy up to 10,000 kW has been used to power cellular systems, supplementing persistent supplies from power grid [12]. Efficient techniques such as ON/OFF BS switching [3], online scheduling [4, 5], and power control [6] have been proposed to reduce the power consumption and delay, or achieve a near-optimal throughput region for energy harvesting powered users.

While cellular networks are evolving, the revolution of power grid is also underway. The next-generation smart grid, equipped with advanced smart meters and control capability, will be flexible, versatile, and able to support many new functionalities such as distributed energy generation, two-way energy flows, energy trading and redistribution, and energy demand management [7]. Traditional energy users, such as cellular networks, are potentially becoming an integral part of the smart grid, helping generate and redistribute energy.

From a management and productivity point of view, cellular networks are uniquely positioned to interoperate with smart grid. In particular, the sheer scale and ubiquity of cellular networks result in a significant amount of energy, either purchased off the grid or harvested from ambient environments. The amount is non-negligible to the load of the entire smart grid. Moreover, the centralized close control of cellular networks resembles to that of the smart grid. This can provide efficient redistribution of energy and effective price negotiation with the smart grid [8].

Figure 1 illustrates the new interoperable framework of 5G and smart grid, where BSs equipped with energy harvesting devices are connected to the smart grid through smart meters. The BSs are also connected to the core network (i.e., the gateway and Internet) through broadband backhaul links using gigabit or carrier-grade Ethernet [9]. Effective interoperability between 5G and the smart grid is not only feasible, but also important to both 5G and the smart grid.

A number of new functionalities become possible under this new interoperable framework.

Two-way energy trading (TWET): Cellular BSs, as an integral part of the grid, can purchase energy off the grid in shortage of renewable energy, and sell energy back to the grid when renewable energy is in abundance [7]. The abundant renewable energy can be redistributed through the smart grid for environmental benefits, as well as financial gains of 5G. This helps balance energy

 1536-1284/17/$25.00 © 2017 IEEE

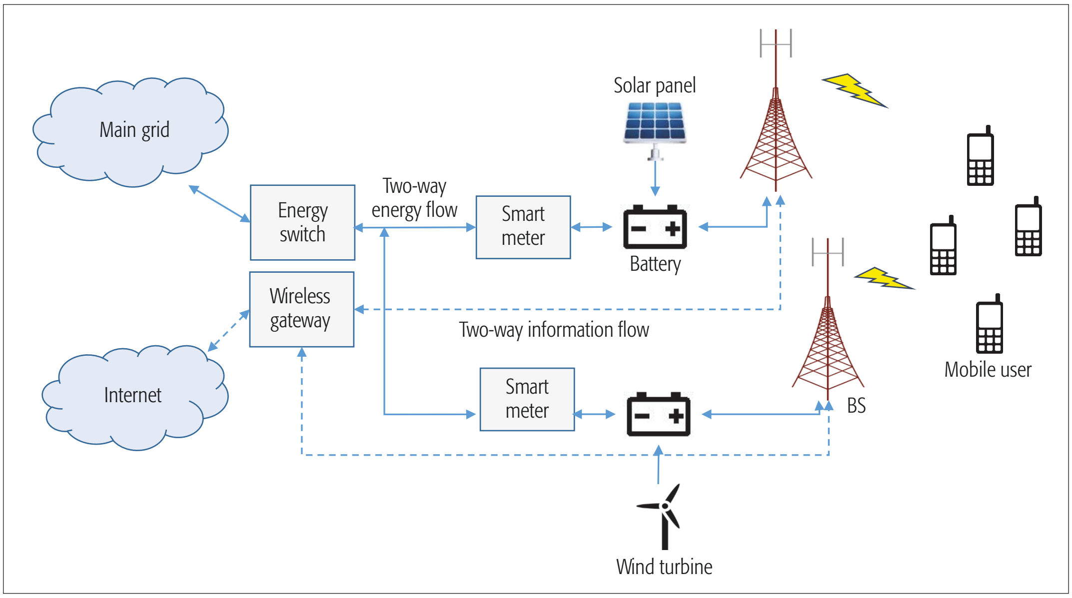

FIGURE 1. A new interoperable framework of 5G and smart grid.

Simulation results show that Lyapunov control over TWET and MTEP has the potential for a 65 percent reduction in the operational cost of 5G on energy. It is also revealed that reducing the dissipation of the batteries at 5G BSs is crucial to improve the cost saving.

load and relieve pressure on the grid, and hence improve the reliability of the grid.

Dynamic energy pricing: As a result of intermittent renewable energy and TWET, energy prices are expected to exhibit strong dynamics in smart grid. Dynamic pricing is important to regulate the energy demands, and encourage users such as 5G networks to consume energy wisely and efficiently. The prices of both selling and buying energy fluctuate over time to reflect the real-time energy demand and supply availability.

Multi-timescale energy planning (MTEP): The interoperability of 5G and smart grid needs to be supported over multiple different timescales (i.e., for grid-energy pricing, energy harvesting, and wireless transmission), as shown in Fig. 2. The different timescales are due to the physical properties of wireless channels and energy harvesting, the time-varying demand and supply across smart grid, and the marketing strategies of electricity utility companies:

- The wireless timescale depends on the channel coherence time of typically tens of milliseconds. The BS's update transmission is scheduled based on this interval to keep up with changing wireless channels.
- The smart grid energy pricing timescales are regulated by the electricity utility companies, depending on demand and supply, and marketing strategies. Different business models and contractual arrangements can be made. Long-term pricing, lasting for up to days or months, reflects medium- to-long-term demand and supply, and changes in the fuel market. On the other hand, short-term pricing reflects real-time changes in demand and supply. It can apply the wireless timescale, since wireless transmissions drive the changes.
- Energy harvesting is typically a slowly changing continuous process, under the current low energy transfer rate (e.g., 1 mW/cm^2 for solar panels) [4]. Nevertheless, it can readily be discretized due to the discrete nature of trading. To capture the real-time changes of energy consumption in wireless transmissions and also reduce the battery requirement, it is reasonable to discretize energy harvesting based on the wireless timescale.

Taking these different timescales into account, a foresighted plan of energy usage in advance will be of significance to reduce the operational cost of 5G networks.

Other new interoperable functionalities between 5G and smart grid include energy- and spectrum-efficient wireless transmission, energy redistribution, wireless energy transfer, grid management, and control monitoring [10].

In this article, we are particularly interested in TWET and MTEP, which are of practical value to reduce the operational expenditure of 5G. Specifically, we introduce TWET and MTEP of 5G, discuss the challenges of their implementations, and investigate the applications of stochastic control theory to optimize TWET and MTEP. In particular, Lyapunov control is assessed for the intended applications, and its effectiveness is verified by extensive simulations in practical scenarios without a priori knowledge on future wireless channels, and energy pricing and harvesting. Simulation results show that Lyapunov control over TWET and MTEP has the potential for a 65 percent reduction in the operational cost of 5G on energy. It is also revealed that reducing the dissipation of the batteries at 5G BSs is crucial to improve the cost saving.

TWET AND MTEP FOR 5G

Figure 1 shows a promising 5G architecture coupled with smart grid, where each BS is equipped with a smart meter, an energy harvesting device, and a battery with finite capacity. The battery level needs to remain above a certain threshold to avoid excessively discharging; otherwise, permanent damage can be done to the battery. At any time, energy can be purchased off the smart grid at a real-time buying price. Unused energy, either previously purchased or locally harvested, can be stored in the battery for future use, or sold back to the grid through the smart meter at a real-time selling price.

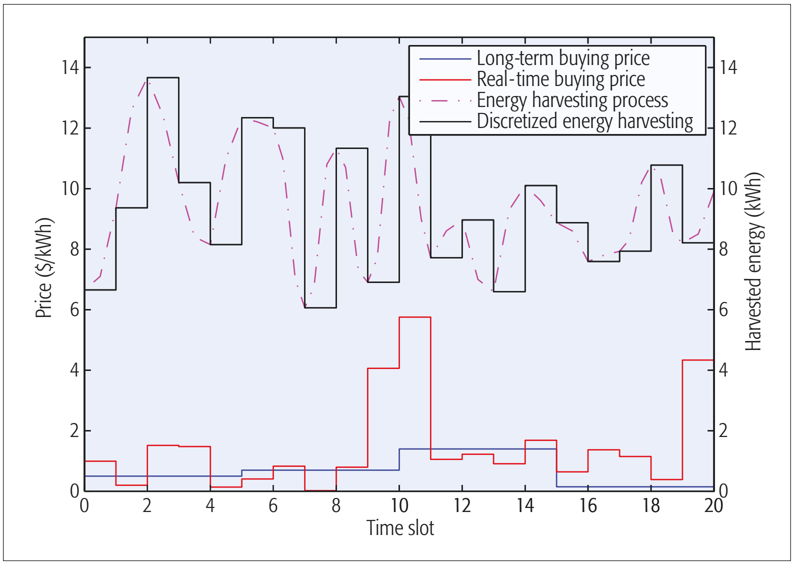

FIGURE 2. Multiple timescales of energy pricing and harvesting in the interoperable framework of future 5G and smart grid.

Energy-efficient coordinated multipoint (CoMP) techniques can be adopted at the BSs, as extensively studied in 3GPP and specified in standards [11]. The BSs jointly form multiple wireless beams toward different users to deliver data traffic. Every user has a requirement on the minimum data rate, based on its specific traffic type or quality of service (QoS) requirement. Such a minimum data rate requirement can be translated to a signal-to-interference-plus-noise ratio (SINR) target.

Depending on the channel state information of the users, the beams are designed to achieve the SINR target while minimizing the transmit power of the BSs. By this means, inter-user and inter-cell interference can be suppressed, and energy efficiency can be improved, thereby enhancing the sustainability of the BSs with reduced demand for energy supply from the grid.

With the aforementioned discretization of wireless transmission, energy harvesting, and pricing timescales, TWET can be formulated to minimize the time-average energy cost of the BSs across all time slots, as given by

$$\min \lim_{T\to\infty} \frac{1}{T}\sum_{t=1}^{T}\sum_{i}\underbrace{(\alpha_t^{\mathrm{rt}}\Phi_{i,\mathrm{buy}}^{t} - \beta_t^{\mathrm{rt}}\Phi_{i,\mathrm{sell}}^{t})}_{G_i(t)} \quad (1)$$

where
- α_t^{rt} is the real-time energy buying price at slot t.
- β_t^{rt} is the real-time energy selling price at slot t.
- Both $\Phi_{i,\mathrm{buy}}^{t}$ and $\Phi_{i,\mathrm{sell}}^{t}$ indicate the difference between the total of the energy consumed and purchased to be pre-stored at BS i, and the energy harvested by the BS during slot t. In the case that the difference is positive, $\Phi_{i,\mathrm{buy}}^{t}$ is the shortage of energy and needs to be purchased from the grid, and $\Phi_{i,\mathrm{sell}}^{t}$ is zero. In the case that the difference is negative, $\Phi_{i,\mathrm{sell}}^{t}$ is the surplus of energy and can be sold back to the grid, and $\Phi_{i,\mathrm{buy}}^{t}$ is zero.

At any slot, energy can be either purchased from or sold to the grid. The energy purchased to be immediately consumed and/or stored for future use, or the energy sold to the grid, is to be optimized in Eq. 1. The energy can be stored in the batteries of the BSs. Typically, the energy that can be charged into or discharged from a battery is bounded during a time period.

In practice, a battery can also undergo energy dissipation. Storage efficiency, typically denoted by $\eta \in (0, 1]$, indicates a leakage of $(1 - \eta)$% of the battery level during a time slot. It is important to keep the batteries at a proper level to avoid excessive leakage of energy.

Note that the long-term minimization of Eq. 1 cannot be achieved by myopically optimizing over each individual slot. This is due to the fact that the (dis)charging decisions are coupled across time through the change of the battery levels. The decision at any slot can have a non-negligible impact on the decisions further in the future. Also, the minimization of Eq. 1 is subject to non-convex constraints posed by CoMP, such as the quadratic function of the beamforming vectors to calculate the energy consumption. The minimization does not provide a tractable structure, and cannot be readily solved using well-developed techniques such as convex optimization.

In the ideal case where the energy prices, energy harvesting, and wireless channels are a priori known over time, TWET can be optimized at once using offline approaches [12]. Specifically, the non-convex constraints posed by CoMP can be reformulated using semi-definite relaxation. The resultant convex problem can readily be solved using standard convex optimization solvers, such as the interior point method, with optimality rigorously proved using Lagrange duality theory. In practice, however, the information of real-time energy prices, energy harvesting, and wireless channel conditions is unavailable ahead of time due to causality. Of limited applications in practice, the offline optimum can quantify a lower bound for the energy cost of the BSs, and set up a clear goal for practical designs of TWET.

A more general case of energy trading between 5G and smart grid can involve multiple asynchronous timescales of real-time wireless transmission and short-term energy pricing, energy harvesting, and long-term energy pricing, as discussed earlier. On average, a long-term energy buying price is lower than a real-time price; see Fig. 2. This discrepancy can be exploited to further reduce the energy cost of 5G compared to TWET. Taking advantage of the discrepancy, MTEP is expected to plan energy use and purchase over multiple timescales. Having the same objective as TWET, MTEP is clearly even more challenging due to the fact that the ahead-of-time planning and real-time trading are closely correlated and coupled along time.

Lyapunov Control and Optimization

Given the stochastic process of TWET, control theory is a promising candidate to solve TWET. The control variables are the total energy consumption of the BSs and the battery (dis)charging amount during every slot, both of which depend on the beamforming vectors of the BSs, the channels, and the SINR targets of the users. The battery level is restricted between $C^{\min}$ and $C^{\max}$, which are the minimum threshold that the battery needs to remain above and the maximum battery capacity, respectively.

Lyapunov control is a powerful tool to control and stabilize queueing systems, and has been successfully applied to data queues in computer networks [13] and energy queues in smart grid [14]. A Lyapunov function $L(t)$ is defined as a non-negative scalar measure of queue lengths. The function becomes large as the queueing system moves toward unstable states. System stability can be achieved by taking control actions that harness the Lyapunov function at any slot. Consider a network of I queues $(Q_1^t, Q_2^t, ..., Q_I^t)$, each with a stationary (stochastic) arrival process, where the queue length Q_i^t can take any real value. A typical quadratic Lyapunov function is $L(t) = 1/2 \, \Sigma_{i=1}^{I} (Q_i^t)^2$.

A Lyapunov drift, defined as $\triangle L(t) = L(t + 1) - L(t)$, measures the difference of the Lyapunov function between two consecutive slots. Minimizing the drift per slot provides a practical means to restrain the Lyapunov function, prevents the queue lengths from unbounded growth, and hence preserves system stability [13].

A general Lyapunov drift-plus-penalty can be specified by $\triangle L(t) + Vp(t)$, where, apart from the Lyapunov drift $\triangle L(t)$, $p(t)$ is a penalty function and V is a predefined non-negative weight of the penalty. By minimizing the upper bound of the drift-plus-penalty at every slot, we can stochastically minimize the time average of the penalty $p(t)$ while stabilizing the queues. Through proper selection of the penalty function $p(t)$, this technique can then be used to stochastically minimize specific metrics of stochastic systems with asymptotic optimality [13]. Lyapunov optimization is desirable for TWET, as it enables the optimization of the control decisions to be decoupled across slots, in contrast to the offline optimization over all slots with full knowledge of future channel, energy price, and harvest realizations.

There can be a gap between the stochastically minimized time average of $p(t)$ and the ideal offline optimum. Such an optimality gap exists because the queue stability is accounted for in the instantaneous minimization through the drift-plus-penalty objective, and only causal system information is used per time slot. As a typical trade-off of Lyapunov optimization, a queue length of $\mathcal{O}(V)$ is required to achieve an optimality gap of $\mathcal{O}(1/V)$.

In this sense, the optimality gap can asymptotically diminish at the expense of increasing steady-state queue lengths.

Lyapunov Control over TWET

Given the intrinsic resemblance of the logic queue Q_i^t and the battery level in BS i at any slot t, denoted by C_i^t in TWET, Lyapunov control has great potential to be applied to optimize TWET for CoMP [14]. Particularly, C_i^t can be mapped to Q_i^t, and the total energy cost of all the BSs, $\Sigma_i G_i(t)$, can specify the penalty function $p(t)$. As a result, sequentially minimizing the upper bound of such a Lyapunov drift-plus-penalty during each slot can lead to the minimization of the time average of the total energy cost in the long term, while stabilizing all the batteries.

A nontrivial extension of Lyapunov optimization is required for its application to TWET, though. On one hand, the battery level C_i^t needs to be strictly within $[C^{min}, C^{max}]$, while the queue length, Q_i^t, can generally take any real values. On the other hand, different from the data queues in [13], batteries can have energy leakage due to storage inefficiency. To tackle these challenges, Q_i^t can be modeled as a biased battery level C_i^t with a bias Γ so that Q_i^t is consistent with the definition of Lyapunov control. The value of Γ can be specified offline by exploiting the queue stabilizing property of Lyapunov control.

The Lyapunov control of TWET for CoMP can be automated following the steps below:

- **Initialization**}: Set up Γ and V to ensure the feasibility of TWET, and initialize $Q_i^0 = C_i^0 + \Gamma$.
- **TWET and CoMP**: At any slot t,
  - Given energy buying/selling prices, harvested energy amount and channel state information, obtain the optimal beams and battery (dis)charging amount to minimize the upper bound of the drift-plus-penalty $\triangle L(t) + V\Sigma_i G_i(t)$, subject to the SINR requirements.
  - Buy energy amount of $\Phi_{i,buy}^t$ from, or sell energy amount of $\Phi_{i,sell}^t$ to, the smart grid.
- **Battery (dis)charging**: Update $C_i^t = \eta \, C_i^{t-1} + E_{b,}^t$ and $Q_i^t = C_i^t + \Gamma$, where $E_{b,i}^t$ is the battery (dis)charging amount of BS i.

Note that the minimization of the upper bound of the drift-plus-penalty can be convexified with respect to the beamforming vectors and battery (dis)charging amount if the constraint of $C^{min} \leq C_i^t \leq C^{max}$ is relaxed. As a result, it can be minimized efficiently using convex optimization techniques. On the other hand, the relaxed battery constraint remains inviolated once the batteries start to stabilize. This is due to the queue stabilizing property of Lyapunov control; that is, the dynamic range of a stabilized queue with a length of $\mathcal{O}(V)$ depends on V and can be limited within $(C^{max} - C^{min})$ by adjusting V and Γ.

Also note that in the case of perfect batteries, $\eta = 1$, the aforementioned trade-off of Lyapunov control holds between a battery level and the optimality gap (i.e., the gap from the ideal offline optimum). In other words, the Lyapunov control over TWET exhibits improving optimality as the battery capacity C^{max} increases. However, the trade-off no longer exists if the batteries are imperfect (i.e., $0 < \eta < 1$). In this case, the minimum optimality gap is not monotonic with respect to V, since practically the battery leakage enlarges as C^{max} grows. Nevertheless, following the recent work [15], the minimum optimality gap can be numerically computed by a one-dimensional search for V.

Lyapunov Control over MTEP

Supporting the interoperability of 5G and smart grid over multiple timescales, MTEP is able to further reduce the energy cost of 5G compared to TWET. Particularly, ahead-of-time planning is carried out to leverage typically lower long-term energy buying prices and reduce instant energy shortage at individual slots. The Lyapunov control can be applied to MTEP. Particularly, the forecast (i.e., ahead-of-time) energy trading decision over a larger timescale can be accommodated in the Lyapunov optimization framework, like TWET running at longer intervals. MTEP now essentially consists of multiple asynchronous Lyapunov control processes running at the intervals of wireless transmission, real-time energy pricing, and long-

Supporting the interoperability of 5G and smart grid over multiple timescales, MTEP is able to further reduce the energy cost of 5G compared to TWET. Particularly, ahead-of-time planning is carried out to leverage typically lower long-term energy buying prices and reduce instant energy shortage at individual slots.

term energy pricing. Nevertheless, the processes have the common objective of stochastically minimizing the time average of energy cost.

The Lyapunov control running in real time depends on that running ahead of time over large timescales. For illustration convenience, here we consider two different timescales of energy pricing: real time for a short slot (with a duration of τ_{rt}) and ahead of time for a long interval (with a duration of τ_{lt}). In this case, the energy purchased ahead of time is persistently output from the grid during an upcoming interval (i.e., evenly distributed across slots within the interval). This sets a consistent offset on the energy that can be purchased or sold in real time, and becomes part of the drift-plus-penalty for the Lyapunov control over TWET at every slot within the interval.

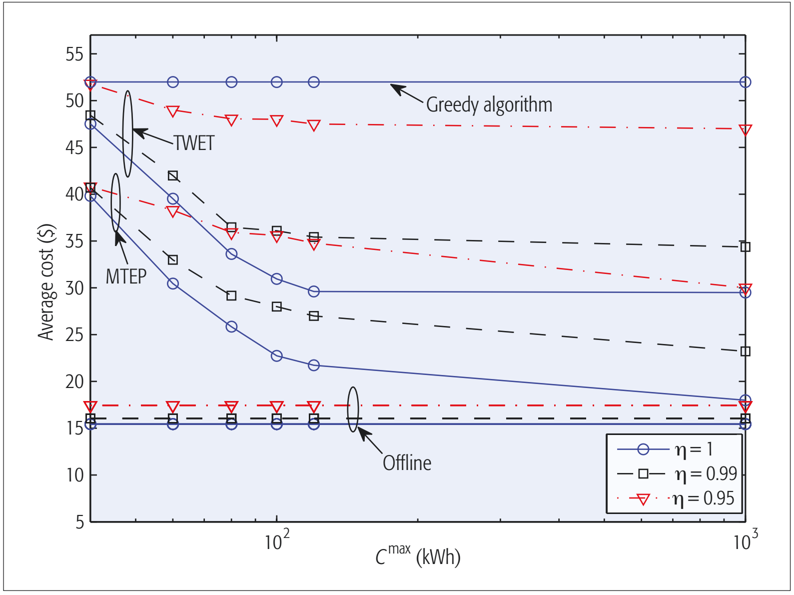

FIGURE 3. Time-average energy cost vs. battery capacity C^{max}, where γ_k^{req} = 5 dB, C^{min} = 1 kWh, and η = 0.95,0.99 and 1.

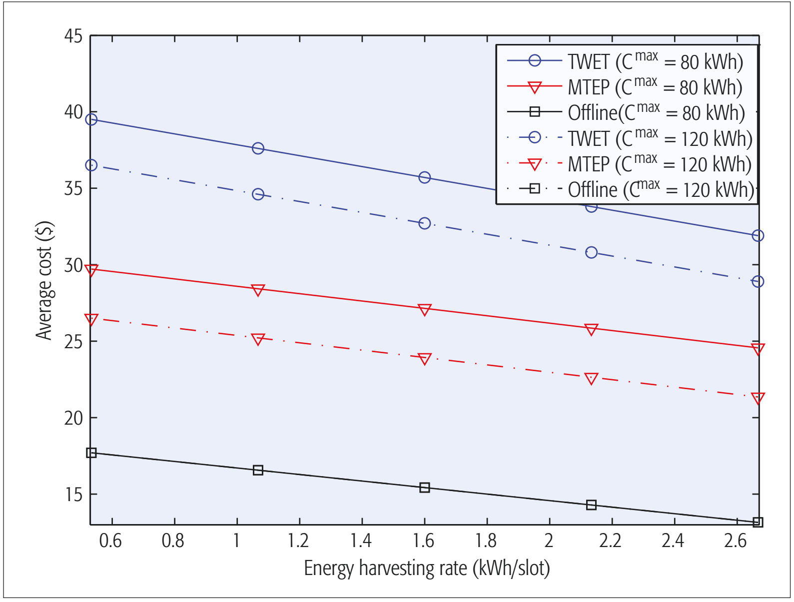

FIGURE 4. Time-average energy cost vs. energy harvesting rate of TWET, MTEP, and the offline optimum, where γ_k^{req} = 5dB, C^{max} = 80 and 120 kWh, and C^{min} = 1 kWh.

The energy purchased or sold ahead of time can be optimized by minimizing the upper bound of the drift-plus-penalty of the Lyapunov control running at the long interval. For an upcoming interval, this drift-plus-penalty adds up those of the Lyapunov control over TWET at all slots within the interval [15]. In this sense, both controls, running at the long interval and by slots, have a unified drift-plus-penalty with respect to every single slot; in other words, minimizing the upper bound of the drift-plus-penalty on the interval basis does not violate (i.e., is equivalent to) that on the slot basis. Given their common objective of minimizing the time average of the penalty (i.e., energy cost), the legitimacy of coupling the two Lyapunov controls stands, preserving the asymptotic optimality of MTEP as well as the trade-off between the battery level and optimality gap.

As mentioned earlier, in MTEP, the drift-plus-penalty per slot contains an unknown energy offset that depends on the ahead-of-time decision to be optimized at the beginning of the corresponding interval. This is different from TWET. A stochastic subgradient method can be used to update the ahead-of-time decision for an upcoming interval. The convex techniques developed for TWET can be used to optimize the real-time decisions for all the slots within the interval. These can be carried out in an alternating manner until the upper bound of the drift-plus-penalty is minimized for the interval; equivalently, the upper bounds are minimized across all slots within the interval.

PERFORMANCE AND DISCUSSION

Consider a 5G network of two BSs and three single-antenna mobile users. Each BS is equipped with two transmit antennas. We assume the users are in the middle of the two BSs, and the BS-user links experience independent and identically distributed Rayleigh fading channels. Both the maximum charging and discharging energy amounts per slot are 2 kWh. We set the long-term pricing interval τ_{lt} = 1 min and the real-time pricing interval (slot) τ_{rt} = 10 s. The battery storage efficiency is η = 0.95 unless otherwise specified. The long-term and real-time energy buying prices α_n^{lt} and α_t^{rt} are assumed to follow folded normal distributions, with the averages of \$1.5/kWh and \$2.3/kWh, respectively. The long-term and real-time energy selling prices are set as $\beta_n^{lt} = 0.9\alpha_n^{lt}$ and $\alpha_t^{rt} = 0.3\alpha_t^{rt}$, since the buying and selling prices are highly related and both dependent on the demand and supply availability. The energy harvesting also follows a folded normal distribution, with an average rate of 1.2 kWh/slot. Finally, let Γ_k^{req} denote the SINR target for user k.

For the purpose of comparison, we also simulate a greedy algorithm that myopically minimizes the instantaneous cost on energy per slot. In this sense, any surplus energy of a BS is sold to the smart grid, and any shortage in energy needs to be purchased from the smart grid, at every slot; that is, there is no battery (dis)charging.

Figure 3 demonstrates that TWET and MTEP are able to increasingly reduce the energy cost of wireless operators at the cost of increasing battery capacity. For instance, the average operational cost of TWET under η = 1 is reduced from \$47.5 to \$29.6 as the battery capacity increases from

40 kWh to 120 kWh. It is also shown that exploiting multiple timescales of wireless transmission and energy pricing, real-time energy trading, and ahead-of-time energy planning can significantly reduce the cost. With perfect batteries (η = 1), reductions of 43 and 65 percent can be achieved using TWET and MTEP at the battery capacity of 1000 kWh, respectively, compared to the myopic greedy algorithm. This is because the exploitation of multiple timescales facilitates predicting future energy pricing and harvesting, and hence refining current trading decisions.

In fact, we show that the Lyapunov control over MTEP can closely approach the offline optimum, which is only possible when full a priori knowledge is available. This is due to the fact that MTEP can take advantage of multi-timescale energy pricing, while TWET can only work with real-time prices. We also see that imperfect batteries can have a non-negligible impact on the efficiency of TWET and MTEP. The conclusion drawn is that the installation of batteries with low dissipation is crucial to save the energy cost of 5G.

We proceed to evaluate the requirement of energy harvesting capabilities in real-time energy trading and future planning. Figure 4 plots the time-average energy cost against the energy harvesting rate (in kilowatt-hours per slot). We see that the cost declines linearly with the growth of energy harvesting capability in both TWET and MTEP. Also, it is observed that the gap between MTEP and the offline absolute optimum remains almost unchanged, while that between TWET and MTEP decreases as the harvested energy increases. In other words, the ahead-of-time energy planning in MTEP is particularly important to systems with limited energy harvesting capabilities.

Finally, we show that the saving of energy cost, through real-time energy trading and future planning, can be further increased in large wireless networks. In Fig. 5, the number of the BSs increases from one to six. We see that the increasing number of BSs can effectively reduce the energy cost per user, especially in the case where there are more users. This is due to the improved beamforming accuracy and reduced interference of CoMP. Particularly, the cost saving grows but the growth rate decreases as the number of BSs increases. This is because the channels become increasingly orthogonal among the users, and the inter-user interference diminishes, as the total number of transmit antennas increases. As a result, for each user, the beamforming becomes increasingly close to spatial matched filtering, which is optimal in terms of minimizing the total transmit power given the SINR requirements in interference-free channels. The total transmit power of the BSs asymptotically approaches the minimized power of spatial matched filtering, which only depends on the SINR requirements. We also observe that the average costs increase as the SINR target grows (e.g., from 5 dB to 20 dB). This is reasonable, since more energy needs to be consumed (and thus purchased) to meet more stringent SINR targets.

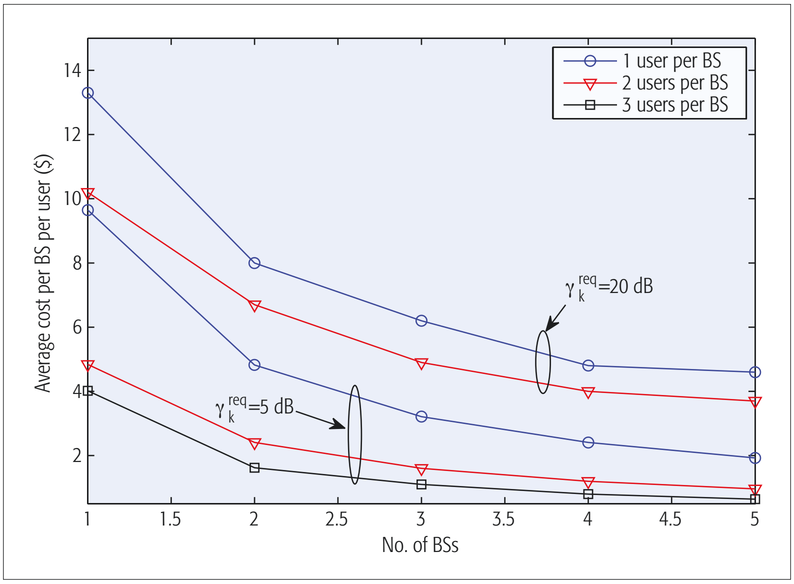

Figure 5. Time-average energy cost per BS per user vs. the number of BSs, where the SINR requirement is γ_k^{req} = 5 and 20 dB for all users, C^{max} = 80 kWh, and C^{min} = 1 kWh.

Conclusions and Future Works

In this article, we discuss the potential applications of Lyapunov control to TWET and MTEP in future 5G networks. We demonstrate that Lyapunov control is able to decouple decision making over time without the need for a priori knowledge on future wireless channels, energy prices, and renewable resources, while still preserving optimality in a stochastic sense. Simulation results show that effective real-time energy trading and planning is able to save 65 percent of the operational cost of 5G on energy, and the saving can be further increased by enlarging the wireless network. The results also reveal that the battery dissipation can have a non-negligible adverse impact on the cost saving, and the development and installation of batteries with low dissipation are crucial.

In light of the current framework, future directions include leveraging the predicted information (e.g., energy prices and renewable generation) in energy trading and planning, and the decentralized implementation of Lyapunov control as well as integration of power distribution networks, both of which facilitate the adaptation to large-scale network deployments.

References

[1] M. Agiwal, A. Roy, and N. Saxena, "Next Generation 5G Wireless Networks: A Comprehensive Survey," *IEEE Commun. Surveys & Tutorials*, vol. 18, no. 3, 2016, pp. 1617–55.

[2] T. Han and N. Ansari, "Powering Mobile Networks with Green Energy," *IEEE Wireless Commun.*, vol. 21, no. 1, Feb. 2014, pp. 90–96.

[3] G. Lee *et al.*, "Online Ski Rental for Scheduling Self-Powered, Energy Harvesting Small Base Stations," *Proc. IEEE ICC*, Kuala lumpur, Malaysia, May 2016.

[4] X. Chen *et al.*, "Provisioning Quality-of-Service to Energy Harvesting Wireless Communications," *IEEE Commun. Mag.*, vol. 53, no. 4, Apr. 2015, pp. 102–109.

[5] X. Chen *et al.*, "Optimal Quality-of-Service Scheduling for Energy-Harvesting Powered Wireless Communications," *IEEE Trans. Wireless Commun.*, vol. 15, no. 5, May 2016, pp. 3269–80.

[6] H. A. Inan and A. Ozgur, "Online Power Control for the Energy Harvesting Multiple Access Channel," *Proc. WiOpt*, Tempe, AZ, 2016.

[7] X. Fang *et al.*, "Smart Grid – The New and Improved Power Grid: A Survey," *IEEE Commun. Surveys & Tutorials*, vol. 14, no. 4, 2012, pp. 944–980.

[8] J. Xu, L. Duan, and R. Zhang, "Cost-Aware Green Cellular Networks with Energy and Communication Cooperation," *IEEE Commun. Mag.*, vol. 53, no. 5, May 2015, pp. 257–63.

[9] Z. Ghebretensae, J. Harmatos, and K. Gustafsson, "Mobile Broadband Backhaul Network Migration from TDM to Carrier Ethernet," *IEEE Commun. Mag.*, vol. 48, no. 10, Oct. 2010, pp. 102–09.

[10] A. Mahmood, N. Javaid, and S. Razzaq, "A Review of Wireless Communications for Smart Grid," *Renewable & Sustainable Energy Reviews*, vol. 41, 2015, pp. 248–60.

[11] R. Irmer *et al.*, "Coordinated Multipoint: Concepts, Performance, and Field Trial Results," *IEEE Commun. Mag.*, vol. 49, no. 2, Feb. 2011, pp. 102–11.

[12] X. Wang *et al.*, "Robust Smart-Grid Powered Cooperative Multipoint Systems," *IEEE Trans. Wireless Commun.*, vol. 14, no. 11, Nov. 2015, pp. 6188–99.

[13] M. Neely, *Stochastic Network Optimization with Applications to Communication and Queueing Systems*, Morgan & Claypool, 2010.

[14] X. Wang *et al.*, "Dynamic Energy Management for Smart-Grid Powered Coordinated Multipoint Systems," *IEEE JSAC*, vol. 34, no. 5, May 2016, pp. 1348–59.

[15] X. Wang *et al.*, "Two-Scale Stochastic Control for Integrated Multipoint Communication Systems with Renewables," *IEEE Trans. Smart Grid*, to appear; https://arxiv.org/pdf/1602.08805v2.pdf.

Biographies

Xiaojing Chen [S'14] received her B.E. degree in communication science and engineering from Fudan University, China, in 2013. Currently she is working toward Ph.D. degrees at both Fudan University and Macquarie University. Her research interests include wireless communications, energy-efficient communications, stochastic network optimization, and network functions virtualization. She received a National Scholarship from China in 2016.

Wei Ni [SM'15] received his B.E. and Ph.D. degrees in electronic engineering from Fudan University in 2000 and 2005, respectively. He is currently a senior scientist with the Digital Productivity and Service Flagship, CSIRO, Australia. He also holds adjunct positions with Macquarie University and the University of Technology Sydney. From 2005 to 2008, he was a research scientist and a deputy project manager with the Bell Labs R&I Center, Alcatel/Alcatel-Lucent. From 2008 to 2009, he was a senior researcher with Devices R&D, Nokia. His research interests include radio resource management, software-defined networking, network security, and multiuser MIMO. He has been the Secretary of the IEEE New South Wales Vehicular Technology Society Chapter since 2015.

Tianyi Chen [S'14] received his B. E. degree (with highest honors) in communication science and engineering from Fudan University, and his M.Sc. degree in electrical and computer engineering from the University of Minnesota (UMN) in 2014 and 2016, respectively. Since July 2016, he has been working toward a Ph.D. degree at UMN. His research interests lie in online convex optimization, stochastic optimization, and reinforcement learning with applications to future sustainable cloud networks. He received a Student Travel Grant from the IEEE Communications Society in 2013, a National Scholarship from China in 2013, and the UMN ECE Department Fellowship in 2014.

Iain B. Collings [F'15] received his B.E. degree in electrical and electronic engineering from the University of Melbourne and his Ph.D. degree in systems engineering from Australian National University in 1992 and 1995, respectively. Currently, he is a department head and professor of engineering with Macquarie University. Prior to this, he was a deputy chief (Research) with the Computational Informatics Division, CSIRO; an associate professor with the University of Sydney; and a lecturer with the University of Melbourne. He has authored over 300 research papers in the area of wireless digital communications. He served as an Editor for *IEEE Transactions on Wireless Communications* (2002–2009), and the *Elsevier Physical Communication Journal* (2008–2012).

Xin Wang [SM'09] received his B.Sc. and M.Sc. degrees from Fudan University in 1997 and 2000, respectively, and his Ph.D. degree from Auburn University, Alabama, in 2004, all in electrical engineering. From September 2004 to August 2006, he was a postdoctoral research associate with the Department of Electrical and Computer Engineering, UMN. In August 2006, he joined the Department of Computer & Electrical Engineering and Computer Science, Florida Atlantic University, where he is an associate pofessor (on leave). He is currently a Distinguished Professor with the Department of Communication Science and Engineering, Fudan University. His research interests include stochastic network optimization, energy-efficient communications, cross-layer design, and signal processing for communications. He currently serves as an Associate Editor for *IEEE Transactions on Signal Processing* and as an Editor for *IEEE Transactions on Vehicular Technology*.

Georgios. B. Giannakis [F'97] received his Diploma in electrical engineering from the National Technical University of Athens, Greece, in 1981. From 1982 to 1986 he was with the University of Southern California, where he received his M.Sc. in electrical engineering in 1983, his M.Sc. in mathematics in 1986, and his Ph.D. in electrical engineering in 1986. He was with the University of Virginia from 1987 to 1998, and since 1999 he has been a professor with UMN, where he holds an Endowed Chair in Wireless Telecommunications, a University of Minnesota McKnight Presidential Chair in ECE, and serves as director of the Digital Technology Center. His general interests span the areas of communications, networking, and statistical signal processing — subjects on which he has published more than 400 journal papers, 700 conference papers, 25 book chapters, two edited books, and two research monographs (h-index 124). His current research focuses on learning from big data, wireless cognitive radios, and network science with applications to social, brain, and power networks with renewables. He is the (co-) inventor of 30 patents issued, and the (co-) recipient of 8 best paper awards from the IEEE Signal Processing (SP) and Communications Societies, including the G. Marconi Prize Paper Award in Wireless Communications. He also received Technical Achievement Awards from the SP Society (2000) and EURASIP (2005), a Young Faculty Teaching Award, the G. W. Taylor Award for Distinguished Research from UMN, and the IEEE Fourier Technical Field Award (2015). He is a Fellow of EURASIP, and has served IEEE in a number of posts, including that of a Distinguished Lecturer for the IEEE Signal Processing Society.