Optimal Allocation of Heterogeneous Smartgrid Traffic to Heterogeneous Networks

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***Abstract*— A key element to realizing the smart energy grid of the future is the deployment of an efficient and reliable information network. An intelligent combination of wired networks (the Internet), wireless networks and power line communication networks can be used to deliver control and application messages generated by the smart grid. Integration of these three network types is non-trivial due to the distinct differences in deliverable quality of service and financial cost. Traffic assignment across these distinct networks poses a novel research problem which must be solved to realize the smart grid. Herein, an algorithm which dynamically allocates traffic with different Quality of Service requirements in terms of throughput, delay and failure probability to information networks with different performance characteristics is proposed. A detailed queueing model for the system is defined which accounts for input queues buffering smart grid packets and external applications injecting traffic into the buffers of the networks. A Lyapunov optimization based- algorithm selects the packet allocation strategy based on input/output queue states and guarantees the required QoS to the input queues while minimizing financial cost.**

I. Introduction

The current energy grid is predicted to be unable to handle the demands of a future energy delivery system. An intense research and design effort is under way to define the future energy grid, which is generally referred to as the *smart grid* [1]–[3].

The traditional energy grid is a tree-like hierarchically-controlled structure which delivers energy to consumers. A smart energy grid presumes an entirely different model. The introduction of renewable energy sources and distributed production models, the deployment of an energy market, and the implementation of demand response all require the grid to convey both *energy and information*. The increased complexity of the production and consumption model necessitates for the design of a distributed control structure operating at different scales where the different control entities can fully coordinate. Thus, the control of the grid requires the timely and reliable exchange of critical information among the control entities. In the energy market, an information network is needed to trade energy. The effective implementation of demand response requires individual households and commercial buildings to receive periodic energy pricing information.

The traffic generated to control the grid and to sustain the activity of the many connected applications is heterogeneous in terms of Quality of Service requirements (maximum delay, minimum throughput, reliability, etc.). For instance, control packets are likely small packets with stringent delay and reliability constraints, whereas large best effort packets may be routed through the network to collect energy production and consumption statistics.

The heterogeneous traffic generated by the smart grid can be routed through existing information networks, *e.g.*, internet and wireless cellular networks, or delivered through dedicated networks, *e.g.*, power line communication (PLC) networks. The various available information networks provide different performances in terms of bit rate, delay and packet delivery rate. Moreover, routing packets through existing commercial networks might be associated with a financial cost for the utility, whereas a dedicated and utility-owned information network, once deployed, routes packets without additional charge. Thus, the assignment of the heterogeneous traffic generated by the smart grid to the information networks (referred to as *output networks* in the following) is a critical design choice.

In this paper, we propose a scheduling algorithm which dynamically allocates smart grid packets to different output networks. A detailed queueing model is constructed, where smart grid traffic with different QoS requirements is buffered in different *input queues* and then assigned to the buffers of the output networks. Additional traffic is injected into the buffers of the output networks to model those scenarios in which some networks are shared with other applications (*e.g.*, internet shared with web traffic). The allocation decision is based on the state of the input and output queues, as well as on the state of the links connecting the input queues to the output networks.

The scheduling algorithm is based on Lyapunov optimization theory [4] and ensures queue stability and the required QoS while minimizing an objective function (*e.g.*, the financial cost), as long as a feasible allocation policy exists. Dynamic packet allocation offers an improved reliability with respect to static allocation, which would result into undesirable services breakdowns in case of network failure or congestion. For instance, a dynamic allocation could avoid an internet-based energy market to breakdown in case of local internet network failures or congestion by re-routing the traffic through other networks (*e.g.*, PLC networks or wireless cellular networks). Moreover, networks are subject to variations over time of the provided quality of service and might be temporarily unable to support traffic with critical QoS requirements (*e.g.*, production control packets over internet).

Packet transmission and forwarding in heterogeneous networks have been studied in prior literature [5]–[11]. Policy based routing (*e.g.*, [12], [13]) was proposed to improve

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QoS of communication networks. However, the smart grid scenario considered herein differs from those investigated in prior literature. The perspective we take is that of *allocating packets to networks* with distinct characteristics in order to meet heterogeneous QoS constraints, rather than optimizing the operations of the networks. The networks then deliver the allocated packets according to their standard protocols.

The rest of the paper is organized as follows. In Section II discusses the smart grid scenario and the main challenges in terms of information delivery among the entities of the grid. Section III describes the queueing model considered herein. The optimization algorithm is presented in Section IV. Section V provides illustrative numerical results and Section VI concludes the paper.

II. Smart Grid and Information Networks

The smart grid differs from the traditional energy grid in many aspects. We list in the following some of the key elements and issues of the smart grid.

- **Distributed production:** the diffusion of renewable energy may shift the energy production model from a scenario with a relatively small number of large production sites to a large number of small production sites spread over the territory [14]. For instance, individual households or commercial buildings may install photovoltaic panels and geothermic systems and inject in the energy grid the excess of produced energy.
- **Stochastic production:** conversely to fossil fuel-based energy production, which can be controlled by the utility, renewable energy production of most renewable sources is stochastic [15], [16]. For instance, the amount of energy produced by photovoltaic panels and eolic turbines depends on metereological variables (sun irradiation and wind speed).
- **Energy market:** whereas in the traditional energy grid there is a rigid individual seller to individual consumer market model, the distributed production model may generate an energy market in which individual producer-consumer entities trade energy on the grid. In this scenario, individual producer-consumers/producers control the amount of produced, consumed and traded energy based on utility grid and market information [17], [18]
- **Load stress:** stochastic and distributed production and price-based consumption correlate in space the availability of energy and make the grid more sensible to local overload. Coordination among local controllers is crucial to avoid local grid failures. In addition to that, the technological shift to electric vehicles is going to generate a considerable, and time-space correlated, load stress to the grid due to battery charging. Coordination among charging stations and timely load information might be critical to avoid breakdown of the utility grid [19], [20].

The control and management of the smart grid is considerably more challenging than in traditional utility grids. Stochastic and diffused production, price-based local consumption and production make control much harder than in a simple energy demand-and-delivery system. In this scenario a centralized control rationale is likely ineffective. One of the leitmotifs of smart grid is, in fact, to push intelligence to the edges of the grid, which means a distributed *local* control structure operating at different scales of the system. However, distributed control requires a certain degrees of coordination, and thus information exchange, among the control entities.

The scenario sketched above, besides the deployment of a physical *energy network*, requires the physical or logical construction of an *information network* to provide information to the control entities, as well as to support other smart grid applications. The entities of the energy grid are sources of traffic with potentially different characterization (*e.g.*, size of the packets) and Quality of Service (QoS) requirements (*e.g.*, delay, reliability, rate). For instance, distributed control may require the exchange of short packets with critical delay and reliability constraints (*e.g.*, packets triggering an injection of energy into the grid to face an unexpected increase of demand), and larger packets with relaxed delay and reliability constraints (*e.g.*, cyclic exchange of production/consumption statistics). Production sites may need to broadcast production information, whereas battery charging station may send load information. The energy market may generate delay and reliability critical packets for financial transactions and larger packets conveying pricing information. Additionally, individual households may deploy local networks to control energy consumption and production.

It is clear from the previous discussion that in order to achieve a mature smart grid technology, the information grid needs to support a wide range of services generating a heterogeneous traffic with a wide range of QoS requirements. However, the information grid might not be a physical network dedicated to the control/management of energy grid, but rather a *logical network collecting existing networks and dedicated networks*. Fractions of the huge smart grid traffic volume can be routed through internet (locally connected by wireless Local Area Networks), wireless cellular networks and Power Line Communications (PLC) networks. Clearly, each individual network has different characteristics. For instance, internet potentially has a much larger rate than PLC networks, but is shared with web traffic and subject to congestion, delay and packet dropping, whereas small rate PLC connections may be deployed on the energy grid itself and be dedicated to the management of the grid. Wireless networks are subject to fading and interference, and, again, mainly dedicated to other applications. The deployment of a dedicated network handling the whole energy-related traffic is financially challenging and unlikely, so that the part of the traffic is likely routed through existing networks, which are shared with other applications. The various services and different kind of traffics generated by the smart grid need, then, to be allocated to the different available networks, taking into account the requirements in terms of QoS of the packets and the characteristics of the networks.

III. System Model

In this section, we describe the system model considered in this paper. The system is divided into *input queues*, comprised

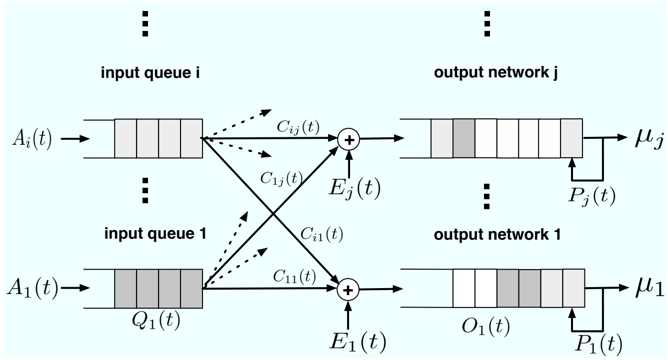

Fig. 1. System model as described in Section III.

of buffers associated with a different QoS requirement and characterization, and *output networks*, representing the various options for the delivery of the packets. The two sets are connected by links associated with a, potentially time varying channel in order to model variations in fading and capacity.

A. Queueing Model

Consider the system depicted in Fig. 1 with N_q input queues and N_o output networks. Slotted time operations are assumed, where the duration of a time slot is equal to τs. The size of the packets in the network are expressed in units corresponding to buffer slots.

The random variable $A_i(t) \in \mathcal{A}_i \subseteq \mathbb{N}_0^+$, $i{=}1,\ldots,N_q$, is equal to the number of packets injected in the input queue i in the time slot $t \in \mathbb{N}_0^+$, where $\mathbb{N}_0^+ {=} \mathbb{N}^+ \cup 0$. Packets entering the input queue i have fixed size equal to ℓ_i^q units. $Q_i(t)$ is the number of buffer slots of the input queue i which store packets at time $t\tau^+$, $i{=}1,\ldots,N_q$.

The output network j characterized by a fixed average delivery delay δ_js which represents the end-to-end delay of packets routed through the network to their destination. The interface to the output network j is composed of a queue (network queue) which buffers all the packets to be transmitted and a random variable $E_j(t)$ which represents exogenous packets of size ℓ_j^o entering the network queue at time t. The number of buffer slots storing packets in the queue of the output network j at time $t\tau^+$ is $O_j(t)$.

At the beginning of each time slot t $U_{ij}(t)$, with $i{=}1,\ldots,N_q$ and $j{=}1,\ldots,N_o$, units are removed from the input queue i and sent to the output network j, where $0 \leq U_{ij}(t) \leq \min[C_{ij}(t), Q_i(t)]$ and $C_{ij}(t)$ is the maximum number of buffer units per slot supported by the channel between input queue i and output network j. We assume that $C_{ij}(t)$ is finite for any t. Fractions of packets cannot be transferred from a buffer to another, and thus $U_{ij}(t){=}n\ell_i^q$, $n{=}0,1,\ldots$.

Once transferred to the buffer of the output network, the output network is in charge of forwarding the packet to its final destination. The framework proposed herein controls packet transfers from the input queues to the output networks, whereas packet forwarding through the network is performed according to standardized protocols which are associated with network specific delay, rate and failure probability.

Packets in the network queue j are served at rate μ_j units/slot. Packet failure and retransmission are incorporated in the model. In particular, packets originating from the input network i are retransmitted at most F_{ij} times by the output network j and that packet failure occurs with probability ρ_{ij}. similarly, exogenous packets entering the output network j are retransmitted at most F_j times and fails with probability ρ_j. The random sequences $P_j(t)$, $t \in \mathbb{N}_0^+$ track packet failures. The delivery delay associated with the output queue j is denoted by D_j. Note that in real systems, μ_j, ρ_{ij} and D_j may be time varying and need to be estimated by the controller. These aspects of the system are left for future developments of the framework.

The system described above captures the important features of the scenario of interest. Input queues model the arrival and buffering of the packets associated with the various services generated by the smart grid, with service-specific traffic volume and packet size. The exogenous stochastic traffic injected in the output networks account for the possibility that the network is shared with other local applications and may be temporarily congested. Different service rates, failure probabilities and retransmission protocols account characterize the performance of the output network. As will be detailed later, the system also allows the definition of individual input queue performance metrics to be used as objective and constraint function in the optimization problem.

B. System Dynamics

We define in the following the stochastic evolution of the variables describing the state of the system. For the sake of simplicity, it is assumed in the following that arrivals variables $A_i(t)$ and $E_j(t)$, with $i{=}1,\ldots,N_q$ and $j{=}1,\ldots,N_o$, are *i.i.d.* random variables. The inclusion in the model of correlated arrivals is left for future research.

The update rule for the number of units of traffic in the input queue i is

$$Q_i(t+1) = Q_i(t) + \ell_i^q \; A_i(t) - \sum_{j=1}^{N_o} U_{ij}(t). \tag{1}$$

Note that each packet arrival occupies ℓ_i^q buffer units.

The update rule for the number of units of traffic in the queue in the output network j is

$$O_j(t{+}1) = O_j(t) {+} R_j \ell_j^o \; E_j(t) {+} R_{ij} \sum_{i=1}^{N_q} \ell_i^q \; U_{ij}(t) {-} \mu_j, \tag{2}$$

where R_j and R_{ij} are multiplication factors accounting for retransmissions. In particular, when a packet is transferred from the input queue i to the output network j, R_{ij} replicas are created. For the sake of simplicity, we assume that the number of replicas is fixed and equal to the minimum integer larger than or equal to the average number of retransmissions, that is $\lceil R_{ij} \rceil$ where

$$R_{ij} = 1 + \sum_{f=1}^{F_{ij}} {\rho_{ij}}^f. \tag{3}$$

More sophisticated models accounting for variable per packet retransmissions can be included in the framework without significant modifications to the discussion and results. R_j is defined analogously for the exogenous traffic entering the output network j.

The variables $U_{ij}(t)$ are controlled by the system and are determined according to a randomized policy which maps the state of the system (queues and links) to packet transfers to the output queues.

C. Performance Metrics

Input queues correspond to smart grid services with different QoS requirements. In particular, individual service throughput, packet overall delay and packet failure probability are considered as performance metrics.

The throughput associated with the input queue i expressed in buffer units per time slot is the time average

$$\lim_{T\to\infty} \sup \frac{1}{T} \sum_{t=0}^{T-1} \sum_{j=1}^{N_o} E[U_{ij}(t)]\Phi_{ij}, \tag{4}$$

where $\Phi_{ij}{=}1{-}\rho_{ij}^{F_{ij}}$ is the overall success probability provided by the output network j to packets transferred from the input queue i and $E[\cdot]$ denotes expectation. Thus, the throughput is the average number of units of traffic transferred to the output networks and then successfully delivered.

The overall average delay of a packet arrived in the input queue i has three components: the waiting time in the buffer of the input queue i, the average waiting time in the buffer and the average delivery delay of the output network. Note that the three components are all functions of the transfer policy from the input queue to the output networks. In fact, the transfer policy determines the average rate at which packets are removed from the input queue, and thus the average permanence of time of the packets, but also the fraction of packets assigned to the various output networks given their buffer status. By Little's law, the average waiting time in the input queue i expressed in slots is

$$\lim_{T\to\infty} \sup \frac{1}{\lambda_i^{in} T} \sum_{t=0}^{T-1} E[Q_i(t)]. \tag{5}$$

where λ_i^{in} is the average arrival rate in units per slot $\lim_{T\to\infty} 1/T \sum_{t=0}^{T-1} \sup \ell_i^q A_i(t)$.

Given that a packet is assigned to the output network j, and that the units of traffic in the output buffer are $O_j(t)$ the time (in slots) spent by the packet before being served by the output queue is $O_j(t)\mu_j$. Therefore, the average time spent by a packet transferred from the input queue i to the output network j is

$$\lim_{T\to\infty} \sup \frac{1}{T} \sum_{t=0}^{T-1} \sum_{j=1}^{N_o} \frac{1}{\lambda_i^{in}\mu_j} E[U_{ij}(t)O_j(t)]. \tag{6}$$

The average time spent by the packet in the buffer of the various output networks is weighted by the assignment probability.

Similarly, the delivery delay of a packet needs to be averaged over the output networks as follows

$$\lim_{T\to\infty} \sup \frac{1}{T} \sum_{t=0}^{T-1} \sum_{j=1}^{N_o} \frac{1}{\lambda_i^{in}} E[U_{ij}]R_{ij}D_j. \tag{7}$$

The probability that a packet is successfully delivered to its final destination is simply

$$\lim_{T\to\infty} \sup \frac{1}{\lambda_i^{in} T} \sum_{t=0}^{T-1} \sum_{j=1}^{N_o} E[U_{ij}(t)]\Phi_{ij}. \tag{8}$$

An average financial cost can be associated to the allocation strategy if we define L_j as the cost per unit of traffic transfered. We then define

$$\lim_{T\to\infty} \sup \frac{1}{\lambda_i^{in} T} \sum_{t=0}^{T-1} \sum_{i=1}^{N_q} \sum_{j=1}^{N_o} E[U_{ij}(t)]L_j. \tag{9}$$

IV. Scheduling via Lyapunov Optimization

The performance metrics defined in the previous section are all functions of the allocation policy, which determines the amount of packets transferred from the input queues to the output networks in every time slot. We address the general problem of minimizing/maximizing one of the average performance metrics given inequality constraints on a set of others average performance metrics with guarantees on the mean rate stability of the queues in the system. Define the cost functions $y_k(t)$, $k{=}0,\dots,N_c$. The optimization problem, then, is formulated as

$$\text{Minimize} : \lim_{T\to\infty} \sup \frac{1}{T} \sum_{t=0}^{T-1} E[y_0(t)], \tag{10}$$

$$\begin{aligned}
\text{s.t.} : &\lim_{T\to\infty} \sup \frac{1}{T} \sum_{t=0}^{T-1} E[y_k(t)] {\leq} \overline{y}_k,\ \ k{=}1,...,N_c,\\
&\lim_{T\to\infty} \sup \frac{1}{T} E[Q_i(t)]{=}0,\ \ i{=}1,...,N_q,\\
&\lim_{T\to\infty} \sup \frac{1}{T} E[O_j(t)]{=}0,\ \ j{=}1,...,N_o,\\
&U_{ij}(t){\leq}C_{ij}(t),\ \ \forall i,j.
\end{aligned} \tag{11}$$

The equality constraints describe the limiting behavior of the packet arrival and departure rates from the queues. The inequality constraints force the policy to meet QoS requirements in terms of throughput, delay and delivery probability according to the metrics defined in the previous section. For instance, the cost function $y_k(t){=}\overline{\Theta}_i{-}U_{ij}(t)\Phi_{ij}$ with $\overline{y}_k{=}0$ forces the throughput of the input queue i to be larger that $\overline{\Theta}_i^{\min}$. Specific examples will be discussed in Sec. V.

We use the Lyapunov drift optimization framework proposed in [4] to optimize the allocation strategy. The optimization algorithm realizes a tradeoff between the average number of packets in the stabilized queues and the time average of the objective function. Note that the allocation policy is shown to be optimal [4] A set of *virtual* queues $Z_k(t)$ is defined. The update rule for the virtual queues is

$$Z_k(t+1) = \max(0, Z_k(t) + y_k(t) - \overline{y}_k). \tag{12}$$

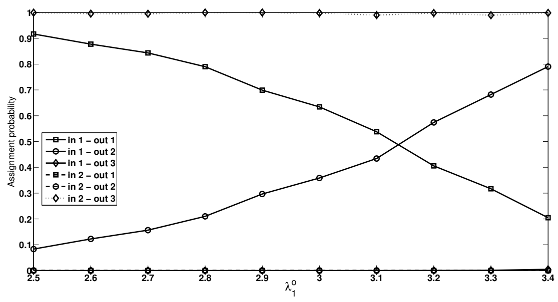

Fig. 2. Assignment rates as a function of the arrival rate in the output queue 1 from an external application (λ_1^o).

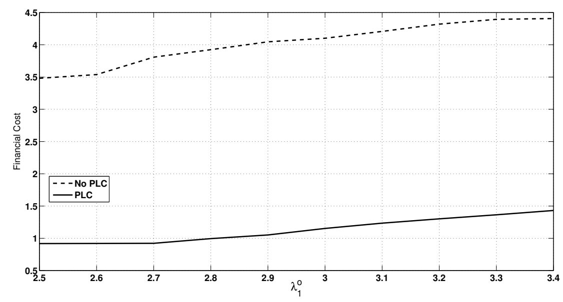

Fig. 3. Financial cost as a function of the arrival rate in the output queue 1 from an external application (λ_1^o).

Thus, virtual queues accumulate cost instead of packets.

Define the vector $\mathbf{\Theta}(t)=\{Q_i(t), O_j(t), Z_k(t)\}_{\forall i,j,k}$ and the Lyapunov function

$$L(\mathbf{\Theta}(t))=\frac{1}{2}\sum_{i=1}^{N_q} Q_i(t)^2+\frac{1}{2}\sum_{i=1}^{N_o} O_i(t)^2+\frac{1}{2}\sum_{i=1}^{N_c} Z_i(t)^2, \quad (13)$$

and the Lyapunov drift

$$\Delta(\mathbf{\Theta}(t)) = L(\mathbf{\Theta}(t+1)) - L(\mathbf{\Theta}(t)). \quad (14)$$

The allocation algorithm greedily selects the transfer variables $U_{i,j}(t) \leq \min[C_{ij}(t), Q_i(t)]$, $\forall i, j$, which minimize the drift-plus-penalty

$$\Delta(\mathbf{\Theta}(t)) + VE[y_0(t)|\mathbf{\Theta}(t)], \quad (15)$$

where V is a positive weight that realizes a tradeoff between the average queue (including virtual queues) size and the objective function. This strategy is proved to stabilize the queues while keeping the objective function within a bounded distance from the optimum. The larger V, the closer the time average of the objective function is to the optimum and the larger the average size of the real and virtual queues. As shown in [4], mean rate stability of the virtual queues guarantees the policy to meet the inequality constraints.

V. Numerical Results

In this section, numerical results are provided to illustrate how the algorithm allocates packets from the input queues to the output networks depending on the characteristics of the output networks and the QoS requirements of the input traffic. We consider a scenario with two input queues where the first and second input queue buffer large packets with relaxed delay constraints and small packets with stringent delay constraints, respectively. The output networks are:

- **output queue** 1**:** shared wired internet network with large output rate and small delivery delay. Concurrent applications inject a large amount of traffic in the output buffer. Packets sent to this output network incur a small financial cost.
- **output queue** 2**:** shared wireless networks with relatively large output rate and small delivery delay. Concurrent applications inject a large amount of traffic in the output buffer. Packets sent to this output network incur a high financial cost.
- **output queue** 3**:** dedicated PLC network with a small output rate and a large delivery delay. No concurrent applications and the packets sent to this output network incur no financial cost.

Packet arrivals in the input queue i=1, 2 are assumed Poisson with rate λ_i^{in} pkt/slot. Arrivals in the output buffer j, j=1, 2, 3 from external applications are Poisson with parameter λ_j^o pkt/slot. The objective of the algorithm is to minimize the overall financial cost while keeping the queues stable and meet constraints on the throughput and output buffer plus delivery delay.

Fig. 2 depicts the assignment rates, that is, the fraction of packets transferred from an input queue to the various output networks, as a function of λ_1^o (in the figure, the assignment rates from the input queue 2 to the output network). Fig. 3 and 4 depict the financial cost and the delay as a function of the same parameter.

If λ_1^o is small compared to the output rate of the output network 1, then the output buffer is almost empty of exogenous packets from other applications. Thus, the optimal strategy is to send all the packets from the input queue 1, which can be delivered with a relatively high delay, to the PLC network, which is the network with the largest delay, but the smallest financial cost. Delay critical packets are sent to the wired internet network, which, if the corresponding output buffer is empty, provides low latency in the output buffer and delivery delay, as well as a small financial cost.

As λ_1^o increases, the output buffer of the output network 1 fills with packets from the exogenous applications. As a consequence, the latency of the packets assigned to that output network increases. Moreover, the constraint on the stability of the output queue forces the algorithm to assign lesser packets to that output network as λ_1^o is increased. Thus, packets from the input queue 2 are redirected to the output network 2, which is more expensive, but provides lower latency and remains stable even with a larger amount of injected packets. The output buffer latency plus delivery delay of packets from the input queue 2 increases. In fact, those packets routed through the output network 1 incur a larger buffer latency, while those assigned to the output queue 1 incur an overall delay larger than those assigned to the output network 1 if λ_1^o is small.

It is possible to observe that the algorithm reacts to the increasing congestion of the output network 1, which was ini-

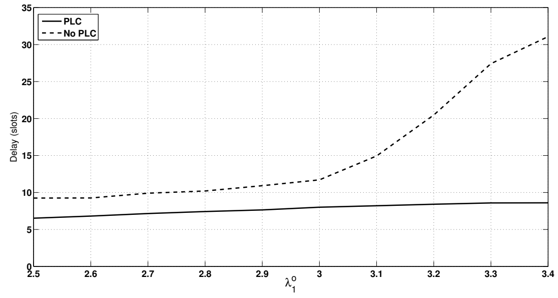

Fig. 4. Output buffer plus delivery delay of packets from the input queue 2 as a function of the arrival rate in the output queue 1 from an external application (λ_1^o).

TABLE I

SYSTEM PARAMETERS.

Arrival rates (input queues)	λ_1^{in}=λ_2^{in}=0.5 pkt/slot
Arrival rates (exogenous appl.)	λ_2^o=1.5, λ_3^o=0 pkt/slot
Packet size	ℓ_1^q=2, ℓ_2^q=1, ℓ_1^o=ℓ_2^o=ℓ_3^o=1 units
Failure probabilities	$\rho_{:,:}$=0.05
Output rates	μ_1=3.5, μ_2=2.5, μ_3=1.5units/slot
Financial cost	L_1=2, L_2=4, L_3=0dollar/unit
Maximum delay in. queue 1	20 slots
Maximum delay in. queue 2	10 slots
Minimum thr. in. queue 1	0.5 units/slot
Maximum thr in. queue 2	0.4 units/slot

tially in charge of the delivery of all the delay critical packets. A static allocation would have incurred a large delay for these packets due to large number of packets in the output queue 1. Note that for large λ_1^o the exogenous applications injecting traffic over internet would have incurred poor performance as well if a large fraction of packets were allocated from the input queues of the smart grid.

Fig. 3 and 4 also depict the financial cost and delay in a scenario in which the PLC network is not available, that is, no packets can be transferred to that output network. As λ_1^o increases, the algorithm is forced to allocate an increasing fraction of the packets to the wireless network (output queue 2), which incur a high financial cost. Moreover, the latency in the buffer of the wireless network becomes larger as more packets are injected from the input queues and the associated buffer becomes more and more congested. Note that the delay requirement of the packets from the input queue 2 is not met for high λ_1^o. The availability of more options, and especially of dedicated networks, appears to be critical to guarantee QoS to the heterogeneous traffic generated by the smart grid.

VI. CONCLUSIONS

An algorithm for the management of smart grid traffic with heterogeneous Quality of Service requirements was proposed. The algorithm, based on Lyapunov optimization theory, allocated packets to the various output networks based on the current state of the input and output buffers. The algorithm was shown to effectively assign packets to the output networks as a function of the performance profile of the output networks and the QoS requirements of the smart grid packets.

REFERENCES

[1] H. Farhangi, "The path of the smart grid," *Power and Energy Magazine, IEEE*, vol. 8, no. 1, pp. 18–28, 2010.

[2] C. Shuyong, S. Shufang, L. Lanxin, and S. Jie, "Survey on smart grid technology," *Power System Technology*, vol. 33, no. 8, pp. 1–7, 2009.

[3] R. Brown, "Impact of Smart Grid on distribution system design," in *Power and Energy Society General Meeting-Conversion and Delivery of Electrical Energy in the 21st Century, 2008 IEEE*. IEEE, 2008, pp. 1–4.

[4] M. Neely, "Stochastic Network Optimization with Application to Communication and Queueing Systems," *Synthesis Lectures on Communication Networks*, vol. 3, no. 1, pp. 1–211, 2010.

[5] M. Neely, E. Modiano, and C. Li, "Fairness and optimal stochastic control for heterogeneous networks," *Networking, IEEE/ACM Transactions on*, vol. 16, no. 2, pp. 396–409, 2008.

[6] L. Badia, M. Miozzo, M. Rossi, and M. Zorzi, "Routing schemes in heterogeneous wireless networks based on access advertisement and backward utilities for QoS support [Quality of Service based Routing Algorithms for Heterogeneous Networks]," *Communications Magazine, IEEE*, vol. 45, no. 2, pp. 67–73, 2007.

[7] T. Braun and T. Staub, *End-to-end quality of service over heterogeneous networks*. Springer, 2008.

[8] F. Berman, R. Wolski, S. Figueira, J. Schopf, and G. Shao, "Application-Level Scheduling on Distributed Heterogeneous Networks (Technical Paper)," in *proceedings of Supercomputing*, vol. 96. Citeseer, 1996, pp. 1–28.

[9] P. Goyal, S. Lam, and H. Vin, "Determining end-to-end delay bounds in heterogeneous networks," in *Network and Operating Systems Support for Digital Audio and Video*. Springer, 1995, pp. 273–284.

[10] M. Maheswaran, S. Ali, H. Siegel, D. Hensgen, and R. Freund, "Dynamic matching and scheduling of a class of independent tasks onto heterogeneous computing systems," in *hcw*. Published by the IEEE Computer Society, 1999, p. 30.

[11] P. Goyal, H. Vin, and H. Chen, "Start-time fair queueing: A scheduling algorithm for integrated services packet switching networks," in *ACM SIGCOMM Computer Communication Review*, vol. 26, no. 4. ACM, 1996, pp. 157–168.

[12] T. Lakshman and D. Stiliadis, "High-speed policy-based packet forwarding using efficient multi-dimensional range matching," in *ACM SIGCOMM Computer Communication Review*, vol. 28, no. 4. ACM, 1998, p. 214.

[13] C. Chau, "Policy-based routing with non-strict preferences," in *Proceedings of the 2006 conference on Applications, technologies, architectures, and protocols for computer communications*. ACM, 2006, pp. 387–398.

[14] G. Chicco and P. Mancarella, "Distributed multi-generation: a comprehensive view," *Renewable and Sustainable Energy Reviews*, vol. 13, no. 3, pp. 535–551, 2009.

[15] T. Hammons, "Integrating renewable energy sources into European grids," *International Journal of Electrical Power & Energy Systems*, vol. 30, no. 8, pp. 462–475, 2008.

[16] A. Mohd, E. Ortjohann, A. Schmelter, N. Hamsic, and D. Morton, "Challenges in integrating distributed energy storage systems into future smart grid," in *Industrial Electronics, 2008. ISIE 2008. IEEE International Symposium on*. IEEE, 2008, pp. 1627–1632.

[17] A. Chuang and M. McGranaghan, "Functions of a local controller to coordinate distributed resources in a smart grid," in *Power and Energy Society General Meeting-Conversion and Delivery of Electrical Energy in the 21st Century, 2008 IEEE*. IEEE, 2008, pp. 1–6.

[18] D. O'Neill, M. Levorato, A. Goldsmith, and U. Mitra, "Residential Demand Response Using Reinforcement Learning," in *Smart Grid Communications (SmartGridComm), 2010 First IEEE International Conference on*. IEEE, 2010, pp. 409–414.

[19] A. Brahma, Y. Guezennec, and G. Rizzoni, "Optimal energy management in series hybrid electric vehicles," in *American Control Conference, 2000. Proceedings of the 2000*, vol. 1, no. 6. IEEE, 2000, pp. 60–64.

[20] K. Turitsyn, N. Sinitsyn, S. Backhaus, and M. Chertkov, "Robust Broadcast-Communication Control of Electric Vehicle Charging," in *Smart Grid Communications (SmartGridComm), 2010 First IEEE International Conference on*. IEEE, 2010, pp. 203–207.