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Towards Cross-Layer Design of Communication Network for Smart Grid with Real-Time Pricing

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***Abstract*—The efficiency of the emerging smart power grid infrastructure critically depends on the ability of the communication network to deliver real-time energy prices to the consumers. This paper's contribution is twofold. First, it derives the relevant Quality of Service (QoS) communication requirements and proposes the corresponding overall performance criterion for the communication network, which quantifies the negative effect of delaying energy pricing information on the grid operations. Second, this paper demonstrates that the conventional Network Utility Maximization (NUM) based cross-layer optimization framework can be enhanced to incorporate the specific requirements of the smart power grid infrastructure. The conventional NUM based cross-layer network optimization balances tradeoffs between bandwidth requirements of multiple users, given limited network resources. The proposed enhanced NUM also allows the system to balance user requirements for (a) communication reliability by taking advantage of multipath routing in presence of network outages, and (b) communication delays by taking advantage of priority packet scheduling. Future research should quantify advantages of the proposed robust and QoS-aware NUM as compared to the conventional NUM for specific operation scenarios of the smart power grid infrastructure.**

Keywords—smart power grid; real-time pricing; communication network; cross-layer optimization

I. Introduction

The emerging smart power grid infrastructure is expected to optimize power production, consumption, and distribution by taking advantage of the real-time energy pricing [1]-[3]. However, these expectations critically depend on the ability of the communication network to guarantee timely delivery of the pricing information to the customers. This paper's contribution is twofold. First, it derives the relevant Quality of Service (QoS) communication requirements and proposes the corresponding overall performance criterion for the communication network, which quantifies the negative effect of delaying energy pricing information on the grid operations. Second, this paper demonstrates that the conventional Network Utility Maximization (NUM) based cross-layer optimization framework can be extended to incorporate at least some specific requirements of the smart power grid.

Following [1]-[3] we assume that strategic power consumers attempt to maximize their net utilities, which are the difference between utilities of the consumed energy and the energy cost. Communication delay results in the aggregate net utility loss due to outdated pricing information. We estimate this loss using the Market Efficiency Hypothesis (MEH) [4] and assuming small communication delays. Then we propose cross-layer optimization framework for the communication network intended to minimize this loss in presence of potential network outages.

This optimization framework can be viewed as an enhancement of both, QoS routing for smart grid proposed in [3] and the conventional NUM for cross-layer network optimization [5]-[6], which balances tradeoffs between bandwidth requirements of multiple users given network resources. The main advantage of the proposed in this paper robust, QoS-aware NUM is in its ability to balance user requirements for (a) communication reliability by taking advantage of multipath routing in presence of network outages, and (b) communication delays by taking advantage of priority packet scheduling. The proposed optimization framework can be implemented with an appropriately designed Multipath TCP/IP in combination with Active Queue Management (AQM) [7].

Tractability of the enhanced cross-layer optimization is due to M/G/1 approximation, which assumes statistical independence of queues on different links. This approximation, known as M/G/1 hypothesis, has been widely used for First In First Out (FIFO) queues in wireline networks [8]. Since then the M/G/1 hypothesis has been shown to be asymptotically correct when the arriving flow on each link is a sum of a large number of "small" flows from adjacent links and thus can be approximated by Poisson process. Numerous simulations demonstrated applicability of the M/G/1 hypothesis in practical situations. Application of the M/G/1 hypothesis to priority queues in wireless networks has been proposed in [9].

The paper is organized as follows. Section II quantifies the impact of communication QoS on the smart power grid performance. Section III maps these communication QoS requirements into the network-level parameters by expressing the corresponding QoS parameters as functions of the network resource allocation. Section IV proposes distributed cross-layer network optimization aimed at minimization of the aggregate expected loss. The important features of this optimization are taking advantage of multipath routing and priority traffic scheduling to mitigate communication outages and communication delays respectively. Finally, the conclusion summarizes and discusses directions of future research.

II. Communication Performance

This section quantifies the impact of communication QoS on the smart power grid performance. We assume strategic energy consumers who draw certain utility from consuming energy. Each consumer attempts to maximize the net utility, which is the difference between the drawn utility and the cost. Since energy price fluctuates, communication delays and outages result in suboptimal decisions by energy consumers. Subsection A quantifies energy consumer losses due to outdated power pricing information. Subsection B derives flow and packet level communication utilities.

A. Impact of Outdated Energy Prices

Following [1]-[3] we assume that a decision on power consumption by consumer s is based on minimization of the individual net utility

$$x_s = \arg\max_{x\geq 0}[u_s(x) - px] \tag{1}$$

where $u_s(x)$ is the consumer s utility of consuming instantaneous power x and p is the corresponding energy price. We assume utilities $u_s(x)$ to be increasing, strictly concave and continuously differentiable functions with $u'_s(\infty) = 0$. Then, the optimal power consumption level is given by $x_s(p) = u_s^{-1}(p)$.

However, in real life the instantaneous energy prices are not known to the consumers since (a) power prices are random due to numerous factors, e.g., fluctuations in the power generation and consumption levels, and (b) unavoidable delays in the communicating of the real-time prices to the consumers. In the rest of this subsection we quantify inefficiencies in the levels of power consumption due to these delays. According to the Market Efficiency Hypothesis (MEH) [4], we assume that on the time scale of interest, energy price follows a Brownian motion:

$$p(t+\tau) = p(t) + \omega\eta(\tau) \tag{2}$$

where $\eta(\tau)$ is the Wiener process, parameter $\omega > 0$ characterizes price volatility, and τ is the delay in communicating the real-time prices. Note that the assumption of "short" delays ensures price non-negativity.

The consumer s net utility loss due to the delay τ in communicating the real-time pricing information is

$$\begin{aligned} L_s = [u_s(x_s^{opt}) - (p+\omega\eta(\tau_s))x_s^{opt}] \\ -[u_s(\tilde{x}_s) - (p+\omega\eta(\tau_s))\tilde{x}_s] \end{aligned}, \tag{3}$$

where the "optimal" energy consumption level $x_s^{opt} = u_s^{-1}(p+\omega\eta(\tau_s))$ is based on the instantaneous price $p+\omega\eta(\tau_s)$, and the "estimated" energy consumption $\tilde{x}_s = u_s^{-1}(p)$ is based on the "best" estimate of the unknown instantaneous price $\tilde{p} = p$. Since this loss is random due to randomness in the price evolution even for deterministic delays τ, we consider the consumer s average loss $\tilde{L}_s(\tau_s) := E[L_s|\tau_s]$ conditioned on the delay τ_s, and characterize the aggregate average conditional loss as the sum of all the corresponding consumer losses: $\tilde{L}(\tau) := \sum_s \tilde{L}_s(\tau_s)$, where vector $\tau = (\tau_s)$.

Expanding the consumer utility about the estimated energy consumption and leaving the first three terms:

$$u_s(x) \approx u_s(\tilde{x}) + u'_s(\tilde{x})(x-\tilde{x}) + [u''_s(\tilde{x})/2](x-\tilde{x})^2 \tag{4}$$

we obtain the following approximations for the "optimal" energy consumption:

$$x_s^{opt} \approx \tilde{x}_s + y_s \tag{5}$$

and consumer net utility loss:

$$L_s \approx u'_s(\tilde{x})y_s + (1/2)u''_s(\tilde{x})y_s^2 - [p+\omega\eta(\tau_s)]y_s, \tag{6}$$

where

$$y_s = \omega\eta(\tau_s)/u''_s(\tilde{x}_s). \tag{7}$$

Averaging (6) over $\dot{\eta}(\tau_s)$ for a given τ_s, and taking into account that $E[y_s] = 0$ and $E[\eta^2(\tau_s)] = \tau_s$, we obtain the following estimate for the average consumer net utility loss:

$$\tilde{L}_s = -\tau_s/u''_s(\tilde{x}_s). \tag{8}$$

In (8) we got rid of multiplicative constant $\omega^2/2$ by appropriate scaling consumer utilities. Note that since $u''_s(\tilde{x}_s) < 0$, average net utility loss (8) is non-negative.

B. Communication QoS Utility

We assume that pricing information is delivered by a store-and-forward packet communication network, and thus a consumer relies on the price delivered by the last received packet. In a case of a regular stream of packets of rate f_s, the pricing information delivered by the last packet to consumer s contains price, on average having latency $1/(2f_s)$. On top of this latency, a user is faced with the random packet delay d_s due to finite propagation time, communication channel impairments, queuing delays, etc. Note that loss (8) depends on both flow and packet level communication network performance metrics.

Increase in the flow rate increases packet delays creating a tradeoff between flow and packet level performances for each user. There are also tradeoffs between performances of different users. These tradeoffs can be quantified by combining individual losses/utilities into an aggregate utility to be optimized over communication resource allocation. The specific definition of combined loss/utility should on the one hand be relevant to practical needs, and on the other hand should produce tractable solutions. Straightforward combination of flow and packet level losses by adding $1/(2f_s)$ and $E[d_s]$ appears to be objectionable mostly due to relevancy. Indeed, our derivation of losses assumed small latency of pricing information. However, high packet delay volatility due to communication outages or heavy load may violate this assumption.

We alleviate these concerns by combining flow and packet level losses with a heavier weighting assigned to packet-level losses. This approach can be justified in heavy load regime, when packet delays are distributed exponentially, and thus larger weights to the average packet delays can be linked to the corresponding level of confidence. Following this line of reasoning we construct the aggregate performance criterion as follows. The aggregate loss due to the real-time price sampling error is:

$$Loss_f := \sum_s (\alpha_s / f_s), \qquad (9)$$

and the aggregate loss due to packet delay by the corresponding weighted average packet delay:

$$Loss_d := \sum_s \alpha_s f_s \tilde{d}_s, \qquad (10)$$

where $\alpha_s := -1/u_s''(\tilde{x}_s)$ and $\tilde{d}_s := E[d_s]$. The combined aggregate loss $Loss := Loss_f + \gamma Loss_d$ is

$$Loss = \sum_s \alpha_s[(1/f_s) + \gamma f_s \tilde{d}_s], \qquad (11)$$

where the parameter $\gamma \geq 1$ quantifies the relative weighting of packet vs. sampling delays.

In practice packets may be significantly delayed or even lost due to communication outages. We model this possibility by assuming that while d_s characterizes packet delays on short time scale, communication outages are described by assuming that flow rates f_s are random on the long time scale. The corresponding averaged loss (9) is

$$\tilde{L}oss_f := \sum_s \alpha_s E[1/f_s]. \qquad (12)$$

The loss (12) becomes infinite in a case of outages $f_s = 0$. This is an artifact of our assumption of small delays. In practice, in a case of outage, losses are finite since communication may recover and during outages consumers may rely on the static pricing. Thus we assume the random flow rates f_s are always low bounded away from zero: $f_s \geq \breve{f}_s > 0$.

In a normal operating network, the relative variability of flow rates is small: $\sigma_s / \tilde{f}_s << 1$, where $\tilde{f}_s := E[f_s]$ and $\sigma_s^2 := E[(f_s - \tilde{f}_s)^2$. In this case the flow-level loss (12) can be approximated as follows:

$$\tilde{L}oss_f \approx \sum_s \alpha_s \left(\frac{1}{\tilde{f}_s} + \frac{\sigma_s^2}{\tilde{f}_s^3} \right). \qquad (13)$$

Due to time scale separation, we approximate the long time scale aggregate packet-level loss as follows

$$\tilde{L}oss_d := \sum_s \alpha_s \tilde{f}_s \tilde{d}_s(\tilde{f}), \qquad (14)$$

where $\tilde{d}_s(\tilde{f}) := E[d_s | f = \tilde{f}]$ is the average packet delay conditioned on the flow vector $f = \tilde{f}$. The combined long-term aggregate loss $\tilde{L}oss := \tilde{L}oss_f + \gamma \tilde{L}oss_d$ is

$$\tilde{L}oss \approx \sum_s \alpha_s \left(\frac{1}{\tilde{f}_s} + \frac{\sigma_s^2}{\tilde{f}_s^3} + \gamma \tilde{f}_s \tilde{d}_s(\tilde{f}) \right). \qquad (15)$$

III. Network Utility

The losses (13) and (14) represent QoS-level negative utilities at the flow and packet levels respectively. Network Utility Maximization (NUM) based cross-layer network optimization aims at minimizing these losses, given network resources. However, performing this optimization requires first mapping QoS-level utilities into network-level utilities by expressing the corresponding QoS parameters, i.e., aggregate flows f_s and packet delays d_s, as functions of the network resource allocation. Subsections A and B provide mappings for flow and packet level QoS parameters respectively.

A. Flow-level Utility

We assume that communication network delivers real-time pricing information to each user $s \in S$ over a set of feasible routes $r \in R_s$, each route r being a collection of links $l \in r$. Assuming that each link is either operational or non-operational, we obtain the following expression for consumer s aggregate information flow:

$$f_s = \max\left\{ \breve{f}_s, \sum_{r \in R_s} f_{sr} \left(1 - \prod_{l \in r} (1 - \delta_l) \right) \right\}, \qquad (16)$$

where $f_{sr} \geq 0$ is user s flow rate over route r, binary variable $\delta_l = 0$ if link l is operational and $\delta_l = 1$ otherwise.

The average aggregate flow rate for user s can be approximated as follows:

$$\tilde{f}_s \approx \max\left\{ \breve{f}_s, \sum_{r \in R_s} f_{sr} E\left[\prod_{l \in r} (1 - \delta_l) \right] \right\}. \qquad (17)$$

The variance of the aggregate flow rate for user s is

$$\sigma_s^2 = \sum_{r\in R_s} f_{sr}^2 \sum_l \bar{\delta}_l (1-\bar{\delta}_l) + \sum_{r_1, r_2 \in R_s} f_{sr_1} f_{sr_2} \sum_{l\in r_1 \bigcap r_2} \bar{\delta}_l (1-\bar{\delta}_l), \tag{18}$$

where $\bar{\delta}_l := E[\delta_l]$. In a typical case of low link outage probabilities, $\bar{\delta}_l << 1$, and sufficiently high aggregate flow rate: $\sum_{r\in R_s} f_{sr}\left(1-\sum_{l\in r}\bar{\delta}_l\right) > \breve{f}_s$, expression (17) simplifies as follows:

$$\tilde{f}_s \approx \sum_{r\in R_s} f_{sr}\left(1-\sum_{l\in r}\bar{\delta}_l\right). \tag{19}$$

B. Packet-level Utility

Since the average packet delay for user s conditioned on the current set of flows (f_{sr}) is the weighted sum of the corresponding averages delays over all feasible routes $r \in R_s$, and the average delay over each route r is the sum of the corresponding average delays $\tilde{d}_l$ over all links $l \in r$, we have:

$$\tilde{d}_s(f) = \frac{1}{f_s}\sum_{r\in R_s} f_{sr} \sum_{l\in r} \tilde{d}_{sl}(f), \tag{20}$$

where $f = (f_{sl})$ is the vector of current flows, and average delay for a consumer s packet on a link l is the sum of the propagation time θ_l and average queuing time $w_{sl}(\tilde{f})$: $\tilde{d}_{sl}(\tilde{f}) = \theta_l + w_{sl}(\tilde{f})$. For simplicity we further assume that $\theta_l << w_{sl}(\tilde{f})$, and thus

$$\tilde{d}_s(f) \approx \frac{1}{f_s}\sum_{r\in R_s} f_{sr} \sum_{l\in r} w_{sl}(f). \tag{21}$$

The generalization is straightforward.

Substituting (21) into (14) we obtain the following approximation for the long time scale aggregate packet-level loss:

$$\widetilde{Loss}_d \approx \sum_s \alpha_s \sum_{r\in R_s} \tilde{f}_{sr} \sum_{l\in r} w_{sl}(\tilde{f}). \tag{22}$$

Generally, average queuing delays on a link l depend on the entire flow vector $\tilde{f}$ since queues at different links are statistically interdependent. Fortunately, empirical observations, simulations, and some analytical results suggest that for practical purposes discounting these interdependencies results in acceptable approximation. Moreover, queues at different links can be approximated by jointly statistically independent queues with Poisson incoming streams of requests. This approximation under the name M/G/1 hypothesis has been widely used for First In First Out (FIFO) queues in wireline networks starting with [8]. Application of the M/G/1 hypothesis to priority queues in wireless networks has been proposed in [9]. One may expect that the M/G/1 approximation is applicable when arriving flow on each link is a sum of a large number of "small" flows from adjacent links and thus can be approximated by a Poisson process.

Given the priority mechanism implementation, the average queuing delay w_{sl} under M/G/1 approximation is a function of the vector of flows passing through directed link l: $\tilde{w}_{sl} = \tilde{w}_{sl}(\tilde{g}_l)$, where $\tilde{g}_l := (\tilde{g}_{sl})$ and $\tilde{g}_{sl} := \sum_{r:l\in r} \tilde{f}_{sr}$. Changing the order of summation in (22) we obtain

$$\widetilde{Loss}_d \approx \sum_l \varphi_l(\tilde{g}_l), \tag{23}$$

where

$$\varphi_l(\tilde{g}_l) := \sum_s \alpha_s \tilde{g}_{sl} w_{sl}(\tilde{g}_l). \tag{24}$$

In a case of FIFO scheduling, all packets experience the same average queuing delay

$$\tilde{w}_{sl} = \frac{\rho_l b_l^2}{2(c_l - \tilde{g}_l^{agg})}, \tag{25}$$

which depends on the link l capacity c_l, aggregate load $\tilde{g}_l^{agg} = \sum_i \tilde{g}_{il}$, utilization $\rho_l = \tilde{g}_l^{agg}/c_l$, and parameter $b_l^2 \geq 1$ characterizing the variability of link l throughput per packet.

In this subsection, we have demonstrated that M/G/1 approximation allows one to estimate the average waiting times w_{sl} making network performance evaluation computationally tractable. In addition to that, the M/G/1 Conservation Law [8] allows one to quantify constraints on the average waiting times w_{sl}, and thus on the packet-level network performance, given a flow vector $(\tilde{f}_{sr})$. Assuming for simplicity that packet sizes do not depend on the recipient consumer, the M/G/1 Conservation Law [8] states that

$$\sum_s \rho_{sl} w_{sl} \geq \frac{\rho_l W_l}{1-\rho_l}, \tag{26}$$

where link l utilization by consumer s traffic is $\rho_{sl} = \tilde{g}_{sl}/c_l$, link l aggregate utilization is $\rho_l = \sum_s \rho_{sl} < 1$, link l capacity is c_l, and W_l is a constant, which does not depend on the packet scheduling discipline on link l. Note that a generalization of (26) allowing for $\rho_l \geq 1$ is possible [8].

IV. Towards Cross-Layer Network Optimization

This Section proposes distributed cross-layer network optimization aimed at minimization of the aggregate expected loss. Due to time scale separation, Subsection A proposes to implement this optimization as follows. On the short time scale, the loss is minimized over packet scheduling for given current flow rates and subject to the capacity constraints. On the long time scale, the loss is minimized over flow rates. Subsection B discusses the packet scheduling optimization, and Subsection C discusses the flow optimization, which includes congestion control and routing.

A. Cross-Layer Optimization Problem

Combining (15) with (23)-(24) we obtain the expression for the aggregate loss $Loss := Loss_f + \gamma Loss_d$,

$$\widetilde{L}oss \approx \sum_s \alpha_s \left(\frac{1}{\widetilde{f}_s} + \frac{\sigma_s^2}{\widetilde{f}_s^3} \right) + \gamma \sum_l \sum_s \alpha_s \widetilde{g}_{sl} w_{sl} \,. \quad (27)$$

We formalize cross-layer network optimization as the following optimization problem:

$$\min_{(\widetilde{f}_{sr}),(w_{sl})} \widetilde{L}oss \quad (28)$$

subject to (18)-(19), (27). Note that waiting times w_{sl} in (27) play the role of penalty functions preventing violation of the link capacity constraints.

Due to time scale separation, the solution to the optimization problem (28) can be implemented in two steps as follows. In the short time scale, given set of current link flows (g_{sl}), packet scheduling on each link l is determined by the solution to the following optimization problem:

$$\varphi_l(g_{sl}) := \min_{(w_{sl})} \sum_s \alpha_s g_{sl} w_{sl} \quad (29)$$

subject to constraints (26). Then the optimal set of flows (f_{sr}) is determined by the solution to the following optimization problem:

$$\min_{(f_{sr})} \left\{ \sum_s \alpha_s \left(\frac{1}{\widetilde{f}_s} + \frac{\sigma_s^2}{\widetilde{f}_s^3} \right) + \gamma \sum_l \varphi_l \left(\sum_{r:l \in r} \widetilde{f}_{sr} \right) \right\} \quad (30)$$

subject to constraints (18)-(19).

B. Packet Scheduling

Solution to optimization problem (29) is known within various classes of scheduling discipline [8]. For example, in widely used class of Head-Of-the-Line (HOL) scheduling disciplines, optimization (29) yields HOL priority scheduling which assigns higher priority to traffic flows with higher packet importance α_s [8]. Despite this explicit solution to (29), two major issues require more research. First, it is costly to implement a queue supporting a large number of priorities. In practice the number of priority classes K is much smaller than the number of consumers, and the question is how to assign consumers to different priority classes. A second issue is security, which in particular requires flow separation to mitigate the effect of denial-of-service attacks. The rest of this subsection briefly discusses these issues.

The question becomes how to map users s into priority classes k for each link l: $k_l(s)$. Without loss of generality we assume that all users s are arranged in the order of non-decreasing packet importance α_s: $\alpha_1 \le \alpha_2 \le \ldots$. It is clear that at each link l, user j packets should have at least as high priority as user i packets if $\alpha_i \le \alpha_j$. This implies that for each link l, $k_l(s)$ is a non-decreasing function of user $s = 1,..,S$, such that $k_l(1) = 1$ and $k_l(S) = K$. An open question is identifying "the border" users s_l^* for each link l, such that $k_l(s_l^* + 1) = k_l(s_l^*) + 1$. Our conjecture is that reasonably good flow aggregation into priority classes can be obtained by balancing the "priority class weights" $\sum_{s=s_l^*}^{s_l^*+1} \alpha_s g_{sl}$. The same general approach applies to other types of priorities allowing some degree of traffic separation intended to mitigate effect of denial of service attacks. Here we only note that while the "optimal" traffic separation can be achieved with Leaky Bucket Regulators (LBR) [10]-[11], optimal selection of the LBR parameters is a difficult problem [12].

C. Flow Control & Routing

In a scenario without communication outages: $\sigma_s^2 = 0$, $\forall s$, optimization problem (30) takes the following form:

$$\min_{(f_{sr})} \left\{ \sum_s \frac{\alpha_s}{f_s} + \gamma \sum_l \varphi_l \left(\sum_{r:l \in r} f_{sr} \right) \right\}, \quad (31)$$

subject to (29). This is a particular case of $(2, \alpha_s)$-fair resource allocation [14]-[15] with $\beta = 2$ and the solution to this optimization problem is

$$f_{sr}^* = \left(\alpha_s \Big/ \gamma \sum_{l \in r} q_l^* \right)^{1/2}, \; r \in R_s^* \subseteq R_s \,, \quad (32)$$

and $f_{sr}^* = 0$ for $r \notin R_s^*$, where R_s^* is the set of feasible minimum cost routes, and the link costs are defined as follows:

$$q_l^* = [d\varphi_l(y)/dy] \Big|_{y=\sum_{r:l \in r} f_{sr}^*} \quad (33)$$

with appropriately defined link costs.

Equations (32)-(33) form a closed system of equations which yields unique solution for the optimal link costs (33) and optimal flows (32) on the minimum cost routes [13]-[14]. This solution (32)-(33) can be implemented in a distributed way by a combination of adaptive, state-dependent, minimum cost routing and specific form of Transmission Control Protocol (TCP), which is known as TCP-Reno, and Active Queue Management (AQM) [7], [13]-[14].

The scenario with communication outages is significantly more complex since parameters σ_s^2 depend on flow vector

(f_{sr}). Intuition suggests that the result of optimization (30) should include multipath routing, which mitigates communication outages [15]-[19]. However, this beneficial effect of multipath routing is achieved as a result of using "non-optimal" routes, and thus creates a tradeoff reducing the throughput or increasing the delay.

It is possible to increase robustness/resilience further by sending redundant information over multiple routes. Some initial approaches to managing these tradeoffs have been discussed in [19]. In the context of smart grid communication, the approach [19] implies replacing in the flow-level loss (13) the average aggregate flow rates $\tilde{f}_s$ with "reliable rates" $\hat{f}_s := \tilde{f}_s - \chi_s \sigma_s$, where parameter $\chi_s \geq 0$ quantifies consumer s preference for reliable communication. This transforms problem (30) into the following optimization problem

$$\min_{(f_{sr})} \left\{ \begin{aligned} & \sum_s \alpha_s \left(\frac{1}{\tilde{f}_s - \chi\sigma_s} + \frac{\sigma_s^2}{(\tilde{f}_s - \chi\sigma_s)^3} \right) \\ & + \gamma \sum_l \varphi_l \left(\sum_{r:l\in r} \tilde{f}_{sr} \right) \end{aligned} \right\}. \quad (34)$$

V. CONCLUSION

This paper discusses some possible extensions of conventional Network Utility Maximization (NUM) based cross-layer communication network optimization intended to ensure timely delivery of real-time energy pricing information to intended recipients in smart power grid. While conventional NUM allows for balancing different user requirements for the limited bandwidth, incorporating specific smart power grid QoS requirements is a challenging problem. Packet scheduling can mitigate communication delays due to short time scale congestion. However, communication outages due to failures of unreliable network elements can be mitigated with multipath routing. Sending packet streams over multiple routes may preserve at least a portion of the information stream even when some network links or nodes fail. It is possible to increase resiliency even further by employing route diversity coding, i.e., sending redundant data over different routes.

Multipath routing, especially in combination with diversity coding, mitigates the communication outages at the cost of reducing information throughput or increasing communication delay due to limited networking resources. The described in this paper approach to balancing these tradeoffs requires mapping the specific consumers QoS requests into combination of network resources required to implement the requested QoS. Assuming that each consumer's preferences can be characterized by some utility function, the goal of balancing competing requirements for each user as well as across different users is to maximize the system aggregate utility.

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