Adaptive Transmission Scheduling in Time-Varying Underwater Acoustic Channels

Zhaohui Wang, Chaofeng Wang, and Wensheng Sun

Dept. of Electrical and Computer Engineering, Michigan Technological University, Houghton, MI 49931, USA

***Abstract*—We consider an underwater acoustic communication system where each packet arrives periodically at the transmitter, and is required to be sent to the receiver under an individual and predetermined delay constraint. Given the high temporal dynamics of underwater acoustic channels, it is desirable to adapt the transmission schedule to channel conditions for transmission energy efficiency. With a goal of minimizing the total packet transmission energy consumption, and assuming perfect and non-causal channel knowledge, a waterfilling algorithm is developed to recursively determine the optimal transmission schedule of each packet. Given the channel causality in practical systems, we focus on a particular type of underwater acoustic channels that exhibit periodic dynamics, and apply the Holt-Winters approach for channel prediction. An online scheduling algorithm is designed to decide the optimal action of each time slot (i.e., to transmit or hold the packet on the top of the transmitter packet queue) based on the predicted channel condition in future time slots and the packet queue status. The proposed algorithms are evaluated in simulated channels and using channel measurements from field experiments. Numerical results demonstrate that the proposed algorithms yield considerable transmission energy saving relative to a benchmark method that transmits each packet upon its arrival.**

***Index Terms*—Transmission scheduling, underwater acoustic channels, energy efficiency, channel prediction.**

I. Introduction

Acoustic communication can be used for wireless information transfer in a wide range of aquatic operations. Due to limited battery power supply and large energy consumption of acoustic transmissions, energy efficiency is crucial for long-term underwater acoustic system operation [1]. In this work, we consider energy-efficient packet transmission scheduling in the long-term and light-traffic underwater acoustic systems (e.g., underwater static acoustic sensor networks for scientific data collection). Two typical characteristics of such systems are exploited: first, the arrival of sampling data packets is predictable; and secondly, the data packets are often delay tolerant hence could be stored at the source node and transmitted in good channel conditions. Given the large temporal dynamics of underwater acoustic channels, adapting transmission scheduling to the channel dynamics is expected to yield considerable energy saving [2], [3].

Channel-aware transmission scheduling has been extensively investigated in terrestrial radio networks. Existing works differ in one or several aspects, such as the channel model, the data traffic model, the packet delay constraint, or the approach to finding the optimal solution [3]. Assuming independently and identically distributed (i.i.d.) channel states at different time slots, a channel-aware scheduling scheme is developed in [4] to allocate information bits of a data packet to different transmission time slots under a packet delay constraint, where the optimal number of bits to be allocated to a slot is determined by the number of remaining time slots and the channel state of this slot. In [5], assuming a prior knowledge of the long-term channel transmission loss and a short-term channel statistical distribution, opportunistic transmission scheduling of a packet under a delay constraint is investigated based on the optimal stopping theory, and threshold policies are developed to determine the optimal action (i.e., to transmit or hold the packet) in each time slot. In [6], under a finite-state Markov channel (FSMC) model, energy-optimal transmission scheduling is studied to transmit a batch of data packets before a common deadline. The problem is solved via dynamic programming and different levels of the channel state information (CSI) at the transmitter are considered. The work in [7] also assumes a FSMC model and considers the transmission of a packet batch under a common deadline. It formulates the scheduling problem as a Markov Decision Process (MDP) that minimizes the total transmission cost and a penalty on packet loss. A threshold policy is developed using the concept of supermodularity. In [8], a channel prediction-aware scheduling algorithm is developed for downlink transmission in the cellular network, where the active user in each time slot is determined based on the current channel estimate and the channel prediction in future time slots, with a goal of improving the tradeoff between system throughput and user fairness.

Compared to radio networks, studies on transmission scheduling in underwater acoustic networks have been limited. Assuming a FSMC model and a non-negligible cost of sending channel probing sequences, [3] studies energy-efficient scheduling to transmit a batch of packets with a common deadline, aiming to minimize the transmission attempts of both data packets and probing sequences, where each attempt consumes a fixed amount of energy. The above work is extended in [9] when partial data queue state information is available at each time slot. For the uplink transmission in an underwater acoustic cluster network, a channel-dependent time slot allocation scheme is proposed in [2] to maximize the overall network throughput, where the number of slots allocated to an ordinary node is determined by the packet error rate of each ordinary node's transmission to the cluster head.

In this work, we consider an underwater point-to-point acoustic communication system where data packets arrive periodically at the data queue of the source node (e.g., information bits from sensor readings), and each data packet is

978-0-933957-43-5 ©2015 MTS

required to be delivered to the receive node under an individual and predetermined delay constraint. To exploit the acoustic channel dynamics, channel-adaptive transmission scheduling will be investigated to minimize the total packet transmission energy under the packet delay constraint. First, assuming a perfect and noncausal CSI knowledge (including the CSI in the past, current, and future time slots), we develop a recursive waterfilling algorithm to determine the optimal transmission schedule, which establishes the scheduling energy efficiency performance upper bound, and provides insights into the relationship between the optimal action of each slot and the CSI at different slots. In practical systems, the channel-adaptive scheduling is constrained by the channel causality, namely, the transmitter can only access the CSI of the past and current time slots. Nevertheless, underwater acoustic channels exhibit temporal coherence that can be leveraged for channel prediction [10], [11]. In this work, we focus on a particular type of channels that exhibit periodic dynamics (e.g., diurnal variations), and apply the Holt-Winters approach [12] for channel prediction. An online transmission scheduling scheme is then designed to determine the optimal action of each time slot based on the channel prediction in future time slots and the data packet queue status. The developed algorithms will be evaluated via simulated channels and channel measurements from field experiments. Numerical results demonstrate that adapting transmission schedule to channel dynamics can significantly reduce the packet transmission energy consumption.

The rest of the paper is organized as follows. The system model for channel-adaptive transmission scheduling is described in Section II. Assuming perfect and noncausal channel knowledge, the recursive waterfilling algorithm for optimal transmission scheduling is developed in Section III. The online algorithms that perform channel prediction and channel-adaptive transmission scheduling in practical systems are described in Section IV. Performance evaluation of developed algorithms is presented in Section V. Conclusions are drawn in Section VI.

II. System Model

We consider a point-to-point underwater acoustic transmission system which operates in a time-slotted fashion. Denote T as the duration of each time slot, and define k as the time slot index with the first slot denoted by $k = 0$. The starting time of the kth slot is $t_k := kT$. In every G time slots, a data packet arrives at the transmitter data queue in the beginning of a time slot, and will be transmitted in the current or following time slots within one time slot duration on a first-in-first-out (FIFO) basis. Assume that the first packet arrives at the time slot $k = 0$, and the arrival time slot of the mth packet is $g_m := (m-1)G$. Each packet is required to be delivered under a delay constraint of D time slots upon its arrival, namely, the transmission deadline of the mth packet is $d_m := g_m + D$. Once a packet is delivered, it will be removed from the data queue. The channel is assumed time-invariant within each time slot and could vary across time slots. A short pulse is sent by the receiver at the beginning of each time

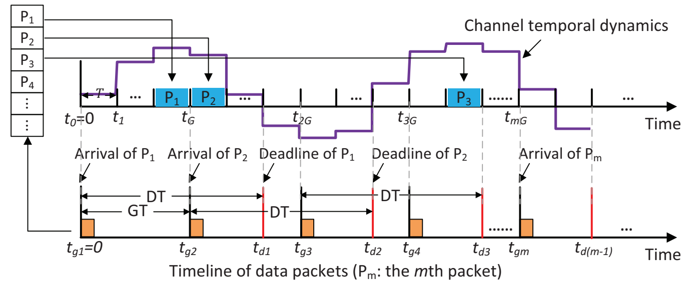

Fig. 1. An illustration of channel-adaptive transmission scheduling. In this illustration, the delay $D < 2G$, while algorithms developed in this work apply to larger values of D.

slot for the transmitter to measure the channel quality[1]. We take the channel signal-to-noise ratio (SNR) as an indicator of the channel quality, which is defined as the receive SNR corresponding to a transmission power of one unit. Denote c_k as the channel SNR at the kth time slot. To achieve a desired packet delivery ratio, the transmission power at an active time slot is required to be sufficiently large to ensure a receive SNR being no less than a predetermined threshold. In this work, we assume that each transmitted packet can be successfully decoded by the receiver through, e.g., choosing a high receive SNR threshold and a large error correction coding rate, and the proposed algorithms can be appropriately modified for the scenario with packet transmission errors. Based on the channel temporal dynamics, the packet transmission schedule can be optimized with a goal of minimizing the total packet transmission energy consumption under the packet delay constraint. An example of the channel-adaptive transmission scheduling is illustrated in Fig. 1.

Define $u(k)$ as a binary indicator of the activity at the kth time slot, with $u(k) = 1$ for being active, and $u(k) = 0$ for being idle, and denote $P_{\mathrm{tx},k}$ as the transmission power of the kth time slot when $u(k) = 1$. For a time window of $N \to \infty$ time slots, the channel-adaptive transmission scheduling can be cast into an optimization problem:

$$\min_{\{u(k), P_{\mathrm{tx},k}\}} \sum_{k=0}^{N} P_{\mathrm{tx},k} u(k) \tag{1a}$$

$$\text{s.t.} \quad \sum_{n=0}^{k} u(n) \geq \left\lfloor \frac{k-D}{G} \right\rfloor + 1, \tag{1b}$$

$$\sum_{n=0}^{k} u(n) \leq \left\lfloor \frac{k}{G} \right\rfloor + 1, \tag{1c}$$

$$P_{\mathrm{tx},k} c_k \geq \Gamma_{\mathrm{rx,th}} u(k), \tag{1d}$$

for $k = 0, \cdots, N$, where $\lfloor \cdot \rfloor$ is the floor function; (1b) ensures that each packet is transmitted in one active time slot before its deadline, where $\left\lfloor \frac{k-D}{G} \right\rfloor + 1$ is the total number of packets with deadlines no larger than the kth time slot; (1c) constrains that the number of active slots is no more than the number of packets, where $\left\lfloor \frac{k}{G} \right\rfloor + 1$ is the total number of packets that arrived before and at the kth time slot; and (1d) ensures that

[1] We assume that the duration of each time slot is much larger than the one-way sound propagation delay, and each data packet could consist of multiple real packets in practical systems.

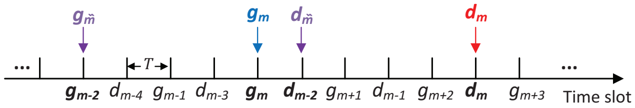

Fig. 2. An illustration of the timeline in the recursive waterfilling algorithm.

the receive SNR is no less than a predetermined threshold $\Gamma_{\rm rx,th}$, and this constraint can be automatically satisfied when $u(k) = 0$.

Given the objective function in (1a) and the constraint in (1d), the optimal transmission power for time slot $u^*(k) = 1$ should be the minimal transmission power that meets the receive SNR threshold, i.e., $P^*_{{\rm tx},k} = \Gamma_{\rm rx,th}/c_k$. Moreover, since $P^*_{{\rm tx},k}$ is inversely proportional to c_k, the optimization objective function can be further simplified as $\max_{\{u(k)\}} \sum_{k=0}^{N} c_k u(k)$. Hence, determining the energy-efficient transmission time slots is essential to solving the optimization problem. When $D < G$, the problem is trivial, as the optimal transmission slot for each packet (e.g., the mth packet) can be selected individually, which is the slot that has the highest channel SNR within the feasible transmission time slot window (e.g., $[g_m, d_m]$). In this work, we mainly focus on the scenario when $D \geq G$, namely, when the feasible transmission time windows of consecutive packets overlap.

In the sequel, we will develop an optimal scheduling algorithm to minimize the total packet transmission energy with perfect and noncausal channel knowledge, and then proceed to online algorithms that determine the optimal transmission schedule in practical systems when only causal channel knowledge is available.

III. Transmission Scheduling with Perfect CSI

Based on a perfect knowledge of the packet arrival time and the noncausal CSI, the optimal transmission schedule can be determined before the system starts. Denote k_m as the transmission time slot of the mth packet. Denote $M \to \infty$ as the total number of packets to be transmitted. The optimization problem can be recast as

$$\min_{\{k_m\}} \sum_{m=1}^{M} \Gamma_{\rm rx,th}/c_{k_m} \tag{2a}$$

$$\text{s.t.} \quad g_m \leq k_m \leq d_m, \tag{2b}$$

$$k_m \neq k_{m'}, \quad \forall m \neq m' \tag{2c}$$

for $m = 1, \cdots, M$, where (2b) states the packet transmission causality and the delay constraint, and (2c) ensures that only one packet is assigned to each time slot. Similar to (1), the optimization objective function can be simplified as $\max_{\{k_m\}} \sum_{m=1}^{M} c_{k_m}$. A recursive algorithm will be developed next to determine the optimal transmission schedule. As to be clear shortly, the algorithm is essentially a variant of the waterfilling algorithm [13] for packet allocation in time under the packet delay constraint.

In each recursion, we refer the selected transmission slots in previous recursions as *occupied slots* and other slots as *available slots*. Denote $\mathcal{A}_{m-1}$ as the set of selected transmission time slots in the $(m-1)$th and early recursions for the transmission of packets $1, \cdots, m-1$. A new transmission slot will be selected in the mth recursion, which combined with $\mathcal{A}_{m-1}$ will yield the transmission schedule for packets $1, \cdots, m$. Note that the transmission time slot of the mth packet should be within $[g_m, d_m]$, while some slots within this interval could have been selected as occupied slots in previous recursions and are within $\mathcal{A}_{m-1}$. We denote $\tilde{m}$ as the packet which has the minimal deadline among all the packets whose deadlines are within the interval $[g_m, d_m]$; see an illustration in Fig. 2. A new time slot will be selected as follows. Should any occupied time slot be within $[g_m, d_m]$, the available slot with the highest channel SNR within $[g_{\tilde{m}}, d_m]$ will be selected as a new transmission slot; otherwise, the slot with the highest channel SNR within $[g_m, d_m]$ will be selected as a new transmission slot. The new transmission slot will be combined with $\mathcal{A}_{m-1}$ to form $\mathcal{A}_m$. The same procedure will be repeated for the $(m+1)$th and the following packets.

Two remarks of this algorithm are in order.

Remark 1: The feasibility of the obtained solution is ensured by enforcing that for each packet (e.g., the mth packet), there is always an active time slot within its feasible transmission window (e.g., $[g_m, d_m]$). In addition, since the new transmission time slot selected within each recursion has the highest channel SNR among all the available slots under the feasibility constraint, the proposed algorithm is optimal, namely, achieving the minimal packet transmission energy.

Remark 2: In the mth and following recursions, the optimal activity of each slot before $g_{\tilde{m}}$ will remain unchanged. The optimal transmission activities of slots within $[g_{\tilde{m}}, g_{\tilde{m}+1} - 1]$, to be fixed after the mth recursion, will be determined based on $\mathcal{A}_{m-1}$ (more specifically, the active time slots within $[g_{\tilde{m}}, g_{\tilde{m}+1} - 1]$) and the channel qualities within $[g_{\tilde{m}}, d_m]$. The channel quality of time slots beyond d_m will not influence the optimal transmission schedule of slots up to $g_{\tilde{m}+1} - 1$.

IV. Transmission Scheduling based on Channel Prediction

In practical systems, the channel SNRs in future time slots are not available. Nevertheless, by exploiting the channel temporal coherence property, the future channel SNRs can be predicted based on current and historical measurements. In this section, we will first present a prediction algorithm for seasonal[2] (periodic) channels and then proceed to an adaptive transmission scheduling scheme based on channel predictions.

A. Holt-Winters Approach for Seasonal Channel Prediction

Due to the impact of environment conditions (e.g., temperature, tidal effect, and water surface conditions), underwater acoustic channels could exhibit seasonality (periodicity) at different scales, e.g., daily, months, and years. Seasonal time series analysis techniques [14] can be adopted for channel SNR modeling and prediction. A method for seasonal data analysis is the Holt-Winters (HW) Exponential Smoothing approach [12]. Due to its simplicity, fully automatic feature and

[2]We follow the terminology in statistical forcasting, and use *seasonality* to refer *periodicity*. The seasonal cycle herein is not necessarily a calender season.

robust performance, the HW approach has been widely used for univariate time series analysis in a range of applications, e.g., economic forecasting, power load prediction, and traffic characterization. In this work, we adopt an additive HW model for channel prediction. The additive HW model decomposes the channel SNR at each time slot (e.g., c_k in the kth time slot) into a summation of a deseasonalized local mean m_k and a seasonal factor F_k, i.e., $c_k = m_k + F_k + \epsilon_k$, where ϵ_k is an additive error which consists of measurement noise and modeling error. Denote L as the number of observations in a seasonal cycle. An exponentially weighted moving average (EWMA) is used to model the evolution of the local mean m_k and the seasonal factor F_k individually,

$$m_k = (1-\alpha)m_{k-1} + \alpha(c_k - F_{k-L}), \tag{3}$$
$$F_k = (1-\beta)F_{k-L} + \beta(c_k - m_k), \tag{4}$$

where α and β are weighting coefficients. The p-step ahead prediction of the channel SNR can be obtained as

$$\hat{c}_{k+p} = m_k + F_{k-L+p}. \tag{5}$$

The weighing coefficients α and β can be updated "on the fly" via the recursive least squares (RLS) estimator to minimize the mean square channel SNR prediction error [15].

B. Channel-Prediction based Adaptive Scheduling

In the system under consideration, the transmitter maintains a data packet queue and a channel queue. At each time slot, it decides whether to *transmit* or to *hold* the packet on the top of the data queue, which corresponds to $u(k) = 1$ or 0 for the kth time slot, respectively. As revealed in Section III, the optimal action of the kth time slot is determined by (i) the channel queue that consists of channel SNRs in the time slots $k, k+1, \cdots, k+I$, which is denoted by $s_{\mathrm{ch},k} := [c_k, c_{k+1}, \cdots, c_{k+I}]$, where $I := \left\lfloor \frac{k+D}{G} \right\rfloor G + D - k \leq 2D$, c_k is the channel SNR measured at the beginning of the kth time slot, and $c_{k+1}, \cdots c_{k+I}$ are the unknown channel SNRs in future time slots; and (ii) the data queue $s_{\mathrm{data},k}$ which is formed by the data packets that have arrived and not been transmitted prior to the kth time slot and the packets to arrive within the time slots $[k, k+D]$. In the data queue, each packet is associated with a number of remaining time slots under the delay constraint. Denote $p(c_{k+1}, c_{k+2}, \cdots, c_{k+I} \mid c_0, \cdots, c_k)$ as the probability density function of the channel SNRs in future time slots conditional on the current and historical channel SNR measurements. Define $E(s_{\mathrm{ch},k}, s_{\mathrm{data},k} \mid u(k))$ as a function of the channel queue $s_{\mathrm{ch},k}$, the data queue $s_{\mathrm{data},k}$, and the action of the kth time slot $u(k)$, which represents the minimal energy consumption to transmit all the packets within the data queue during the interval $[k, k+I]$, conditioned on $u(k) = 0$ or 1 and with the channel states specified in the channel queue. The recursive waterfilling algorithm developed in Section III can be applied to determine the optimal transmission schedule, hence to compute $E(s_{\mathrm{ch},k}, s_{\mathrm{data},k} \mid u(k))$. The optimal action to be taken as the kth time slot is the one that minimizes the average energy consumption,

$$u^*(k) = \arg \min_{\{u(k)=0,1\}} \int \cdots \int E(s_{\mathrm{ch},k}, s_{\mathrm{data},k} \mid u(k)) \times p(c_{k+1}, c_{k+2}, \cdots, c_{k+I} \mid c_0, \cdots, c_k) dc_{k+1} \cdots dc_{k+I}. \tag{6}$$

Note that (6) requires the temporal statistical distribution of channel SNRs, which however, has not been well investigated in the field. In this work, we use the HW-approach based channel prediction to determine the optimal action of the kth time slot,

$$u^*(k) = \arg \min_{\{u(k)=0,1\}} E(\hat{s}_{\mathrm{ch},k}, s_{\mathrm{data},k} \mid u(k)), \tag{7}$$

where $\hat{s}_{\mathrm{ch},k} := [c_k, \hat{c}_{k+1}, \cdots, \hat{c}_{k+I}]$ is the predicted channel queue. The packet on the top of the data queue will be transmitted if $u^*(k) = 1$, and be held otherwise. The optimal action of the $(k+1)$th slot will be similarly determined based on the updated data queue and channel queue.

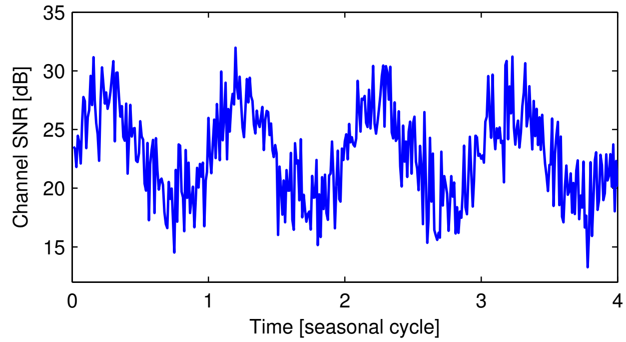

Fig. 3. A realization of the channel SNR series in simulations.

V. Algorithm Evaluation

In this section, we evaluate and compare the performance of three transmission scheduling strategies in the following.

- *Benchmark method:* Each packet is transmitted upon its arrival, using the minimal transmission power that meets the predetermined receive SNR threshold;
- *Genie-aided channel-adaptive scheduling:* Assuming perfect and noncausal channel knowledge, the recursive waterfilling algorithm is applied to determine the optimal transmission schedule;
- *Channel-prediction based adaptive scheduling:* Applying the HW approach for seasonal channel prediction, the transmission schedule of each time slot is determined sequentially based on the data packet queue and the predicted channel queue.

Denote $\bar{P}$ as the average power consumption per packet transmission. Taking $\bar{P}_{\mathrm{benchmark}}$ in the benchmark method as reference, a performance metric of transmission scheduling energy efficiency is defined as

$$\eta := 1 - \frac{\bar{P}}{\bar{P}_{\mathrm{benchmark}}} \tag{8}$$

with $0 \leq \eta < 1$, which specifies the percentage of energy saving relative to the benchmark method.

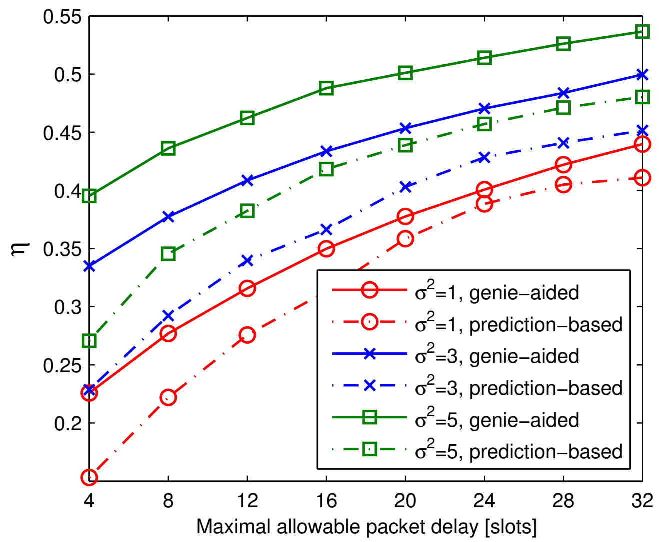

Fig. 4. Transmission scheduling efficiency *versus* the maximal allowable packet delay. Each packet arrives every 4 time slots.

A. Performance in Simulated Channels

The seasonal channel SNR series is modeled as

$$c_k[\mathrm{dB}] = \sigma_{\mathrm{ch}} \sin(2\pi k/L) + \mu_{\mathrm{ch}} + n(k), \tag{9}$$

where L is the seasonal cycle, σ_{ch} and μ_{ch} is the standard deviation and the mean of the seasonal dynamics, respectively, and $n(k) \sim \mathcal{N}(0, \sigma^2)$ models the nonseasonal channel variation and is assumed following a zero-mean Gaussian distribution with variance σ^2. We use the channel parameters measured in a field experiment conducted in August, 2014 (to be presented in Section V-B) for simulation, namely, $L = 96$, $\sigma_{\mathrm{ch}} = 4.46$, and $\mu_{\mathrm{ch}} = 22.7$. A realization of the channel SNR series with $\sigma^2 = 5$ is shown in Fig. 3.

Averaged over a total number of packets $M = 200$ and 200 channel realizations, Fig. 4 shows the scheduling efficiency of the genie-aided approach and the channel-prediction based approach for a packet arrival period of $G = 4$ and different noise variance levels. One can observe that in both approaches, the scheduling efficiency increases with the maximal allowable packet delay D and the noise variance σ^2, indicating that more channel temporal diversity can be harvested for transmission energy efficiency. In addition, the performance gap of the two approaches increases with σ^2, primarily because higher random channel variation incurs larger channel prediction inaccuracy, hence degrades the scheduling performance.

B. Performance in Real Channels

We conducted two experiments in August, 2014 and May, 2015, respectively, to measure the large-scale dynamics of underwater acoustic channels in a local lake using two orthogonal frequency-division multiplexing (OFDM) modems; see the experiment setup in Fig. 5. The two experiments had an identical setting, and each lasted for $4 \sim 5$ days. The water depth of the experiment area varies from 3 m to 6 m. Both the transmit modem and the receive modem were deployed 1 m below water surface. The transmit modem sent

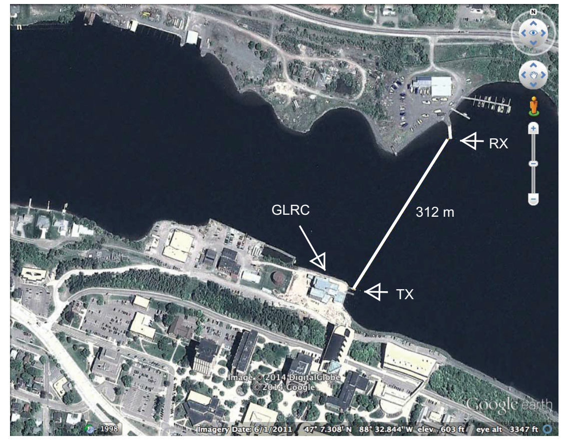

Fig. 5. Experiment setup over the Keweenaw Waterway adjacent to the Great Lakes Research Center (GLRC) at Michigan Tech.

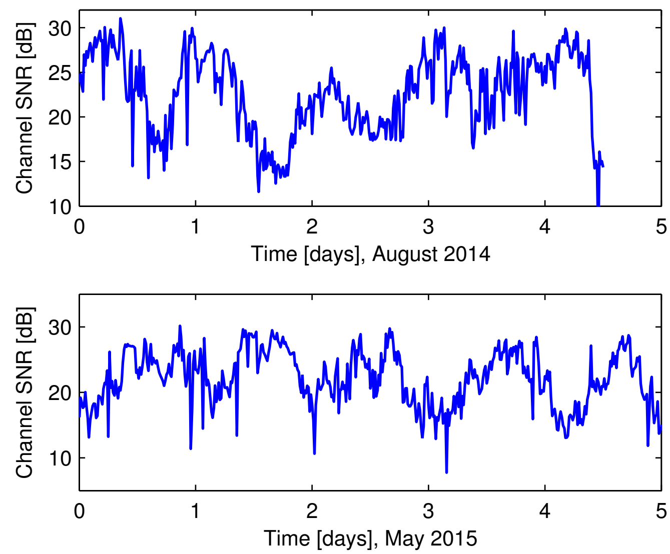

Fig. 6. Measured channel SNR series in August, 2014 starting at 00:00:25, 08/27, and in May, 2015 starting at 12:59:42, 05/28.

an acoustic waveform every 15 mins. The waveform included 20 OFDM blocks and was received by four hydrophones at the receive modem. Fig. 6 shows the average pilot SNR of each transmission in both experiments, where the pilot SNR is defined as the ratio between the average symbol energy on pilot subcarriers and the noise energy on null subcarriers [16]. In both experiments, the channel SNR exhibits a diurnal pattern: the SNRs in the night-time transmissions are much higher than those in the daytime transmissions, which could be caused by the temperature-induced change of the sound speed profile, surface wave conditions, and the ambient noise introduced by human and marine animal activities.

To illustrate the HW-approach based channel prediction performance, Fig. 7 depicts the channel prediction in day 5 using the channel measurements in the first four days of the experiment in May, 2015. One can see that the prediction can closely approximate the measured channel SNRs.

Assuming a packet arrival period of 4 slots (one hour for $T = 15$ min), Fig. 8 shows the transmission scheduling effi-

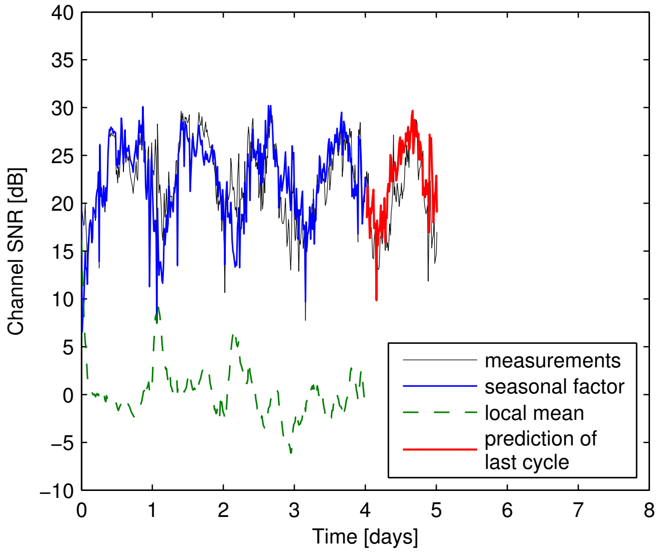

Fig. 7. Performance of the HW-approach based channel prediction using the measured channel SNR series in May, 2015.

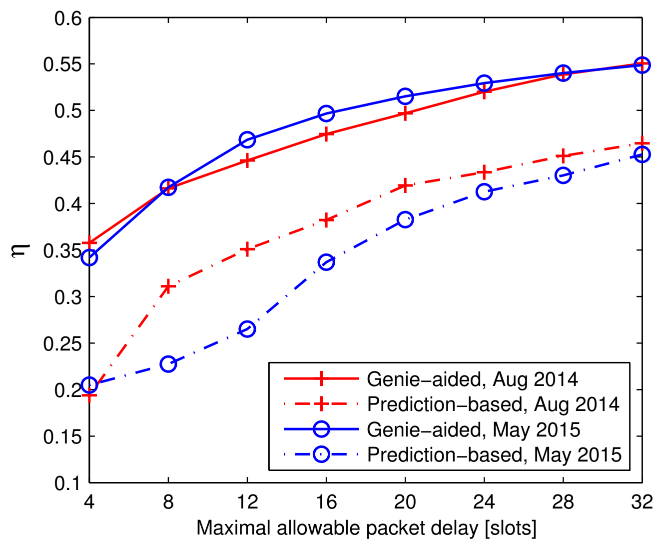

Fig. 8. Transmission scheduling efficiency *versus* the maximal allowable packet delay using experimental data sets. Each packet arrives every 4 time slots.

ciency of the genie-aided approach and the channel-prediction based approach. Similar to the simulation results in Fig. 4, the scheduling efficiency of the two approaches increases with the maximal allowable packet delay. Although the two channel SNR series exhibit nonseasonal variations of different forms, the SNR series in August, 2014 has a smaller performance gap between the two approaches than that in May, 2015, especially for small values of the packet delay, which is possibly due to the relatively higher nonseasonal short-term variations hence larger channel prediction inaccuracy in the latter.

VI. Conclusions

In this work, adaptive transmission scheduling for point-to-point underwater acoustic communications was investigated to collect the channel temporal diversity for transmission energy efficiency. Assuming a perfect and non-causal channel knowledge, a recursive waterfilling algorithm was developed to determine the optimal transmission schedule, and established the scheduling energy efficiency upper bound. To address channel causality in practical systems, the temporal coherence of underwater acoustic channels was exploited to predict future channel conditions. In particular, we focused on seasonal channels, and applied the HW approach for channel prediction. An online scheduling algorithm was designed to determine the optimal action of each time slot based on the channel prediction and the transmitter data queue status. Numerical results showed that the proposed algorithms yields considerable transmission energy saving relative to a benchmark method with a fixed transmission schedule.

References

[1] I. F. Akyildiz, D. Pompili, and T. Melodia, "Underwater acoustic sensor networks: Research chanllenges," *Ad Hoc Networks*, vol. 3, pp. 257–279, 2005.

[2] J. Jagannath, A. Saji, H. Kulhandjian, Y. Sun, E. Demirors, and T. Melodia, "A hybrid MAC protocol with channel-dependent optimized scheduling for clustered underwater acoustic sensor networks," in *Proc. of the ACM Intl. Conf. on Underwater Networks (WUWNet)*, Kaohsiung, Taiwan, Nov. 2013.

[3] B. Tomasi and J. C. Preisig, "Energy-efficient transmission strategies for delay constrained traffic with limited feedback," *IEEE Trans. Wireless Commun.*, vol. 3, no. 14, pp. 1369–1379, Mar. 2015.

[4] J. Lee and N. Jindal, "Energy-efficient scheduling of delay constrained traffic over fading channels," *IEEE Trans. Wireless Commun.*, vol. 8, no. 4, pp. 1866–1875, Apr. 2009.

[5] M. I. Poulakis, A. D. Panagopoulos, and P. Constantinou, "Channel-aware opportunistic transmission scheduling for energy-efficient wireless links," *IEEE Trans. Veh. Technol.*, vol. 62, no. 1, pp. 192–204, Jan. 2013.

[6] R. Srivastava and C. E. Koksal, "Energy optimal transmission scheduling in wireless sensor networks," *IEEE Trans. Wireless Commun.*, vol. 9, no. 5, pp. 1550–1560, May 2010.

[7] M. H. Ngo and V. Krishnamurthy, "Optimality of threshold policies for transmission scheduling in correlated fading channels," *IEEE Trans. Commun.*, vol. 57, no. 8, pp. 2474–2483, Aug. 2009.

[8] H. J. Bang, T. Ekman, and D. Gesbert, "Channel predictive proportional fair scheduling," *IEEE Trans. Wireless Commun.*, vol. 7, no. 2, pp. 482–487, Feb. 2008.

[9] B. Tomasi and J. C. Preisig, "Efficient heuristic scheduling with partial queue and channel state information," in *Proc. of the ACM Intl. Conf. on Underwater Networks (WUWNet)*, Rome, Italy, 2014.

[10] N. M. Carbone and W. S. Hodgkiss, "Effects of tidally driven temperature fluctuations on shallow-water acoustic communications at 18 kHz," *IEEE J. Ocean. Eng.*, vol. 25, no. 1, pp. 84–94, Jan. 2000.

[11] W. Sun, Z. Wang, M. Jamalabdollahi, and S. A. Zekavat, "Experimental study on the difference between acoustic communication channels in freshwater rivers/lakes and in oceans," in *Proc. of Asilomar Conf. on Signals, Systems, and Computers*, Pacific Grove, CA, 2014.

[12] C. C. Holt, "Forecasting seasonals and trends by exponentially weighted moving averages," *ONR Research Memorandum*, 1957.

[13] D. Tse and P. Viswanath, *Fundamentals of Wireless Communication*. Cambridge University Press, 2005.

[14] G. E. P. Box, G. M. Jenkins, and G. C. Reinsel, *Time Series Analysis: Forecasting and Control*, 4th ed. Wiley, 2008.

[15] S. Haykin, *Adaptive Filter Theory*. Prentice-Hall, Inc., 4th edition, 2002.

[16] L. Wan, H. Zhou, X. Xu, Y. Huang, S. Zhou, Z. Shi, and J.-H. Cui, "Field tests of adaptive modulation and coding for underwater acoustic OFDM," in *Proc. of the ACM Intl. Conf. on Underwater Networks (WUWNet)*, Kaohsiung, Taiwan, Nov. 2013.