

AGE-OF-INFORMATION MINIMIZATION FOR WIRELESS NETWORKS WITH ENERGY HARVESTING

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**AGE-OF-INFORMATION MINIMIZATION FOR
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HARVESTING**

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Under the guidance of
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*Dedicated to my father late Shri Mukesh Kumar Jaiswal,
and my brother late Mr. Abhishek Kumar Jaiswal,
whose memories have been my constant source of strength.
This thesis honors your lasting impact in my life.*

Certificate

This is to certify that the thesis entitled **Age-of-Information Minimization for Wireless Networks with Energy Harvesting** being submitted by **Ms. Akanksha Jaiswal** to the Department of Electrical Engineering, Indian Institute of Technology Delhi for the award of the degree of Doctor of Philosophy is a record of bonafide research work carried out by her under my guidance and supervision. In my opinion, the thesis has reached the standards fulfilling the requirements of the regulations relating to the degree.

The results contained in this thesis are original and have not been submitted either in part or full to any other University or Institute for the award of any other degree or diploma.

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Akanksha Jaiswal

Abstract

For numerous time-critical sensing and communication applications, including IoT systems, it is essential for the decision-making node to access the most up-to-date data. Age of Information (AoI) is a widely used metric for evaluating the freshness of information in such systems and has been extensively studied to enable ultra-reliable low-latency communication (URLLC) in 5G networks. However, implementing such real-time status update systems faces two major challenges: limited battery capacity and constrained communication bandwidth. The issue of limited battery life can be mitigated by employing energy harvesting (EH) nodes. Meanwhile, to overcome bandwidth limitations, multiple sources often share a common frequency band to transmit their time-sensitive status updates to a monitoring node. In order to avoid interference among these nodes and to fully leverage the EH feature available at the source nodes, intelligent scheduling policies are essential. To this end, this dissertation aims to develop novel techniques for the AoI minimization problem in single/multiple energy harvesting source(es) with channel probing capabilities working under (non-) stationary environments for various wireless system settings. Additionally, we aim to develop novel online learning algorithms to address challenges in unknown environments.

As a first step, we consider the AoI minimization problem for a single EH source that opportunistically samples one or more processes at discrete time instants and transmits status updates to a sink node over a wireless fading channel. At each time instant, the EH node decides whether to probe the link quality and, based on the channel probe outcome, whether to sample a process and transmit. We formulated the problem as an infinite-horizon Markov decision process (MDP) for independent and identically distributed (i.i.d.) and Markovian system models where energy arrivals and channel fading processes follow i.i.d. and Markovian dynamics, respectively. It has been observed that the optimal sampling policy after channel probing is a threshold policy. For both i.i.d. and Markovian systems with unknown channel states and EH characteristics settings, a variant of the Q-learning algorithm is proposed to learn the optimal policy for the two-stage action model.

Further, we consider the problem of source sampling and transmission scheduling to minimize the AoI in a system comprising multiple EH sources and a sink node. At each time step, the scheduler selects one of the sources and measures the quality of its channel to the sink, which is then used to determine the sampling decision for the selected

source in that time slot. The problem is formulated as a constrained Markov decision process (CMDP) under the assumption of i.i.d. energy arrival and channel fading processes, which is then relaxed using a Lagrange multiplier and decoupled into various sub-problems across source nodes. We propose a novel Whittle's index and threshold based source scheduling and sampling (WITS3) policy which applies Whittle's index policy for source scheduling to probe the channel state and leverages the threshold policy structure to sample and transmit data from the selected source. Also, for scenarios where the underlying processes are not known to the scheduler, we propose a variant Q-WITS3 of WITS3 that utilizes Q-learning assisted by two timescale asynchronous stochastic approximation. This technique enables the system to learn both Whittle's indices and optimal policies for an unknown environment.

In the next study, we address the problem of AoI minimization for a single EH source working in a non-stationary environment where energy harvesting characteristics and channel statistics are varying with time. Here, we assume that at each time instant, the probed channel quality is known to the source, which decides whether to sample and transmit a data packet to a sink node based on the evaluation of channel quality, available energy, and AoI of a process. We propose an age-energy-channel based sliding window upper confidence bound reinforcement learning (AEC-SW-UCRL2) algorithm to handle unknown and time-varying energy harvesting rate and channel statistics, motivated by the popular SW-UCRL2 algorithm for non-stationary reinforcement learning (RL). This algorithm is applicable when an upper bound is available for the total variation of each of these quantities over a time horizon. Furthermore, in situations where these variation budgets are not accessible, we introduce a novel technique called age-energy-channel based bandit-over-reinforcement learning (AEC-BORL) algorithm, motivated by the well-known BORL algorithm.

Lastly, we consider the AoI minimization problem for multiple sources working in a non-stationary environment under the constraint that only one of the sources can be selected by a central scheduler to probe the quality of its channel to the sink node, and thereafter, a selected source can determine a sampling decision. Here, we utilize Whittle's index based source scheduling policy and a threshold policy for source sampling in multiple source system working in a stationary environment to develop a Whittle's index and threshold based sliding window upper confidence bound reinforcement learning (WIT-SW-UCRL2) algorithm to handle unknown time-varying energy harvesting rates and channel statistics while adhering to their respective variation budgets. Addition-

ally, we propose Whittle’s index and threshold based bandit-over-reinforcement learning (WIT-BORL) algorithm to address scenarios with unknown variation budgets. Simulation results demonstrate the policy structures, performance trade-offs, and efficacy of our proposed algorithms.

सारांश

कई समय-संवेदनशील सेंसिंग और संचार अनुप्रयोगों—जैसे कि आई ओ टी सिस्टम—के लिए यह अत्यंत आवश्यक है कि निर्णय लेने वाले नोड को सबसे अद्यतन डेटा प्राप्त हो। ऐज ऑफ़ इनफार्मेशन (ऐ. ओ. आई.) एक व्यापक रूप से उपयोग किया जाने वाला मापदंड है, जिसका उपयोग ऐसे सिस्टमों में सूचना की ताजगी को मापने के लिए किया जाता है, और इसे विशेष रूप से 5G नेटवर्क में अल्ट्रा-विश्वसनीय व न्यून-विलंबता संचार (यु आर एल एल सी) सक्षम करने के लिए व्यापक रूप से अध्ययन किया गया है। हालांकि, ऐसे वास्तविक समय की स्थिति अद्यतन सिस्टम को लागू करने में दो प्रमुख चुनौतियाँ होती हैं: सीमित बैटरी क्षमता और सीमित संचार बैंडविड्थ। बैटरी जीवन की इस सीमा को ऊर्जा संचयन (एनर्जी हार्वेस्टिंग-ई एच) सक्षम नोड्स द्वारा कम किया जा सकता है। वहीं, बैंडविड्थ की सीमा को दूर करने के लिए, कई स्रोत प्रायः एक ही फ्रीक्वेंसी बैंड साझा करते हैं ताकि वे अपने समय-संवेदनशील स्थिति अद्यतन एक निगरानी नोड तक भेज सकें। ऐसे में इन स्रोतों के बीच हस्तक्षेप से बचने और उनके ई एच गुणों का अधिकतम लाभ उठाने के लिए, बुद्धिमान अनुसूचित नीतियों की आवश्यकता होती है। इसी दिशा में, यह शोधप्रबंध विभिन्न वायरलेस सिस्टम सेटिंग्स के अंतर्गत एकल/एकाधिक ऊर्जा संचयन स्रोतों के लिए ऐ. ओ. आई. न्यूनतमकरण तकनीकों के विकास को लक्ष्य बनाता है, जिनमें चैनल प्रोबिंग क्षमता हो और जो गैर-स्थिर परिवेश में कार्य कर रहे हों। इसके अतिरिक्त, हम अज्ञात परिवेशों में आने वाली चुनौतियों का समाधान करने के लिए नवीन ऑनलाइन लर्निंग एल्गोरिदम विकसित करने का भी उद्देश्य रखते हैं।

सबसे पहले, हम एकल ऊर्जा संचयन स्रोत के लिए ऐ. ओ. आई. न्यूनतमकरण की समस्या पर विचार करते हैं, जो समय के विशिष्ट क्षणों पर एक या अधिक प्रक्रियाओं का अवसरवादी नमूना लेता है और वायरलेस फेडिंग चैनल के माध्यम से एक सिंक नोड को स्थिति अद्यतन भेजता है। प्रत्येक समय बिंदु पर, ई एच नोड यह निर्णय लेता है कि क्या लिंक की गुणवत्ता की जांच की जाए और जांच के परिणाम के आधार पर क्या नमूना लिया जाए और ट्रांसमिट किया जाए। इस समस्या को हमने अनंत-काल क्षितिज मार्कोव निर्णय प्रक्रिया के रूप में सूत्रबद्ध किया है, जिसमें ऊर्जा आगमन और चैनल फेडिंग प्रक्रियाएँ क्रमशः आई. आई. डी. और मार्कोवियन डायनामिक्स का पालन करती हैं। अवलोकन किया गया कि चैनल प्रोबिंग के बाद की सर्वोत्तम सैंपलिंग नीति एक "थ्रेशोल्ड पॉलिसी" होती है। आई. आई. डी. और मार्कोवियन दोनों सेटिंग्स के लिए, जब चैनल स्थिति और ई एच विशेषताएँ ज्ञात नहीं होतीं, तब एक संशोधित क्यू लर्निंग एल्गोरिदम प्रस्तावित किया गया है, जो दो-चरणीय कार्य मॉडल के लिए सर्वोत्तम नीति सीखने में सक्षम है।

इसके बाद, हम एक ऐसी प्रणाली पर विचार करते हैं जिसमें कई ई एच स्रोत और एक सिंक नोड होते हैं। यहाँ, हर समय बिंदु पर शेड्यूलर स्रोतों में से किसी एक को चुनता है, उसके चैनल की गुणवत्ता को मापता है, और उसी आधार पर नमूना लेने का निर्णय करता है। यह समस्या आई. आई. डी. ऊर्जा आगमन व चैनल फेडिंग मानकर एक सीमाबद्ध मार्कोव निर्णय प्रक्रिया के रूप में तैयार की गई है, जिसे बाद में एक लैग्रांज गुणांक द्वारा सरल बनाकर कई उप-समस्याओं में विभाजित किया गया है।

इसके समाधान हेतु हम एक नवीन नीति WITS3 (व्हिटले'स इंडेक्स एंड थ्रेसहोल्ड बेस्ड सोर्स सचेंडुलिंग एंड सैंपलिंग) प्रस्तावित करते हैं, जो स्रोत चयन हेतु व्हिटले'स इंडेक्स का उपयोग करता है, और चयनित स्रोत से डेटा सैंपल व ट्रांसमिट करने के लिए थ्रेशोल्ड पॉलिसी लागू करता है। इसके अलावा, उन परिदृश्यों के लिए जहाँ अंतर्निहित प्रक्रियाएं अनुसूचक को ज्ञात नहीं हैं, हम WITS3 के एक संस्करण Q-WITS3 का प्रस्ताव करते हैं जो दो समय-पैमाने वाले अतुल्यकालिक स्टोकेस्टिक सन्निकटन द्वारा सहायता प्राप्त क्यू लर्निंग का उपयोग करता है। यह प्रणाली अज्ञात परिवेश में व्हिटले'स इंडेक्स और नीति दोनों सीखने में सक्षम होती है।

इसके अगले अध्ययन में, हम गैर-स्थिर परिवेश में कार्यरत एकल ई एच स्रोत के लिए ऐ. ओ. आई. न्यूनतमकरण की समस्या को संबोधित करते हैं, जहाँ ऊर्जा संचयन और चैनल सांख्यिकी समय के साथ बदलती रहती है। यहाँ यह माना गया है कि हर समय बिंदु पर स्रोत को प्रोब किया गया चैनल ज्ञात होता है, और वह उपलब्ध ऊर्जा, चैनल की गुणवत्ता और ऐ. ओ. आई. को देखते हुए यह निर्णय लेता है कि डेटा भेजा जाए या नहीं। इस परिदृश्य के लिए, हमने AEC-SW-UCRL2 एल्गोरिदम (ऐज-एनर्जी-चैनल बेस्ड स्लाइडिंग विंडो अप्पर कॉन्फिडेंस बाउंड रिइंफोर्स्मेंट लर्निंग) प्रस्तावित किया है, जो SW-UCRL2 से प्रेरित है और ऊर्जा संचयन दर व चैनल सांख्यिकी में समय परिवर्तन के लिए प्रभावी है—जब इन परिवर्तनों की कुल सीमा ज्ञात हो। यदि ये वेरिएशन बजटस ज्ञात नहीं हों, तो हम एक नवीन एल्गोरिदम AEC-BORL (बैंडिट ओवर रिइंफोर्स्मेंट लर्निंग) प्रस्तावित करते हैं, जो लोकप्रिय BORL एल्गोरिदम से प्रेरित है।

अंत में, हम एक गैर-स्थिर वातावरण में काम कर रहे कई स्रोतों के लिए एओआई न्यूनतमकरण समस्या पर विचार करते हैं, इस प्रतिबंध के तहत कि केंद्रीय अनुसूचक द्वारा सिंक नोड के लिए उसके चैनल की गुणवत्ता की जांच करने के लिए केवल एक स्रोत का चयन किया जा सकता है, और उसके बाद, एक चयनित स्रोत एक नमूनाकरण निर्णय निर्धारित कर सकता है। यहाँ, हम अज्ञात समय-भिन्न ऊर्जा संचयन दरों और चैनल आँकड़ों को संभालने के लिए व्हिटले 'स इंडेक्स एंड थ्रेसहोल्ड बेस्ड

स्लाइडिंग विंडो अप्पर कॉन्फिडेंस बाउंड रिइंफोर्स्मेंट लर्निंग (WIT-SW-UCRL2) एल्गोरिदम विकसित करने के लिए एक स्थिर वातावरण में काम कर रहे कई स्रोत प्रणाली में स्रोत नमूनाकरण के लिए क्विटल के सूचकांक आधारित स्रोत शेड्यूलिंग नीति और एक सीमा नीति का उपयोग करते हैं, जबकि उनके संबंधित भिन्नता बजट का पालन करते हैं। सिमुलेशन परिणाम हमारे प्रस्तावित एल्गोरिदम की नीति संरचनाओं, प्रदर्शन समझौतों और प्रभावकारिता को प्रदर्शित करते हैं।

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List of Symbols

t	Discrete time index
t'	Iteration index
N_p	Number of processes
N	Number of sources
$\mathbb{P}$	Probability operator
$\mathbb{E}$	Expectation operator
B/B_i	Energy buffer size of source/ i -th source
A/A_i	Number of energy packet arrivals of source/ i -th source in a slot
E/E_i	Energy available at the energy buffer of source/ i -th source
E_p	Energy required for probing the channel
E_s	Energy required for sensing and communicating a data packet
$C(t)/C(i, t)$	Channel state of source/ i -th source at time t
m	Finite number of channel states; $C(t)/C(i, t) \in \{C_1, C_2, \dots, C_m\}$
$p(t)/p(i, t)$	Packet success probability of source/ i -th source at time t ; $p(C_j) = p_j$
$q_j/q_{j,i}$	Probability of being in a channel state C_j for source/ i -th source
λ/λ_i	Energy arrival rate of source/ i -th source
$K/K_k/K_i$	AoI of the process/ k -th process/ i -th source
b/b_i	Indicator of probing channel state for source/ i -th source
a/a_i	Indicator of sampling a process for source/ i -th source
r/r_i	Indicator of successful packet transmission for source/ i -th source
c/c_i	Single-stage cost of source/ i -th source
s/s_i	Generic primary state of source/ i -th source
v/v_i	Generic intermediate state of source/ i -th source
$\mathcal{S}/\mathcal{S}_i$	State space of source/ i -th source
$\mathcal{V}/\mathcal{V}_i$	Intermediate state space of source/ i -th source
$\mathcal{A}/\mathcal{A}_i$	Action space of source/ i -th source

α	Discount factor
H_1	Harvesting state of the Markovian channel model
H_2	Non-harvesting state of the Markovian channel model
$h_{1,2}$	The transition probability from state H_1 to state H_2
ϵ	Exploration probability
$\mathbf{1}$	Indicator term
$d(t), f(t)$	Step sizes, where $t \geq 0$
τ	Last time instant when the channel state was probed
$\nu_t(\cdot, \cdot)$	Number of occurrences of the state-action pair up to iteration t
$\hat{\mu}$	Penalty cost
$\mathcal{WI}_i$	Whittle's index of source i
T	Finite time horizon length
w/w_i	Collection of state transition probabilities for all t of source/ i -th source
$V_\lambda/V_{\lambda,i}$	Variation budget on energy generation rate of source/ i -th source
$V_q/V_{q,i}$	Variation budget on channel state distribution of source/ i -th source
$V_w/V_{w,i}$	Variation budget on state transition probability of source/ i -th source
ρ	Number of episodes
$\tau(\rho)$	Starting of episode ρ
δ	Confidence parameter
ϵ'	Precision parameter
W	Window size
θ	Number of blocks
L	Block length
$\tilde{N}$	Mini slots
$K_{max}/K_{i,max}$	Maximum age of a process of source/ i -th source

List of Abbreviations

AoI	Age of Information
EH	Energy Harvesting
WSN	Wireless Sensor Network
IoT	Internet of Things
CPS	Cyber Physical Systems
URLLC	Ultra Reliable Low Latency Communication
RF	Radio Frequency
BS	Base Station
MDP	Markov Decision Process
CMDP	Constrained Markov Decision Process
I.I.D.	Independent and Identically Distributed
RL	Reinforcement Learning
DM	Decision Maker
MAB	Multi-Armed Bandit
RMAB	Restless Multi-Armed Bandit
UCB	Upper Confidence Bound
SW-UCRL2	Sliding Window Upper Confidence Bound Reinforcement Learning
BORL	Bandit Over Reinforcement Learning
EVI	Extended Value Iteration
MAF	Maximum Age First
HARQ	Hybrid Automatic Repeat Request
CC	Control Center
BUR	Best-Effort Uniform Updating with Re-transmission
GWI	Generalized Whittle Index
GPWI	Generalized Partial Whittle Index
LOS	Line of Sight