RESOURCE-EFFICIENT STRATEGIES FOR MASSIVE MACHINE-TYPE COMMUNICATION

MAYUKH ROY CHOWDHURY

DEPARTMENT OF ELECTRICAL ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY DELHI

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RESOURCE-EFFICIENT STRATEGIES FOR MASSIVE MACHINE-TYPE COMMUNICATION

by

MAYUKH ROY CHOWDHURY

Department of Electrical Engineering

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To my beloved parents,

Shri Manik Roy Chowdhury

and

Smt. Uma Roy Chowdhury

Certificate

This is to certify that the dissertation entitled **Resource-Efficient Strategies for Massive Machine-type Communication**, submitted by **Mr. Mayukh Roy Chowdhury**, a Research Scholar, in the *Department of Electrical Engineering*, *Indian Institute of Technology Delhi*, *New Delhi*, *India*, for the award of the degree of **Doctor of Philosophy**, is a record of an original research work carried out by him under my supervision and guidance. The dissertation fulfills all requirements as per the regulations of this Institute and in my opinion has reached the standard needed for submission. Neither this dissertation nor any part of it has been submitted for any degree or academic award elsewhere.

Prof. Swades De
(Supervisor)
Department of Electrical Engineering
Indian Institute of Technology Delhi
New Delhi, 110016, India.

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Mayukh Roy Chowdhury

Mayukh Roy Chowdhury

Abstract

Massive Machine-type Communications (mMTC) is one of the principal features of the 5th Generation and beyond mobile network services as par the International Telecommunication Union. It is intended to support connecting high density of machine-type devices. With the advent of Internet of Things (IoT), there has been a huge rise in the number of machine-type communication (MTC) devices connected over the network. Massive number of constrained MTC devices sharing the network resources lead to the critical challenge of efficient resource management while coping up with unique and diverse quality of service (QoS) requirements of the individual nodes. To this end, this dissertation has proposed resource-efficient strategies for solving some of the critical issues in mMTC.

We propose a machine learning assisted energy-efficient sampling scheme for air pollution monitoring IoT. Air pollution monitoring systems with energy-intensive sensors cannot afford to sample frequently in order to maximize time between successive recharges. In particular, we demonstrate that temporal correlation of pollutant concentration can be exploited to select optimum sampling period of an energy-intensive sensor to reduce sensing energy consumption without losing much information. Support Vector Regression is used to predict the missing samples during the period sensor is turned off.

As another example of IoT application, recent advances in electric metering infrastructure has given rise to generation of gigantic chunks of data. Transmission of all of these data certainly poses a significant challenge in a bandwidth and storage constrained IoT where smart meters act as sensors. In the first part of the dissertation, a novel multivariate data compression scheme is proposed for smart metering IoT. The proposed algorithm exploits the cross-correlation between different variables sensed by smart meters to reduce the dimension of data. Subsequently sparsity in each of the decorrelated streams is exploited for temporal compression. To examine the quality of compression, the multivariate data is characterized using Multivariate Normal - Autoregressive Integrated Moving Average modeling before compression as well as after reconstruction of the compressed data. Our performance studies indicate that compared to the state of the art, the proposed technique is able to achieve impressive bandwidth saving for transmitting the data over communication network without compromising faithful reconstruction of data at the receiver. The proposed algorithm is tested in a real smart metering set-up and its time complexity is also analyzed. It is notable that, the proposed two-step multivariate

compression technique involving data dimensionality reduction and temporal compression is customizable to the other semi-real-time/non-real-time multivariate sensing IoT applications as well.

Subsequently we focus on the radio resource management (RRM) to tackle massive access level challenges in large-scale machine-to-machine (M2M) communications. Due to sparse but synchronous MTC nature, a large number of devices tend to access a base station simultaneously for transmitting data, leading to congestion in mMTC. Cellular network seems to be the most promising solution for machine-to-machine (M2M) communication because of its well-established infrastructure and large coverage. To accommodate a large number of simultaneous arrivals in mMTC, efficient congestion control techniques like access class barring (ACB) are incorporated in random access of 4G LTE or 5G networks. ACB introduces access delay which may not be acceptable in delay-constrained scenarios, such as, eHealth, self-driven vehicles, and smart grid applications. In such scenarios, MTC devices may be forced to drop packets that exceed their delay budget, leading to a decreased system throughput. To this end, in the second exercise of this dissertation, a novel delay-aware priority access classification (DPAC) based ACB is proposed, where the MTC devices having packets with lesser leftover delay budget are given higher priority in ACB. A reinforcement learning (RL) aided framework, called DPAC-RL, is also proposed for online learning of DPAC model parameters. Simulation studies show that the proposed scheme increases successful preamble transmissions by up to 75% while ensuring that the access delay is well within the delay budget.

Finally, we look into efficient RRM in buffer/storage constrained mMTC scenarios. In devices which are repeatedly ignored by ACB, queue of data packets keeps growing. In storage constrained IoT nodes with limited buffer, this may lead to packet drop due to buffer overflow, causing a decline in the overall throughput of the system. To address this issue, a novel queue-aware prioritized access classification (QPAC) based ACB technique is proposed in this part of the work, where machine-type devices having data queue size close to its buffer limit are dynamically given higher priority in ACB. To study the queue build-up at each MTC device, a node-centric analysis of ACB in buffer-constrained scenario is performed using a two-dimensional Markov chain. It is shown that the proposed QPAC scheme, with optimal model parameters obtained by maximizing overall system utility, offers up to 70% gain in throughput compared to the nearest competitive dynamic ACB scheme.

सारांश

मैसिव मशीन-टाइप कम्युनिकेशंस (एमएमटीसी) ५वीं पीढ़ी की प्रमुख विशेषताओं में से एक है और अंतर्राष्ट्रीय दूरसंचार संघ के अनुसार मोबाइल नेटवर्क सेवाओं से परे है। इसका उद्देश्य मशीन-प्रकार के उपकरणों के उच्च घनत्व को जोड़ने का समर्थन करना है। इंटरनेट ऑफ थिंग्स (आईओटी) के आगमन के साथ, नेटवर्क से जुड़े मशीन-प्रकार संचार (एमटीसी) उपकरणों की संख्या में भारी वृद्धि हुई है। नेटवर्क संसाधनों को साझा करने वाले विवश एमटीसी उपकरणों की बड़ी संख्या अलग-अलग नोड्स की अद्वितीय और विविध गुणवत्ता सेवा (क्यूओएस) आवश्यकताओं के साथ मुकाबला करते हुए कुशल संसाधन प्रबंधन की महत्वपूर्ण चुनौती का कारण बनती है। इसके लिए, इस शोध प्रबंध ने एमएमटीसी में कुछ महत्वपूर्ण मुद्दों को हल करने के लिए संसाधन-कुशल रणनीतियों का प्रस्ताव दिया है।

हम वायु प्रदूषण निगरानी आईओटी के लिए मशीन लर्निंग असिस्टेड एनर्जी एफिशिएंट सैंपलिंग स्कीम का प्रस्ताव करते हैं। ऊर्जा-गहन सेंसर के साथ वायु प्रदूषण निगरानी प्रणाली लगातार रिचार्ज के बीच समय को अधिकतम करने के लिए बार-बार नमूना लेने का जोखिम नहीं उठा सकती है। विशेष रूप से, हम प्रदर्शित करते हैं कि प्रदूषक सांद्रता के अस्थायी सहसंबंध का उपयोग ऊर्जा-गहन सेंसर की इष्टतम नमूना अवधि का चयन करने के लिए किया जा सकता है ताकि अधिक जानकारी खोए बिना ऊर्जा खपत को कम किया जा सके। सपोर्ट वेक्टर रिग्रेशन का उपयोग सेंसर के बंद होने की अवधि के दौरान लापता नमूनों की भविष्यवाणी करने के लिए किया जाता है।

आईओटी एप्लिकेशन के एक अन्य उदाहरण के रूप में, इलेक्ट्रिक मीटरिंग इन्फ्रास्ट्रक्चर में हालिया प्रगति ने डेटा के विशाल भाग को जन्म दिया है। इन सभी डेटा का प्रसारण निश्चित रूप से एक बैंडविड्थ और भंडारण की कमी वाले आईओटी में एक महत्वपूर्ण चुनौती है जहां स्मार्ट मीटर सेंसर के रूप में कार्य करते हैं। शोध प्रबंध के पहले भाग में, स्मार्ट मीटरिंग आईओटी के लिए एक नई बहुभिन्नरूपी डेटा संपीड़न योजना प्रस्तावित है। प्रस्तावित एल्गोरिदम डेटा के आयाम को कम करने के लिए स्मार्ट मीटर द्वारा महसूस किए गए विभिन्न चर के बीच क्रॉस-सहसंबंध का फायदा उठाता है। संपीड़न की गुणवत्ता की जांच करने के लिए, बहुभिन्नरूपी डेटा को संपीड़न से पहले और साथ ही संपीड़ित डेटा के पुनर्निर्माण के बाद बहुभिन्नरूपी सामान्य - ऑटोरेग्रेसिव इंटीग्रेटेड मूविंग एवरेज मॉडलिंग का उपयोग करने की विशेषता है। हमारे प्रदर्शन अध्ययनों से संकेत मिलता है कि अत्याधुनिक की तुलना में, प्रस्तावित तकनीक रिसीवर पर डेटा के वफादार पुनर्निर्माण से समझौता किए बिना संचार नेटवर्क पर डेटा संचारित करने के लिए प्रभावशाली बैंडविड्थ बचत प्राप्त करने में सक्षम है। प्रस्तावित एल्गोरिदम का परीक्षण वास्तविक स्मार्ट मीटरिंग सेट-अप में किया जाता है और इसकी समय जटिलता का भी विश्लेषण किया जाता है। यह उल्लेखनीय है कि,

प्रस्तावित दो-चरण बहुभिन्नरूपी संपीड़न तकनीक जिसमें डेटा आयामीता में कमी और अस्थायी संपीड़न शामिल है, अन्य अर्ध-वास्तविक-समय / गैर-वास्तविक-समय बहुभिन्नरूपी संवेदन आईओटी अनुप्रयोगों के लिए भी अनुकूलन योग्य है।

इसके बाद हम बड़े पैमाने पर मशीन-टू-मशीन (एम2एम) संचार में बड़े पैमाने पर पहुंच स्तर की चुनौतियों से निपटने के लिए रेडियो संसाधन प्रबंधन (आरआरएम) पर ध्यान केंद्रित करते हैं। विरल लेकिन सिंक्रोनस एमटीसी प्रकृति के कारण, बड़ी संख्या में डिवाइस डेटा ट्रांसमिट करने के लिए एक साथ बेस स्टेशन तक पहुंच जाते हैं, जिससे एमएमटीसी में भीड़भाड़ हो जाती है। सेलुलर नेटवर्क मशीन-टू-मशीन (एम2एम) संचार के लिए सबसे आशाजनक समाधान प्रतीत होता है क्योंकि इसकी अच्छी तरह से स्थापित बुनियादी ढांचे और बड़े कवरेज के कारण। एमएमटीसी में एक साथ बड़ी संख्या में आगमन को समायोजित करने के लिए, एक्सेस क्लास बैरिंग (एसीबी) जैसी कुशल भीड़ नियंत्रण तकनीकों को ४जी एलटीई या ५जी नेटवर्क के रैंडम एक्सेस में शामिल किया गया है। एसीबी ने पहुंच में देरी की शुरुआत की है जो देरी-बाधित परिदृश्यों में स्वीकार्य नहीं हो सकती है, जैसे कि ई-हेल्थ, स्व-चालित वाहन और स्मार्ट ग्रिड एप्लिकेशन। ऐसे परिदृश्यों में, एमटीसी उपकरणों को अपने विलंब बजट से अधिक पैकेट छोड़ने के लिए मजबूर किया जा सकता है, जिससे सिस्टम थ्रूपुट कम हो जाता है। इस उद्देश्य के लिए, इस शोध प्रबंध के दूसरे अभ्यास में, एक उपन्यास विलंब-जागरूक प्राथमिकता पहुंच वर्गीकरण (डीपीएसी) आधारित एसीबी प्रस्तावित है, जहां कम बचे हुए विलंब बजट वाले एमटीसी उपकरणों को एसीबी में उच्च प्राथमिकता दी जाती है। डीपीएसी-आरएल नामक एक सुदृढीकरण सीखने (आरएल) सहायता प्राप्त ढांचा, डीपीएसी मॉडल मापदंडों के ऑनलाइन सीखने के लिए भी प्रस्तावित है।

अंत में, हम बफर/भंडारण बाधित एमएमटीसी परिदृश्यों में कुशल आरआरएम पर गौर करते हैं। एसीबी द्वारा बार-बार नजरअंदाज किए जाने वाले उपकरणों में डेटा पैकेट की कतार बढ़ती रहती है। सीमित बफर के साथ सीमित भंडारण वाले आईओटी नोड्स में, इससे बफर ओवरफ्लो के कारण पैकेट ड्रॉप हो सकता है, जिससे सिस्टम के समग्र थ्रूपुट में गिरावट आ सकती है। इस मुद्दे को हल करने के लिए, काम के इस हिस्से में एक उपन्यास कतार-जागरूक प्राथमिकता वाले एक्सेस वर्गीकरण (क्यूपीएसी) आधारित एसीबी तकनीक का प्रस्ताव है, जहां मशीन-प्रकार के उपकरण जिनकी बफर सीमा के करीब डेटा कतार आकार वाले एसीबी में गतिशील रूप से उच्च प्राथमिकता दी जाती है। प्रत्येक एमटीसी डिवाइस पर क्यू बिल्ड-अप का अध्ययन करने के लिए, बफर-विवश परिदृश्य में एसीबी का नोड-केंद्रित विश्लेषण द्वि-आयामी मार्कोव श्रृंखला का उपयोग करके किया जाता है। यह दिखाया गया है कि प्रस्तावित क्यूपीएसी योजना, समग्र सिस्टम उपयोगिता को अधिकतम करके प्राप्त इष्टतम मॉडल मापदंडों के साथ, निकटतम प्रतिस्पर्धी गतिशील एसीबी योजना की तुलना में थ्रूपुट में सत्तर प्रतिशत तक का लाभ प्रदान करती है।

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