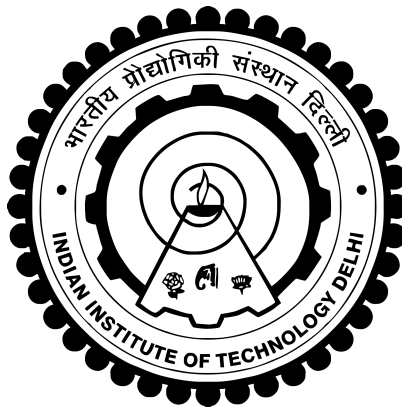


DISTRIBUTION SYSTEM LOAD SYNTHESIS THROUGH SMART METER DATA ANALYTICS

PARTIK KUMAR



**DEPARTMENT OF ELECTRICAL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY DELHI**

MARCH, 2025

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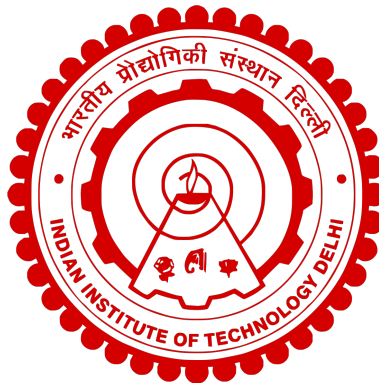
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DEPARTMENT OF ELECTRICAL ENGINEERING

Submitted

in fulfillment of requirements of degree of Doctor of Philosophy

to the



INDIAN INSTITUTE OF TECHNOLOGY DELHI

MARCH, 2025

CERTIFICATE

This is to certify that the thesis entitled '**Distribution System Load Synthesis through Smart Meter Data Analytics**', being submitted by **Partik Kumar** to **Indian Institute of Technology, Delhi** is a record of bonafide research work carried out under my supervision and I consider it worthy for consideration of the award of the degree **Doctor of Philosophy** in Electrical Engineering. The results obtained here have not been submitted to any other University or Institute for the award of any degree or diploma.

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Date: March 26, 2024

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Partik Kumar

Abstract

The ability to assess energy consumption behaviour is important for utility companies in designing effective demand reduction programs. Understanding household appliance usage patterns allows for more precise energy consumption behaviour assessment for a community load. Non-Intrusive Load Monitoring (NILM) is a key tool in identifying appliance-level activities, offering significant insights into energy usage without the need for installing individual sensors at each appliance. NILM's ability to disaggregate household-level consumption into appliance-specific data directly contributes to distribution system load synthesis, enabling utility companies to derive insights about total load composition and its temporal variations from smart meter data.

Distribution system load synthesis involves reconstructing a detailed and accurate load profile for the entire distribution network by leveraging smart meter data analytics. NILM frameworks provide the foundation for this synthesis by identifying the contribution of various appliances to overall load, allowing for more precise modelling of load behaviour at the feeder, transformer, and community levels. NILM outcomes can also be utilized to build appliance recommendation systems, detect faulty appliances, improve load forecasting, and provide real-time feedback on energy consumption. However, existing NILM models suffer from two main challenges: limited accuracy and high computational complexity. As the number of appliances within a household increases, these challenges become even more pronounced, limiting the practical deployment of these models in real-world applications.

This thesis aims to address these limitations by proposing novel NILM frameworks that enhance both solution accuracy and computational efficiency. The proposed frameworks integrate several advancements, including the modelling of inter-appliance operational dependencies, considerations of the differential in appliance operating states over time, and appliance switching and operating duration patterns into the NILM modelling process. These innovations make the frameworks particularly well-suited for low-sampling-rate datasets typically captured by utility-installed smart meters, ensuring their applicability in real-world energy management systems.

The thesis develops NILM models based on optimization techniques, the factorial hidden

Markov model (FHMM), and machine learning approaches. To validate the proposed frameworks, case studies are performed using three publicly available NILM datasets: AMPds, REDD, and UKDALE. These datasets, collected from different geographic regions, allow for a comprehensive evaluation of the models across varying household conditions and data characteristics. The results demonstrate that the proposed frameworks outperform state-of-the-art NILM models in terms of both accuracy and solving time. In some cases, the accuracy is significantly higher, while in others, the proposed frameworks provide comparable accuracy with much lower computational complexity, making them more practical for real-world deployment.

The research presented in this thesis lays the groundwork for further advancements in NILM and its applications, including demand flexibility estimation, appliance recommendation systems, and real-time energy monitoring systems. By addressing the challenges of existing NILM models, this work contributes to the development of robust, fast, and accurate NILM frameworks that can be applied to real-world energy management tasks.

Key Terms: Load Synthesis, Non-Intrusive Load Monitoring, Factorial Hidden Markov Model, Change Point Detection, Load Disaggregation, and Energy Consumption Behaviour.

सारांश

प्रभावी मांग कटौती कार्यक्रमों को डिजाइन करने में उपयोगिता कंपनियों के लिए ऊर्जा खपत व्यवहार का आकलन करने की क्षमता महत्वपूर्ण है। घरेलू उपकरण उपयोग पैटर्न को समझने से सामुदायिक भार के लिए अधिक सटीक ऊर्जा खपत व्यवहार मूल्यांकन की अनुमति मिलती है। गैर-घुसपैठ लोड मॉनिटरिंग (एनआईएलएम) उपकरण-स्तरीय गतिविधियों की पहचान करने में एक महत्वपूर्ण उपकरण है, जो प्रत्येक उपकरण पर अलग-अलग सेंसर स्थापित करने की आवश्यकता के बिना ऊर्जा उपयोग में महत्वपूर्ण अंतर्दृष्टि प्रदान करता है। एनआईएलएम की घरेलू स्तर की खपत को उपकरण-विशिष्ट डेटा में विभाजित करने की क्षमता सीधे वितरण प्रणाली लोड संश्लेषण में योगदान देती है, जिससे उपयोगिता कंपनियों को स्मार्ट मीटर डेटा से कुल लोड संरचना और इसकी अस्थायी विविधताओं के बारे में जानकारी प्राप्त करने में सक्षम बनाया जाता है।

वितरण प्रणाली लोड संश्लेषण में स्मार्ट मीटर डेटा एनालिटिक्स का लाभ उठाकर संपूर्ण वितरण नेटवर्क के लिए एक विस्तृत और सटीक लोड प्रोफाइल का पुनर्निर्माण शामिल है। एनआईएलएम फ्रेमवर्क समग्र लोड में विभिन्न उपकरणों के योगदान की पहचान करके इस संश्लेषण के लिए आधार प्रदान करता है, जिससे फीडर, ट्रांसफार्मर और सामुदायिक स्तरों पर लोड व्यवहार के अधिक सटीक मॉडलिंग की अनुमति मिलती है। एनआईएलएम परिणामों का उपयोग उपकरण अनुशंसा प्रणाली बनाने, दोषपूर्ण उपकरणों का पता लगाने, लोड पूर्वानुमान में सुधार करने और ऊर्जा खपत पर वास्तविक समय प्रतिक्रिया प्रदान करने के लिए भी किया जा सकता है। हालाँकि, मौजूदा एनआईएलएम मॉडल दो मुख्य चुनौतियों से ग्रस्त हैं: सीमित सटीकता और उच्च कम्प्यूटेशनल जटिलता। जैसे-जैसे घर में उपकरणों की संख्या बढ़ती है, ये चुनौतियाँ और भी अधिक स्पष्ट हो जाती हैं, जिससे वास्तविक दुनिया के अनुप्रयोगों में इन मॉडलों की व्यावहारिक तैनाती सीमित हो जाती है।

इस थीसिस का उद्देश्य नए एनआईएलएम ढाँचे का प्रस्ताव करके इन सीमाओं को संबोधित करना है जो समाधान सटीकता और कम्प्यूटेशनल दक्षता दोनों को बढ़ाते हैं। प्रस्तावित ढाँचे कई प्रगति को एकीकृत करते हैं, जिसमें अंतर-उपकरण परिचालन निर्भरता का मॉडलिंग, समय के साथ उपकरण संचालन राज्यों में अंतर पर विचार, और एनआईएलएम मॉडलिंग प्रक्रिया में उपकरण स्विचिंग और संचालन अवधि पैटर्न शामिल हैं। ये नवाचार फ्रेमवर्क को विशेष रूप से उपयोगिता-स्थापित स्मार्ट मीटर द्वारा कैप्चर किए गए कम-सैंपलिंग-दर डेटासेट के लिए उपयुक्त बनाते हैं, जिससे वास्तविक दुनिया की ऊर्जा प्रबंधन प्रणालियों में उनकी प्रयोज्यता सुनिश्चित होती है।

थीसिस अनुकूलन तकनीकों, फैक्टोरियल हिडन मार्कोव मॉडल (एफएचएमएम), और मशीन लर्निंग दृष्टिकोण के आधार पर एनआईएलएम मॉडल विकसित करती है। प्रस्तावित रूपरेखाओं को मान्य करने के लिए, तीन सार्वजनिक रूप से उपलब्ध NILM डेटासेट का उपयोग करके केस अध्ययन किया जाता है: AMPds, REDD, और UKDALE। विभिन्न भौगोलिक क्षेत्रों से एकत्र किए गए ये डेटासेट, अलग-अलग घरेलू स्थितियों और डेटा विशेषताओं में मॉडल के व्यापक मूल्यांकन की अनुमति देते हैं। परिणाम दर्शाते हैं कि प्रस्तावित ढाँचे सटीकता और समाधान समय दोनों के मामले में अत्याधुनिक एनआईएलएम मॉडल से बेहतर प्रदर्शन करते हैं। कुछ मामलों में, सटीकता काफी अधिक है, जबकि अन्य में, प्रस्तावित ढाँचे बहुत कम कम्प्यूटेशनल जटिलता के साथ तुलनीय सटीकता प्रदान करते हैं, जिससे वे वास्तविक दुनिया में तैनाती के लिए अधिक व्यावहारिक बन जाते हैं।

इस थीसिस में प्रस्तुत शोध एनआईएलएम और इसके अनुप्रयोगों में आगे की प्रगति के लिए आधार तैयार करता है, जिसमें मांग लचीलापन अनुमान, उपकरण अनुशंसा प्रणाली और वास्तविक समय ऊर्जा निगरानी प्रणाली शामिल है। मौजूदा एनआईएलएम मॉडल की चुनौतियों का समाधान करके, यह कार्य मजबूत, तेज और सटीक एनआईएलएम ढाँचे के विकास में योगदान देता है जिसे वास्तविक दुनिया के ऊर्जा प्रबंधन कार्यों पर लागू किया जा सकता है।

मुख्य शब्द: लोड संश्लेषण, गैर-घुसपैठ लोड मॉनिटरिंग, फैक्टोरियल हिडन मार्कोव मॉडल, चेंज पॉइंट डिटेक्शन, लोड डिसएग्रीगेशन, और ऊर्जा खपत व्यवहार।

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Nomenclature

Acronyms/Abbreviations

AFAMAP	Additive Factorial Approximation Maximum A Posteriori
ALIP	Aided Linear Programming
AMPds	The Almanac of Minutely Power Dataset
BQPP	Binary Quadratic Programming with Post-processing
CDE	Clothes Dryer
CO ₂	Carbon Dioxide
CPD	Change Point Detection
D.W.	Dish Washer
DSM	Demand Side Management
EQE	Security/Network
FHMM	Factorial Hidden Markov Model
FRE	HVAC/Furnace
FSM	Finite State Machine

GRE	Garage
HMM	Hidden Markov Model
HPE	Heat Pump
HSMM	Hidden Semi Markov Model
IKMC	Iterative k-means Clustering
ILP	Integer Linear Programming
IQP	Integer Quadratic Programming
MFHMM	Modified Factorial Hidden Markov Model
MINLP	Mixed-Integer Non-Linear Programming
MIQP	Mixed Integer Quadratic Programming
MW	Microwave
NILM	Non-Intrusive Load Monitoring
NRMSE	Normalized Root Mean Square Error
OFE	Home Office
PEC	Percentage Energy Contribution
PELT	Pruned Exact Linear Time
REDD	Reference Energy Disaggregation Dataset
SIQCP	Segmented Integer Quadratic Constraint Programming
SO	Sparse Optimization

STIP	State Transition Integer Programming
TB-CPD	Threshold-Based Change Point Detection
TVE	Ent TV/PVR/AMP
UKDALE	UK Domestic Appliance-Level Electricity
UTE	Utility Room Plug
W.M.	Washing Machine