

Energy Management Strategies for Residential Distribution System Using Smart Meter Data

by

Hafiz Muhammad Usman Butt

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Examining Committee Membership

The following served on the Examining Committee for this thesis. The decision of the Examining Committee is by majority vote.

Supervisor: Ramadan El-Shatshat
Lecturer,
Department of Electrical and Computer Engineering
University of Waterloo

Co-Supervisor: Ayman El-Hag
Lecturer,
Department of Electrical and Computer Engineering
University of Waterloo

Internal Member: Magdy Salama
Professor,
Department of Electrical and Computer Engineering
University of Waterloo

Internal Member: Kshirasagar Naik
Professor,
Department of Electrical and Computer Engineering
University of Waterloo

Internal-External Member: Samir Elhedhli
Professor,
Department of Management Sciences
University of Waterloo

External Member: Maher Azzouz
Associate Professor,
Department of Electrical and Computer Engineering
University of Windsor

Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Energy management (EM) strategies for a power distribution system have attracted attention in the past few decades. EM within smart residential distribution systems is a long-standing challenge that involves effective scheduling of electric vehicle charging and discharging while utilizing available photovoltaic resources and efficiently drawing power from the electric grid to meet household energy demands. This dissertation introduces four important research problems that provide the power distribution system operator with crucial cybersecurity insights. These insights facilitate real-time monitoring of the Distribution Transformer (DT) kVA load, prediction of its end of remaining-useful life, and disaggregation of behind-the-meter solar generation — all using just smart meter data from residential customers processed at the electric utility’s server.

The first research proposes a novel non-intrusive approach based on the Universal Adaptive Stabilization (UAS) algorithm for real-time assessment of behind-the-meter (BTM) solar generation using smart meter data from residential customers. This approach is characterized by its simplicity, robustness, and unsupervised operation, eliminating the need for complex system dynamics. The accuracy and convergence of the proposed method are mathematically justified and evaluated against advanced algorithms using publicly available datasets.

The second research presents a hardware-free strategy for DT kVA load estimation using smart meter data from residential customers. The proposed DT kVA load estimation algorithm operates at the utility server level without requiring a fixed power factor assumption or reactive power load information across residential customers. The proposed strategy provides a simple, effective fixed-point iteration-based formulation for a balanced secondary distribution network, that is extended for an unbalanced three-phase underground secondary distribution network. Theoretical analysis on convergence and stability of the proposed DT kVA load estimation method is also provided.

Building upon the second research work, the third research proposes a four-layer framework that utilizes the DT kVA load estimation algorithm for assessing the remaining useful life (RUL) of a DT. The first layer stores residential smart meter data used for DT kVA load estimation in the second layer. In the third layer, two powerful forecasting tools, Time Series Decomposition and Hidden Markov Model, are compared. The historical and forecast data, along with the DT’s thermal parameters, are employed to assess its RUL. Numerical validation is conducted using real-world data from fifteen households in London, Ontario, Canada.

The three aforementioned research problems are seamlessly integrated into the fourth, presenting a fuzzy logic-based real-time energy management control system, from the per-

spective of an electric utility. The primary objectives of the fourth research work are to utilize available energy resources in a smart residential distribution system, optimize grid power consumption, minimize electricity costs for both the utility and customers, ensure reliable power grid operation, and mitigate DT overloading.

This dissertation aims to propose a fast, efficient, and real-time energy management strategy for smart residential distribution systems. The three integrated research problems offer precise estimation of real-time BTM solar generation, ensuring system reliability while providing accurate DT kVA load estimation to mitigate DT overloading. As a result, the proposed real-time energy management control strategy with its integrated parts makes a valuable contribution to the advancement of smart grid technologies and various distribution automation applications.

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Dedication

*to
Imtanan and Rehana,
my family,
Hira,
and Rayhan Ali*

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List of Abbreviations

EV Electric Vehicle	xi
EVs Electric Vehicles	1
HEMS Home Energy Management System	1
TOU Time-of-Use	1
DT Distribution Transformer	xiv
DTs Distribution Transformers	1
SM Smart Meter	1
SMs Smart Meters	1
RUL Remaining Useful Life	xiv
LDC Local Distribution Company	2

HOEP Hourly Ontario Energy Price	86
RTP Real-Time Pricing	4
LDCs Local Distribution Companies	4
DR Demand Response	4
BTM Behind-The-Meter	xiii
RTEMC Real-Time Energy Management Controller	xi
PV Photovoltaic	xiii
UAS Universal Adaptive Stabilizer	x
LOL Loss-of-Life	8
SoC State-of-Charge	10
NREL National Renewable Energy Laboratory	5
AI Artificial Intelligence	5
HMM Hidden Markov Model	xv
MHMM Mixed Hidden Markov Model	6

ANN Artificial Neural Network	7
BES Battery Energy Storage	8
BSS Battery Storage System	8
CTR Charging Time Required	71
EVCM EV Charging Multiplier	73
MF Membership Function	73
MFs Membership Functions	73
FIS Fuzzy Inference System	76
FLC Fuzzy Logic Control	xi
NTS Nussbaum-Type Switching	17
TSD Time Series Decomposition	xv
SDS Secondary Distribution System	xi
BIBC Bus-Injection to Branch-Current	13
BCBV Branch-Current to Bus-Voltage	13

MCMC Markov chain Monte Carlo	8
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List of Symbols

$RSOC_t$	Remaining state-of-charge of EV
SOC_{min}	Threshold SoC for EV
$EVCap$	Battery capacity of EV (kWh)
P_{EVCHG}	Maximum EV charging power (kW)
P_{EVDSG}	Maximum EV discharging power (kW)
TUD_t	Time until EV departure (hours)
CTR_t	Charging time required to charge EV (hours)
TOU_t	Time-of-Use electricity tariff (cents/kWh)
$TOUCTR,t$	TOU after CTR_t (cents/kWh)
$P_{Load,t}$	Household load consumption (kW)
$P_{PV,t}$	PV generation (kW)
η_t	Fuzzy logic control signal
$P_{EV,t}$	Charging/Discharging power of EV (kW)
$P_{Grid,t}$	Power drawn from the grid (kW)
$L(t)$	Residential load consumption
$M(t)$	Smart meter data
$\hat{L}(t)$	Estimated residential load consumption
$\hat{M}(t)$	Estimated smart meter data
$x_1(t)$	Observer variable for BTM PV generation
$x_2(t)$	Observer variable for residential load
$u(t)$	UAS-based control input
$G(\theta(t))$	High adaptation gain
$E_\alpha(\cdot)$	Mittag-Leffler function
α, λ	Tuning variables for Mittag-Leffler function
S_{ab}^{inj}	Complex power branch flow injected in line ab
P_{ab}^{inj}	Real power branch flow injected in line ab
Q_{ab}^{inj}	Reactive power branch flow injected in line ab

P_{ab}^{Loss}	Real power losses in line ab
Q_{ab}^{Loss}	Reactive power losses in line ab
P_a^{Load}	Real power load at node a
Q_a^{Load}	Reactive power load at node a
V_a	Voltage at node a
I_a	Current at node a
I_{ab}	Current injection in branch ab
$\mathcal{O}_t$	Time series data at time $t \in \mathbb{R}_{\geq 0}$
$T(t)$	Trend in time series data at time t
$S(t)$	Seasonality in time series data at time t
$C(t)$	Cyclic index in time series data at time t
$R(t)$	Randomness in time series data at time t
X_t	Set of hidden states at time t
A	State transition probability matrix
B	Emission probability matrix
π	Initial probability matrix
λ	Hidden Markov Model
$P(\mathcal{O}_t)$	Likelihood of certain observation at time t
$\Theta_H(t)$	Winding hottest-spot temperature
$\Theta_A(t)$	Real ambient temperature
$\Delta\Theta_{TO}(t)$	Top-oil rise over ambient temperature
$\Delta\Theta_H(t)$	Winding hottest-spot rise over top-oil temperature
$\Delta\Theta_{TO,u}$	Ultimate top-oil rise
$\Delta\Theta_{TO,i}$	Initial top-oil rise
K_u	Ratio of ultimate load $\mathcal{O}_t$ to rated load $\mathcal{O}_{rated}$
K_i	Ratio of initial load $\mathcal{O}_{t=0}$ to rated load $\mathcal{O}_{rated}$
$\Delta\Theta_{H,u}$	Ultimate winding hottest-spot rise
$\Delta\Theta_{H,i}$	Initial winding hottest-spot rise
FAA	Distribution transformer aging acceleration factor
t	Index for time, $t \in \mathbb{R}_{\geq 0}$
G	Set of buses
N	Set of distinct states
T	Set of observations
k	Index for iteration
i	Index for initial value
u	Index for ultimate value
a, b	Index for bus
$\Theta_{TO,R}$	Top-oil rise over ambient temperature at rated load

$\Theta_{H,R}$	Hottest-spot rise over top-oil temperature at rated load
τ_{TO}	Oil thermal time constant at rated load
τ_{ω}	Winding time constant at hottest-spot location at rated load
R	Load loss at rated load to no-load loss ratio
n	Exponent of loss function for top-oil rise
m	Exponent of loss function for winding gradient
Z_{ab}	Service drop cable impedance of line ab

Chapter 1

Introduction

1.1 Motivation

The rapid growth of Electric Vehicles (EVs) presents significant challenges to the electrical power distribution system. Uncoordinated charging of EVs at residential premises can cause three major interrelated issues: elevated electricity usage bills for residential customers, reduced lifespan of power system assets, and decreased system reliability. To address the issue of elevated electricity bills, residential customers can consider installing a Home Energy Management System (HEMS) to manage EV charging and household load, and benefit from Time-of-Use (TOU) pricing. However, widespread adoption of HEMS based on TOU pricing may result in a large demand peak during the lowest-priced time period, potentially leading to a rise in DT temperature. This rise in temperature can cause DT insulation deterioration and its premature replacement [8, 9].

A regular Smart Meter (SM) stores kWh consumption, kW usage, and service voltage information; and transmits them to a central repository of the utility. However, the existing functionality of Smart Meters (SMs) installed at North American residential premises does not include reactive power consumption or power factor measurement [10]. Therefore, despite knowing the network configuration, kW usage information from each residential customer, and line parameters of a small-sized secondary distribution system, the accurate kVA load of a DT cannot be estimated. The accurate kVA load information of a DT is critical to assess its loss of life, and, more importantly, to avoid its unexpected failure. The normal life expectancy of Distribution Transformers (DTs), without considering EV loads, can be 20 years or longer under various loading conditions. However, frequent EV charging can overload DTs that were not originally designed to accommodate EV penetration in

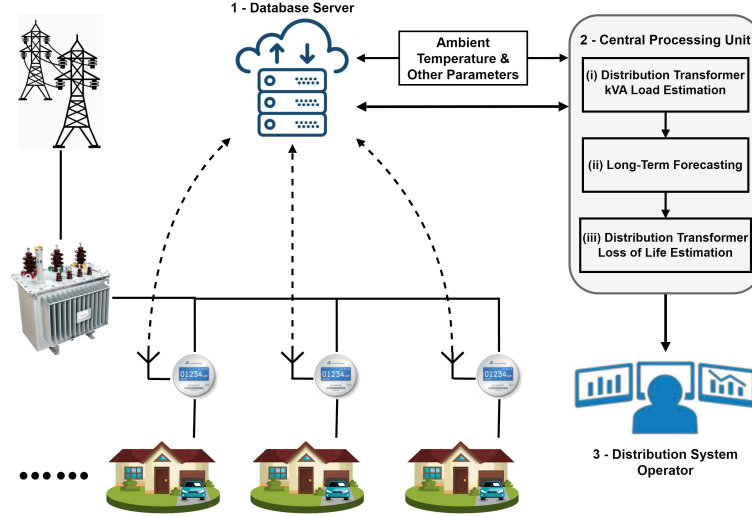


Figure 1.1: Steps to implement the proposed framework in the practical scenario.

the power system, resulting in early failure and premature replacement of DTs. Currently, DTs rated 100 kVA or below are not managed or monitored in North America. These DTs are typically protected against excessive loading by a fuse or internal circuit breaker, rated between 125% and 150% of the DT rating. However, the primary cause of DT failure is lightning strikes rather than overloading. As a result, the DT protection devices are often rated in the range of 200% to 300%, leaving DTs exposed to excessive loading and accelerated aging [11, 12]. Unlike substation DTs, the health of residential DTs is not monitored due to their large population, low cost, and lack of remote communication. Therefore, it becomes crucial to assess the current and anticipated RUL of residential DTs. This information would allow us to identify:

- The required upsizing of DTs, installed over the past few decades without considering anticipated EV penetration, are now experiencing excessive overloading and require premature replacement.
- Acute overloading of a particular DT and the feasibility of sharing the load with other DT(s) in the system, due to the deployment of fast EV chargers where each charger may demand up to 6.6 kW during peak periods.
- An incentive scheme in a demand response program for EV owners that could delay EV charging and thus mitigates DT aging while maintaining overall profit for the Local Distribution Company (LDC).

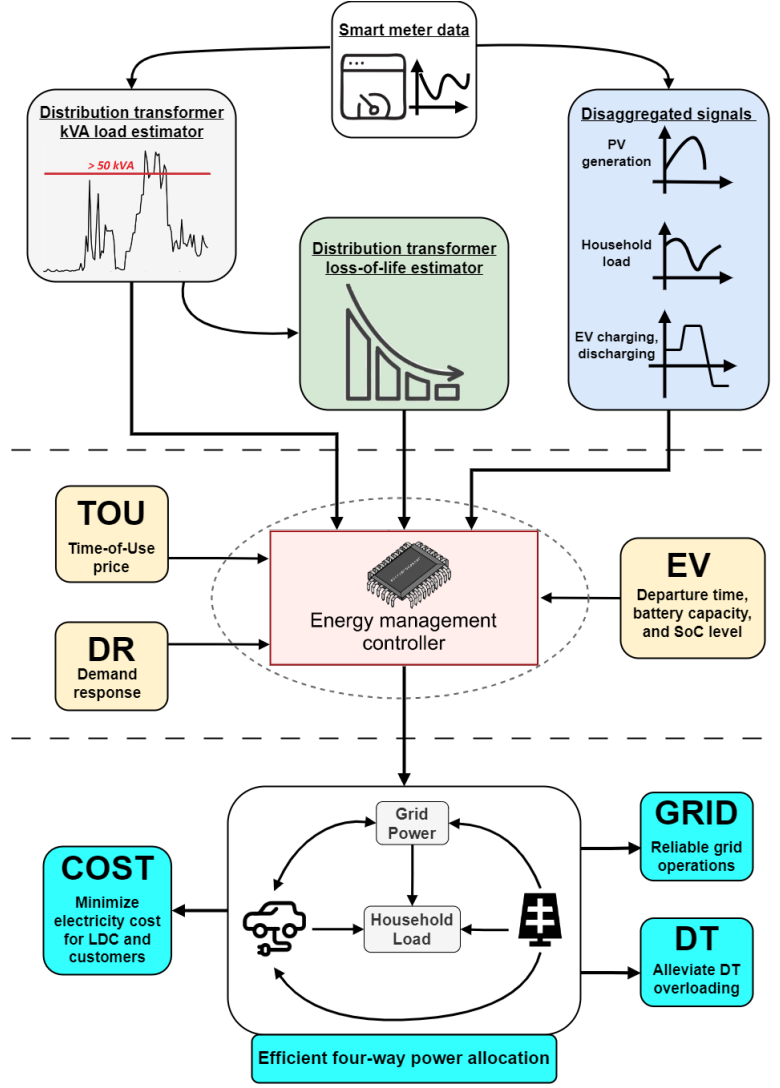


Figure 1.2: Flowchart illustrating the integration of all subsets into the real-time energy management controller for smart residential homes.

The whole system for DT kVA load estimation and assessing its RUL is automated and end-to-end coded, and it is executed on a central processing unit of the local distribution company. Figure 1.1 depicts the essential steps for the practical implementation of the DT kVA load estimation and assessing its RUL.

The high penetration of EVs can cause an imbalance between electricity supply and

demand, leading to elevated electricity Real-Time Pricing (RTP) for Local Distribution Companies (LDCs) and reduced system reliability. LDCs can address this situation by implementing Demand Response (DR) programs to incentivize customers to efficient electricity usage during periods of higher RTP or lower system reliability. However, developing an energy management scheme that simultaneously reduces electricity costs, prevents DT overloading, and responds to DR signals to improve system reliability is an ongoing challenge.

In addition, the increasing utilization of BTM solar PV systems adds complexity to efficient network and market operations. These systems introduce variability and uncertainty in power generation, making accurate net load prediction challenging. Limited visibility and analysis of hosting capacity further exacerbate this issue. Biased system monitoring and forecasts resulting from BTM solar contributions can impact the reliability and security of grid operations. Precise, robust forecasting of BTM solar generation is crucial for effectively balancing supply and demand, avoiding disruptions, and maintaining system reliability [13].

The thesis consists of four parts, each addressing a specific aspect of the research topic. The first part introduces a UAS-based simple, robust, and fully unsupervised method for real-time disaggregation of BTM solar PV generation from SM data. The second part focuses on the accurate estimation of kVA load for the DT. The third part proposes a comprehensive four-layer framework for assessing the anticipated aging of a DT and estimating its RUL. The fourth part introduces a fuzzy logic-based real-time energy management control system (RTEMC). This controller is designed to allocate power efficiently from various household energy sources, including PV power, EV battery power, and electric grid power. To illustrate the integration of all subsets into the RTEMC, Figure 1.2 presents the complete framework of the thesis.

1.2 Literature Review

In this section, the literature review will present relevant research and studies related to the main framework and its associated subsets, following the order described above.

1.2.1 A Non-Intrusive Framework for Real-Time Disaggregation of Behind-the-Meter Solar Generation from Smart Meter Data

The mainstream literature on this subject can be generally divided into two main approaches: model-based and data-driven. The disaggregation problems at both the feeder or transformer and at customer levels can be addressed using either of the two approaches. Model-based methods utilize pre-existing models, such as those created by the National Renewable Energy Laboratory (NREL) [14] and Sandia National Laboratory [15], for BTM solar PV generation estimation. Some advanced model-based PV generation estimation strategies are reported in [16–18] that deploy optimization routines to calibrate model parameters by utilizing solar irradiation, PV size, module orientation, location, and weather information as decision variables. However, model-based approaches have major drawbacks, including uncertainty in PV model parameters, geometry, and degradation level. These limitations can significantly hinder the effectiveness of model-based approaches. In addition, data-driven methods are typically categorized as supervised, semi-supervised, and unsupervised. Supervised methods mainly rely on Artificial Intelligence (AI)-based algorithms and require historical smart meter data and its disaggregated components to train the algorithms. The authors in [19] proposed a two-stage feature extraction and support vector regression-based scheme, while [16] presents a regional PV generation estimation scheme that incorporates correlation analysis in neural networks. Moreover, several AI-based methods have been reported in the literature [20–22] on PV generation forecast. Yet, the main concern of supervised methods is the need for a large historical dataset to train AI-based algorithms, which is not readily available. Additionally, supervised methods are computationally intensive, and a prior cleaning of a dataset is desired.

Mostly, optimization or regression-based methods are employed for semi-supervised approaches and require the historical PV generation data from small, fully observable sites and/or climate data for correlation analysis and to calibrate a simplified PV model. The authors in [23] correlate climate data with unobserved signals and formulate a convex optimization-based problem for PV generation estimation. Reference [24] uses feeder-level and solar irradiance measurements to develop multiple linear regression-based strategies for PV generation estimation at the feeder level. A game-theoretic strategy is presented in [25] for accurate solar generation disaggregation at the feeder level. Semi-supervised methods have been widely adopted in recent research [2, 26–29] because they have been shown to be more effective than supervised and unsupervised counterparts.

Although semi-supervised approaches have been demonstrated to provide multiple advantages over their supervised and unsupervised counterparts, including accuracy and effi-

cient utilization of computational resources, potential limitations hinder the real-time implementation of semi-supervised strategies. For example, semi-supervised methods require PV generation data from small fully observable sites for offline calibration of a simplified version of the PV model via optimization routines, relying on precise selection of initial conditions, since most of the optimization formulations are non-convex in literature. Moreover, some semi-supervised methods utilize climate/weather data for correlation analysis, e.g., very recent state-of-the-art works in [30,31]. Further, the performance of regression-based semi-supervised methods can be greatly affected by data outliers.

In contrast, unsupervised frameworks exclusively leverage optimization routines with some implicit conditions. Some unsupervised methods are based on Markov chain models, such as those described in references [32] and [33]. Recently, a Mixed Hidden Markov Model (MHMM) reported in [4] claims to outperform advanced methods for PV generation estimation. Unlike semi-supervised methods, unsupervised frameworks do not rely on BTM solar PV generation data for calibration or correlation analysis. However, they typically comprise task-dependent multistage and optimization-based algorithms. These algorithms are often complex, requiring high computational resources, and the performance of a subsequent stage is directly linked to the prior stage. Moreover, the performance of unsupervised methods relies on underlying assumptions related to variances and random effects following random distribution patterns, which may not be obvious in many cases. Additionally, the MHMM scheme [4] is iterative, and the accuracy and computational time can be affected by the initial settings.

Discussion

To summarize, the major limitations in the existing literature include the need for historical datasets of small fully observable sites, offline optimization for learning/training, multistage task-dependent algorithms, feeder-level disaggregation, and complex schemes that require high computational resources. To our knowledge, no previous work in the literature has been able to address all the aforementioned limitations simultaneously.

1.2.2 Distribution Transformer kVA Load Estimation Using Residential Smart Meter Data

The current practice to determine distribution network bus voltages for a DT kVA load estimation requires fixed power factor assumption across all residential customers, along with their kW usage data, in addition to the details of network configuration and the

line parameters of a small-sized secondary distribution system. However, the existing functionality of [SMs](#) installed at North American residential premises lacks reactive power or power factor measurement. Therefore, to cope with reactive power or power factor measurement unavailability, different methods through which the power factor assumption can be made have been reported in the literature, such as historical data, network losses, load survey, and pseudo reactive power measurement [\[34–38\]](#).

The power factor assumption, in essence, boils down the problem to a regular radial load flow that can be solved by readily available iterative algorithms such as Forward-Backward [\[39–41\]](#), Newton-Raphson [\[42\]](#), and Gauss-Seidel methods [\[43\]](#). Despite the benefit that the power factor assumption may provide, a fixed power factor assumption across all residential customers is not practical in a realistic secondary power distribution system. Some of the closely related research has been reported in earlier literature on distribution feeders and distribution transformers load estimation. For instance, the authors in [\[44\]](#) present a thermal model for computing the electric load on distribution feeders and transformers. Additionally, the work in [\[45\]](#) estimates a transformer’s peak load from monthly kWh consumption using different regression models for residential, commercial, and industrial customers. Moreover, the real power losses (kW) in a distribution system are evaluated in [\[46\]](#) by employing an Artificial Neural Network ([ANN](#)) method. This method exploits the mean and standard deviation of kW load profiles of residential and small commercial customers. Conversely, in [\[47\]](#) and [\[38\]](#), the customer load profiles (kW) are represented by trapezoidal fuzzy membership function, used to design different linguistic load levels to identify the kW load of a [DT](#).

Discussion

The load in [\[44\]](#) is assumed to consist of electric space heating, electric water heating, and other miscellaneous devices. Moreover, the work in [\[45\]](#) requires a considerable amount of data for accurate regression model, with the assumption that the model remains unchanged over time. Furthermore, the [ANN](#) methods for a transformer’s load estimation in [\[46\]](#) pose another problem, as these methods require an enormous amount of data for training purposes and intense computational efforts. The major issues in the existing related research works include the fixed power factor assumption across all the residential customers and only kW load estimation of a [DT](#) instead of kVA load estimation.

1.2.3 Distribution Transformer Remaining Useful Life Estimation Considering Electric Vehicle Penetration

Extensive research work on DT aging/health assessment, in general, is available in the literature. The study in [48] adopts K-mean clustering strategy to extract 24-hour representative load and temperature profiles describing the common behavior of a large dataset of residential customers. Each representative profile is then scaled up based on the number of customers connected to a residential transformer and subsequently utilized to estimate the transformer's hottest-spot temperature and Loss-of-Life (LOL).

In [5], residential customers owning high-power fast EV chargers along with rooftop solar panels and battery energy storage are considered for daily and yearly probabilistic quantification of distribution transformer aging. The study in [5] employs a Markov chain Monte Carlo (MCMC)-based scheme to generate synthetic data for residential customers, ambient temperature, rooftop solar panels, and EV charging in an iterative manner. The MCMC-based scheme preserves the correlation in the synthetic data and allows the evaluation of DT aging for any number of years. The results in [5] present yearly LOL considering various penetration levels of EV, PV, and Battery Energy Storage (BES). Similar to [5], the work in [6] also employs the MCMC scheme to generate synthetic data. However, various parameters' uncertainties linked with EV charging, i.e., driver behavior and travel patterns, are incorporated in [6] for a more accurate representation of the yearly LOL assessment. Unlike [5], the work in [6] considers the upper stream of a power distribution system, where the end users' power consumption not only accelerates the aging of DTs in a secondary system but also impacts the main substation transformer and may cause voltage imbalance. Toward the end of [6], a control strategy is proposed to mitigate DT overloading by utilizing a home battery storage system. Likewise, adequate research has been carried out to improve DT aging by charging EVs at TOU pricing [49] by incorporating different penetration levels of PV generation and/or Battery Storage System (BSS) or by a coordination strategy among EV, PV generation, and BSS [50, 51].

The studies in [53] and [54] proposed a smart EV charging scheme to alleviate DT aging. The problem formulation in [53] and [54] leverages residential load forecasting and entails a trade-off between minimizing DT aging and maximizing EV charging quality. However, the work in [54] goes a step further by proposing a fuzzy logic-based framework to minimize the computational cost and determining an incentive for EV owners that could delay EV charging and thus mitigate DT aging while maintaining overall profit for the electric utility. Recently, a state-space model is proposed in [55] to estimate the transformer's RUL, and particle filtering method is adopted to solve the nonlinear state-space model. Likewise, the work in [56] integrates an AI-based model in a particle filtering framework for medium-

Table 1.1: Comparison of important attributes of the proposed framework with previous studies.

Studies	Real household electricity consumption data	Practical circuit configuration and cable parameters	Real time ambient temperature	Real time kVA load of a DT	Long-term prediction	Anticipated end of DT RUL	Computationally less intensive and simple
[48]	✓	×	✓	×	✓	×	✓
[5], [6]	×	✓	✓	×	×	×	×
[7], [50]	×	✓	×	×	×	×	✓
[49], [52]	×	✓	×	×	×	×	✓
[53], [54]	×	×	✓	×	✓	×	✓
[55], [56]	×	×	×	×	✓	✓	×
Proposed DT RUL estimation approach	✓	✓	✓	✓	✓	✓	✓

term estimation of the transformer’s RUL. The model in [55,56] requires the transformer’s condition monitoring data along with ambient temperature and DT loading profile. Also, the ambient temperature and loading profile are synthetically generated through stochastic processes, ignoring EV penetration. Moreover, the case study in [55] considers a small-scale 5kVA transformer, and the particle filtering method has higher computational cost. Besides, the work in [56] makes an impractical assumption that the transformer’s top-oil temperature is measured. Thus, the study in [55,56] may not be applicable for realistic RUL estimation in a practical distribution system. The attributes in Table 1.2 are considered important for precise estimation of the anticipated end of DT RUL.

Discussion

Although the existing literature related to DT aging/health assessment has merits, the existing research works address one problem at a time, lack comprehensiveness, and do not have the ability to incorporate various attributes that not only provide realistic insight but also help in distribution system planning. For instance, recovering erroneous load data at the consumer level [48,53,54] may not be computationally efficient compared to that at DT level. Further, the accuracy of results in [5,6] may be prone to the number of iterations of the proposed algorithm for different case studies. Also, the work in [5,6] performs analysis on synthetically generated data. In addition, refs [5,6] adopt a model-based approach that is prone to under-modeling and may not be suitable for real-world applications, since a system’s structure is never perfectly known [57]. Moreover, the work in [7,50] investigates the effect of long-range EV charging on DT aging, considering a fixed value of ambient temperature. Besides, to the best of authors’ knowledge, no particular research predicts the end of RUL for a DT on residential premises. Last, it is worth mentioning that the currently installed SMs at North American residential premises lack power factor or reactive power measurement. Therefore, all the existing works assume a fixed power factor across the residential customers to determine DT kVA load and utilize it for DT aging/health index

assessment, which is not practical in a realistic distribution system [58]. Further, there has been no single comprehensive research to date in the sense that: (i) it is conducted on real measurement data (not on synthetically generated household power or fixed ambient temperature, e.g. [5–7, 55, 56]); (ii) it is applied on a practical SDS (unlike most of the existing works that are studied on IEEE primary distribution systems); (iii) it estimates the kVA load of a DT from household’s SM data (in contrast to assuming a fixed power factor for residential customers); (iv) it incorporates the actual growth of EV penetration over the years (contrary to several assumed case studies); and finally (v) it anticipates end of DT RUL over the years (not just yearly %LOL).

1.2.4 Real-Time Energy Management Control System for Smart Residential Homes

In recent years, state-of-the-art research has shown significant interest in exploring the potential of EV charging and discharging for the purpose of reducing energy costs and improving the lifespan of power system assets [59–61]. For instance, the work in [62] develops a centralized model that aims to co-optimize the DT LOL and the charging/discharging schedule of electric vehicles. This approach suggests incentivizing EV owners to allow control over their EV schedules, with the goal of maximizing DT lifespan, and resulting in benefits for both the power grid and EV owners. Likewise, the work in [63] presents a day-ahead co-optimization strategy that seeks to mitigate system-level energy losses and DT LOL by efficiently managing EV charging schedules. Further, the study in [64] reveals that large-scale adoption of HEMS at the lowest-priced time period has the potential to increase the DT LOL. Thus, the study in [64] determines the optimal penetration of HEMS by regulating their participation through incentive amounts. Moreover, a real-time energy management algorithm is proposed in [65] to enable power-sharing among EV charging parks, PV systems, and the power grid. The work in [65] treats these entities as a collective unit of bulk power, with the goal of reducing overall charging costs while mitigating voltage deviations. To achieve this, the algorithm adjusts charging rates in real-time based on the EV State-of-Charge (SoC)

In [66], a distributed charging algorithm is presented using a game theory approach that optimizes the energy consumption and EV charging schedule for each residential customer. This research aims to minimize the charging cost for each customer and the degradation of the DT over time. Besides, the adverse effects of HEMS may result in overvoltage due to the reverse power flow from the surplus PV output, thereby violating the voltage limits. Thus, two-way communication is established in [67] between HEMS, which controls

Table 1.2: Comparison of important attributes of the proposed fuzzy logic-based RTEMC with previous studies.

Studies	Full control over EV charge and discharge, or home appliances	Computationally less intensive and simple	Real-time operation, or no load forecast	Four-way power sharing: Grid, PV, EV, and Home	Able to respond DR signals	Reduce electricity cost	Mitigate DT overloading
[62]	×	✓	✓	×	×	✓	✓
[63]	×	✓	×	×	×	✓	✓
[64]	×	×	×	×	✓	✓	✓
[65]	✓	✓	✓	✓	×	✓	✓
[66]	✓	×	✓	×	×	✓	✓
[67]	×	×	×	✓	✓	✓	✓
[68]	×	✓	✓	×	×	✓	×
[69]	×	✓	✓	×	×	✓	✓
Proposed RTEMC	✓	✓	✓	✓	✓	✓	✓

household loads, EV charging/discharging, and PV curtailment, and the Grid EMS, which adjusts the taps of on-load tap changers, using day-ahead power profiles. The approach in [67] not only reduces residential operational costs but also prevents voltage fluctuations in the distribution system. Additionally, a heuristic optimization-based approach is proposed in [68] for scheduling EV charging and discharging considering the time-of-use electricity tariff. The proposed method discharges the EV during high-priced time periods and charges it during low-priced time periods, thereby ensuring a reduction in the electricity bill. Last, the study in [69] introduces a smart EV charging scheme to alleviate DT aging. This is accomplished through a fuzzy logic-based framework that minimizes computational costs and offers incentives to EV owners to delay charging, resulting in reduced DT aging while maintaining overall profit for the electric utility. A comparison is made between the proposed approach and previous studies in Table 1.2.

Discussion

Several research studies, including [62], suggest a centralized control approach for managing EV charging and discharging, while imposing further operational constraints on household appliances, as suggested in [63, 64]. Although a centralized control strategy for managing EVs and appliances can offer benefits to the service provider and prevents DT overloading, it may face limited acceptance from customers due to the associated inconveniences and limited control over their EVs and appliances. Other research works, including [66, 67], require complex optimization processes, involving the use of intense mathematical equations, multistage algorithms, or a high level of human interaction. In addition, several studies cannot be executed in real-time due to their dependence on day-ahead PV and load forecasts, as in [63, 64, 67].

Numerous research studies have employed limited power-sharing technologies, such as Grid-to-Vehicle (G2V) when TOU pricing is low and energy arbitrage technologies such

as Vehicle-to-Grid (V2G) or Vehicle-to-Home (V2H) when **TOU** pricing is high (e.g., [62, 65, 67]). However, there is limited research into the integration of **PV** power, namely PV-to-Grid (PV2G), PV-to-EV (PV2EV), or PV-to-Home (PV2H), which would enable the utilization of power sharing among all available resources. As a final point, **DR** signals hold significant importance since they are issued by electric utilities in various scenarios. These scenarios include situations where there is an expected peak in electricity demand to prevent power outages or when the grid’s reliability is compromised due to unexpected events. Furthermore, **DR** signals may facilitate the integration of renewable energy sources by encouraging the shifting of power demand to periods when green energy is abundant or by reducing the cost of constructing new power plants or transmission lines. At the retail level, **DR** signals are reflected as time-varying **RTP**. Therefore, it is recommended that **DR** signals be integrated into an energy management framework that satisfies the utility’s requirements while providing incentives to customers.

1.3 Research Objectives

In light of the comprehensive literature review and thorough discussions conducted, this thesis establishes the following primary research objectives:

- The first objective of this thesis is to introduce a non-intrusive Universal Adaptive Stabilization algorithm for real-time disaggregation of behind-the-meter solar **PV** generation and residential electricity consumption from the smart meter measurement. The proposed **UAS**-based framework is simple, robust, fully unsupervised, and does not require detailed system dynamics.
- The second objective of this thesis is to propose a simple and robust, yet effective, method of determining distribution network bus voltages for a **DT** kVA load estimation. The novelty in this work lies in the development of a **DT** kVA load estimation strategy that does not require any fixed power factor assumption or reactive power load information across all residential customers.
- The third objective of this thesis is to develop a systematic framework for determining an anticipated end of **DT RUL** in a residential setting. The proposed strategy is hardware-free and operates at the **LDC**’s server level. This work extends the third part to another level by utilizing an algorithm for the accurate estimation of **DT** kVA load.

- The fourth objective of this thesis is to develop a novel fuzzy logic-based real-time energy management controller for efficient allocation of power from various household energy sources, including PV power, EV battery power, and electric grid power. The fuzzy logic-based RTEMC aims to minimize electricity cost for both LDC and customers, ensure reliable power grid operation, and mitigate distribution transformer overloading while delivering results in a few milliseconds.

1.4 Thesis Outline

- Chapter 2:** introduces a UAS-based BTM PV generation disaggregation strategy utilizing smart meter data from residential customers. The proposed method's robustness is rigorously evaluated, considering extreme cases and real-life disturbances. The efficacy of the method is further assessed using ten BTM solar PV generation profiles from small residential properties in different countries. Comparative analysis against advanced algorithms confirms the superior performance of the proposed framework. Additionally, this study establishes the mathematical foundation for BTM PV generation estimation, demonstrating the convergence of estimated values with true values.
- Chapter 3:** utilizes the Bus-Injection to Branch-Current (BIBC) and Branch-Current to Bus-Voltage (BCBV) matrices [70] to formulate DT kVA load estimation strategy. The chapter specifically addresses the estimation of DT kVA loads in unbalanced three-phase underground secondary distribution networks, providing necessary treatments for accurate estimation. The proposed strategy's effectiveness and claims are validated through Monte Carlo simulations, encompassing 1,000 load profiles that incorporate uncertainties from smart meter data. The analysis includes the presentation of histograms and statistical analysis of kVA load estimation errors. Additionally, the chapter investigates the convergence and numerical stability of the proposed methodology, highlighting key factors that may lead to divergence and instability.
- Chapter 4:** expands on the work presented in Chapter 3 and introduces a comprehensive four-layer framework for assessing the anticipated aging of a DT and estimating its RUL. The proposed framework is rigorously validated using real-world data sources, including (i) electricity consumption data from fifteen households provided by London Hydro, a LDC in Ontario, Canada,

(ii) ambient temperature data of London, Ontario, obtained from the government of Canada’s official website [71], (iii) data on triplex service drop cables [72], (iv) a practical archetype circuit configuration representative of an SDS [73], (v) thermal parameters of the DT derived from IEEE Standard C57.91-2011 [74], and (vi) specification data pertaining to the most popular EVs in Canada [6, 7].

Chapter 5: presents a detailed mathematical description of a fuzzy logic control-based RTEMC framework. The effectiveness of the proposed RTEMC is then demonstrated through a detailed analysis of a test case, involving PV and household load profiles over a 24-hour period. The RTEMC efficiently manages grid and PV power by identifying the most suitable schedules for EV charging and discharging, considering key decision factors. Additionally, the efficacy of fuzzy logic-based RTEMC is analyzed first on a practical SDS, followed by an investigation at the feeder level that supplies power to a diverse range of SDS, utilizing true dataset.

Chapter 6: presents a summary of the main conclusions and contributions of this thesis, while highlighting potential areas for future research.

Chapter 2

A Non-Intrusive Framework for Real-Time Disaggregation of Behind-the-Meter Solar Generation from Smart Meter Data

This chapter presents the development of the Universal Adaptive Stabilizer (UAS)-based methodology, which aims to estimate Behind-the-meter (BTM) PV generation from residential smart meter data. The formulation of this methodology is discussed, along with a comprehensive mathematical justification that will be provided later in the chapter. Furthermore, the proposed strategy is evaluated in the results section by comparing it against PV profiles collected from six different countries.

2.1 Proposed Methodology

Figure 2.1 illustrates the schematic of the proposed UAS-based methodology. The methodology comprises two key blocks: the first block models the dynamics of BTM solar PV generation and residential load consumption, while the second block is the UAS-based adaptive observer. The subsequent subsections provide detailed descriptions of the components and mathematical models used in each block.

As illustrated in Figure 2.1, the end users' smart meter data is composed of residential load minus PV generation. This relationship is expressed in (2.1) by denoting the PV

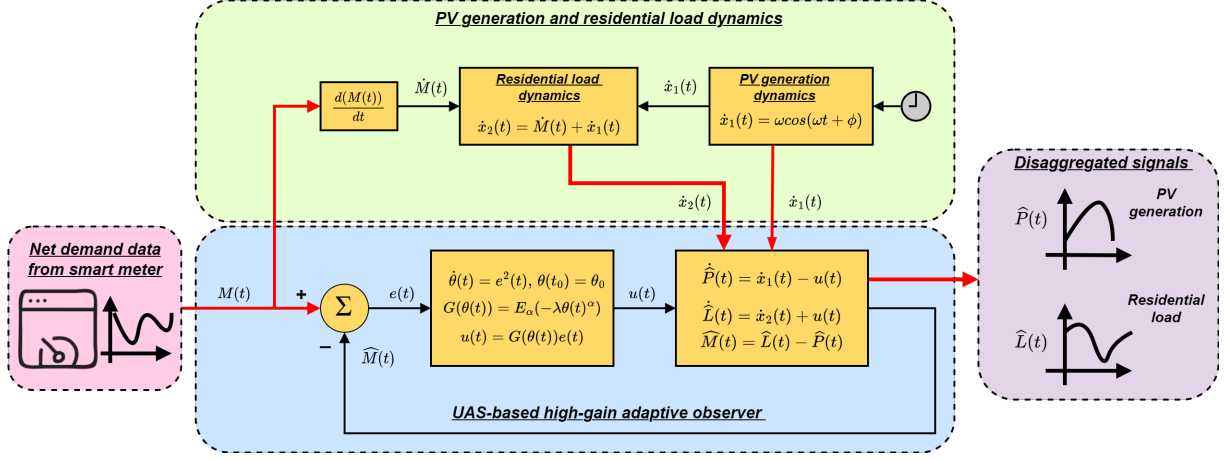


Figure 2.1: Proposed **UAS**-based adaptive framework for disaggregation of BTM solar PV generation and residential load consumption from the smart meter measurement.

generation, residential load consumption, and smart meter data at $t \in \mathbb{R}_{\geq 0}$ as $P(t)$, $L(t)$, and $M(t)$, respectively. The symbol $\mathbb{R}_{\geq 0}$ denotes positive real numbers.

$$M(t) = L(t) - P(t), \quad t \in \mathbb{R}_{\geq 0}. \quad (2.1)$$

The accurate disaggregation of **BTM** solar **PV** generation and residential load from smart meter measurement requires a multi-step methodology. First, the structural dynamics of the **BTM** solar **PV** generation are synthesized, and the residential load structural dynamics are obtained by adding the rate of change of the smart meter measurement to the output of the **BTM** solar **PV** generation block. Next, the observer variables, $\hat{P}(t)$ and $\hat{L}(t)$, are formulated by incorporating the structural characteristics of **BTM** solar **PV** generation and residential load, respectively, and utilizing the **UAS**-based control input, $u(t)$, to compensate for exact **BTM** solar **PV** and residential load models. The error, $e(t)$, is then utilized to determine the sign and magnitude of the **UAS**-based function, $G(\theta(t))$, which automatically adapts the $\hat{P}(t)$ and $\hat{L}(t)$ values to accurately track the actual smart meter measurement, $M(t)$. A detailed mathematical proof of the methodology can be found in section 2.2.

2.1.1 Proposed Mathematical Models

Unlike the existing mainstream strategies in literature, here the objective is to disaggregate $M(t)$ signal into $L(t)$ and $P(t)$ signals in a real-time setting without requiring historical

datasets, real-time data of some fully observable sites, offline optimization, multistage complex algorithms, or any implicit assumption. The philosophy of this work is to adaptively adjust the estimates of BTM solar PV generation and residential load, so that the estimated smart meter value closely tracks the actual smart meter measurement, even with an uncertain system model and smart meter measurement noise. This is achieved by a UAS-based framework, which is designed by utilizing a Nussbaum-Type Switching (NTS) function, presented in Appendix B.

Equation (2.1) provides an expression for the actual smart meter measurement, $M(t)$. Similarly, we can express the estimated smart meter value, $\widehat{M}(t)$, using equation (2.2). The observer variables for BTM solar PV generation and residential load are $\widehat{P}(t)$ and $\widehat{L}(t)$, respectively. These observer variables are formulated using structural dynamics for BTM solar PV generation, $x_1(t)$, and residential load, $x_2(t)$, as presented in (2.3) and (2.4). The specific details of these features are discussed in sections 2.1.1 and 2.1.1.

$$\widehat{M}(t) = \widehat{L}(t) - \widehat{P}(t), \quad t \in \mathbb{R}_{\geq 0}, \quad (2.2)$$

$$\dot{\widehat{P}}(t) = \dot{x}_1(t) - u(t), \quad (2.3)$$

$$\dot{\widehat{L}}(t) = \dot{x}_2(t) + u(t). \quad (2.4)$$

This control input $u(t)$ is adaptively tuned by the NTS function, outlined in Appendix B, to ensure that the estimated smart meter value $\widehat{M}(t)$ accurately tracks the actual smart meter measurement $M(t)$. In practice, PV generation patterns are typically observed to be distorted semi-sinusoidal functions. Such distortions may arise from a variety of factors, including weather conditions, sensor uncertainty, age-related wear and tear, and loose cable connections, among others. To address these distortions, the PV generation dynamics are modeled as a semi-cosine-shaped function, presented in 2.1.1, and utilizing $u(t)$, described in 2.1.1. It is important to note that even with an uncertain system model and smart meter measurement noise, the input $u(t)$ in (2.3) and (2.4) ensures asymptotic stability by quickly adapting to the correct magnitude and sign [75, 76]. Additionally, the input $u(t)$ drives $\widehat{P}(t)$ and $\widehat{L}(t)$ to converge to the actual PV generation $P(t)$ and residential load $L(t)$, respectively. We provide a detailed description of the PV generation and residential load dynamics, as well as the formulation of the UAS-based input.

PV generation dynamics

Due to the presence of distortion, the actual PV generation often takes on a semi-sinusoidal shape, thus it is appropriate to model $x_1(t)$ as a semi-sinusoidal function with minima at times t_{sunrise} and t_{sunset} . Furthermore, $\dot{x}_1(t)$ can be represented as a semi-cosine-shaped function to capture the PV generation dynamics.

$$\dot{x}_1(t) = \frac{d(\sin(\omega t + \phi))}{dt} = \omega \cos(\omega t + \phi), \quad (2.5)$$

Here, $\dot{x}_1(t) = \omega \cos(\omega t + \phi)$ if $t \in \{t_{\text{sunrise}}, \dots, t_{\text{sunset}}\}$; $\dot{x}_1(t) = 0$ otherwise. The ω and ϕ should be chosen such that the minimum of $x_1(t)$ is achieved at t_{sunrise} and t_{sunset} . This time range ensures that the PV generation within this period is non-zero. The user can specify the appropriate time range within the sunrise and sunset period, which can be readily obtained from reliable online sources that provide accurate sunrise and sunset times worldwide. By incorporating this time factor, our model accommodates the variations caused by daylight savings and ensures that it reflects the corresponding changes in PV generation. Thus, the BTM solar PV generation can be mathematically represented by substituting (2.5) in (2.3), presented in (2.6).

$$\dot{\hat{P}}(t) = \omega \cos(\omega t + \phi) - u(t), \quad (2.6)$$

$$\dot{\hat{P}}(t) = \omega \cos(\omega t + \omega t_0) - u(t). \quad (2.7)$$

Here, t_0 represents the time shift constant, which allows for the adjustment of the model according to the specific time shift during sunrise. This adjustment guarantees that the model accurately accounts for the time shift and ensures consistent result quality across all seasons.

Residential load dynamics

By taking the rate of change of equation (2.1), the actual residential load dynamics are represented as $\dot{L}(t) = \dot{M}(t) + \dot{P}(t)$. The term ‘load’ refers to the aggregation of electricity consumption from all household appliances, rather than a single load. In practical settings, the smart meter data from end-users is easily accessible, allowing the real-time computation of the actual rate of change $\dot{M}(t)$. The smart meter provides sampled data of $M(t)$, with sampling every ‘h’ minutes. The discrete time approximation $\dot{M}(t) \approx (M(t+h) - M(t))/h$,

with $h \neq 0$ is utilized to calculate the rate of change of $M(t)$ at $t \in \mathbb{R}_{\geq 0}$. The dynamics of residential load can be represented as a semi-cosine-shaped function $\dot{x}_1(t)$ added to the actual time derivative of smart meter measurement $\dot{M}(t)$. The input $u(t)$ is also included to account for uncertainties and compensate for the actual time derivative of BTM solar PV generation $\dot{P}(t)$. The modeling choice described in Equation (2.8) reflects this approach. Note that, similar modeling choices for observer formulation can be found in established literature for parameter estimation of DC motors [77], for Li-ion batteries [78, 79], for detecting Li-ion battery terminal voltage collapse [80], and for parameters estimation of proton-exchange membrane fuel cells [81]. Considering equation (2.1), the most intuitive way to approximately model the dynamics for residential load is by adding the dynamics of PV generation $\dot{x}_1(t)$ from (2.5) and the dynamics of smart meter measurement $\dot{M}(t)$. Thus, the dynamics of residential load are mathematically represented by substituting (2.8) in (2.4), described in (2.9).

$$\dot{x}_2(t) = \dot{M}(t) + \dot{x}_1(t), \quad (2.8)$$

$$\dot{\hat{L}}(t) = \dot{M}(t) + \omega \cos(\omega t + \phi) + u(t). \quad (2.9)$$

Universal Adaptive Stabilization-based control input formulation, $u(t)$

The UAS-based control input $u(t)$ is formulated in equations (2.10)-(2.13).

$$e(t) = M(t) - \widehat{M}(t), \quad (2.10)$$

$$\dot{\theta}(t) = e^2(t), \theta(t_0) = \theta_0 > 0, \quad (2.11)$$

$$G(\theta(t)) = E_\alpha(-\lambda\theta(t)^\alpha), \quad (2.12)$$

$$u(t) = G(\theta(t))e(t). \quad (2.13)$$

The high adaptation gain $G(\theta(t))$ in equation (2.12) is governed by the NTS function (outlined in Appendix B), which allows it to take values from $+\infty$ to $-\infty$ (as shown in equations (B.5) and (B.6)) based on $e(t)$. The values of α and λ used in this work are determined through inspection, and set to $\alpha = 2.5$ and $\lambda = 0.001$.

2.2 Mathematical Justification

The subsequent theorem and its proof validate the accuracy and convergence of the estimated BTM solar PV generation and residential load to their actual values.

Theorem 1. *Suppose $P(t)$, $L(t)$, $\dot{P}(t)$, $\dot{L}(t)$, $\dot{x}_1(t)$, and $\dot{x}_2(t)$ are bounded, $e(t)$ is smooth, and $C \in \mathbb{R}$. Using $u(t) = G(\theta(t))e(t)$ as the high-gain adaptive function, we have $\lim_{t \rightarrow \infty} \theta(t) = \theta_\infty$, where $\theta_\infty \in \mathbb{R}$, $\lim_{t \rightarrow \infty} e(t) = 0$, the following results are obtained:*

- $\lim_{t \rightarrow \infty} \hat{P}(t) = P(t) + C$,
- $\lim_{t \rightarrow \infty} \hat{L}(t) = L(t) + C$.

Proof. Consider the smart meter measurement includes a bounded additive offset $B(t)$ (i.e. noise or disturbance). Take the time derivative of (2.10), then use (2.3) and (2.4), and thereafter addition and subtraction of $L(t)$ into R.H.S (Right Hand Side) yield the following

$$\dot{e}(t) = \dot{M}(t) - \dot{\hat{M}}(t) + \dot{B}(t), \quad (2.14)$$

$$\dot{e}(t) = \dot{L}(t) - \dot{P}(t) + \dot{x}_1(t) - \dot{x}_2(t) - 2u(t) + L(t) - L(t) + \dot{B}(t). \quad (2.15)$$

Assuming the load type is consumer, i.e. $L(t) \geq 0$ or $-L(t) \leq 0$, and let $\delta_1(t) = L(t) + \dot{L}(t) - \dot{P}(t) + \dot{x}_1(t) - \dot{x}_2(t) + \dot{B}(t)$. Addition of $\delta_1(t) - 2u(t)$ on both side of $-L(t) \leq 0$ gives us the following

$$\dot{e}(t) \leq \delta_1(t) - 2u(t). \quad (2.16)$$

Let $\delta_2(t) = -P(t) - \dot{P}(t) + \dot{L}(t) + \dot{x}_1(t) - \dot{x}_2(t) + \dot{B}(t)$. Similar to (2.15), addition and subtraction of $P(t)$ into R.H.S of (2.14), then considering $P(t) \geq 0$, and thereafter addition of $\delta_2(t) - 2u(t)$ on both side of $P(t) \geq 0$ gives us the following

$$\dot{e}(t) \geq \delta_2(t) - 2u(t). \quad (2.17)$$

Equations (2.16) and (2.17) are important and they are used for the two cases of error, i.e. $e(t)$ being positive or negative, respectively.

Case 1: Consider $e(t) > 0$ for $t \in \mathbb{R}_{\geq 0}$.

Multiplication of (2.16) by $e(t)$ gives

$$e(t)\dot{e}(t) \leq \delta_1(t)e(t) - 2u(t)e(t). \quad (2.18)$$

Consider the following fact: $\left(\delta_1(t) - e(t)\right)^2 \geq 0$, or $\frac{1}{2}\delta_1^2(t) + \frac{1}{2}e^2(t) \geq \delta_1(t)e(t)$. Using this in (2.18), and substituting (2.13) gives

$$e(t)\dot{e}(t) \leq \frac{1}{2}\delta_1^2(t) + \frac{1}{2}e^2(t) - 2G(\theta(t))e^2(t). \quad (2.19)$$

Since $\frac{d}{dt}\left(\frac{1}{2}e^2(t)\right) = e(t)\dot{e}(t)$, integration of (2.19) from t_0 to t , and using (2.11) yields

$$\frac{1}{2}e^2(t) \leq \frac{1}{2} \int_{t_0}^t \delta_1^2(\tau) d\tau + \frac{1}{2} \left(\theta(t) - \theta(t_0) \right) - 2 \int_{t_0}^t G(\theta(\tau)) \dot{\theta}(\tau) d\tau. \quad (2.20)$$

Let $\tilde{\theta}(t) = \theta(t) - \theta(t_0)$, and recognize $\int_{t_0}^t G(\theta) \dot{\theta} dt = \int_{\theta(t_0)}^{\theta(t)} G(\tau) d\tau$. Simplification of (2.20) gives

$$\frac{e^2(t)}{\tilde{\theta}(t)} \leq \frac{1}{\tilde{\theta}(t)} \int_{t_0}^t \delta_1^2(\tau) d\tau + 1 - \frac{4}{\tilde{\theta}(t)} \int_{\theta(t_0)}^{\theta(t)} G(\tau) d\tau. \quad (2.21)$$

Equation (2.21) is important and we shall revisit (2.21) after obtaining a similar equation from Case 2 below, i.e. error being negative.

Case 2: Consider $e(t) < 0$ for $t \in \mathbb{R}_{\geq 0}$.

Multiplication of (2.17) by $e(t)$ gives

$$e(t)\dot{e}(t) \leq \delta_2(t)e(t) - 2u(t)e(t). \quad (2.22)$$

Notice that (2.22) and (2.18) are very similar, except $\delta_1(t)$ and $\delta_2(t)$ terms. Following the same steps as (2.19)-(2.20), one can get (2.23).

$$\frac{e^2(t)}{\tilde{\theta}(t)} \leq \frac{1}{\tilde{\theta}(t)} \int_{t_0}^t \delta_2^2(\tau) d\tau + 1 - \frac{4}{\tilde{\theta}(t)} \int_{\theta(t_0)}^{\theta(t)} G(\tau) d\tau. \quad (2.23)$$

Since $P(t)$, $L(t)$, $B(t)$, their derivatives along with $\dot{x}_1(t)$, and $\dot{x}_2(t)$ are bounded, and they can not be infinite practically, the terms $\frac{1}{\tilde{\theta}(t)} \int_{t_0}^t \delta_1^2(\tau) d\tau$ and $\frac{1}{\tilde{\theta}(t)} \int_{t_0}^t \delta_2^2(\tau) d\tau$ are bounded

in (2.21) and (2.23), respectively. Now if $\theta(t) \rightarrow \infty$ as $t \rightarrow \infty$ then by definition of NTS function in (B.5), $\int_{\theta(t_0)}^{\theta(t)} G(\tau) d\tau$ term can approach to $+\infty$ in (2.21) and (2.23) and contradict the positiveness of L.H.S (Left Hand Side) of (2.21) and (2.23). Therefore, the assumption $\theta(t) \rightarrow \infty$ as $t \rightarrow \infty$ is false, and it is bounded as $t \rightarrow \infty$. This implies $\lim_{t \rightarrow \infty} \theta(t) = \theta_\infty$ and $\lim_{t \rightarrow \infty} \dot{\theta}(t) = 0$. From (2.11), this further implies $\lim_{t \rightarrow \infty} e(t) = 0$ and thus $\lim_{t \rightarrow \infty} (M(t) - \widehat{M}(t)) = 0$. This can be written as

$$(L(t) - P(t)) - (\widehat{L}(t) - \widehat{P}(t)) = 0. \quad (2.24)$$

This implies that the L.H.S of (2.24) can only be zero if $\lim_{t \rightarrow \infty} \widehat{L}(t) = L(t) + C$, and $\lim_{t \rightarrow \infty} \widehat{P}(t) = P(t) + C$, where $C \in \mathbb{R}$. This completes the proof. $\square$

Remarks: Up to this point, it is established that the UAS-based observer is capable of capturing non-linear dynamics of multiple state variables concurrently, but an equal amount of constant offset $C \in \mathbb{R}$ may or may not be present in individual estimates. The offset $C \in \mathbb{R}$ cannot be imposed to 0 using the proposed approach. However, if the offset C is known and injected to the initial values of $\widehat{P}(0)$ and $\widehat{L}(0)$ such that $\widehat{P}(0) = P(0)$ and $\widehat{L}(0) = L(0)$, the estimated $\widehat{P}(t)$ and $\widehat{L}(t)$ converge to their real values $P(t)$ and $L(t)$, respectively, throughout the adaptive estimation process.

Practically, it is not hard to know the initial value of $P(0)$, because the UAS-based technique is proposed to run just before sunrise time when the solar irradiance is essentially zero. Further, if the initial value $P(0)$ is known, we have $\widehat{P}(0) = P(0)$. Afterward, $\widehat{L}(0)$ can be easily obtained by the following: $\widehat{L}(0) = \widehat{P}(0) + \widehat{M}(0)$, since $\widehat{P}(0) = P(0)$ and $\widehat{M}(0) = M(0)$. Here, $M(0)$ is readily known because the access to smart meter data $M(t)$ is available throughout the adaptive estimation process.

Further, it is worth mentioning that the proof requires $t \rightarrow \infty$, which is a standard control theoretic technique [75, 80, 82] required to derive mathematical results. In practice, $t \rightarrow \infty$ would cause the estimation process to take too long. However, this is exactly why we use a high-gain adaptive observer which shows rapid convergence in practice. This can be observed in the results presented.

2.3 Results and Analysis

Numerical studies have been conducted to evaluate the proposed UAS-based framework, categorized into two distinct groups. First, the robustness of the proposed scheme is rigorously validated against the simulated datasets. Second, the accuracy of the proposed work is assessed by comparing it against several mainstream state-of-the-art smart meter data disaggregation schemes, utilizing publicly available datasets.

2.3.1 Robustness analysis

Validation against simulated datasets

As mentioned earlier, the publicly available datasets are fairly smooth, and the robustness of any available data disaggregation scheme in the literature cannot be explicitly justified. This section validates the robustness of the proposed method by utilizing the PV model created by NREL [14]. The PV model developed by NREL has been subjected to modifications with all known real-life disturbances, including the impact of weather intermittency, inverter clipping, shading events, sensor/device uncertainty, system aging, and loose cable connections, to simulate extreme case scenarios. Four simulated datasets are utilized to evaluate the robustness, and the details of these datasets are provided below.

- D1:** Load profile is the combination of increasing linear and sinusoidal functions, random noise, and a load loss event occurring from 5 hour to 7 hour, Figure 2.2a.
PV profile contains random noise, a shading event occurring from 6 hour to 8 hour, and inverter clipping above 1.6 kW, Figure 2.2b.
- D2:** Load profile is the combination of increasing exponential function, random noise, and multiple load drops and load loss events occurring at 2, 4, and 8 hours, respectively, Figure 2.2c.
PV profile contains random noise, two shading events occurring from 1 hour to 3 hour and from 6 hour to 8 hours, and inverter clipping above 1.6 kW, Figure 2.2d.
- D3:** Load profile is the combination of an increasing staircase function, random noise, and a load drop event occurring from 6 hour to 6.5 hour, Figure 2.2e.
PV profile contains random noise, a shading event occurring from 1 hour to 3 hour, and inverter clipping above 1.6 kW, Figure 2.2f.

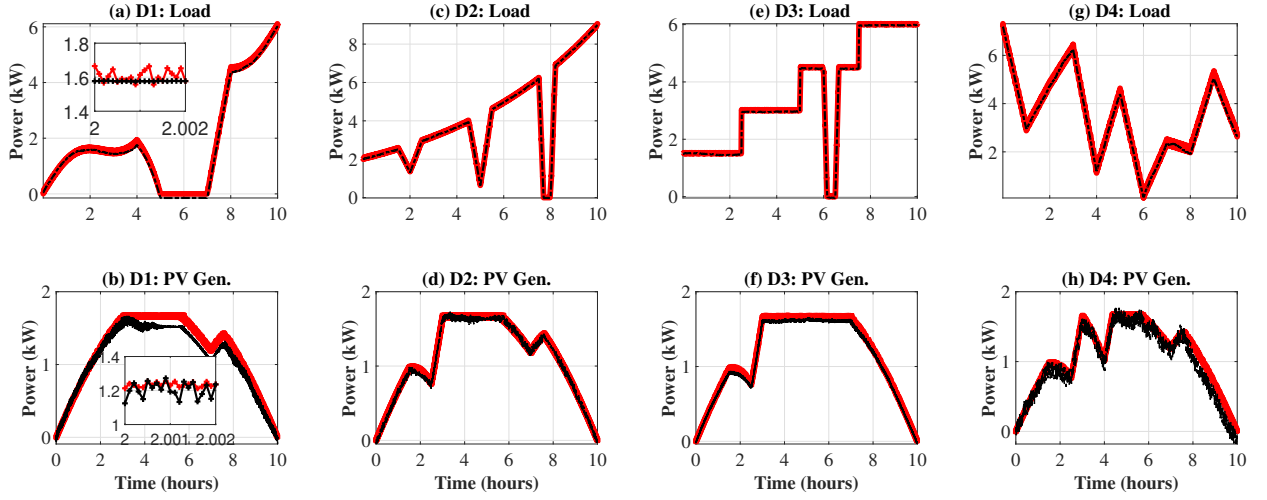


Figure 2.2: Tracking ability of the proposed UAS-based framework for BTM solar PV generation and residential load estimation from available smart meter measurement. The simulated profile is shown in red, while the estimated profile is represented by the black trace.

D4: Load profile is the random function containing random noise, Figure 2.2g.

PV profile contains random shading events along with random noise with no inverter clipping, Figure 2.2h. This signifies the uncertainty in various weather conditions.

Table 2.1: Statistical analysis to quantify the robustness of proposed UAS-based framework for BTM solar PV generation and residential load estimation from available smart meter measurement.

Error Metrics	State Variables	D1	D2	D3	D4
RMSE	Load	0.1109	0.0374	0.0538	0.1296
	PV Gen.	0.1780	0.1679	0.1714	0.2188
MAE	Load	0.0980	0.0314	0.0467	0.1045
	PV Gen.	0.1357	0.0787	0.0951	0.1450
Median	Load	-0.1099	-0.0229	-0.0478	-0.0832
	PV Gen.	-0.1200	-0.0208	-0.0498	-0.0908
Mode	Load	-0.2300	-0.1076	-0.8069	-0.3729
	PV Gen.	-0.7862	-0.8441	-0.8408	-0.8397
Standard Deviation	Load	0.0680	0.0301	0.0298	0.0990
	PV Gen.	0.1153	0.1520	0.1426	0.1780

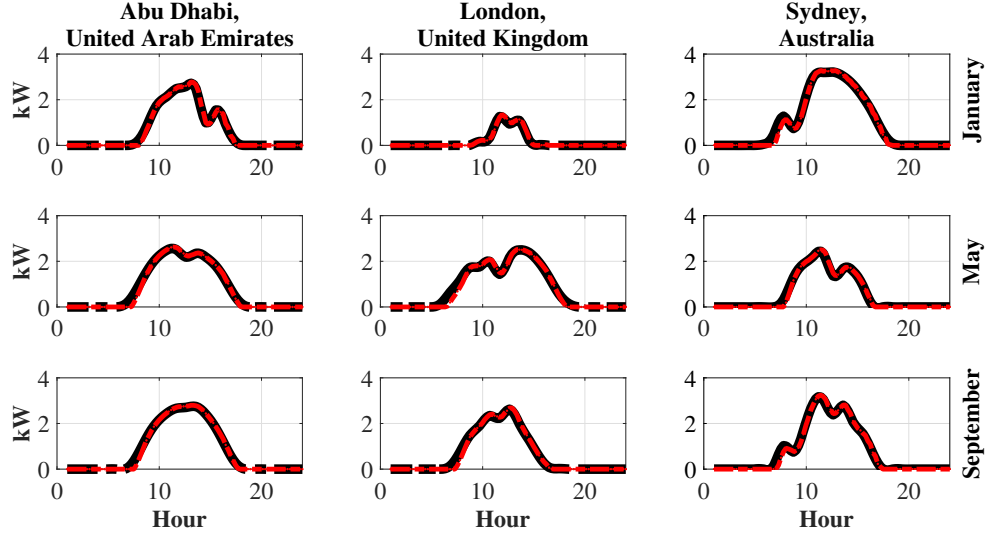


Figure 2.3: Validation of the proposed UAS-based method against nine PV generation profiles - in three different months for three different countries [1]. (Black trace represents actual profile; Red trace represents estimated profile).

Despite the presence of random noise, uncertainty in weather conditions, and various perturbing events in the datasets, the proposed scheme very closely tracks the actual BTM solar PV generation and residential load with reasonable accuracy, as shown in Figure 2.2. In section 2.3.1, the measurement resolution for the dataset is 1 millisecond. This resolution ensures accurate capturing of the time-dependent variables and provides a sufficiently detailed analysis. Further, this resolution captures and analyzes the dynamics of the system at a granular level, facilitating the interpretation of the observed trends. In this dataset, a uniform random noise function is employed. The amplitude range of this function corresponds to a variation within $\pm 2\%$ of the actual PV generation value at each respective instance. It is important to note that the constant error observed in Figure 2.2(b) may be attributed to the imprecision of α and λ tuning. While our mathematical proof assumes perfect tuning of these parameters, it is worth mentioning that achieving perfect tuning in real-life scenarios can be challenging. Regarding the presence of noise in the PV estimation but not in the load curve, we intentionally injected noise into the dataset to demonstrate the robustness of our proposed method. The noise in the PV generation measurements is representative of real-world scenarios where sensor or device inaccuracies can introduce fluctuations. By incorporating this noise, we aimed to showcase the ability of our method to handle such uncertainties and still provide accurate

estimations. Furthermore, in the mathematical proof of convergence, we explicitly account for the effect of noise and disturbances in the smart meter measurements, thus further validating the proposed framework.

The Signal-to-Noise (SNR) values for PV estimates in Figure 2.2 are as follows. D1: 32.793 dB, D2: 33.572 dB, D3: 40.695 dB, and D4: 24.639 dB. The enlarged views in Figure 2.2 show the presence of noise in the entire simulated dataset. The enlarged view for only Figure 2.2a and Figure 2.2b is provided, since it shows a similar pattern (the presence of noise) across all subplots of Figure 2 for any time interval. Quantitative analysis of the proposed scheme’s robustness is conducted using several error metrics, including mean square error (MSE), mean absolute error (MAE), median, mode, and standard deviation. Table 2.1 presents the results of the analysis. Since the real-time measurement $\hat{M}(t)$ updates the approximate model $\hat{x}_2(t)$, as shown in (2.8). Whereas, $\hat{x}_1(t)$ is approximately modeled as a simple semi-cosine-shaped function, and no real-time measurement updates it, as shown in (2.5). Therefore, owing to the real-time measurement update in the load modeling, the load estimation error is lower than that of PV generation in Table 2.1. Also, the small standard deviation values indicate that the error distribution is tightly clustered around a small mode value, implying a lower degree of error dispersion. Overall, the small values of various error matrices in Table 2.1 imply that the proposed UAS-based scheme is highly robust; it effectively combats random noise, uncertainty in weather conditions, and load drop/loss events; and it closely tracks the actual BTM solar PV generation and residential load with high accuracy. The errors presented in Table 2.1 and Table 2.2 are derived by calculating the mean squared error and mean absolute error on a point-by-point basis.

Validation against ten PV generation profiles - in four different months for four different countries

Solar irradiance varies widely across different seasons and countries. The performance of the proposed method is assessed using real-world data from the PVWatts Calculator developed by National Renewable Energy Laboratory [1], with analyses conducted across various seasons and locations. One-day PV generation profiles are collected in three different months (January, May, and September) for three different countries (London – United Kingdom, Abu Dhabi – United Arab Emirates, Sydney – Australia), resulting in nine PV generation profiles. Without any model calibration, the UAS-based model is showcased to perform effectively across various locations and seasons globally in Figure 2.3. The upper and lower boundaries of the RMSE across all results in Figure 2.3 are found to be 0.1256 and 0.0474, respectively. In sections 2.3.1 and 2.3.2, the measurement resolution for the

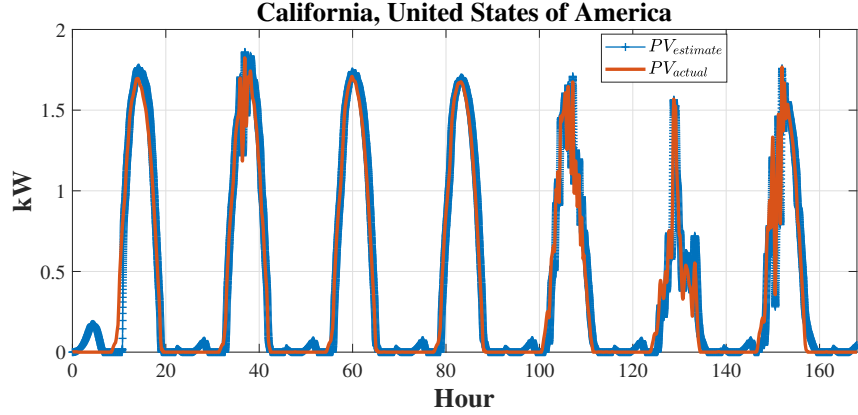


Figure 2.4: Performance comparison of the proposed **UAS**-based framework utilizing a residential solar generation dataset from California, spanning October 2, 2014, to October 8, 2014.

dataset is 15 minutes. Further, we have included a consecutive seven-day profile obtained from a California resident by [83]. This profile exhibits distinctive shapes and variations among the individual days, providing a more comprehensive representation of the diverse PV profiles encountered in real-world scenarios, as illustrated in Figure 2.4. The RMSE in Figure 2.4 is 0.0860.

2.3.2 Real-world comparison of the proposed **UAS**-based framework against advanced methods on a publicly available dataset

The proposed scheme’s effectiveness is compared against mainstream state-of-the-art smart meter data disaggregation methods from [2–4] using a publicly available dataset of residential electricity consumers in Austin, Texas, U.S. acquired by Pecan Street Inc. [84] with 15-minute data acquisition rate. This dataset has been widely used in more than 300 peer-reviewed research articles [83]. The comparison of proposed and mainstream methods on the accurate tracking of unobserved **BTM** solar **PV** generation and residential load is shown in Figure 2.5. The proposed method closely follows the real **PV** generation and load profiles, and it outperforms the mainstream algorithms. The estimation error for all techniques depicted in Figure 2.5 is subjected to statistical analysis, presented in Table 2.2. The results displayed in Table 2.2 highlight the superior performance of the proposed method over mainstream techniques, including some recent methods from [4,85]. The com-

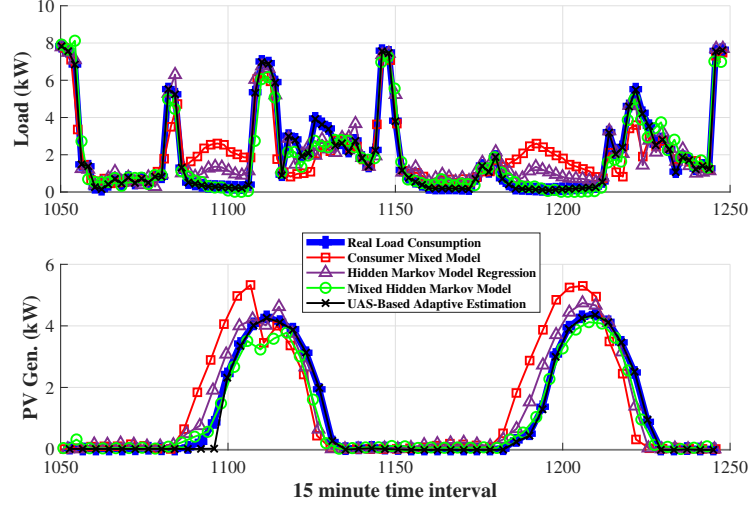


Figure 2.5: Performance comparison of the proposed UAS-based framework with advanced schemes for BTM solar PV generation and residential load estimation using available smart meter measurement from October 11, 2015 to October 12, 2015

putational time comparison presented in Table 2.2 was conducted on different processors. Despite this, the computational time of the proposed method is markedly lower, being nearly 100 times faster. Given this significant difference in magnitude, even if the methods were compared on the same processor, the proposed method would still demonstrate superior efficiency.

Figure 2.6 shows the histogram of estimation errors for all the Figure 2.5 participant techniques. The results suggest that, unlike the mainstream methods, the proposed scheme offers very low estimation error, as shown in Figure 2.6g and Figure 2.6h. Numerical studies confirm that the proposed UAS-based adaptive method is highly robust to effectively combat several perturbing events and significantly outperforms the mainstream strategies in terms of accurately estimating unobserved profiles of BTM solar PV generation and residential load consumption.

Sensitivity Analysis for λ

The value of α in the high-gain adaptation function $G(\theta(t))$ is system-dependent. Each system, such as a DC motor or Li-ion battery, has a specific α value associated with it. Typically, the value of α falls within the range of 2 to 3, making it relatively straightforward

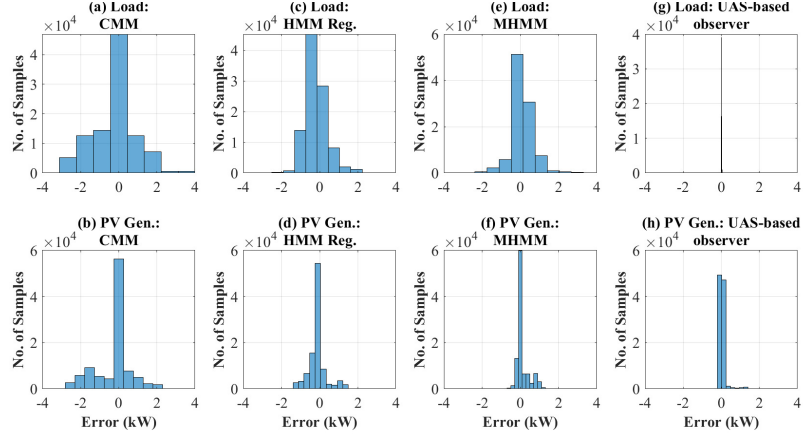


Figure 2.6: Comparison of the histogram plots for Consumer Mixed Model (CMM) [2], Hidden Markov Model Regression (HMM Reg.) [3], Mixed Hidden Markov Model (MHMM) [4], and the proposed UAS-based framework for BTM solar PV generation and residential load estimation.

Table 2.2: Performance comparison of the proposed UAS-based framework against advanced schemes for BTM solar PV generation and residential load estimation.

Error Metrics	State Variables	UAS-based Observer	MHMM [4]	HMM Reg. [3]	CMM [2]
RMSE	Load	0.1	0.346	0.424	0.608
	PV Gen.	0.2	0.346	0.424	0.608
MAE	Load	0.02	0.42	0.48	0.74
	PV Gen.	0.06	2.11	2.58	3.85
Computation Time (sec)	-	0.03	10	4.5	46

to obtain a suitable value for α for a given system. Regarding λ , its value can be adjusted based on the delay in the system response. The user can perform a few trial runs to tune λ specifically for a particular system. In this work, we have found that a smaller value for λ works effectively. However, we recommend that the user starts by adjusting λ from a smaller value, taking into account the specific delay in the system response. By refining the value, the user can find an appropriate λ that improves the performance of the method for their specific system. The sensitivity analysis for λ is shown in Figure 2.7

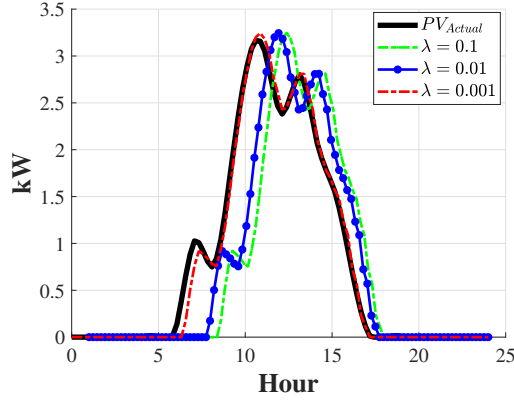


Figure 2.7: Sensitivity analysis of the proposed UAS-based scheme with $\alpha = 2.5$ and different λ values.

2.4 Summary

The study in this chapter introduces a novel approach for real-time estimation of behind-the-meter solar PV generation and residential load using smart meter measurements, based on an adaptive framework that utilizes Universal Adaptive Stabilization. The proposed methodology stands out from the mainstream approaches in literature by not relying on accurate system dynamics, avoiding the need for optimization-based or multistage processes, and being fully unsupervised, thus making it computationally efficient. We evaluated the robustness of the proposed method against simulated datasets and real BTM solar PV generation profiles obtained from six different countries. The experimental findings demonstrate that the UAS-based approach proposed in this study outperforms advanced algorithms by a considerable margin. Furthermore, the mathematical proof is presented in this study to support the accuracy of the proposed scheme. Lastly, the proposed UAS-based framework has a computational time that falls within a few milliseconds, making it highly suitable for real-time applications and potential chip implementation.

Chapter 3

Distribution Transformer kVA Load Estimation Using Residential Smart Meter Data

In the chapter, the preliminaries of the proposed work are discussed, followed by the proposed methodology for balanced, and unbalanced three-phase underground secondary distribution systems. The mathematical justification for the proposed methodology is thoroughly examined, accompanied by a theoretical analysis of its convergence properties. The chapter concludes by investigating the results against 1,000 random load profiles through Monte-Carlo simulations which represent uncertainty in smart meter data.

3.1 Background and Proposed Methodology

3.1.1 Preliminaries

As mentioned in the introduction, the proposed work utilizes [BIBC](#) and [BCBV](#) matrices, which provide the basis for numerous and recent research works pertaining to power distribution automation applications [\[86–88\]](#). Although the work presented in [\[70\]](#) has a simple implementation, robust and fast convergence, and low computation, it requires both the active and reactive load information at each node of a distribution network, along with [BIBC](#) and [BCBV](#) matrices, and use basic matrix manipulations to determine the bus voltages of a distribution network. In this section, some preliminary work is discussed by

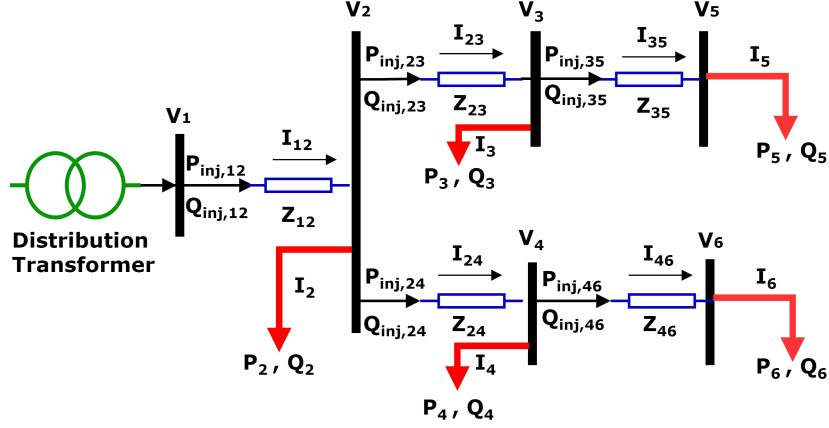


Figure 3.1: Single line representation of a simple 6-bus radial secondary distribution system.

considering a simple 6-bus balanced radial secondary distribution circuit to set up the tone for the proposed methodology afterward. Then, substantive modifications in the proposed methodology are also described for an unbalanced three-phase secondary distribution network.

Figure 3.1 shows a simple 6-bus radial secondary distribution system. Note that the formulation for secondary distribution network bus voltage identification assumes a balanced 3-phase radial system, thereby omitting a 3-phase voltage, current, and impedance notations in this section. For a 3-phase unbalanced system, the voltage-current and impedance notations can simply be substituted for 3×1 vector and 3×3 phase impedance matrix, respectively, throughout the chapter. Referring to Figure 3.1, Kirchhoff's Current Law (KCL) establishes the relation between bus injection and branch currents, and this is described by (3.1).

$$\begin{bmatrix} I_{12} \\ I_{23} \\ I_{24} \\ I_{35} \\ I_{46} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} I_2 \\ I_3 \\ I_4 \\ I_5 \\ I_6 \end{bmatrix}. \quad (3.1)$$

Here, the upper triangular matrix in (3.1) is known as a **BIBC** matrix. Similarly, the bus voltages variation, with respect to branch currents, can be represented by a **BCBV** matrix, as described by (3.2)-(3.3).

$$\begin{bmatrix} V_1 \\ V_1 \\ V_1 \\ V_1 \\ V_1 \end{bmatrix} - \begin{bmatrix} V_2 \\ V_3 \\ V_4 \\ V_5 \\ V_6 \end{bmatrix} = \begin{bmatrix} Z_{12} & 0 & 0 & 0 & 0 \\ Z_{12} & Z_{23} & 0 & 0 & 0 \\ Z_{12} & 0 & Z_{24} & 0 & 0 \\ Z_{12} & Z_{23} & 0 & Z_{35} & 0 \\ Z_{12} & 0 & Z_{24} & 0 & Z_{46} \end{bmatrix} \begin{bmatrix} I_{12} \\ I_{23} \\ I_{24} \\ I_{35} \\ I_{46} \end{bmatrix}, \quad (3.2)$$

$$[\Delta \mathbf{V}] = [\mathbf{BCBV}][\mathbf{BIBC}][\mathbf{I}]. \quad (3.3)$$

The final fixed-point iteration-based expression to determine the bus voltages of a radial distribution network is represented by (3.4)-(3.6) [70].

$$I_i^k = \left(\frac{P_i + jQ_i}{V_i^k} \right)^*, \quad (3.4)$$

$$[\Delta \mathbf{V}^{k+1}] = [\mathbf{BCBV}][\mathbf{BIBC}][\mathbf{I}^k], \quad (3.5)$$

$$[\mathbf{V}^{k+1}] = [\mathbf{V}^0] + [\Delta \mathbf{V}^{k+1}]. \quad (3.6)$$

Here, $[\mathbf{V}^0]$ vector signifies the initialized distribution network bus voltages to begin the iterative process. Next, the proposed method presents an adaptive strategy that adjusts the reactive power consumption at each bus, i.e. Q_i in (3.4), based on network topology, line impedance data, real power consumption, and bus voltages.

3.1.2 Proposed Methodology: Distribution Transformer kVA Load Estimation

Balanced Three-Phase Distribution Network

Referring to Figure 3.1, the first step of the proposed strategy is to evaluate complex power branch flow $S_{ir}^{inj,k}$ by utilizing bus voltage and branch impedance information for N-bus radial distribution system as described in (3.7), where $i = \{1, 2, \dots, N-1\}$ and $r = \{2, 3, \dots, N\}$.

$$S_{ir}^{inj,k} = V_i^k I_{ir}^{k*} = V_i^k \left(\frac{V_i^k - V_r^k}{Z_{ir}} \right)^* = P_{ir}^{inj,k} + jQ_{ir}^{inj,k}. \quad (3.7)$$

Similar to (3.1), the relationship among real power branch flows $P_{ir}^{inj,k}$, real power branch losses $P_{ir}^{Loss,k}$, and real power loads P_r^{Load} can also be established, for Figure 2.1, through KCL manner as described in (3.8).

$$\begin{cases} P_{12}^{inj,k} = P_{12}^{Loss,k} + P_2^{Load} + P_{23}^{Loss,k} + P_3^{Load} + P_{24}^{Loss,k} + P_4^{Load} \\ \quad + P_{35}^{Loss,k} + P_5^{Load} + P_{46}^{Loss,k} + P_6^{Load}, \\ P_{23}^{inj,k} = P_{23}^{Loss,k} + P_3^{Load} + P_{35}^{Loss,k} + P_5^{Load}, \\ P_{24}^{inj,k} = P_{24}^{Loss,k} + P_4^{Load} + P_{46}^{Loss,k} + P_6^{Load}, \\ P_{35}^{inj,k} = P_{35}^{Loss,k} + P_5^{Load}, \\ P_{46}^{inj,k} = P_{46}^{Loss,k} + P_6^{Load}. \end{cases} \quad (3.8)$$

The relationship described by (3.8) can be expressed in a general form as described by (3.9)-(3.10).

$$\begin{bmatrix} P_{12}^{inj,k} \\ P_{23}^{inj,k} \\ P_{24}^{inj,k} \\ P_{35}^{inj,k} \\ P_{46}^{inj,k} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \left(\begin{bmatrix} P_{12}^{Loss,k} \\ P_{23}^{Loss,k} \\ P_{24}^{Loss,k} \\ P_{35}^{Loss,k} \\ P_{46}^{Loss,k} \end{bmatrix} + \begin{bmatrix} P_2^{Load} \\ P_3^{Load} \\ P_4^{Load} \\ P_5^{Load} \\ P_6^{Load} \end{bmatrix} \right), \quad (3.9)$$

$$[\mathbf{P}_{Branch}^k] = [\mathbf{BIBC}] ([\mathbf{P}_{Loss}^k] + [\mathbf{P}_{Load}]). \quad (3.10)$$

Note that **BIBC** matrix in (3.10) is the same as one used in the Equation (3.5). Since $[\mathbf{P}_{Branch}^k]$ vector can be evaluated using (3.7) and the $[\mathbf{P}_{Load}]$ information is available through smart meters, the real power branch losses, i.e. $[\mathbf{P}_{Loss}^k]$ vector, can be calculated by (3.11).

$$[\mathbf{P}_{Loss}^k] = [\mathbf{BIBC}]^{-1} [\mathbf{P}_{Branch}^k] - [\mathbf{P}_{Load}]. \quad (3.11)$$

We know that $P_{ir}^{Loss,k} = I_{ir}^2 R_{ir}$ and $Q_{ir}^{Loss} = I_{ir}^2 X_{ir}$, where R_{ir} and X_{ir} denote the line resistance and reactance respectively, and can be retrieved through conductor data information. From $P_{ir}^{Loss,k}$ and $Q_{ir}^{Loss,k}$ expressions, the reactive power branch losses, i.e. $Q_{ir}^{Loss,k}$, can be evaluated through active power branch losses, i.e. $P_{ir}^{Loss,k}$, by equation (3.12).

Algorithm 1: Distribution Transformer kVA Load Estimation

- 1 **Requirements:** Distribution network structural information, and line impedance data for **BIBC** and **BCBV** matrices formation. Real power consumption $[\mathbf{P}_{Load}] = \{P_1, P_2, \dots, P_N\}$ for N-bus distribution network.
- 2 **Data:** Iteration variable $k = 0$. $[\mathbf{V}^0] = [V_2^0, \dots, V_N^0] = [1 \text{ p.u.}, \dots, 1 \text{ p.u.}]$. Small positive number ϵ . Upper bound of power factor λ_U , and lower bound of power factor λ_L . Upper bound on reactive power estimates, i.e. $[\mathbf{QU}_{Load}] = [QU_1, \dots, QU_N] = [\mathbf{P}_{Load}] \odot \tan(\cos^{-1}(\lambda_L))$. Lower bound on reactive power estimates, i.e. $[\mathbf{QL}_{Load}] = [QL_1, \dots, QL_N] = [\mathbf{P}_{Load}] \odot \tan(\cos^{-1}(\lambda_U))$.
- 3 **Output:** Distribution Transformer kVA Load S_{TRF}^{abc} .
- 4

- 5 **While** $\|[\Delta \mathbf{V}^k]\| > \epsilon$
- 6 Find real and reactive power branch flow matrices elements using (3.7) for $[\mathbf{P}_{Branch}^k]$ and $[\mathbf{Q}_{Branch}^k]$.
- 7 Calculate $[\mathbf{P}_{Loss}^k]$ matrix from (3.11).
- 8 Evaluate $[\mathbf{Q}_{Loss}^k]$ matrix elements from (3.12).
- 9 Find reactive power load matrix $[\mathbf{Q}_{Load}^k]$ from (3.13).
- 10 **For** $h := 1$ to N , *step* = 1 $\triangleright$ This for loop imposes upper and lower bounds of power factor range.
- 11 **If** $((Q_{Load}^k(h) > QU_{Load}(h)) \text{ or } (Q_{Load}^k(h) < QL_{Load}(h)))$
 $Q_{Load}^k(h) \leftarrow \text{mean}(QU_{Load}(h), QL_{Load}(h)),$
- 12 **Else**
- 13 **Continue** loop execution.
- 14 **EndIf**
- 15 **EndFor**
- 16 Evaluate distribution network bus voltages mismatch equation (3.14),

$$[\Delta \mathbf{V}^{k+1}] = [\mathbf{BCBV}][\mathbf{BIBC}] \left(\frac{[\mathbf{P}_{Load}] + j[\mathbf{Q}_{Load}^k]}{[\mathbf{V}^k]} \right)^*.$$
- 17 $[\mathbf{V}^{k+1}] = [\mathbf{V}^0] + [\Delta \mathbf{V}^{k+1}]$.
- 18 $k \leftarrow (k + 1)$.
- 19 **EndWhile**
- 20 Distribution Transformer kVA Load

$$S_{TRF}^{abc} = V_{Base}^{abc} \odot (Y_{12}^{abc}(V_{Base}^{abc} - V_2^{abc}))^* = P_{TRF}^{abc} + jQ_{TRF}^{abc}.$$

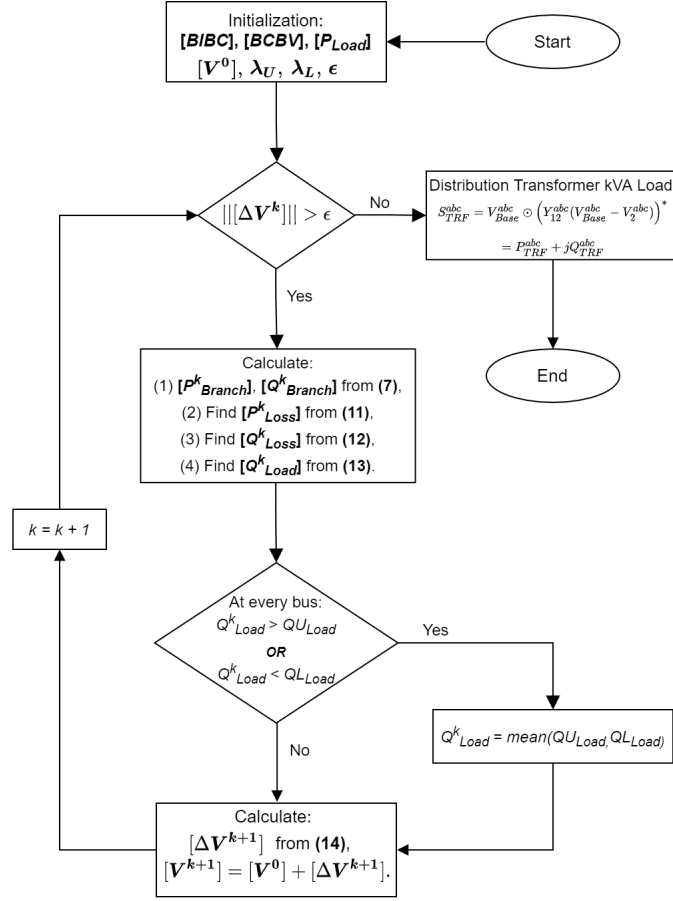


Figure 3.2: Flowchart of the proposed framework for distribution transformer kVA load estimation using residential smart meter data without power factor assumption.

$$Q_{ir}^{Loss,k} = P_{ir}^{Loss,k} \frac{X_{ir}}{R_{ir}}. \quad (3.12)$$

Similar to (3.11), the reactive power load vector $[Q_{Load}^k]$ can be calculated through reactive power branch loss $[Q_{Loss}^k]$ and reactive power branch flow $[Q_{Branch}^k]$ vectors, as described in (3.13).

$$[Q_{Load}^k] = [BIBC]^{-1} [Q_{Branch}^k] - [Q_{Loss}^k]. \quad (3.13)$$

The equation (3.13) can be used directly into equation (3.14). It differs from (3.5) in the sense that $[Q_{Load}^k]$ vector is not provided, rather it is estimated during the iterative process.

$$[\Delta V^{k+1}] = [BCBV][BIBC] \left(\frac{[P_{Load}] + j[Q_{Load}^k]}{[V^k]} \right)^* . \quad (3.14)$$

1. The DT kVA load estimation method begins with initialization of all the distribution network bus voltages to 1 p.u.. The $[P_{Branch}^k]$ and $[Q_{Branch}^k]$ vectors are evaluated using the bus voltages and the line impedance data, described in (3.7).
2. Next, the $[P_{Branch}^k]$ vector along with the $[P_{Load}]$ vector (available through smart meters) is used to calculate the $[P_{Loss}^k]$ vector, described in (3.11). This $[P_{Loss}^k]$ vector is used to find the $[Q_{Loss}^k]$ vector, described in (3.12).
3. Afterward, The $[Q_{Loss}^k]$ vector and $[Q_{Branch}^k]$ vector (obtained in step 1) are used to find the $[Q_{Load}^k]$ vector, described in (3.13). Finally, the $[P_{Load}]$ and $[Q_{Load}^k]$ vectors are employed to update the node voltages for the next iteration in (3.14).

The overall strategy for a DT kVA load estimation is presented in Algorithm 2, and the flowchart of Algorithm 2 is shown in Figure 3.2.

Treatments for an Unbalanced Three-Phase Distribution Network

In Algorithm 2, apart from the substitution of voltage-current and impedance notations to 3×1 vector and 3×3 phase impedance matrix, respectively, other necessary treatments for a three-phase unbalanced distribution system include calculation of three-phase complex power branch flows, and modification of (3.14) to incorporate the effect of line charging for an underground secondary distribution network. The complex power branch flow $S_{inj,ir}^{abc,k}$ for a three-phase system is described (3.15), where operator $\odot$ denotes element-wise product and Y_{ir}^{abc} represents phase admittance matrix. This complex power formulation for a three-phase system is utilized in the proposed Algorithm 2 at Line 2.

$$\begin{aligned} S_{inj,ir}^{abc,k} &= V_i^{abc,k} \odot \left(I_{ir}^{abc,k} \right)^* = V_i^{abc,k} \odot \left(Y_{ir}^{abc} (V_i^{abc,k} - V_r^{abc,k}) \right)^* \\ &= P_{inj,ir}^{abc,k} + jQ_{inj,ir}^{abc,k}, \quad i = \{1, \dots, N-1\}, \quad r = \{2, \dots, N\}. \end{aligned} \quad (3.15)$$

The line capacitance of an underground distribution network is significant compared to an overhead distribution network. Therefore, the effect of charging current cannot be neglected. A simple underground three-phase line segment model is shown in Figure 3.3. The KCL at the receiving end node yields the relation described by (3.16), where $[\mathbf{Y}_C^{abc}]$ represents the shunt admittance matrix.

$$[\mathbf{I}_{Branch}^{abc}] = [\mathbf{I}_{Load}^{abc}] + [\mathbf{I}_{C_r}^{abc}] = [\mathbf{I}_{Load}^{abc}] + \frac{1}{2}[\mathbf{Y}_C^{abc}][\mathbf{V}^{abc}]. \quad (3.16)$$

Unlike the overhead load flow solution in (3.5), where the branch current $[\mathbf{I}_{Branch}]$ is directly related to the load current $[\mathbf{I}_{Load}]$ through BIBC matrix, the underground branch current also includes the charging current component, i.e. $\frac{1}{2}[\mathbf{Y}_C^{abc}][\mathbf{V}^{abc}]$, along with the load current, as shown in (3.17).

$$[\mathbf{I}_{Branch}^{abc}] = [\mathbf{BIBC}^{abc}][\mathbf{I}_{Load}^{abc}] + \frac{1}{2}[\mathbf{Y}_C^{abc}][\mathbf{V}^{abc}]. \quad (3.17)$$

Therefore, the fixed-point iterative solution (3.14) for an underground system is modified as described by (3.18), and utilized in Algorithm 2 at Line 13.

$$[\Delta \mathbf{V}^{abc,k+1}] = [\mathbf{BCBV}^{abc}] \times \left([\mathbf{BIBC}^{abc}][\mathbf{I}_{Load}^{abc,k}] + \frac{1}{2}[\mathbf{Y}_C^{abc}][\mathbf{V}^{abc,k}] \right). \quad (3.18)$$

3.2 Convergence Analysis

For a secondary power distribution system, the convergence of (3.14) can be analyzed theoretically, presented in this section. Since (3.14) takes in a voltage vector $\mathbf{V}$ and evaluating its first order derivative is an arduous task, thus the mathematical proof 3.1 differs from the conventional convergence proof of a fixed-point iterative-based algebraic expression. For simplicity, we represent $[\mathbf{V}^{k+1}] = [\mathbf{V}^0] + [\Delta \mathbf{V}^{k+1}]$ in a general fixed-point iteration-based expression as $\mathbf{V}^k := A(\mathbf{V}^{k-1})$ to be used in theorem 3.1.

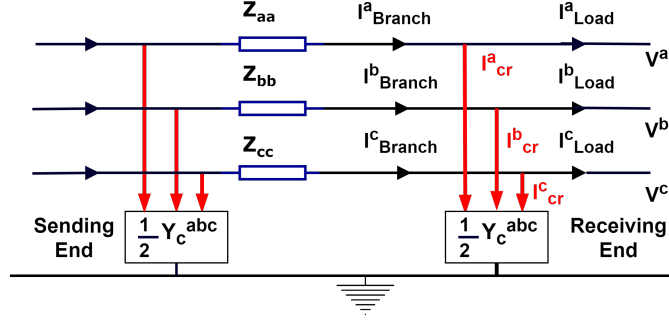


Figure 3.3: Underground three-phase line segment model.

Theorem 3.1. Suppose $\mathbf{V}^k := A(\mathbf{V}^{k-1})$ is a continuous function, where $\{\mathbf{V} \mid \mathbf{V} \in C^N, \mathbf{V} \neq \mathbf{0}\}$, $A : C^N \rightarrow C^N$. Let $G(\mathbf{V}^a, \mathbf{V}^b) := \frac{\|A(\mathbf{V}^a) - A(\mathbf{V}^b)\|}{\|\mathbf{V}^a - \mathbf{V}^b\|} \leq \alpha, \forall (\mathbf{V}^a, \mathbf{V}^b) \in \mathbf{V}$, and $G : (C^N, C^N) \rightarrow \mathbb{R}$. Further, $\mathbf{V}^k := A(\mathbf{V}^{k-1})$ converges to a fixed vector i.e. $\mathbf{V}^k \rightarrow \mathbf{L}, \mathbf{L} \in \mathbf{V}$ after k iterations **iff** $0 < \alpha \leq 1$.

Proof. Suppose the assumptions mentioned in the theorem are satisfied, the function $G(.,.)$ at k_{th} iteration can be written as

$$\begin{aligned} G(\mathbf{V}^{k-1}, \mathbf{L}) &:= \frac{\|A(\mathbf{V}^{k-1}) - A(\mathbf{L})\|}{\|\mathbf{V}^{k-1} - \mathbf{L}\|} \leq \alpha, \\ \text{or } \|A(\mathbf{V}^{k-1}) - A(\mathbf{L})\| &\leq \alpha \|\mathbf{V}^{k-1} - \mathbf{L}\|, \\ \text{or } \|\mathbf{V}^k - \mathbf{L}\| &\leq \alpha \|\mathbf{V}^{k-1} - \mathbf{L}\|. \end{aligned} \quad (3.19)$$

Similarly,

$$\begin{aligned} G(\mathbf{V}^{k-2}, \mathbf{L}) &:= \frac{\|A(\mathbf{V}^{k-2}) - A(\mathbf{L})\|}{\|\mathbf{V}^{k-2} - \mathbf{L}\|} \leq \alpha, \\ \text{or } \|A(\mathbf{V}^{k-2}) - A(\mathbf{L})\| &\leq \alpha \|\mathbf{V}^{k-2} - \mathbf{L}\|, \\ \text{or } \|\mathbf{V}^{k-1} - \mathbf{L}\| &\leq \alpha \|\mathbf{V}^{k-2} - \mathbf{L}\|, \\ \text{or } \alpha \|\mathbf{V}^{k-1} - \mathbf{L}\| &\leq \alpha^2 \|\mathbf{V}^{k-2} - \mathbf{L}\|, \quad \because \alpha > 0. \end{aligned} \quad (3.20)$$

From (3.19) and (3.20), the sequence of inequalities can be described as

$$\begin{aligned} \|\mathbf{V}^k - \mathbf{L}\| &\leq \alpha \|\mathbf{V}^{k-1} - \mathbf{L}\| \leq \alpha^2 \|\mathbf{V}^{k-2} - \mathbf{L}\| \\ &\leq \alpha^3 \|\mathbf{V}^{k-3} - \mathbf{L}\| \dots \leq \alpha^k \|\mathbf{V}^0 - \mathbf{L}\|. \end{aligned} \quad (3.21)$$

Suppose the assumption $0 < \alpha \leq 1$ is satisfied, $\alpha^k \|\mathbf{V}^0 - \mathbf{L}\| \rightarrow 0$ as number of iterations k grows. Thus (3.21) implies $\|\mathbf{V}^k - \mathbf{L}\| \leq 0$. Since $\|\mathbf{V}^k - \mathbf{L}\| \not\leq 0$, therefore $\|\mathbf{V}^k - \mathbf{L}\| = 0$. Further, $\mathbf{V}^k = \{V_2^k, V_3^k, \dots, V_N^k\}$, and $\mathbf{L} = \{L_2, L_3, \dots, L_N\}$. Therefore $\|\mathbf{V}^k - \mathbf{L}\| = 0$ can be expressed as

$$\sqrt{(V_2^k - L_2)^2 + (V_3^k - L_3)^2 + \dots + (V_N^k - L_N)^2} = 0. \quad (3.22)$$

As per the vector norm properties,

$$\begin{bmatrix} V_2^k \\ V_3^k \\ \vdots \\ V_N^k \end{bmatrix} = \begin{bmatrix} L_2 \\ L_3 \\ \vdots \\ L_N \end{bmatrix}. \quad (3.23)$$

This implies $\mathbf{V}^k$ converges to a fixed vector $\mathbf{L}$ after k iterations, i.e. $\mathbf{V}^k = \mathbf{L} = A(\mathbf{L})$. This completes the proof. $\square$

Remarks on Numerical Stability of Algorithm 2: The numerical stability of the expression (3.14) can also be analyzed quantitatively through Lyapunov constant λ , described by (3.24).

$$\lambda = \frac{1}{k} \sum_{i=0}^{k-1} \ln(G(\mathbf{V}^{i+1}, \mathbf{V}^i)). \quad (3.24)$$

The following comments can be made on the numerical stability of (3.14) by observing the value of $G(.,.)$ function during the iterative process.

- If $G(.,.) < 1$ during the iterative process, this implies $\lambda < 0$, the displacement from the fixed vector $\mathbf{L}$ shrinks as we iterate and $\mathbf{L}$ is a stable vector.
- If $G(.,.) > 1$ during the iterative process, this implies $\lambda > 0$, the displacement from the fixed vector $\mathbf{L}$ grows as we iterate and $\mathbf{L}$ is an unstable vector.
- If $G(.,.) = 1$ during the iterative process, this implies $\lambda = 0$, and the decision on fixed vector $\mathbf{L}$ stability can not be made.
- If $G(.,.) = 0$ during the iterative process, this implies $\lambda = -\infty$, the fixed vector $\mathbf{L}$ is a highly stable vector.

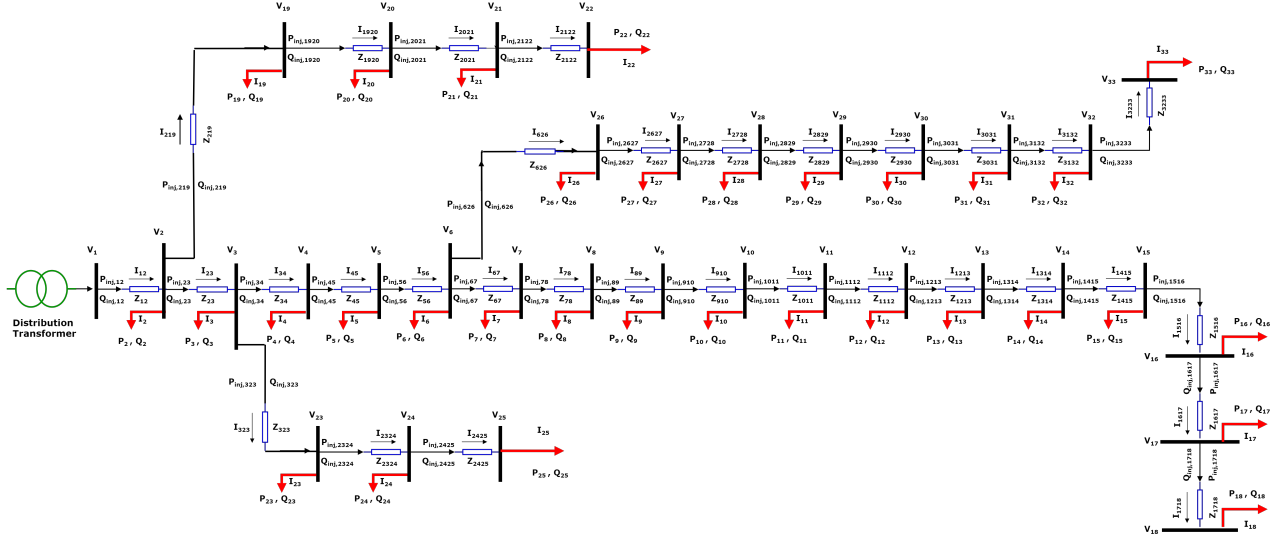


Figure 3.4: Single line representation of a balanced secondary distribution radial test system composed of 33 buses.

In the next section, the histograms and statistical analysis of kVA load estimation error are discussed for balanced, and unbalanced three-phase underground secondary distribution networks.

3.3 Simulation Results

The efficacy of the proposed strategy is corroborated for balanced, and unbalanced three-phase underground secondary distribution networks. It is worth mentioning that the proposed strategy does not claim for very accurate estimations of reactive power consumption or node voltages but rather, provides the results within acceptable error tolerance. Further, the proposed methodology yields more accurate and reliable results, compared to assuming a fixed power factor across all the residential customers, by adaptively varying reactive power consumption based on network topology, line impedance values, real power consumption, and bus voltages. The histogram and statistical analysis of kVA load estimation error for balanced, and unbalanced three-phase underground secondary distribution networks are investigated in this section. Moreover, the convergence and the numerical stability analysis of the proposed iterative framework are also discussed in this section.

The proposed scheme assumes that the kW data is readily available from residential

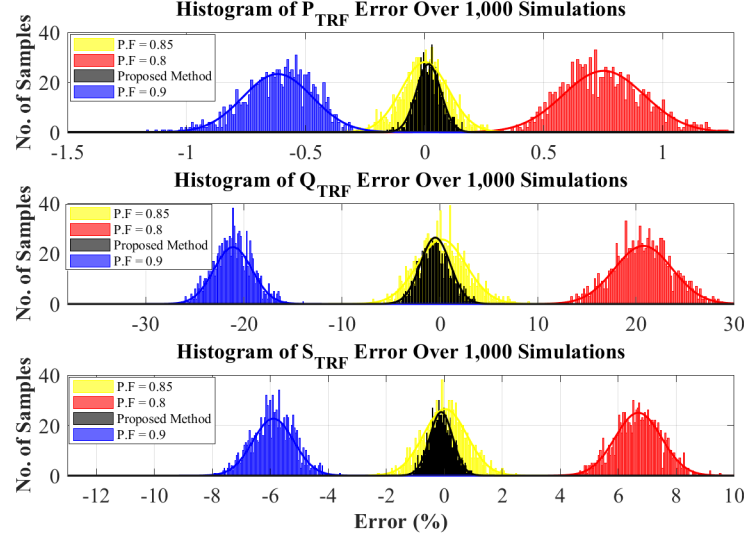


Figure 3.5: Histogram of real (kW), reactive (kVAr), and apparent (kVA) powers' estimation error for proposed method and fixed power factors (balanced secondary distribution test network in Figure 3.4).

smart meters, and a reasonable guess of upper and lower bounds of power factor range for residential customers can be made [89], as described in Algorithm 2. Typically, the power factor of residential customers varies from 0.7 to 0.9 (depending on different seasons), therefore this work assumes 0.7 as a lower bound of power factor and 0.9 as an upper bound of power factor in Algorithm 2.

The proposed work is the first to develop a novel fixed-point iteration-based framework that does not require any fixed power assumption for DT kVA load estimation. Therefore, the only possible way to validate the effectiveness of the proposed work is its comparison with some cases where a fixed assumption is made on power factors for all residential customers. In the simulation results, we study a detailed statistical analysis for the proposed framework and three fixed power factor cases, i.e., 0.8, 0.85, and 0.9, through 1,000 Monte-Carlo simulations.

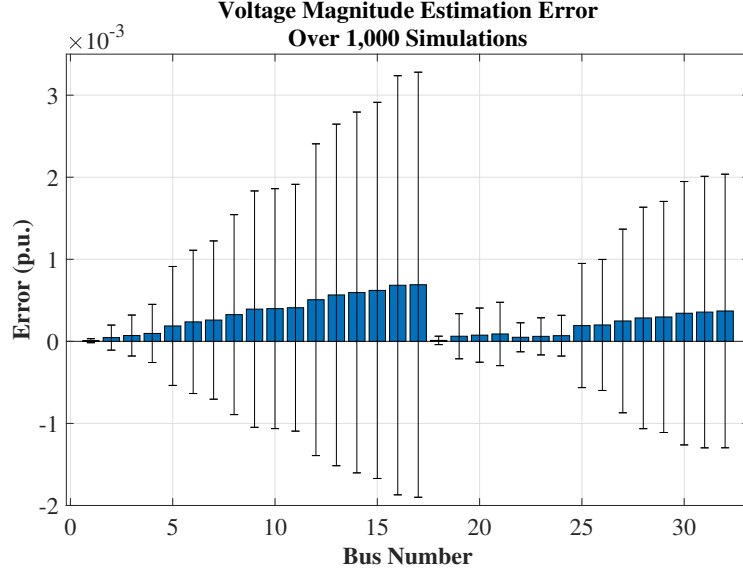


Figure 3.6: Voltage magnitude estimation error (mean, maximum, minimum) for proposed method (balanced secondary distribution test network in Figure 3.4).

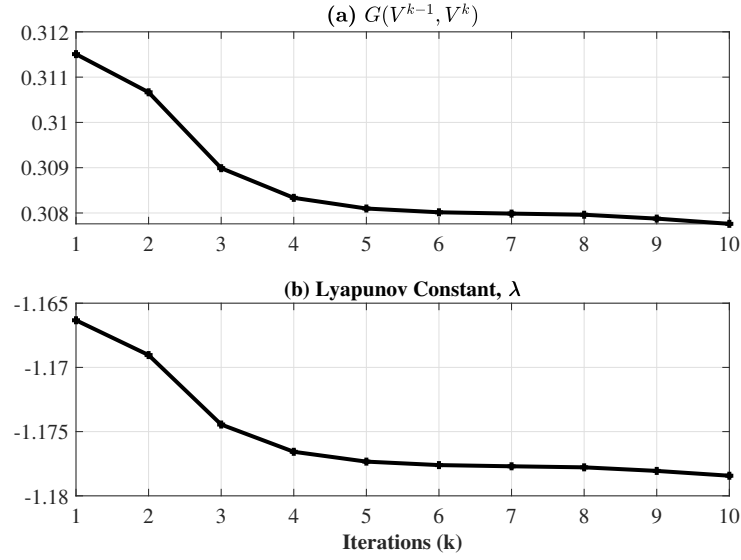


Figure 3.7: Convergence and numerical stability analysis of proposed iterative methodology for a balanced secondary distribution test network in Figure 3.4.

3.3.1 Test Case 1: Balanced Secondary Distribution Radial Test System Composed of 33 buses

A balanced secondary distribution test network composed of 33 buses is developed in Figure 3.4, in a manner similar to that shown in Figure 3.1. The simulation results for a balanced secondary distribution network are analyzed through 1,000 random sets of 33 real and reactive load profiles. The real power load profile is known in Algorithm 2, as it is assumed to be collected from residential smart meters. Figure 3.5 shows the histogram of real (kW), reactive (kVAr), and apparent (kVA) powers' estimation errors for a DT using the proposed method and different fixed power factor assumptions. The results in Figure 3.5 imply that the power factor assumption toward the upper and lower ends, i.e. 0.8 and 0.9, do not provide reliable results. The statistical analysis of kVA estimation error is also provided in Table 3.1. The following observations are made based on histogram and statistical analysis:

- The histogram data in Figure 3.5 for real (kW), reactive (kVAr), and apparent (kVA) powers' estimation errors indicate that the error of the proposed method is less dispersed and has a lower standard deviation of error compared to different fixed power factor assumptions.
- The statistical analysis of different performance indices in Table 3.1 suggests that the proposed strategy yields very reliable results for real power (kW) and apparent power (kVA) load estimation against 1,000 load profiles.

Figure 3.6 shows the voltage magnitude estimation error analysis. The voltage magnitude estimation error may be reasonable enough for distribution applications, such as network planning and expansion. The convergence and numerical stability of voltage vector $\mathbf{V}^k$ during the iterative process for a balanced secondary distribution test system is shown in Figure 3.7(a) and Figure 3.7(b), respectively. It can be observed in Figure 3.7 that the value of $G(V^{k-1}, V^k)$ and λ (described in Theorem 3.1) satisfy the conditions needed for Theorem 3.1 to hold. Further, the convergence criteria for a balanced secondary distribution test system (Figure 3.4) is observed to be satisfied after 10 iterations in the simulation.

A transformer's loss of life (LOL) or life expectancy depends on its winding hot-spot temperature. As per IEEE Std C57.91-2011, a transformer operating beyond 10°C of rated hot-spot temperature experiences almost three times faster aging. Beyond a transformer's nameplate rating, a small increment in kVA load causes a substantial rise in winding hot-spot temperature, and thus expedites a transformer's aging [90]. Urban distribution transformers operate near or beyond the rated kVA load. The fixed power factor assumption

Table 3.1: Statistical analysis of a DT load estimation error over 1,000 Monte-Carlo simulations of the proposed method (balanced secondary distribution test network in Figure 3.4).

	Maximum Error (%)	Minimum Error (%)	Mean Error (%)	Median Error (%)	Mode Error (%)	Standard Deviation
P_{TRF}	0.1584	-0.1564	0.0165	0.0157	-0.1564	0.0511
Q_{TRF}	3.6441	-4.5982	-0.4841	-0.5474	-4.5982	1.5141
S_{TRF}	0.9449	-1.2129	-0.1071	-0.1167	-1.2129	0.3951

could yield the kVA estimation error ranges from -10% to 10%, reflecting a misleading aging assessment for an urban distribution transformer. Whereas, the proposed method yields the kVA estimation error ranges from -1.2% to 1%, which provides the aging assessment much nearer to a true-life expectancy of an urban distribution transformer. Therefore, accurate kVA load information leads to assess the true life expectancy of a transformer, which is very important for on-time transformer replacement, to save financial resources of a distribution utility, and for future planning and expansion of a distribution system [91].

Remarks on Algorithm 2 General Convergence:

The convergence of fixed-point iteration-based expression (3.14) to determine the bus voltages of a distribution network depends on initial voltage vector, i.e. $[\mathbf{V}^0]$, network topology, i.e. $[\mathbf{BIBC}]$; line impedance values, i.e. $[\mathbf{BCBV}]$; and real power consumption, i.e. $[\mathbf{P}_{Load}]$. These components steer $G(\mathbf{V}^a, \mathbf{V}^b) := \frac{\|A(\mathbf{V}^a) - A(\mathbf{V}^b)\|}{\|\mathbf{V}^a - \mathbf{V}^b\|}$ to enter the convergence domain, i.e., $G(.,.) \leq \alpha$, where $0 < \alpha \leq 1$. This leads $\mathbf{V}^k$ to converge to a fixed vector $\mathbf{L}$, i.e., $\mathbf{V}^k \rightarrow \mathbf{L}$, after k iterations. We analyze each component of $\mathbf{V}^k := A(\mathbf{V}^{k-1})$ in detail below to provide general implications for radial distribution networks.

- Initial voltage vector $[\mathbf{V}^0]$: The service voltage of residential customers is maintained to remain within 0.9 p.u. - 1.1 p.u. limit in any possible operational scenario [92]. Therefore, regardless of any network configuration and other parameters of a secondary distribution system, the initial voltage values for all the residential customers in Algorithm 2 should be selected the same as DT secondary voltage level, i.e., 1 p.u..
- Network topology $[\mathbf{BIBC}]$: For convenience, the secondary distribution test system composed of 33 buses in Figure 3.4 is referred to as the original system. To show the efficacy of the proposed algorithm, we analyze the convergence of different network

Table 3.2: Convergence analysis for different network and line data variants of original radial distribution network against 1,000 real power profiles - from 0 kW to 200 kW - through Monte-Carlo simulation.

(X% variation stands for percentage change in line impedance of original data, and C stands for convergence in Table 2.2)

	-2% variation	-1% variation	1% variation	2% variation
Network 1	C	C	C	C
Network 2	C	C	C	C
Network 3	C	C	C	C
Network 4	C	C	C	C
Network 5	C	C	C	C

variants of the original test system. The details of different network variants are listed below.

- Network 1: Original system – complete secondary distribution test system composed of 33 buses as shown in Figure 3.4.
- Network 2: Bus 1 to 6, and Bus 2-19 to 22 of the original system.
- Network 3: Bus 1 to 6, Bus 2-19 to 22, and Bus 3-23 to 25 of the original system.
- Network 4: Bus 1 to 6, Bus 2-19 to 22, Bus 3-23 to 25, and Bus 6-26 to 33 of the original system.
- Network 5: Bus 1 to 15, Bus 2-19 to 22, Bus 3-23 to 25, and Bus 6-26 to 33 of the original system.
- Line impedance [**BCBV**]: The line impedance value of various secondary network conductors does not differ significantly from each other [89]. We analyze the convergence on different variants of line impedance data of the original test system.
- Real power consumption [**P_{Load}**]: The results of the proposed method are investigated against 1,000 random sets of 33 real power profiles through Monte-Carlo simulations. The range of real power profiles is from 0 kW to 200 kW - which is an acceptable range for residential customers.

To show the efficacy of the proposed algorithm, we perform the convergence analysis considering different network and line data variants of the original system against 1,000 random real power profiles (from 0 kW to 200 kW) through Monte-Carlo simulations. The results are presented in Table 3.2.

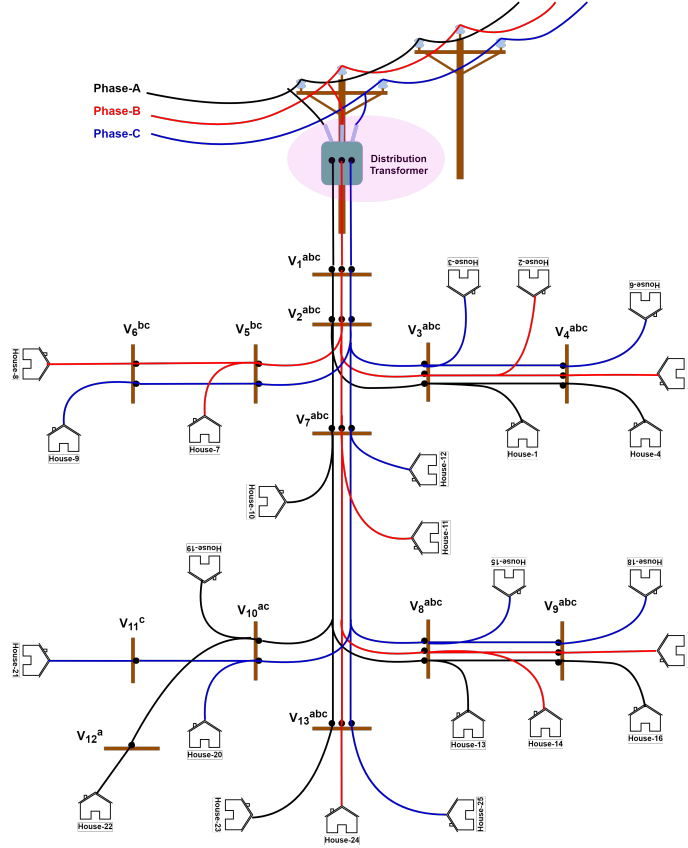


Figure 3.8: Three-phase representation of an unbalanced underground secondary distribution test network composed of 13 buses.

3.3.2 Test Case 2: Unbalanced Three-Phase Underground Secondary Distribution Test Network Composed of 13 buses

For an unbalanced three-phase underground secondary system, a 13-bus network, shown in Figure 3.8, is considered for validation of the proposed method, which also includes the underground line models. Since the proposed method has been shown to outperform fixed power factor assumption counterparts, the results for only the proposed method are discussed in this test case. Figure 3.9 shows the estimation error histograms for real (kW), reactive (kVAr) and apparent (kVA) powers across three phases of a DT. The kVA estimation errors are less dispersed across three phases, and are bound around $\pm 2\%$ error for all 1,000 random load profiles.

Table 3.3: Statistical analysis for a DT kVA load estimation error over 1,000 Monte-Carlo simulations of proposed method (unbalanced three-phase underground secondary distribution test network in Figure 3.8).

kVA Load	Maximum Error (%)	Minimum Error (%)	Mean Error (%)	Median Error (%)	Mode Error (%)	Standard Deviation
$Phase_A$	2.1224	-2.0646	-0.2089	-0.2254	-2.0646	0.7299
$Phase_B$	1.9268	-2.2103	-0.1181	-0.1458	-2.2103	0.6274
$Phase_C$	1.8737	-2.0115	-0.1045	-0.1180	-2.0115	0.6452

The statistical analysis for only three-phase kVA load estimation is also presented in Table 3.3. The voltage estimation error analysis across three phases for all buses (in Figure 3.8) is shown in Figure 3.10. The mean, maximum, and minimum error analysis at each bus is also shown in Figure 3.10. Moreover, the convergence and numerical stability of voltage vector $\mathbf{V}^k$ during the iterative process for the system shown in Figure 3.8 is provided in Figure 3.11(a) and Figure 3.11(b), respectively. This satisfies the conditions needed for Theorem 3.1 to hold for Figure 3.8 network.

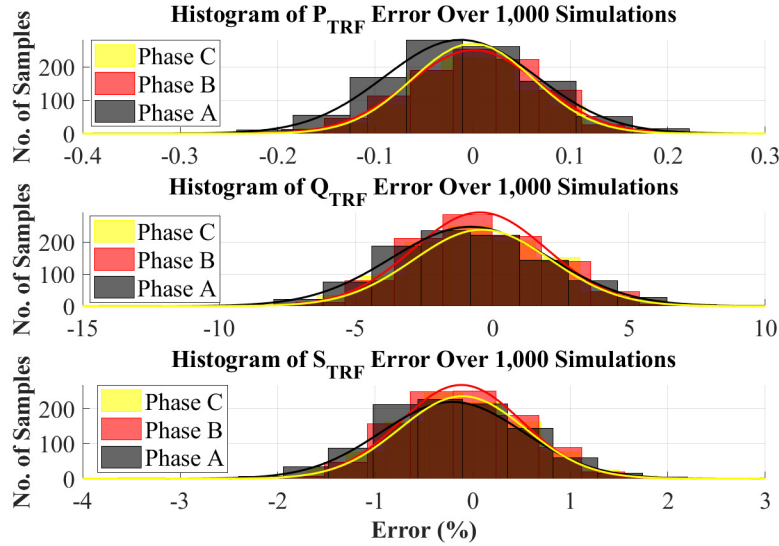


Figure 3.9: Histogram of real (kW), reactive (kVAr), and apparent (kVA) powers' estimation error for proposed method (unbalanced three-phase underground secondary distribution test network in Figure 3.8).

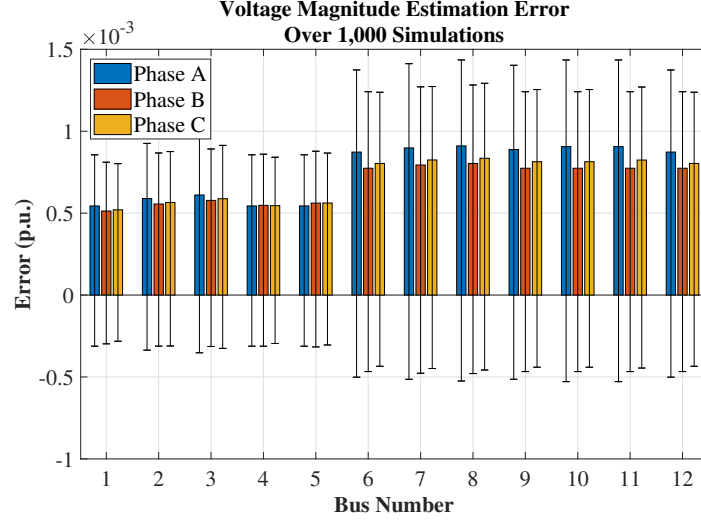


Figure 3.10: Voltage magnitude estimation error (mean, maximum, minimum) for proposed method (unbalanced three-phase underground secondary distribution test network in Figure 3.8).

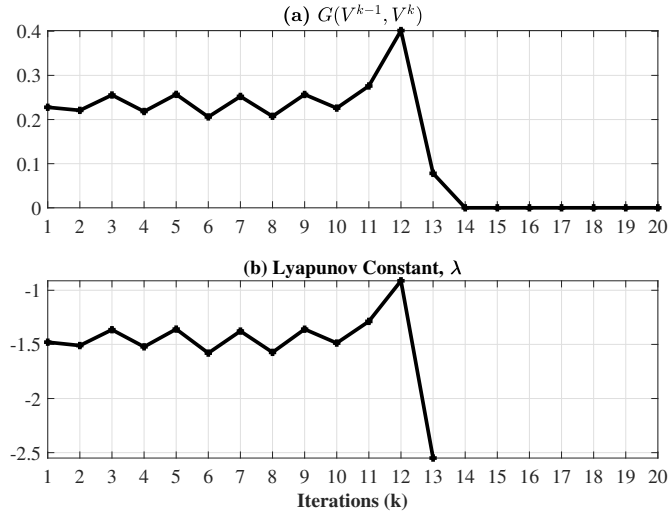


Figure 3.11: Convergence and numerical stability analysis of proposed iterative methodology for an unbalanced three-phase underground secondary distribution test network in Figure 3.8.

3.4 Summary

The work in this chapter presents an algorithm developed to estimate the kVA load of a distribution transformer. The developed algorithm is analyzed for balanced and unbalanced three-phase underground secondary distribution networks. The results are investigated against 1,000 random load profiles through Monte-Carlo simulations which represent uncertainty in smart meter data. The comparison was made among the proposed scheme and different fixed power factor assumptions, such as 0.8, 0.85, and 0.9 across all residential customers. The histograms, and statistical analysis of kVA load estimation error imply that the proposed scheme provides significantly better results compared to fixed power assumptions. The proposed scheme also provides reasonable results for voltage magnitude estimation that could be used in various distribution automation applications. Further, the proposed strategy for a DT kVA load estimation without a fixed power factor assumption across all residential customers can be employed to assess the accurate life expectancy of a transformer and contributes to other smart grid applications such as demand response, asset management, and secure and reliable distribution system operation.

Chapter 4

Distribution Transformer Remaining Useful Life Estimation Considering Electric Vehicle Penetration

In this chapter, the schematic of the proposed four-layer framework is described for [DT RUL](#) estimation, followed by a detailed formulation of each layer in subsequent sections. A numerical validation is conducted on real-world data sources on various initial [EV](#) penetration levels. The chapter also provides a guide on implementing the proposed framework in practical scenarios. Additionally, sensitivity analysis is conducted to investigate the impact of modest changes in [DT](#) loading or ambient temperature on the estimated [LOL](#) value. Moreover, the chapter includes an uncertainty analysis of the proposed framework.

4.1 Proposed Methodology

Figure [4.1](#) shows a detailed schematic of the proposed framework in four layers, i.e., L1, L2, L3, and L4. The description of each layer is provided below.

L1: A single-line diagram of a residential [SDS](#) in Canada is shown. The system comprises a certain number of houses supplied by a [DT](#), and each house is equipped with a regular smart meter ([SM](#)). A regular [SM](#) stores kWh consumption, kW usage, and service voltage information; and transmits them to a central repository of the [LDC](#) [\[93\]](#).

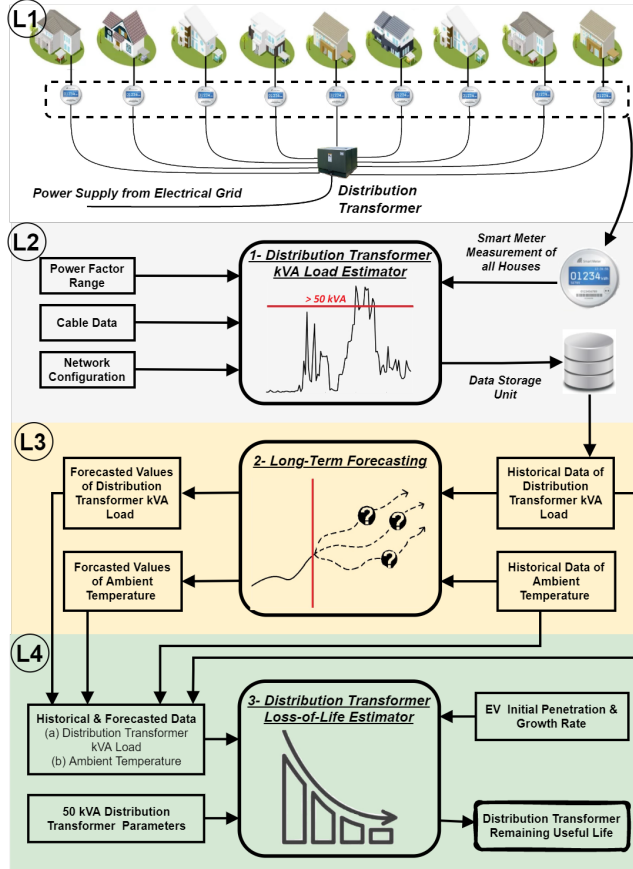


Figure 4.1: Flowchart to determine the anticipated end of DT RUL in a radial SDS providing electricity to residential customers.

L2: The SM data from residential customers are utilized to estimate the kVA load of the DT in real-time, without assuming a fixed power factor across all residential customers. For brevity, sufficient and necessary details of our previous work [93] are revisited in Chapter 4, and the reader is directed to [93] for extensive details and results. The DT kVA load is stored in the LDC's database system along with the real-time ambient temperature.

L3: The historical data of the DT kVA load and ambient temperature - until the most recent time - are fetched from the LDC's database for long-term forecasting over several years. We employ Time Series Decomposition and Hidden Markov Model as the two potential candidates for long-term forecasting, the details are provided in

4.1.2.

L4: The historical as well as predicted values - spanning over a decade - for DT kVA load and ambient temperature along with the actual growth of EV load over the years are used in an algorithm from IEEE Standard C57.91-2011 [74] to determine the insulation aging of a DT. This is used to determine the LOL of a DT over time, and thus, the anticipated end of DT RUL. The details are provided in 4.1.3.

4.1.1 Distribution Transformer kVA Load Estimation Using Residential Smart Meter Data

In Chapter 4, detailed information regarding the estimation of DT kVA load is provided. The initial two layers of the proposed framework are extensively explained in Chapter 4. This chapter aims to build upon the concepts introduced in Chapter 4 by employing an algorithm for the precise estimation of DT kVA load. The magnitude of real-time DT kVA load is denoted as a time series data, $\mathcal{O}_t = |S_{12}^{inj}|$, where $t \in \mathbb{R}_{\geq 0}$. This time series data $\mathcal{O}_t = |S_{12}^{inj}|$, representing the real-time DT kVA load, plays a vital role in the subsequent section, which forms the second layer within the proposed four-layer framework. The next section explains the long-term forecasting of $\mathcal{O}_t = |S_{12}^{inj}|$ time series data, that represents the DT kVA load.

4.1.2 Long-Term Forecasting for Distribution Transformer kVA Load and Ambient Temperature

Time Series Decomposition (TSD)

The time series data $\mathcal{O}_t$ at time $t \in \mathbb{R}_{\geq 0}$ is believed to be made up of a certain pattern plus an error, as shown in (4.1). The TSD method aims to disaggregate the $\mathcal{O}_t$ into four components: $T(t)$, $S(t)$, $C(t)$, and $R(t)$, as shown in (4.2) [94]. Considering the possibility of exponential growth in $\mathcal{O}_t$, and well the acceptance among forecasting practitioners for power system studies [95], $\mathcal{O}_t$ is represented by a multiplicative model for a pattern decomposition, as shown in (4.3).

$$\mathcal{O}_t = \text{pattern} + \text{error}, \quad (4.1)$$

$$\mathcal{O}_t = f(T(t), S(t), C(t), R(t)), \quad (4.2)$$

$$\mathcal{O}_t = T(t) \times S(t) \times C(t) \times R(t). \quad (4.3)$$

First, a suitable trend line $T(t)$ to $\mathcal{O}_t$ is determined using regression techniques: linear, quadratic, exponential, or other. Second, the time series is deseasonalized and its randomness is mitigated by calculating an $L - step$ moving average $M(t)$, where L denotes the seasonality length ($L = 12$ for a monthly time series). Since $M(t)$ contains trend and cycle components, i.e., $M(t) = T(t) \times C(t)$, and $C(t)$ is calculated as follows,

$$C(t) = \frac{M(t)}{T(t)}. \quad (4.4)$$

Third, the seasonality component is isolated by dividing the $\mathcal{O}_t$ with $M(t)$ as follows,

$$\frac{\mathcal{O}_t}{M(t)} = \frac{T(t) \times S(t) \times C(t) \times R(t)}{T(t) \times C(t)} = S(t) \times R(t). \quad (4.5)$$

Averaging over the same months eliminates randomness and yields $S(t)$.

Hidden Markov Model

Markov chain provides a foundation for [HMM](#). In general, a finite number of states generate a set of observations. The actual state sequence is not observable, we can only observe the observation sequence. The following specifications describe [HMM](#) elements in detail [\[96,97\]](#).

1. *Set of hidden states*: $X_t = \{x_1, x_2, \dots, x_N\}$ is a set of N distinct states.
2. *State transition probability matrix*: $A = \{a_{ij}\}$, $1 \leq i, j \leq N$, i.e., transition probability from one state i to state j , subject to $\sum_{j=1}^N a_{ij} = 1 \forall i$. Here, $\{a_{ij}\} = P(x_{t+1} = x_j | x_t = x_i)$ and x_t denotes the hidden state at time $t \in \mathbb{R}_{\geq 0}$.
3. *Sequence of observations*: $\mathcal{O}_t = \{o_1, o_2, \dots, o_T\}$ is a sequence of T observations.
4. *Emission probability matrix*: $B = \{b_j(o_t)\}$, $1 \leq t \leq T$. Here, $\{b_j(o_t)\} = P(o_t | x_t = x_j)$ is the probability of observation o_t being generated from a state j at time $t \in \mathbb{R}_{\geq 0}$.
5. *Initial probability*: $\pi = \{\pi_i\}$, where $\pi_i = P(x_t = x_i)$, $1 \leq i \leq N$ is the probability of Markov chain starts in state i at time $t = 0$. For some states, $\pi_i = 0$, however, $\sum_{i=1}^N \pi_i = 1$.

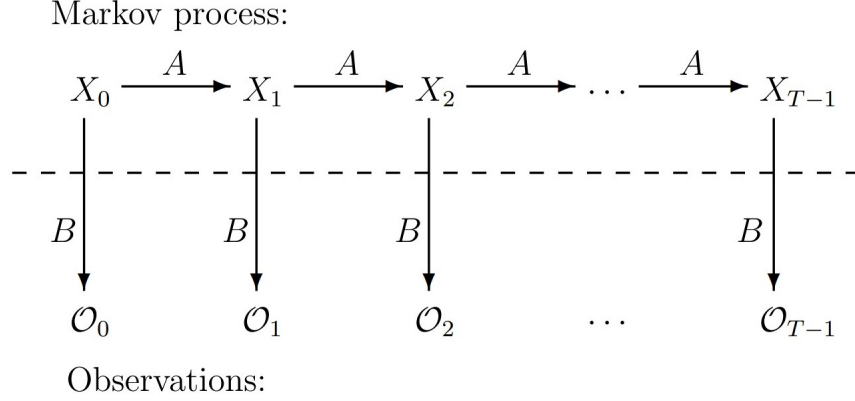


Figure 4.2: Hidden Markov model.

Figure 4.2 shows a generic [HMM](#), we can only observe the sequence $\mathcal{O}_t$ related to the hidden state X_t by matrix B at time $t \in \mathbb{R}_{\geq 0}$. Whereas, the Markov process is hidden behind the dashed line and it is related to previous state X_{t-1} and matrix A at time $t \in \mathbb{R}_{\geq 0}$. [HMM](#)-based prediction strategy first requires the model $\lambda = \{A, B, \pi\}$ to be learned, given a sequence of observations $\mathcal{O}_t$ and the set of states X_t . This aims at training the model $\lambda = \{A, B, \pi\}$ that best fits or maximizes the probability $P(\mathcal{O}_t|\lambda)$. Baum-Welch or forward-backward algorithm [\[98\]](#) is the standard iterative algorithm to train A and B matrices, i.e., transition and emission probabilities. This algorithm computes the initial probability and uses them to compute better estimates iteratively until a desired level of $P(\mathcal{O}_t|\lambda)$ convergence. MATLAB built-in functions ‘*hmmtrain*’ or ‘*hmmestimate*’ [\[99\]](#) can be used for maximum likelihood estimates of A and B matrices. Using the trained model $\lambda = \{A, B, \pi\}$, the next step in the [HMM](#)-based prediction strategy is to compute the likelihood of a certain observation sequence $\hat{\mathcal{O}}_{t+1}$, i.e. $P(\hat{\mathcal{O}}_{t+1}|\lambda)$. For instance, the joint probability of a particular observation sequence $\hat{\mathcal{O}}_{t+1}$ being generated by a particular state sequence X_{t+1} is:

$$P(\hat{\mathcal{O}}_{t+1}, X_{t+1}) = P(\hat{\mathcal{O}}_{t+1} | X_{t+1}) \times P(X_{t+1}) \quad (4.6)$$

$$= \prod_{i=0}^{t+1} P(\hat{\mathcal{O}}_i | X_i) \times \prod_{i=0}^{t+1} P(X_i | X_{i-1}), \quad (4.7)$$

The total probability of a particular observation is obtained by the summation over entire possible hidden states X :

$$P(\hat{\mathcal{O}}_{t+1}) = \sum_X P(\hat{\mathcal{O}}_{t+1}, X) = \sum_X P(\hat{\mathcal{O}}_{t+1} | X)P(X). \quad (4.8)$$

The observation sequence yields maximum likelihood as the expected forecast. It is worth mentioning that the above-mentioned naïve approach requires N^T computations for a particular sequence of observations, which may be infeasible for a large dataset [100]. Instead, the forward algorithm [101] is an efficient dynamic programming-based approach requiring only N^2T multiplications.

4.1.3 Distribution Transformer Insulation Aging and Remaining Useful life assessment

Different methods for power transformer remaining useful life estimation are available in the literature. For instance, (1) Empirical formula methods conduct extensive laboratory tests to establish a relationship that uses chemical indicators, such as furan, carbon dioxide, and carbon monoxide for the transformer's RUL estimation [102, 103]. (2) IEEE/IEC standard models the transformer's insulation thermal aging as a function of loading history and ambient temperature [74, 104]. (3) Kinetic models require water and oxygen contents inside a transformer along with loading and temperature profiles for thermal dynamics of the transformer's insulation aging [105, 106]. (4) Statistical and data-driven method employs Monte Carlo simulation, or Wiener and other algorithms to characterize loading and temperature profiles as well as various uncertainties for later use in IEEE/IEC or Kinetic models [107]. (5) Particle filtering method solves nonlinear state-space model for transformer's insulation aging estimation [55]. (6) Artificial intelligence-based method produces medium range forecast for loading and temperature profiles for later use in IEEE/IEC or Kinetic models [56].

The IEEE Standard C57.91-2011 [74] lays out the procedure to calculate $\Theta_H(t)$, the main factor of DT insulation aging and thus LOL. $\Theta_H(t)$ is comprised of $\Theta_A(t)$, $\Delta\Theta_{TO}(t)$, and $\Delta\Theta_H(t)$, as shown in (4.9).

$$\Theta_H(t) = \Theta_A(t) + \Delta\Theta_{TO}(t) + \Delta\Theta_H(t), \quad (4.9)$$

The $\Delta\Theta_{TO}(t)$ is computed by (4.10), depending on $\Delta\Theta_{TO,u}$ and $\Delta\Theta_{TO,i}$ over ambient temperature, and τ_{TO} . Further, $\Delta\Theta_{TO,u}$ and $\Delta\Theta_{TO,i}$ calculations are shown in (4.11) and (4.12), respectively.

$$\Delta\Theta_{TO}(t) = (\Delta\Theta_{TO,u} - \Delta\Theta_{TO,i}) [1 - e^{-t/\tau_{TO}}] + \Delta\Theta_{TO,i}, \quad (4.10)$$

$$\Delta\Theta_{TO,u} = \Theta_{TO,R} \left[\frac{K_u^2 R + 1}{(R + 1)} \right]^n, \quad (4.11)$$

$$\Delta\Theta_{TO,i} = \Theta_{TO,R} \left[\frac{K_i^2 R + 1}{(R + 1)} \right]^n. \quad (4.12)$$

Similarly, $\Delta\Theta_H(t)$ is computed by (4.13), depending on $\Delta\Theta_{H,u}$ and $\Delta\Theta_{H,i}$ over top-oil temperature, and τ_ω . Moreover, $\Delta\Theta_{H,u}$ and $\Delta\Theta_{H,i}$ calculations are shown in (4.14) and (4.15), respectively.

$$\Delta\Theta_H(t) = (\Delta\Theta_{H,u} - \Delta\Theta_{H,i}) [1 - e^{-t/\tau_\omega}] + \Delta\Theta_{H,i}, \quad (4.13)$$

$$\Delta\Theta_{H,u} = \Theta_{H,R} K_u^{2m}, \quad (4.14)$$

$$\Delta\Theta_{H,i} = \Theta_{H,R} K_i^{2m}. \quad (4.15)$$

The description of the remaining parameters and their values for a DT rated at 50 kVA are provided in Appendix A. The real time $\Theta_H(t)$ is used in (4.16) to calculate $FAA(t)$ in real time.

$$FAA(t) = e^{\left[\frac{15000}{110+273} - \frac{15000}{\Theta_H(t)+273} \right]}. \quad (4.16)$$

Lastly, $FAA(t)$ has an hourly time resolution, which is used to record hourly-based $\%LOL(t)$ out of $TNIL$, as described by (4.17). $TNIL$ of a DT is assumed as $TNIL_{hour} = 180,000$ hours or $TNIL_{year} = 20.5$ years [6, 7, 74]. Further, RUL_T of a DT at hour T is found by (4.18).

$$\%LOL(t) = TNIL_{year} \frac{FAA(t)}{TNIL_{hour}}, \quad (4.17)$$

$$RUL_T = TNIL_{hour} - \sum_{t=0}^T \%LOL(t). \quad (4.18)$$

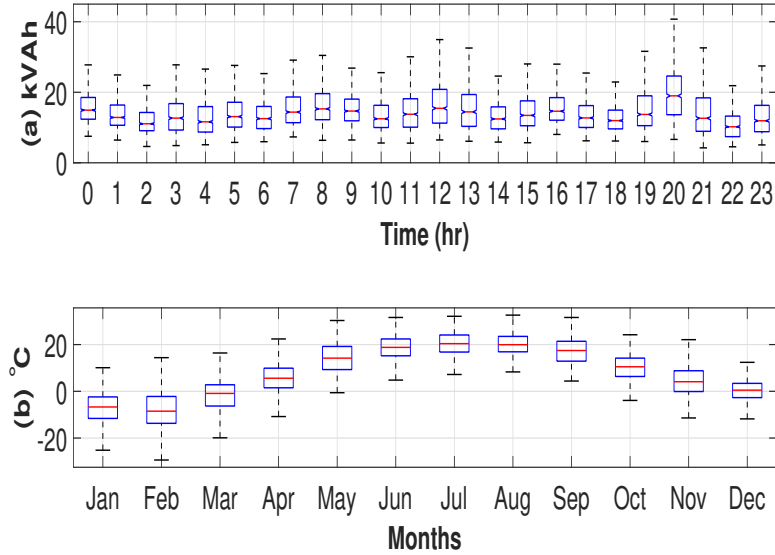


Figure 4.3: (a) Load profile of the 50 kVA DT, and (b) Ambient temperature profile, from 2014 to 2016 in London, Ontario.

4.2 Results and Evaluation

Real-time [SM](#) electricity usage data was collected from fifteen households between January 2014 and December 2016 by London Hydro, an [LDC](#) in London, Ontario, Canada. The fifteen households remain anonymous, and some of them are electricity prosumers who both produce and consume power. Due to privacy concerns imposed by [LDCs](#) in Canada, complete energy usage datasets for Canadian residents over several years are not publicly available. Moreover, to conduct a realistic and practical investigation, the other datasets used in this work also pertain to the same region, such as ambient temperature, electric vehicle growth rate, and secondary distribution network. Mixing publicly available datasets from different regions not only contaminates the entire dataset but also produces unrealistic results.

According to a study conducted in [\[5\]](#) for a Canadian [SDS](#), 10% of the new vehicles sold in 2015 were [EVs](#). In 2017, this percentage increased to 20% and is expected to reach nearly 25% and 75% by 2020 and 2025, respectively. This work considers the aforementioned growth rate of [EV](#) penetration over the years in a real [SDS](#) consisting of fifteen households.

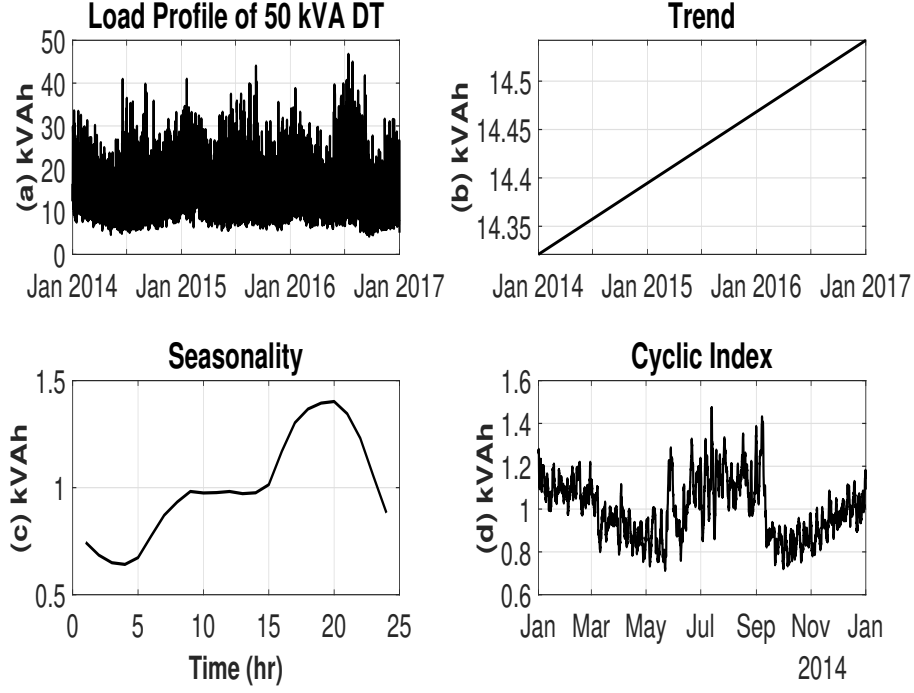


Figure 4.4: (a) Load profile of the 50 kVA DT, (b) Trend line, (c) Twenty-four hours seasonality, and (d) Cyclic index from 2014 to 2016.

Since the initial EV penetration level was not known, we provide a case study for initial EV penetration levels from 1 car to 8 cars in the year 2014. The eight most popular EV types in the Canadian market are considered, and the manufacturing data is provided in Appendix A. Further, the energy required by an EV after a trip is computed by Algorithm 3 in Appendix A. Level 2 AC charger is selected based on SAEJ1772 standard [108] at 6.6 kW and 90% efficiency. And lastly, Monte-Carlo simulations are performed in Algorithm 3 (shown in Appendix A) to address the uncertainty in the daily distance traveled.

The SM electricity data of fifteen households, along with the triplex service drop cable data [72], as well as practical archetype circuit configuration for a real SDS [73] is used to estimate real-time kVA load of a DT, as described in section 4.1.1. The maximum non-coincident demand is observed to be 126.97 kVA from 2014 to 2016. Considering the diversity factor of 2.8 for fifteen households [109], the diversified demand of a real SDS comes out to be 45.35 kVA which suggests 50 kVA as a suitable DT rating. Figure 4.3(a) shows the distribution of the hourly load profile of 50 kVA DT from 2014 to 2016 in London, Ontario. The maximum, minimum, and median load demands along with the 25th

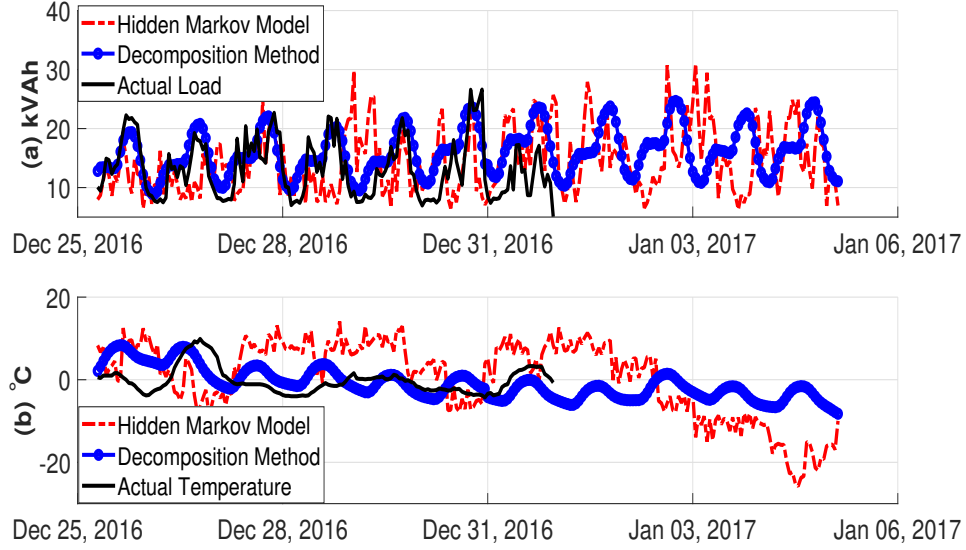


Figure 4.5: Comparison for a portion of long-term forecast results obtained from [TSD](#) method and [HMM](#) method against (a) Actual [DT](#) kVA load, and (b) Ambient temperature.

and 75th percentiles are indicated at each hour over the period of three years. Similarly, the distribution of ambient temperature in London, Ontario is presented in Figure 4.3(b) for each month from 2014 to 2016.

The historical data of the [DT](#) kVA load and ambient temperature - until the most recent time - are fetched from [LDC](#)'s database for long-term forecasting over several years. This work employs [TSD](#) and [HMM](#) methods for long-term forecasting, the details are provided in 4.1.2. Reliable results that are not prone to high computations or no additional tuning steps as the data grows are the major hallmarks of [TSD](#) and [HMM](#) methods for long-term forecasting. The [TSD](#) method provides a detailed insight into the seasonal and cyclic behaviors of a time series. Figure 4.4 shows the trend line for three years, twenty-four hours seasonality, and cyclic index over the year for the load profile of 50 kVA [DT](#). These components are utilized to project the time series over the next several years. Likewise, the trend line, seasonality, and cyclic index for the ambient temperature in London Ontario (2014-2016) are shown in Figure 4.6. For [HMM](#) method, the historical data of [DT](#) kVA load and ambient temperature are categorized and labeled to evaluate A and B matrices, as described in section 4.1.2. The [DT](#) kVA load is categorized into three states as follows: [DT](#) is lightly loaded (less than 25 kVA), normal operation of [DT](#) (greater than 25 kVA and

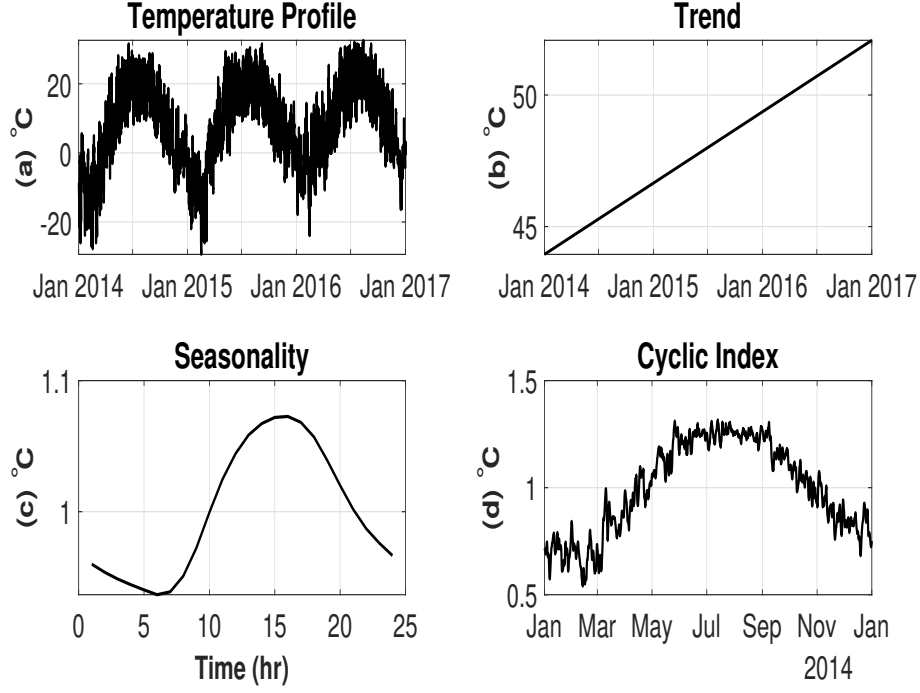


Figure 4.6: (a) Ambient temperature profile, (b) Trend line, (c) Twenty-four hours seasonality, and (d) Cyclic index from 2014 to 2016.

less than 50 kVA), and **DT** is overloaded (greater than 50 kVA). Similarly, the ambient temperature is categorized into three states as follows: cold temperature (less than 0 °C), normal temperature (greater than 0 °C and less than 22 °C), and hot temperature (greater than 22 °C). The matrices A and B along with π are utilized to project the time series over the next several years.

A portion of long-term forecasting results obtained from **TSD** and **HMM** methods are shown in Figure 4.5. The histogram of forecast error from 2014 to 2016 is shown in Figure 4.7. Also, MAE and RMSE from 2014 to 2016 are presented in Table 4.1. The forecast results are analyzed as follows:

1. *DT kVA load*: Figure 4.7(a) shows that 40.7% of the total forecasting error lies within ± 0.1 p.u., and 86% of error is less than ± 0.2 p.u. by employing the **TSD** method. Whereas, Figure 4.7(b) shows 33% of the total forecasting error lies within ± 0.2 p.u., and 76% of error is less than ± 0.4 p.u. by employing **HMM** method. Further,

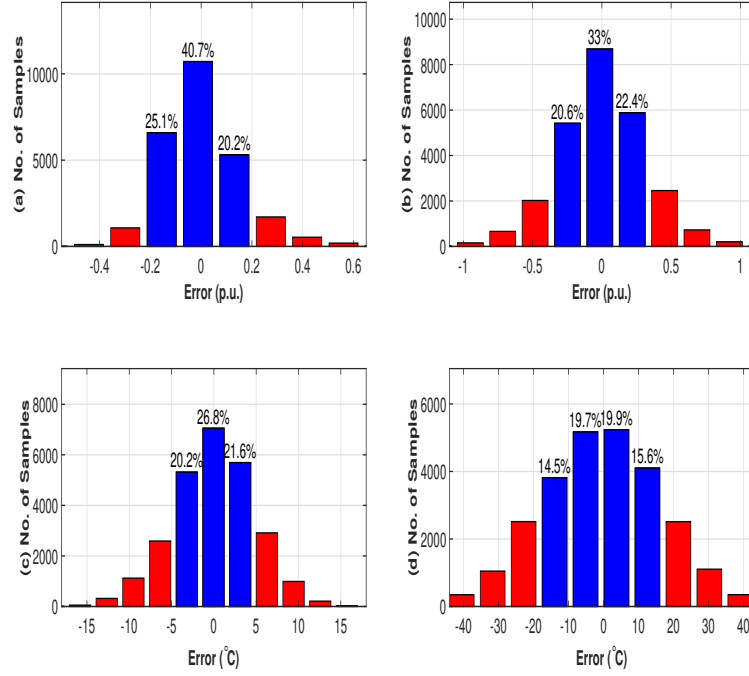


Figure 4.7: Histogram of forecast error from 2014 to 2016 (a) **TSD** method for **DT** kVA load, (b) **HMM** method for DT kVA load, (c) **TSD** method for ambient temperature, and (d) **HMM** method for ambient temperature.

the **TSD** method provides $MAE = 2.94$ and $RMSE = 3.90$, and **HMM** method yields $MAE = 6.00$ and $RMSE = 7.82$.

Table 4.1: Statistical analysis to compare the forecast results of **TSD** and **HMM** methods (2014-2016).

	DT kVA load		Ambient temperature	
	MAE	RMSE	MAE	RMSE
TSD method	2.94	3.90	3.78	4.80
HMM method	6.00	7.82	5.63	6.41

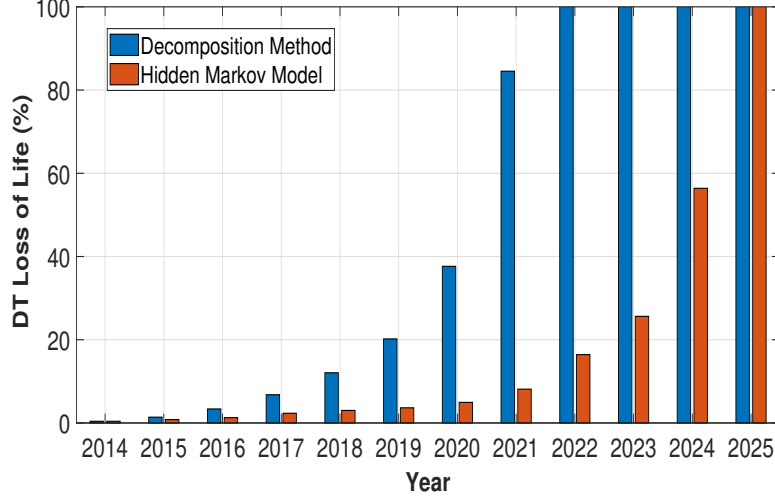


Figure 4.8: Percentage DT life consumed over the years by Time Series Decomposition and Hidden Markov Model methods, considering the initial EV penetration is 33.33%, i.e. 5 cars, and the DT is taken into operation on January 2014.

2. *Ambient temperature:* Figure 4.7(c) shows that 26.8% of the total forecasting error lies within ± 2 °C., and 68.6% of error is less than ± 5 °C by employing the TSD method. Whereas, Figure 4.7(d) shows 39.6% of the total forecasting error lies within ± 10 °C. and 69.7% of error is less than ± 18 °C by employing HMM method. Further, TSD method provides MAE = 3.78 and RMSE = 4.80, and HMM method yields MAE = 5.63 and RMSE = 6.41.

It is important to mention that in order to avoid an infinite sequence of observations and number states in HMM method, the time series observation values are rounded off to two decimal places in this work. This causes an increase in forecasting error for HMM method in Figure 4.7 and Table 4.1 compared to the TSD method.

The historical, as well as long-term forecast data for DT kVA load and ambient temperature, along with the charging demand of EVs are used in an algorithm from IEEE Standard C57.91-2011 to determine insulation aging of a DT, described in section 4.1.3. Figure 4.8 shows DT life consumed over the years, assuming the DT is installed on January 2014, and the initial EV penetration level is 33.33%, i.e. 5 cars in 2014. If the DT were to operate at a continuous rated hottest-spot temperature, the DT life consumed or LOL would be 4.87% every year for 20.5 years of operation. DT life consumed is accumulated to determine RUL_T , as shown in Figure 4.9. Both the TSD and HMM methods show almost

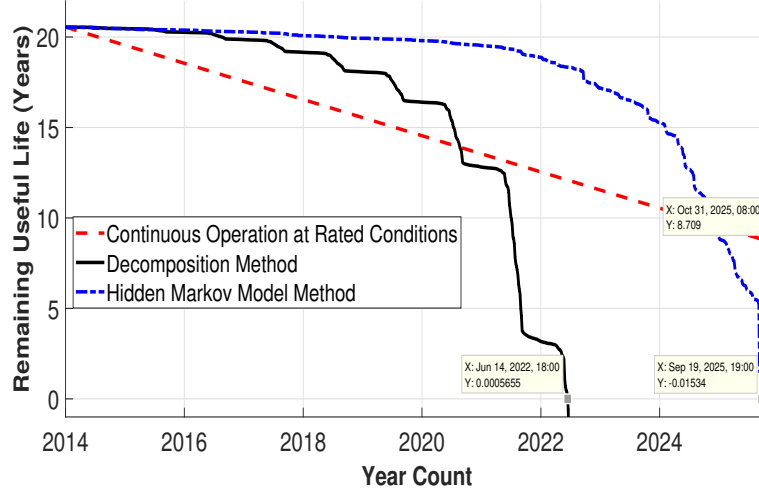


Figure 4.9: Remaining-useful-life of the DT over the years by TSD method, HMM method, and continuous rated hottest-spot operation. considering the initial EV penetration is 33.33%, i.e. 5 cars, and the DT is taken into operation on January 2014.

an exponential trend with very little DT life consumed at the beginning and very severe after a few years of operation. The results are coherent with the realistic SDS since the DT rating is selected such that, it provides electricity to a residential community while staying well below the rated kVA for several years. The TSD and HMM forecasting methods indicate that the anticipated end of DT RUL – which was installed on January 01, 2014, is June 14, 2022, and September 19, 2025, respectively. Whereas continuous rated hottest-spot conditions suggest that the DT may operate for the next 8.7 years on October 31, 2025. The detailed analysis of the anticipated end of DT RUL for various initial EV penetration levels is provided in Table 4.2.

The electrical load of a residential community as well as the EV penetration level is expected to grow over time, and when it surpasses the DT's rated kVA, for instance after a decade of operation, the RUL of the DT decays exponentially. Other reasons for the accelerated aging of a DT insulation include EVs with high energy consumption rates, Level 2 EV chargers, and DT kVA rating. For instance, the growth of EVs with higher energy consumption rate, e.g., Toyota/RAVEV (0.41 kWh/mile), significantly impacts the DT RUL compared to the EVs with lower energy consumption rate, e.g., Tesla/Model 3 (0.23 kWh/mile). Recently, the auto industry has moved to Level 2 or Level 3 fast EV chargers, Level 2 EV chargers of 6.6 kW can triple or even quadruple the LOL of a transformer

Table 4.2: Studied scenarios for various initial EV penetration levels.

Initial EV Penetration	Time Series Decomposition	Hidden Markov model
	Anticipated End of DT RUL	Anticipated End of DT RUL
1 Car (6.67%)	—	—
2 Cars (13.33%)	—	—
3 Cars (20%)	June 25, 2027	—
4 Cars (26.67%)	September 06, 2023	—
5 Cars (33.33%)	June 14, 2022	September 19, 2025
6 Cars (40%)	September 06, 2019	February 01, 2023
7 Cars (46.67%)	January 08, 2017	February 09. 2020
8 Cars (53.33%)	July 05, 2015	May 31, 2016

compared to the Level 1 charger of 3.7 kW. Further, the normal life expectancy of DTs - without considering EV loads - can be 20 years or longer under various loading conditions. However, the existing DTs were initially taken into operation without considering the penetration of emerging loads, such as EVs. Therefore, the frequent EV charging is potentially overloading the DTs, thus, causing early failure and premature replacement of DTs.

Further, in this study, we explore how the remaining useful life of a DT is influenced by factors such as DT loading, ambient temperature, and DT thermal parameters. We operate under the assumption that the DT is constructed from materials of good quality. It should be noted that if the DT were made of inferior materials, such as subpar insulation paper or DT oil, these elements would also have a significant impact on its remaining useful life.

To the best of our knowledge, there has been no field test or laboratory investigation conducted by any LDC or academic researchers in Canada that considers the impact of real-time charging of EVs on the end life of distribution transformers. Some of the reasons are described as follows. The cost of devices to measure the chemical indicators is only justifiable for a power transformer but may surpass the actual price of a distribution transformer. In addition, since the duration of the field test would be unknown, thus, a high level of resource utilization, such as data acquisition, monitoring, and processing for an unknown time duration is not reasonable. Lastly, the end of DT RUL for one DT would be very unique and may not be applicable to any other DT. For the abovementioned reasons, the proposed work is of great importance for the LDC enabling non-intrusive assessment

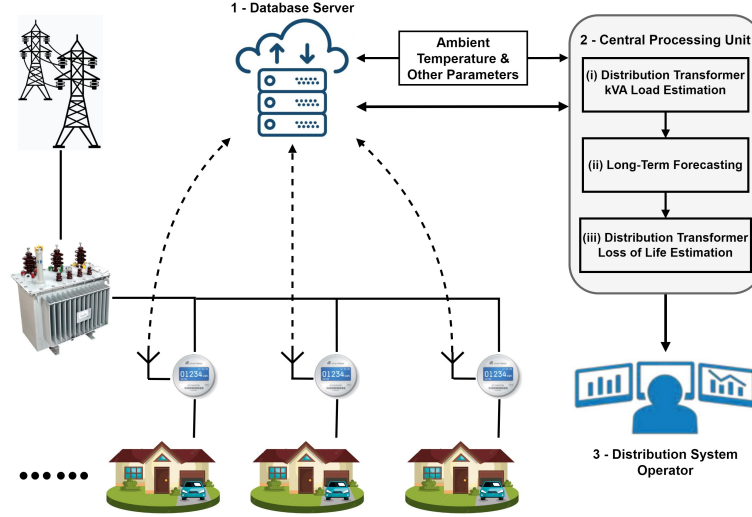


Figure 4.10: Steps to implement the proposed framework in the practical scenario.

of end of DT RUL. In addition, although the studied scenarios among recent state-of-art literature [5–7, 49, 50] and the proposed work is very different, the findings in Figure 4.9 and Table 4.2 are in total agreement with the previous studies [5–7, 49, 50] suggesting that as the electric vehicle penetration level grows over time, the remaining useful life of the distribution transformer decays exponentially.

Battery chargers for plug-in EVs use nonlinear switching devices which may inject significant voltage and current harmonics into the transformer. Various practical studies conducted on EV chargers observe voltage harmonics below 3% [110], which are always within the IEEE Std 519-1992 limits. However, as described in IEEE Std C57.110, non-sinusoidal load current harmonics affect the I^2R losses, winding eddy-current losses, and other stray losses, causing higher hot-spot temperature within the transformer, and thus, reducing expected lifespan. The effects of EV chargers' current harmonics on the power transformer are reported in the recent laboratory investigations [110, 111], and presented as follows: (i) EV charger produces negligible even harmonics due to half wave symmetry in pulse width modulation, (ii) Total harmonic distortion is lower at the beginning of charging cycle and tends to increase toward the end, and (iii) Since, the initial SoC level and charging duration are different for each EV, and EV charger manufacturers in a single residential group could be very different. Therefore, the harmonic patterns of different EV chargers are much more diverse, resulting in notable harmonic cancellations in the transformer. Regarding the effect of nonsinusoidal current harmonics on LOL calculation, an overall total harmonic distortion level below 10% within the transformer may result in

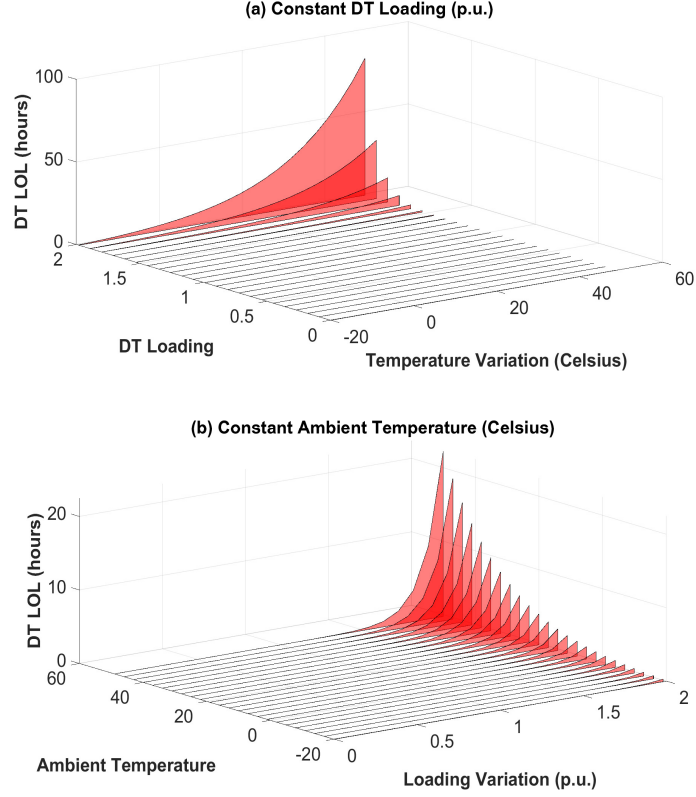


Figure 4.11: Sensitivity analysis of the proposed framework.

LOL calculation uncertainty that is no greater than 10% [112, 113].

The proposed framework is hardware-free; the whole system is automated and end-to-end coded, and it is executed on a central processing unit of the local distribution company. Figure 4.10 depicts the essential steps for the practical implementation of the proposed framework, and the implementation steps are described as follows:

1. Database Server: The real-time SM data of residential customers are transmitted to the database server and stored. The database server also hosts real-time ambient temperature and other parameters, such as service drop cable data, network configuration, and electric vehicle data.
2. Central Processing Unit: Three algorithms are executed on the central processing unit in sequence. (i) Distribution transformer kVA load estimator utilizes SM data

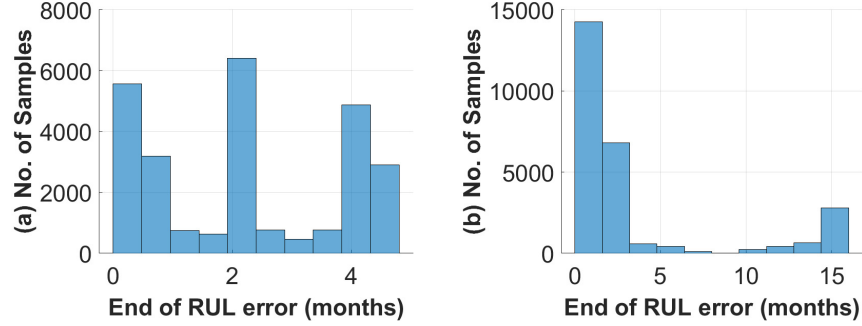


Figure 4.12: Uncertainty analysis of the proposed framework.

of residential customers to calculate real-time DT kVA loading, and store it in the database server. (ii) Long-term forecasting fetches the historical data of the DT kVA load and ambient temperature - until the most recent time - from the database server for long-term forecasting over several years. (iii) Distribution transformer loss of life estimator requires historical as well as forecast values of DT kVA load and ambient temperature, along with the electric vehicles data to determine the insulation aging of a DT, and thus, anticipated end of DT remaining useful life.

3. Distribution System Operator: The real-time updates regarding DT kVA load, DT loss of life, and anticipated end of DT remaining useful life are monitored by the distribution system operator.

The forecasting horizon for DT kVA loading and ambient temperature is 20 years, with a timestep of one hour. Three features are used for the TSD method, i.e., trend, seasonality, and cyclic index. Whereas, two features are used for HMM method, i.e., the current observation and the current state of the observation.

The sensitivity analysis in Figure 4.11 attempts to determine the change in the estimated LOL value that results from the modest change in the DT loading or ambient temperature. Figure 4.11(a) shows the impact of ambient temperature variation from -20 °C to 50 °C on DT LOL when the DT load is constant. The LOL change is noticeable above 1.5 p.u. DT load, and it could reach a maximum of 80 hours at 2.0 p.u. and 50 °C. Whereas, Figure 4.11(b) shows the impact of DT load variation from 0 p.u. to 2 p.u. on DT LOL when the ambient temperature is constant. A similar impact of DT load variation is observed as in Figure 4.11(a), but the change in LOL is less sensitive from the change in DT loading compared to the change in ambient temperature.

Uncertainty analysis in Figure 4.12 attempts to describe the entire set of possible error outcomes. The proposed framework results obtained by using TSD and HMM algorithms are compared with the actual household dataset. The error uncertainty results for TSD and HMM are depicted in Figure 4.12(a) and Figure 4.12(b), respectively. For the TSD algorithm, the mean error is (2.2062 ± 0.0195) months in estimating the end of RUL with a 95% confidence level, and the standard deviation of error is 1.6128 months in estimating the end of RUL. For HMM algorithm, the mean error is (3.3202 ± 0.0611) months in estimating the end of RUL with a 95% confidence level, and the standard deviation of error is 5.0576 months in estimating the end of RUL.

4.3 Summary

The work in this chapter proposes a four-layer framework to quantify the real-time and anticipated aging of a DT, and determines the expected end of DT RUL. A numerical validation is conducted on real-world electricity consumption and ambient temperature data of fifteen households in London, Ontario, along with the penetration of the most popular electric vehicles in Canada, including service drop cable data as well as practical secondary distribution circuit configuration. The first layer records the electricity consumption data through residential SMs and stores it in the database of an LDC. The second layer estimates the kVA load of the DT in real-time, without having to make any fixed power factor assumption on residential customers. The third layer projects the DT kVA load and ambient temperature over the next several years by deploying two computationally less expensive long-term forecasting methods, i.e., Time Series Decomposition and Hidden Markov model. The fourth layer incorporates the predicted results of DT kVA load and ambient temperature along with the actual growth of EV load over the years in IEEE standard C57.91-2011 to identify the DT insulation aging and expected RUL over the years.

The performance of the proposed framework features less computation and scalability to a large number of customers. In addition, the proposed framework does not require any chemical indicator, such as furan, carbon dioxide, and carbon monoxide, as well as any additional hardware installation in the existing distribution system. The proposed framework is not applicable for substation transformers, because the LOL is monitored by directly measuring winding temperature. Further, the proposed methodology is restricted to determining the LOL of multiple distribution transformers at once. Moreover, the accuracy of the proposed work may be compromised if the historical dataset does not include all the possible seasonal variations, i.e., less than a year.

Chapter 5

Real-Time Energy Management Control System for Smart Residential Homes

In this chapter, the proposed **RTEMC** is developed using a rule-based algorithm. To regulate the **EV** charging and discharging rates, a fuzzy logic approach is introduced that utilizes two inputs: (i) the degree of **DT** overload and (ii) the **DR** signal in the form of incentive amount offer. In addition, this section outlines the **DT** overloading and damage cost formulations, as well as the design of the incentives offered. Finally, the effectiveness of the proposed **RTEMC** algorithm is demonstrated through a detailed analysis of a test case that involves **PV** and household load profiles over a 24-hour period, and investigated on a large-scale system.

5.1 Proposed Framework

The proposed Real-Time Energy Management Control (**RTEMC**) framework is illustrated in Figure 5.1. The **RTEMC** is responsible for meeting household demand while also ensuring that the **EV** is fully charged before departure. This objective is achieved through the efficient allocation of available **PV** and grid power resources, coupled with optimal scheduling of **EV** charging and discharging. In addition, the **RTEMC** is equipped with Time-of-Use (**TOU**) pricing, real-time **DT** overloading, and **DR** signals in the form of incentives, resulting in multiple benefits such as reduced electricity costs, mitigation of **DT** overloading,

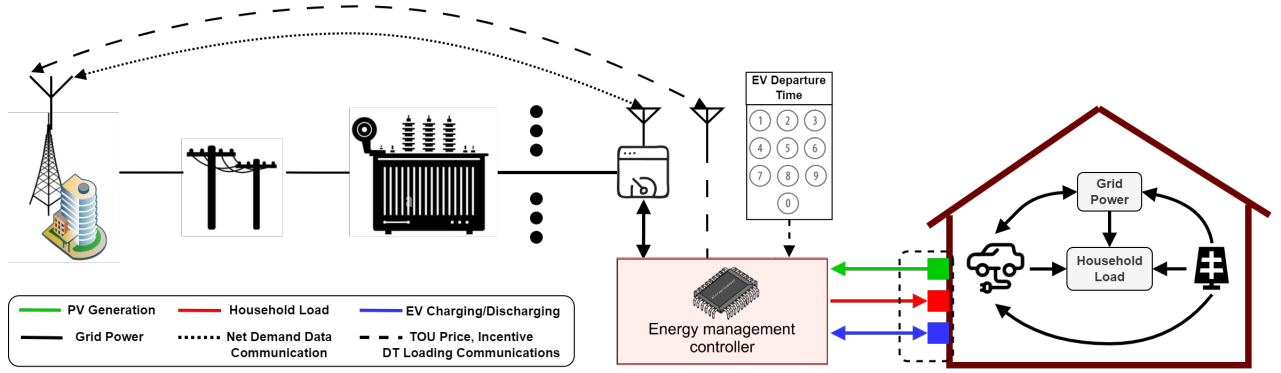


Figure 5.1: Schematic diagram of the proposed real-time energy management controller

and maintenance of a reliable grid. Figure 5.2 shows a single-line diagram of a four-way power-sharing system in a smart residential home that consists of the electric grid, a PV system, an EV battery, and the household load. The bi-directional fully controlled voltage source AC-DC/DC-AC inverter and DC-DC converter enable precise control of the amount of power transferred in either direction. The proposed RTEMC is responsible for efficient power flow in both directions.

In this section, the proposed RTEMC is developed using a rule-based algorithm. To regulate the EV charging and discharging rates, a fuzzy logic approach is introduced that utilizes two inputs: (i) the degree of DT overload and (ii) the DR signal in the form of incentive amount offer. In addition, this section outlines the DT overloading and damage cost formulations, as well as the design of the incentives offered.

5.1.1 Real-Time Energy Management Controller

The rule-based algorithm for RTEMC prioritizes household demand by efficiently balancing power supply from PV and grid sources, and optimizes EV charging and discharging schedules at every time instant $t \in \mathbb{R}_{\geq 0}$, while incorporating important parameters. To make these decisions in real-time, it considers inputs such as remaining SoC, minimum SoC, Charging Time Required (CTR), time upon departure, time-of-use prices at present, and after CTR, among others. The PV power is primarily utilized to meet household needs, with any surplus being directed towards EV charging and subsequently sent back to the grid. The negative sign of $P_{EV,t}$ and $P_{Grid,t}$ indicates that the EV needs to be charged, and excess power is sent back to the grid, respectively. Conversely, a positive sign denotes that the EV is being discharged, and power is drawn from the grid, respectively. The inputs

Table 5.1: Inputs and outputs for RTEMC algorithm

Inputs	
$RSOC_t$	Remaining state-of-charge of EV (0 - 1)
SOC_{min}	Threshold SoC for EV
$EVCap$	Battery capacity of EV (kWh)
P_{EVCHG}	Maximum EV charging power (kW)
P_{EVDSG}	Maximum EV discharging power (kW)
TUD_t	Time until EV departure (hours)
CTR_t	Charging time required to charge EV (hours)
TOU_t	Time-of-Use electricity tariff (cents/kWh)
$TOU_{CTR,t}$	TOU after CTR_t (cents/kWh)
$P_{Load,t}$	Household load consumption (kW)
$P_{PV,t}$	PV generation (kW)
η_t	Fuzzy logic control signal (0 - 1)
Outputs	
$P_{EV,t}$	Charging/Discharging power of EV (kW)
$P_{Grid,t}$	Power drawn from the grid (kW)

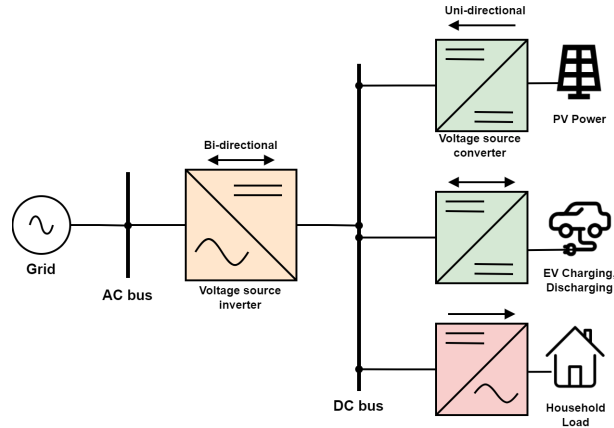


Figure 5.2: A single-line diagram of a four-way power-sharing system in a typical residential home.

and outputs for the **RTEMC** are presented in Table 5.1. The equations and constraints required for **EV** charging and discharging are derived from certain inputs, described from (5.1) – (5.5).

$$0 \leq P_{EV,t}^{charging} \leq P_{EVCHG}, \quad (5.1)$$

$$0 \leq P_{EV,t}^{discharging} \leq P_{EVD SG}, \quad (5.2)$$

$$SOC_{min} \leq RSOC_t \leq SOC_{max}, \quad (5.3)$$

$$RSOC_t = RSOC_{t-1} - \frac{P_{EV,t} \times \Delta t}{EVCap \times T}, \quad (5.4)$$

$$CTR_t = \frac{EVCap(1 - RSOC_t)}{P_{EVCHG}}. \quad (5.5)$$

Here, Δt denotes the time interval between two consecutive instances, and T is used to convert the battery capacity, measured in terms of the sampling interval. The rule-based algorithm for **RTEMC** is described in Algorithm 1. Note that the complete functioning of Algorithm 1 is demonstrated in great detail in Section 5.2.1. This demonstration includes simulated test scenarios involving PV and household profiles over a 24-hour period, effectively showcasing four-way power-sharing dynamics. These dynamics involve power exchange between the grid (G2X or X2G), the utilization of available PV power (PV2X), interactions with electric vehicle battery power (V2X or X2V), and the allocation of power to household loads (X2H).

5.1.2 Fuzzy Logic System to Control the Rate of **EV** Charging and Discharging

The fuzzy control system is integrated in **RTEMC** as η_t (Algorithm 1, lines 3, 5, 8, and 10) to regulate the charging and discharging rates of an **EV** based on two inputs, namely the degree of **DT** overloading (input 1) and the **DR** signal in the form of incentive amount offer (input 2). The output of the fuzzy system is an EV Charging Multiplier (**EVC**), which ranges between 0 and 1, and represents the extent to which the **EV** charging rate needs to be adjusted. To achieve this, Z-shaped and triangular Membership Functions (**MFs**) are selected for input 1 and input 2, respectively, which are widely employed in the literature for similar applications. Similarly, a triangular Membership Function (**MF**) is chosen for the output. The derivations of the **MFs** for input 1, input 2, and output are presented below.

Algorithm 2: Rules of Real-Time Energy Management Controller

```

1 Requirements:  $SOC_{min}$ ,  $EVCap$ ,  $P_{EVCHG}$ ,  $P_{EVDSG}$ .
2 Data:  $RSOC_t$ ,  $TUD_t$ ,  $CTR_t$ ,  $TOU_t$ ,  $TOU_{CTR,t}$ ,  $P_{Load,t}$ ,  $P_{PV,t}$ 
3 Output:  $P_{EV,t}$ ,  $P_{Grid,t}$ .
4
   if  $EV$  is at home at time  $t$  then
5     if  $RSOC_t \leq SOC_{min}$  then
6        $P_{EV,t} \leftarrow -\eta_t \times P_{EVCHG}$ ,  $P_{Grid,t} \leftarrow (P_{Load,t} - P_{PV,t} - P_{EV,t})$ .
7     else if  $CTR_t \geq TUD_t$  then
8        $P_{EV,t} \leftarrow -\eta_t \times P_{EVCHG}$ ,  $P_{Grid,t} \leftarrow (P_{Load,t} - P_{PV,t} - P_{EV,t})$ .
9     else
10      if  $(TOU_t \leq TOU_{CTR,t})$  AND  $(CTR_t > 0)$  then
11         $P_{EV,t} \leftarrow -\eta_t \times P_{EVCHG}$ ,  $P_{Grid,t} \leftarrow (P_{Load,t} - P_{PV,t} - P_{EV,t})$ .
12      else
13         $P_{EV,t} \leftarrow (1 - \eta_t)P_{EVDSG}$ ,  $P_{Grid,t} \leftarrow (P_{Load,t} - P_{PV,t})$ .
14      end if
15    end if
16  else
17     $P_{EV,t} \leftarrow 0 \text{ Watt}$ ,
18     $P_{Grid,t} \leftarrow (P_{Load,t} - P_{PV,t} - P_{EV,t})$ .
19  end if

```

$$\text{Normal DT Load} = \begin{cases} 1, & 0 \leq \text{DT Loading (p.u.)} \leq 1. \\ 0, & 0 > \text{DT Loading (p.u.)} > 1. \end{cases} \quad (5.6)$$

$$\text{DT Overload} = \begin{cases} 0, & 0 \leq \text{DT Loading (p.u.)} \leq 1. \\ 1, & 0 > \text{DT Loading (p.u.)} > 1. \end{cases} \quad (5.7)$$

$$\text{Low Incentive} = \begin{cases} \frac{20 - \text{Incentive}}{20}, & 0 \leq \text{Incentive (cents)} \leq 20 \\ 0, & 0 > \text{Incentive (cents)} > 20 \end{cases} \quad (5.8)$$

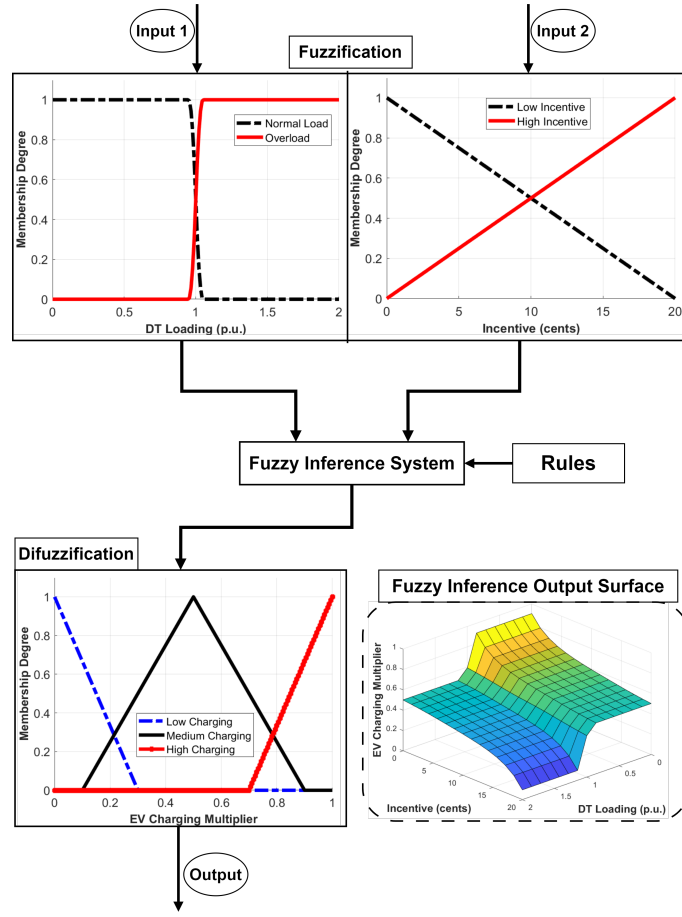


Figure 5.3: Fuzzy control system and fuzzy inference surface output.

$$\text{High Incentive} = \begin{cases} \frac{\text{Incentive}}{20}, & 0 \leq \text{Incentive (cents)} \leq 20 \\ 0, & 0 > \text{Incentive (cents)} > 20 \end{cases} \quad (5.9)$$

$$\text{Low Charging} = \begin{cases} \frac{0.25 - \text{EVCM}}{0.25}, & 0 \leq \text{EVCM} \leq 0.25 \\ 0, & 0 > \text{EVCM} > 0.25 \end{cases} \quad (5.10)$$

$$\text{Medium Charging} = \begin{cases} \frac{\text{EVCN} - 0.1}{0.4}, & 0.1 \leq \text{EVCN} \leq 0.5 \\ \frac{0.9 - \text{EVCN}}{0.4}, & 0.5 \leq \text{EVCN} \leq 0.9 \\ 0, & 0.1 > \text{EVCN} > 0.9 \end{cases} \quad (5.11)$$

$$\text{High Charging} = \begin{cases} \frac{\text{EVCN} - 0.75}{0.25}, & 0.75 \leq \text{EVCN} \leq 1 \\ 0, & 0.75 > \text{EVCN} > 1 \end{cases} \quad (5.12)$$

The MF values above can be customized to incorporate more levels in MF, to meet diverse utility preferences and requirements, facilitating a personalized and flexible decision-making process. In this study, we have chosen 20 cents as the maximum possible incentive amount from the utility when designing the membership function for input 2, considering the on-peak TOU price is 18 cents. It's important to note that this value can vary greatly based on factors like location, customer type, historical power consumption, and a customer's responsiveness to incentives, among others. Our intention here is to present a basic illustration of the potential savings for both customers and utilities. Moreover, this study is specifically developed to residential customers, who typically maintain a power factor between 0.9 to 0.95. Unlike the variable power factors often seen with commercial or industrial customers. Future research can delve deeper into this area, performing a comprehensive sensitivity and uncertainty analysis on the effect of the incentive membership function on savings. Additionally, there's potential to adaptively customize this function using advanced methodologies to ensure optimal decision-making.

Figure 5.3 shows a complete fuzzy control system, including the Fuzzy Inference System (FIS) output for all possible combinations of the two inputs. The FIS output shows the EV charging multiplier value for each combination of input 1 and input 2. The configuration of the fuzzy control system is provided below.

- System Type: Mamdani
- 'AND' Method: Minimum
- Aggregation Method: Maximum

- Implication Method: Minimum
- Defuzzification Method: Centroid

The fuzzy control system is governed by a set of rules, which are outlined in Table 5.2.

Table 5.2: Rules for Fuzzy Logic System

Input 1 \ Input 2	Normal DT Load	DT Overload
Low Incentive	High Charging	Medium Charging
High Incentive	Medium Charging	Low Charging

5.1.3 Distribution Transformer Loading Value and Damage Cost

The first input of the fuzzy logic system is the DT loading value. In order to calculate the DT loading, the well-established forward/backward sweep power flow method [114] can be utilized, which determines the voltage V_t and current I_t at the DT terminal. Subsequently, the monitoring of the DT loading S_t is achieved by $S_t = V_t \times I_t$ (VA). However, In cases where the reactive power consumption of residential customers cannot be directly measured, an alternative approach to estimate DT kVA loading can be found in our work [115], as opposed to the forward/backward method. The DT loading value is then utilized to determine the DT loss of life (LOL) and the DT damage cost incurred by the LDC. The IEEE Standard C57.91-2011 [116] specifies a procedure for calculating the winding hot-spot temperature $\Theta_{H,t}$, which is the primary factor in the DT LOL. $\Theta_{H,t}$ consists of three components: the real-time ambient temperature $\Theta_{A,t}$, the top-oil rise over ambient temperature $\Delta\Theta_{TO,t}$, and the winding hot-spot rise over top-oil temperature $\Delta\Theta_{H,t}$, as presented in (5.13).

$$\Theta_{H,t} = \Theta_{A,t} + \Delta\Theta_{TO,t} + \Delta\Theta_{H,t}, \quad (5.13)$$

The values of $\Delta\Theta_{TO,t}$ and $\Delta\Theta_{H,t}$ depend on the DT's thermal properties and the DT loading condition. For a detailed understanding of the formulation of the DT's thermal properties, we suggest referring to the IEEE Standard C57.91-2011 [116]. The value of $\Theta_{H,t}$ in (5.13) is utilized to compute the DT aging acceleration factor $F_{AA,t}$ in real-time.

$$F_{AA,t} = e^{\left[\frac{15000}{110+273} - \frac{15000}{\Theta_{H,t}+273} \right]}. \quad (5.14)$$

The $F_{AA,t}$ is aggregated over all the time intervals Δt for $k = \{1, 2, \dots, K\}$, where K is the total number of time intervals, to determine the equivalent F_{EQA} and consequently, the monthly **DT LOL**, as presented in (5.15) and (5.16), respectively. Here, $TNIL$ represents the total normal insulation life of a **DT** and is typically recommended as 180,000 hours or 20.5 years [116].

$$F_{EQA} = \frac{\sum_{k=1}^K F_{AA,k} \times \Delta t_k}{\sum_{k=1}^K \Delta t_k}, \quad (5.15)$$

$$\%LOL = \frac{F_{EQA} \times 31}{TNIL} \times 100. \quad (5.16)$$

As suggested by [62], the **DT %LOL** is multiplied by the **DT** price TX^{cost} to obtain the **DT** damage cost that is incurred by the **LDC**, as shown in (5.17). The cost of the **DT**, denoted as TX^{cost} , can be expressed as the product of the nameplate rating and the price per kVA, i.e., $TX^{\text{cost}} = TX^{\text{rating}} \times TX^{\text{price}}$. Here, $TX^{\text{price}} = 166.1$ \$/kVA [62, 63].

$$\text{DT Damage Cost} = TX^{\text{cost}} \sum_{t \in T} \%LOL(t). \quad (5.17)$$

Customers have the option to lower **LDC** expenses by mutually agreeing to alter their **EV** charging or discharging rates. This allows them to qualify for a profit share determined on a monthly basis, at the discretion of the **LDC**, and reflected in their monthly billing statement.

5.1.4 Demand Response Signal in the Form of Incentive Offer

The second input of the fuzzy logic system is the **DR** signal in the form of an incentive offer. An **LDC** can establish a contractual agreement with individual customers to promote **DR** participation. Under this agreement, customers receive a monetary incentive in exchange for adjusting their **EV** charging or discharging rates in a manner that allows their **EV** to be

fully charged before departure and household demand to be met. At the retail level, **DR** signals are represented as time-varying real-time pricing α_t^{RTP} , and the time-of-use pricing is represented as α_t^{TOU} . Let P_{it} denote the power consumption of residential consumer i at time t , and let ΔP_{it} denote the power that the customer is willing to reduce in return for the monetary incentive α_t^{INC} . The α_t^{INC} constraint can be derived to ensure the **LDC** remains profitable, as follows:

$$\sum_{i=1}^N \sum_{t=1}^T \left[\alpha_t^{TOU} P_{i,t} - \alpha_t^{RTP} P_{i,t} \right] \leq \sum_{i=1}^N \sum_{t=1}^T \left[\alpha_t^{TOU} \times \right. \\ \left. (P_{i,t} - \Delta P_{i,t}) - \alpha_t^{RTP} (P_{i,t} - \Delta P_{i,t}) - \alpha_t^{INC} \Delta P_{i,t} \right], \quad (5.18)$$

Simplification of the above expression provides,

$$\alpha_t^{INC} \leq \alpha_t^{RTP} - \alpha_t^{TOU}. \quad (5.19)$$

The constraint (5.19) implies that when **RTP** exceeds **TOU**, the incentive offer must be lower than the difference between **RTP** and **TOU** prices.

5.2 Results and Evaluation

5.2.1 Simulation-based case study on energy management for grid power and electric vehicle charge-discharge

In this section, the effectiveness of the proposed **RTEMC** algorithm is demonstrated through a detailed analysis of a test case that involves **PV** and household load profiles over a 24-hour period, as shown in Figure 5.4(a). The fuzzy logic system is not considered in this particular section to regulate the **EV** charging and discharging rates.

The **RTEMC** algorithm 1 efficiently manages grid and **PV** power by identifying the most suitable schedules for **EV** charging and discharging while considering important factors such as (i) **PV** and household load profiles, (ii) **EV** arrival time, stay-at-home duration, and departure duration, (iii) **TOU** price at present and after the required charging time, (iv) **SoC** limits and constraints, and (v) maximum **EV** charging and discharging powers.

The performance of the **RTEMC** algorithm is compared with a base case that has no intelligent energy management control and simply charges the **EV** upon arrival without

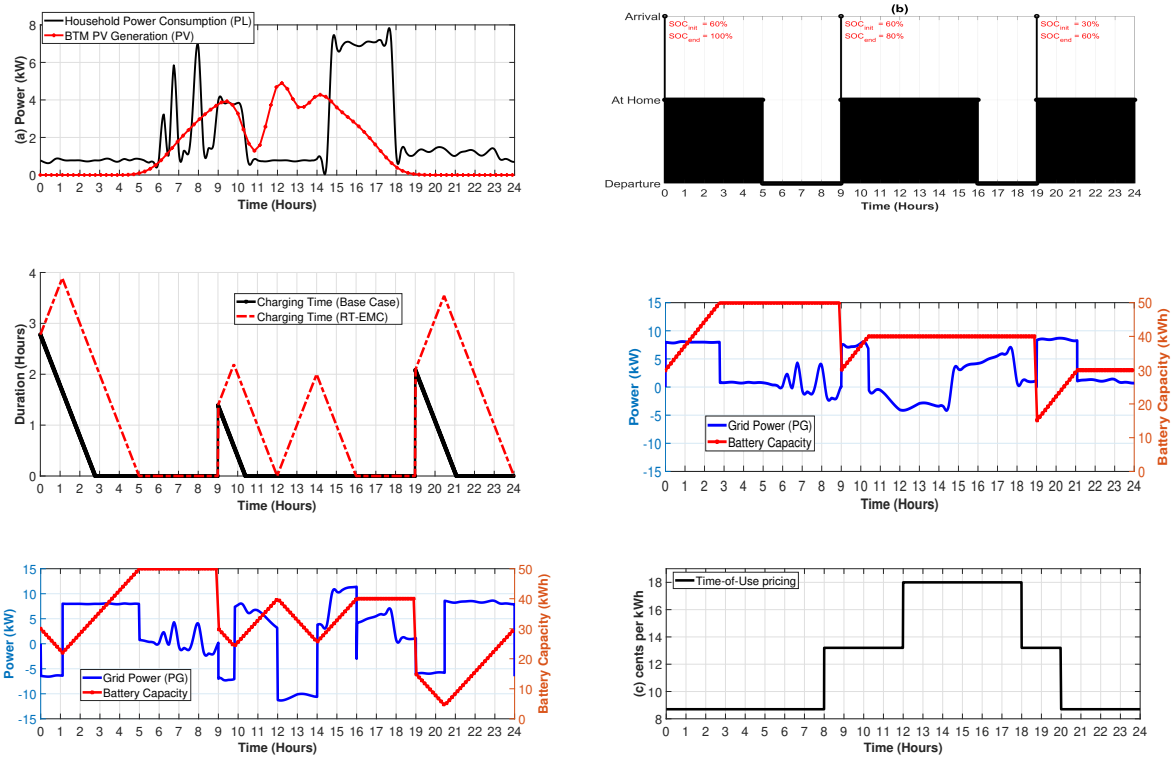


Figure 5.4: Simulation of a 24-hour test case including PV and household loads, EV schedules, grid power and battery capacity, and time-of-use prices.

incorporating the above factors to reduce electricity costs for the residential customer. In Figure 5.4(b), the EV arrives home at 0:00 with an initial SoC of 60% and a desired SoC of 100%, and no PV power is available. From Figure 5.4(c), we observe that the CTR is 3 hours while the time until departure (TUD) is 5 hours, and the TOU price at present and after the CTR is the same. The RTEMC algorithm first discharges the EV for one hour to meet household demand and sell the excess power back to the grid. Similarly, the EV arrives home at 9:00 with an initial SoC of 60% and a desired SoC of 80%. From Figure 5.4(c), the CTR is 1.2 hours while the time until departure (TUD) is 7 hours. The RTEMC algorithm discharges the EV up to 10:00, since the CTR is 2 hours at that time, and the TOU price after 12:00 will be higher. Therefore, it starts charging at 10:00 and finishes at 12:00 to ensure that the EV charging does not occur when the TOU price is high after the CTR.

Table 5.3: Four-way power sharing among grid power (G2X or X2G), available PV power (PV2X), EV battery power (V2X or X2V), and household load (X2H).

Duration (Hour)	PV2H	PV2G	PV2V	V2G	V2H	G2V	G2H
0 - 1							
1 - 2							
2 - 3							
3 - 4							
4 - 5							
5 - 6							
6 - 7							
7 - 8							
8 - 9							
9 - 10							
10 - 11							
11 - 12							
12 - 13							
13 - 14							
14 - 15							
15 - 16							
16 - 17							
17 - 18							
18 - 19							
19 - 20							
20 - 21							
21 - 22							
22 - 23							
23 - 24							

EV at home , PV generation , Base Case , RT-EMC ,
Overlapped region of 'Base Case' and 'RT-EMC' .

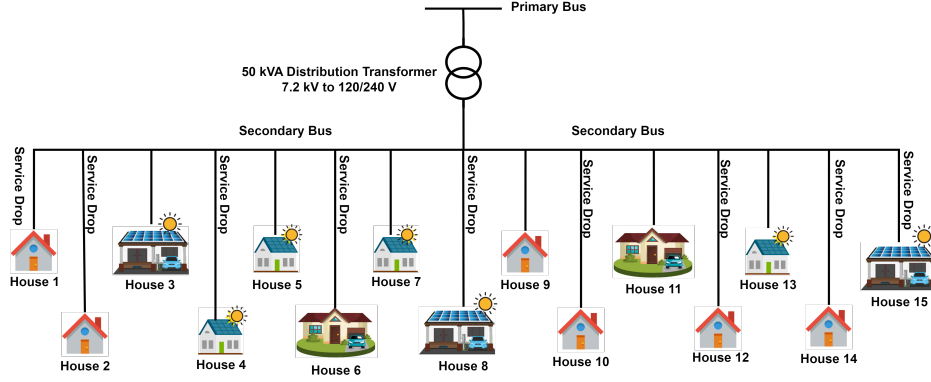


Figure 5.5: Actual secondary distribution system in Canada.

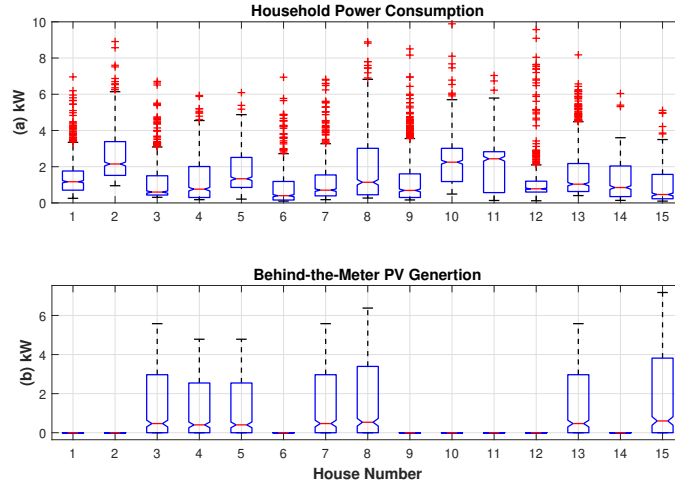


Figure 5.6: (a) Distribution of electricity consumption data for fifteen residential customers in London, Ontario, during July 2016, (b) Distribution of rooftop PV generation for household customers in London, Ontario during July 2016.

However, between 18:00 to 24:00, the RTEMC algorithm saves money on electricity costs. The EV arrives home at 19:00 with an initial SoC of 30% and a desired SoC of 60%. From Figure 5.4(c), the CTR is 2 hours, and the time until departure (TUD) is 5 hours. The base case charges the EV during the mid-peak TOU price, whereas the RTEMC algorithm is intelligent and first discharges the EV to earn a profit, knowing that the TOU price will be cheaper in the future. As a result, the RTEMC algorithm achieves a

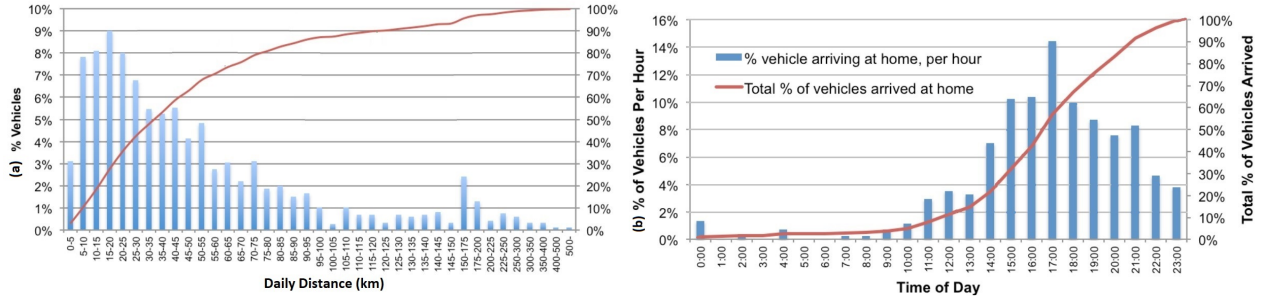


Figure 5.7: (a) Distribution of daily EV distance travel in Canada, (b) Distribution of final EV home arrival time in Canada.

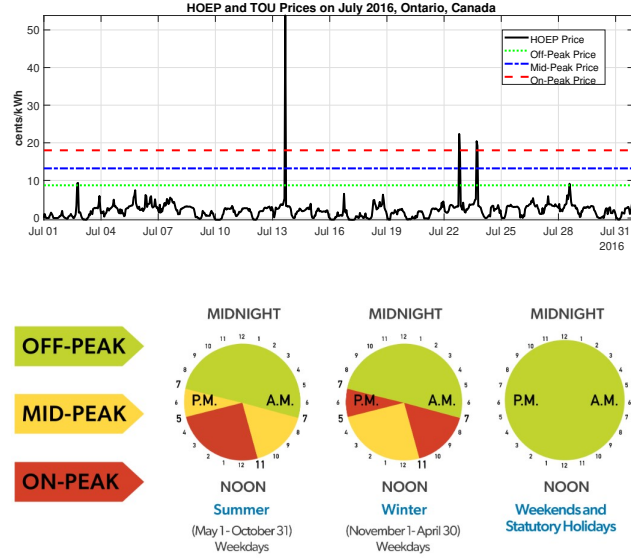


Figure 5.8: Hourly Ontario Energy Price and Time-of-Use price issued by Independent Electricity System Operator, and London Hydro, respectively, in July 2016.

reduction in electricity costs while ensuring timely EV charging prior to departure, without compromising household demand and saving on electricity costs. Table 5.3 provides a detailed visualization of power sharing among the household load, PV power, EV battery power, and grid power for a 24-hour duration. The light shade of color in Table 5.3 represents a transition from the previous state.

Figure 5.4(d) and Figure 5.4(e) show the grid power and battery capacity variations for the base case and the RTEMC algorithm, respectively. In both cases, the total net power from the grid for 24 hours remains the same, at 61.02 kWh. However, by considering the TOU prices shown in Figure 5.4(f), the electricity cost for the base case is \$6.63, while for the RTEMC algorithm, it is \$5.98 for one day.

5.2.2 Real-world case study for FLC-based RTEMC method on Canadian secondary distribution system

In this section, the RTEMC algorithm is integrated with a fuzzy logic control system (FLC-based RT-EMC) to regulate the charging and discharging rates of an EV. The fuzzy system outputs an EV charging multiplier, which ranges from 0 to 1, and adjusts the EV charging rate based on two inputs: the incentive amount offered (input 1) and the degree of DT overloading (input 2). We compare the performance of three cases: (i) the base case, in which the EV gets charged upon arrival with no intelligent energy management control; (ii) RTEMC, which efficiently manages grid and PV powers and identifies suitable charging and discharging schedules to reduce electricity cost; and (iii) FLC-based RTEMC, which integrates the fuzzy logic system into RTEMC to incorporate DT loading and DR signal. From this point onward, a true dataset is utilized for realistic investigation on a practical SDS located in London, Ontario, Canada, shown in Figure 5.5. The details of the data used in this section are provided below.

1. Residential electricity usage data from fifteen households is collected for July 2016 by London Hydro, an LDC in London, Ontario, Canada. Figure 5.6(a) displays the maximum, minimum, and median load demands, along with the 25th and 75th percentiles, for each customer.
2. Ambient temperature data of London, Ontario, Canada for July 2016 is obtained from the government of Canada's website [117].
3. The practical archetype circuit configuration for a real SDS in Canada, along with triplex service drop cable data, is obtained from [118].
4. The PV generation data for London, Ontario customers for July 2016 is obtained from [119]. Figure 5.6(b) shows the PV generation data distribution for the seven residential customers (3, 4, 5, 7, 8, 13, 15 in Figure 5.5) with rooftop PV generation.

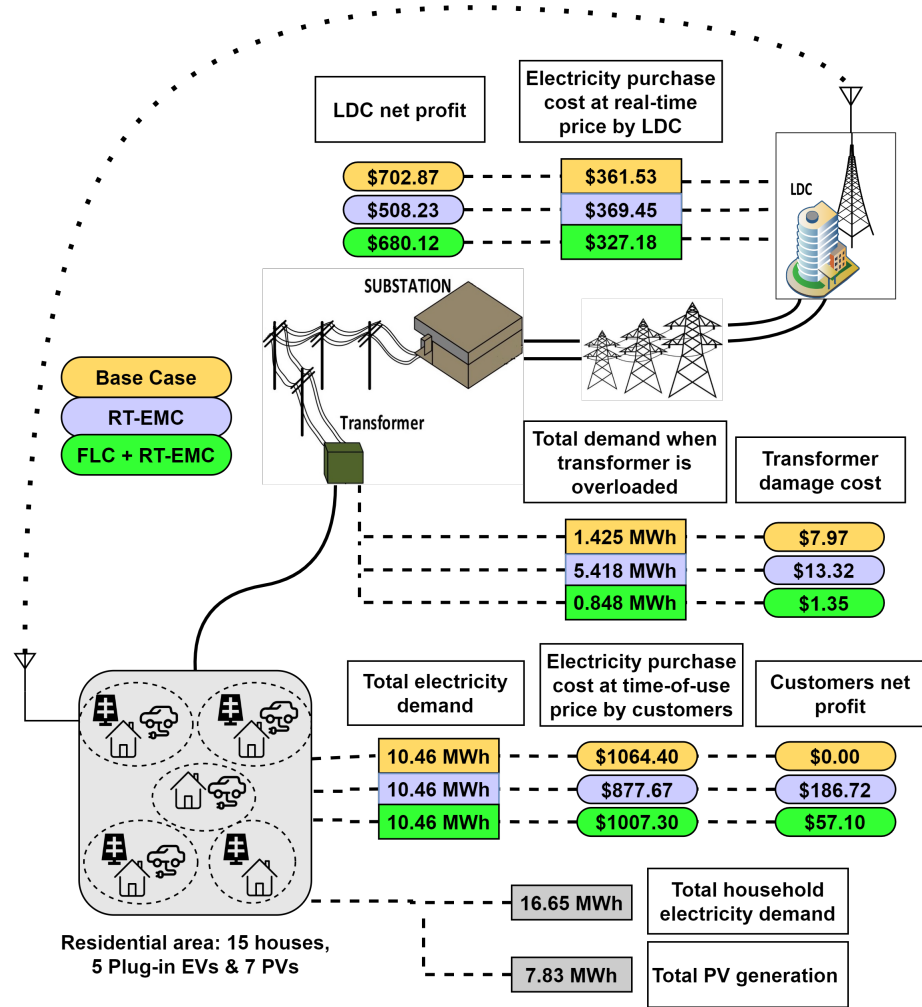


Figure 5.9: Financial analysis of Canadian SDS comprising fifteen houses, and penetration of five EVs and seven rooftop PVs.

5. Specification data for the most popular EVs in Canada is provided in Appendix A. The study includes the five residential customers (3, 6, 8, 11, 15 in Figure 5.5) with EVs.
6. Distributions of daily distance travel (km) and final home arrival time of EV in Canada are obtained from [120] and presented in Figure 5.7.
7. This study utilizes the thermal parameters of the DT in accordance with IEEE Stan-

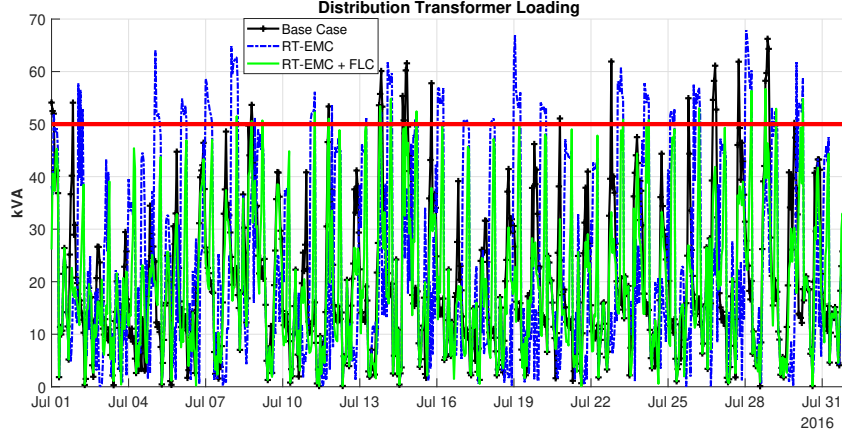


Figure 5.10: Comparison of 50 kVA DT load profiles for ‘Base Case’, ‘RTEMC’, and ‘FLC-based RTEMC’, during July 2016

dard C57.91-2011, which are provided in Appendix A.

8. This study employs the Hourly Ontario Energy Price (HOEP) issued by Independent Electricity System Operator (IESO) [121] in conjunction with the TOU prices issued by London Hydro [122]. Figure 5.8 displays the HOEP and TOU prices for July 2016.

The present study investigates a real case scenario by utilizing actual data from the sources mentioned above, and the results of FLC-based RTEMC are obtained. Input 1 of the FLC is derived from the forward/backward sweep power flow method, utilizing residential and SDS data. Input 2 of the FLC considers the positive sign of α_t^{INC} as a DR signal from (5.19), which is communicated to the customers. For this study, the DR signal is set at 0.3 times alpha. Moreover, the recommended minimum SoC level is 20%. Figure 5.10 illustrates the comparison of DT load profiles for three cases during July 2016. In Figure 5.10, the results of the FLC-based RTEMC show a significant reduction in the duration of DT overloading compared to the base case and RTEMC.

An in-depth analysis of the results is presented in Figure 5.9. Although the total electricity demand remains constant across all cases, the RTEMC case yields the lowest electricity cost for customers, followed by FLC-based RTEMC and the base case. On the other hand, the FLC-based RTEMC case results in the lowest total DT overloading and DT damage cost, followed by the RTEMC and the base case. This pattern is also observed

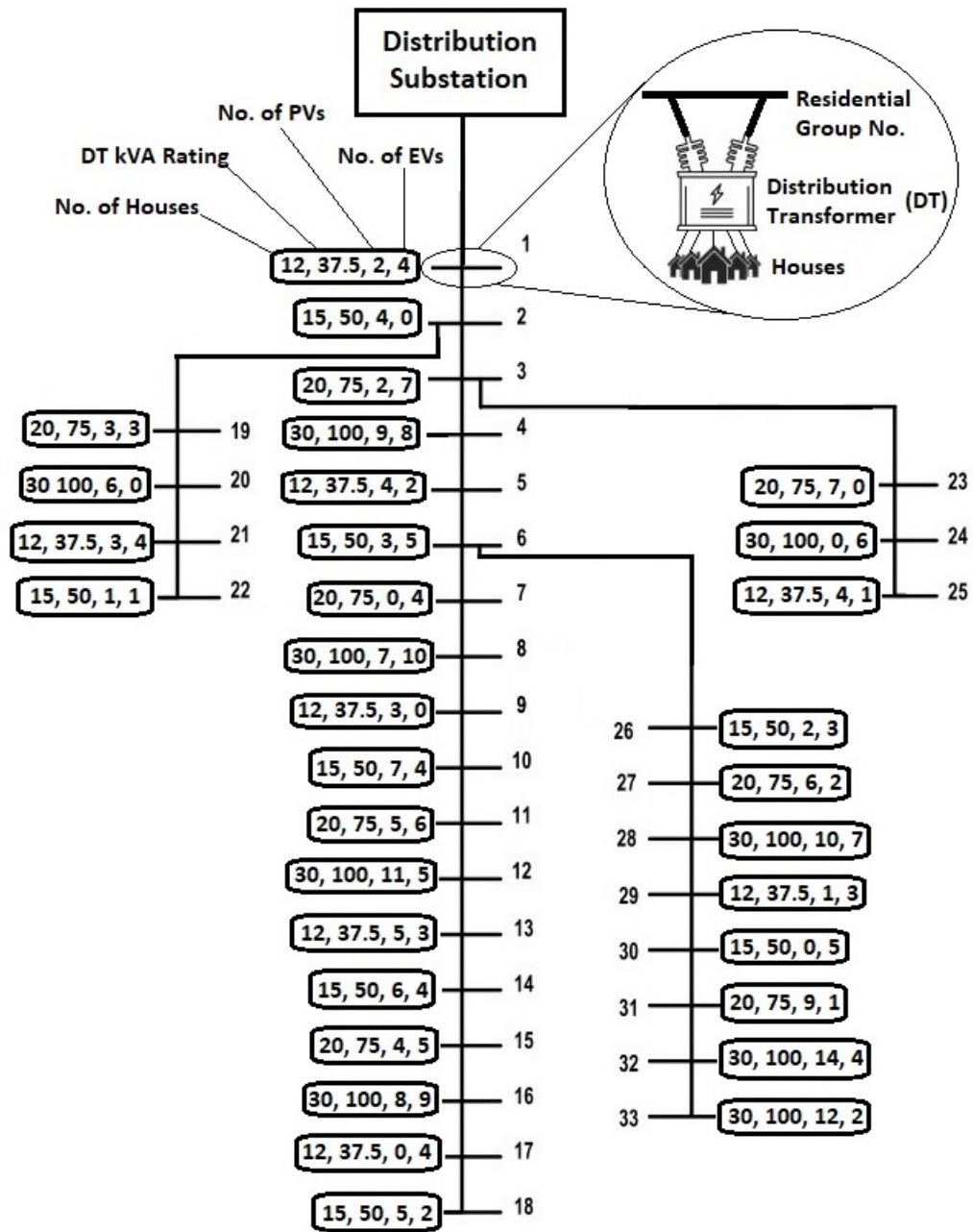


Figure 5.11: Overview of the test power distribution feeder.

Table 5.4: Analysis of electricity purchase costs, net profits, and DT damage costs for the test power distribution feeder.

	Base case	RTEMC	FLC + RTEMC
Total electricity purchase cost of LDC	\$16,757	\$16,465	\$15,748
Total electricity purchase cost of all customers	\$64,926	\$60,538	\$64,053
Net profit of LDC	\$48,169	\$44,072	\$48,304
Net profit of all customers	—	\$4,388	\$873.28
Damage cost of all distribution transformers	\$218.06	\$135.62	\$13.48

in the LDC’s electricity purchase cost and net profit, where FLC-based RTEMC delivers greater benefits by reducing electricity and DT damage costs.

5.2.3 Analysis of power distribution test feeder with diverse SDS groups: A large-scale case study

This section investigates the effectiveness of the proposed approach on a large scale. The main objective of this case study is to evaluate the total savings for both the LDC and customers, as well as the damage cost of DTs, while considering a diverse range of SDS groups of a primary distribution feeder. To conduct this study, we consider a test feeder system comprising 33 SDSs, as illustrated in Figure 5.11. The number of residential customers, penetration of EV and rooftop PV, DT rating for each SDS group are also shown in Figure 5.11. This section employs the dataset from the previous subsection 5.2.2, which has been extended and applied to the test feeder system. Three approaches (i.e., Base Case, RTEMC, and FLC-based RTEMC) for each SDS system are evaluated and their results are aggregated. Table 5.4 presents the total electricity purchase costs, net profits for both the LDC and customers, and the total damage cost of all DTs at the feeder level. The findings in Table 5.4 indicate that the RTEMC case maintains the highest customer-level profit, followed by the FLC-based RTEMC and the Base Case. In contrast, the FLC-based RTEMC case yields the highest net profit for the LDC and the lowest DT damage cost, followed by RTEMC and Base Case. In addition, the power grid is more secure and reliable for the FLC-based RTEMC case.

Table 5.4 presents a financial analysis spanning one month, focusing on the DT damage cost within a single test case diverse community. Over one-month period, there was some reduction in the DT damage cost, decreasing from \$218.06 to \$13.48. While this monthly savings might appear insignificant when compared against the overall profits of residential customers and LDC, however, its cumulative impact becomes significant when extrapolated over several years and across multiple residential communities.

In summary, the installation of RTEMC without a fuzzy system can effectively reduce individual electricity costs for residential customers. However, when adopting FLC-based RTEMC, customers may experience reduced profits while the LDC will benefit greatly. It is now the responsibility of the LDC to create a mutually beneficial contract with customers. If customers adopt FLC-based RTEMC instead of RTEMC, the LDC should share a portion of its profit with them and adjust their electricity bills accordingly. This approach not only promotes reliable grid operation, extends DT lifetime, and increases LDC profits but also enhances customer satisfaction.

5.3 Summary

The work in this chapter develops a novel fuzzy logic-based real-time energy management controller for efficient allocation of power among household load, available PV power, EV battery power, and electric grid power. Firstly, the effectiveness of the proposed approach is demonstrated through a detailed analysis of a test case involving PV and household load profiles over a 24-hour period. Next, the efficacy of the proposed approach is evaluated on a real-world secondary distribution system (SDS) using true datasets. Further investigation is conducted on a large-scale power distribution test feeder with diverse SDS groups. The results, which were delivered in a few milliseconds, demonstrate that the proposed approach provides several benefits, including reduced electricity costs for both the LDC and customers, mitigation of DT overloading, and prioritization of grid reliability. The reduced computation time of the proposed framework enhances its potential for future chip implementation.

Chapter 6

Conclusions

6.1 Summary and Conclusions

In this dissertation, we propose four important research problems that provide the power distribution system operator with crucial cybersecurity insights. These insights facilitate real-time monitoring of the Distribution Transformer [DT](#) kVA load, prediction of its end of remaining-useful life, and disaggregation of behind-the-meter solar generation — all using just smart meter data from residential customers processed at the electric utility’s server.

The first research introduces a novel non-intrusive approach based on the Universal Adaptive Stabilization ([UAS](#)) algorithm, enabling real-time assessment of behind-the-meter ([BTM](#)) solar generation without relying on complex system dynamics. This unsupervised approach proves computationally efficient and outperforms advanced algorithms significantly, as demonstrated through evaluations on simulated and real [BTM](#) solar [PV](#) generation profiles from various countries. Mathematical proof further supports the accuracy of this scheme, and its computational time is exceptionally fast, making it well-suited for real-time applications.

The second research presents a hardware-free strategy for estimating [DT](#) kVA load using smart meter data. Operating at the utility server level, this algorithm eliminates the need for fixed power factor assumptions or reactive power load information across residential customers. The proposed strategy offers a simple, effective fixed-point iteration-based formulation for both balanced and unbalanced three-phase secondary distribution networks. Monte-Carlo simulations with various load profiles confirm the proposed approach outperforms fixed power assumption, providing better kVA load estimation results and reasonable voltage magnitude estimations, suitable for different distribution automation applications.

Expanding upon the second research work, the third research proposes a four-layer framework that utilizes the DT kVA load estimation algorithm to assess the remaining useful life (RUL) of a DT. The framework involves recording electricity consumption data through residential smart meters and estimating the kVA load of the DT in real-time without fixed power factor assumption. Long-term forecasting methods, including Time Series Decomposition and Hidden Markov model, are then deployed to project DT kVA load and ambient temperature over years. By incorporating these predictions with the actual growth of EV load over time, the proposed framework identifies DT insulation aging and expected RUL without requiring additional hardware installations or chemical indicators.

The fourth research proposes a fuzzy logic-based real-time energy management control (RTEMC) system with a focus on smart residential distribution systems from the perspective of electric utilities. The primary objective is to utilize available energy resources efficiently, optimize grid power consumption, minimize electricity costs for the utility and customers, ensure reliable power grid operation, and mitigate distribution transformer (DT) overloading. To validate the effectiveness of our proposed approach, we conduct a detailed analysis of a test case involving PV generation and household load profiles over a 24-hour period. Subsequently, we evaluate the RTEMC system's performance using real-world data from a secondary distribution system (SDS) and conduct further investigations on a large-scale power distribution test feeder with diverse SDS groups. The results show significant benefits, including reduced electricity costs for the utility and customers, DT overloading mitigation, and improved grid reliability. Further, the proposed framework exhibits reduced computation time, enhancing its potential for future chip implementation.

6.2 Contributions

This thesis presents the following main contributions:

A Non-Intrusive Framework for Real-Time Disaggregation of Behind-the-Meter Solar Generation from Smart Meter Data

- Developed a non-intrusive UAS algorithm for real-time disaggregation of behind-the-meter solar PV generation and residential electricity consumption based on smart meter measurements.
- Evaluated the robustness of the proposed method extensively, considering extreme scenarios and real-life disturbances.

- Assessed the efficacy of the algorithm using ten BTM solar PV generation profiles from small residential properties in different countries. Conducted a comparative analysis against advanced algorithms to validate the performance of the proposed framework.
- Established the mathematical foundation for BTM PV generation estimation, proving the convergence of estimated values to their true values.

Distribution Transformer kVA Load Estimation Using Residential Smart Meter Data

- Proposed a strategy for determining DT kVA load estimation in residential customers, without requiring fixed power factor assumptions or reactive power load information. Developed a fixed-point iteration-based formulation for balanced and unbalanced three-phase secondary distribution networks.
- Validated the effectiveness of the proposed strategy through Monte Carlo simulations, using 1,000 load profiles that incorporated uncertainties from smart meter data.
- Investigated the convergence and numerical stability of the proposed methodology, identifying key factors that may lead to divergence and instability.

Distribution Transformer Remaining Useful Life Estimation Considering Electric Vehicle Penetration

- Developed a systematic four-layer framework for anticipating end of DT remaining useful life estimation in a residential setting, by utilizing DT kVA load estimation algorithm.
- Validated the proposed framework using real-world data sources, including electricity consumption and ambient temperature data from fifteen households in London, Ontario, practical archetype SDS circuit configuration, thermal parameters of the DT from IEEE Standard C57.91-2011, and specification data for the most popular EVs in Canada.

Real-Time Energy Management Control System for Smart Residential Homes

- Developed a novel fuzzy logic-based RTEMC for optimizing power allocation from diverse household energy sources: PV power, EV battery power, and electric grid power.

- Formulated the mathematical framework of the fuzzy logic control-based **RTEMC**. Demonstrated the effectiveness of the proposed **RTEMC** through a detailed 24-hour test case analysis.
- Conducted efficacy analysis of the fuzzy logic-based **RTEMC** on a secondary distribution system (**SDS**) and further investigated its performance at the feeder level. The feeder supplies power to a diverse range of **SDS**, and real-world datasets were utilized to validate the results.

6.3 Future Work

In light of the research presented in this thesis, the subsequent matters could be pursued for future investigation:

- Extend the **UAS**-based framework to disaggregate residential smart meter data not only for **BTM PV** generation and load consumption but also for **EV** charging/discharging activities.
- Integrate a nonintrusive event detection algorithm into the **UAS**-based framework for household appliances level disaggregation.
- Develop an adaptive scheme for **DT** kVA load estimation that fine-tunes power factor bounds based on residential load profiles and other relevant factors.
- Modify the **DT** kVA load estimation strategy to incorporate the penetration of Distribution Energy Resources (DERs) for primary distribution system compatibility.
- Explore advanced long-term forecasting methods and compare them with **TSD** and **HMM** techniques for improved **DT** end of **RUL** estimation.
- Conduct a comparative analysis of the IEEE standard algorithm with state-of-the-art methods for loss of life assessment to enhance accuracy in the **DT** end of **RUL** estimation framework.
- Investigate the application of fuzzy neural networks for **RTEMC** parameter optimization.

- Conduct a practical demonstration of RTEMC by physically installing a controller at a residential home to evaluate electricity costs for utility and customers. Further, assess the impact of RTEMC on distribution transformer loading profiles during the practical demonstration.

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APPENDICES

Appendix A

Electric Vehicles and Distribution Transformer Parameters

Table A1: Manufacturing data of electric vehicles [5–7].

Model	Battery Capacity (kWh)	Drive Range (miles)	Energy Consumption (kWh/mile)
Tesla/Model X	85	238	0.36
Tesla/Model 3	50	215	0.23
Chevy/Bolt	60	238	0.25
Toyota/RAV4EV	40	103	0.39
Chevy/Volt	16	40	0.4
Nissan/Leaf	24	73	0.33
Tesla/Model S	100	335	0.30
Toyota/RAVEV	41.8	103	0.41

Table A2: Thermal parameters for 50 kVA distribution transformer [7].

Parameters	Value
At rated load, top-oil rise over ambient temperature ($\Theta_{TO,R}$)	53 °C
At rated load, hottest-spot rise over top-oil temperature ($\Theta_{H,R}$)	27 °C
At rated load, oil thermal time constant (τ_{TO})	6.86 h
At rated load, winding time constant at hottest-spot location (τ_{ω})	6.86 h
Load loss at rated load to no-load loss ratio (R)	4.87
Exponent of loss function for top-oil rise (n)	0.8
Exponent of loss function for winding gradient (m)	0.8

Algorithm 3: EV battery energy requirement [7].

- 1 **Requirements:** E_b : Battery specific capacity (kWh),
 - 2 d : Daily mileage driven (miles),
 - 3 ϵ : Specific energy consumption (kWh/mile),
 - 4 η : charger efficiency.
 - 5 **Output:** E_r : Required energy.
 - 6
 - 7 Calculate the energy consumed: $E_{con} = \frac{d \times \epsilon}{E_b}$.
 - 8 Compute the battery State-of-Charge: $SoC_{req} = E_{con}$.
 - 9 Calculate the battery required energy $E_r = \frac{E_b \times SoC_{req}}{\eta}$.
-

Appendix B

Universal Adaptive Stabilizer

The Universal Adaptive Stabilizer (UAS) controller was developed to relax control conditions, including knowledge of the sign of the high-frequency gain, the relative degree, and the upper bound of the system. The intuition behind this controller is based on the behavior of the switching function $G(\cdot)$ in (2.12). It is designed to alternate between positive and negative values, while maintaining a constant sign over progressively longer intervals. As time progresses, $G(\cdot)$ eventually settles into a sign pattern that is favorable for stabilizing the closed-loop system. This results in the convergence of $u(t)$ in (2.13) to a finite limit, eliminates the need for further switching, and leading to stabilization of the closed-loop system [123]. As discussed in [82], various types of Nussbaum functions have been proposed for UAS-based problems, such as those represented by equations (B.1)-(B.3).

$$E_1(k) = \cos\left(\frac{\pi}{2}k\right) \times e^{k^2}, \quad (\text{B.1})$$

$$E_2(k) = \cos(k) \times k, \quad (\text{B.2})$$

$$E_3(k) = \cos(\sqrt{k}) \times k. \quad (\text{B.3})$$

Whereas, researchers in [75] have demonstrated that a Mittag-Leffler function can serve as a Nussbaum function under specific conditions. In this study, the Mittag-Leffler function, as shown in equation (2.12), is employed as a Nussbaum function. The choice of a Mittag-Leffler type of Nussbaum switching function in this work is motivated by its rapid growth rate, which ensures faster error convergence compared to other types of Nussbaum functions described in equations (B.1)-(B.3).

The switching function is employed for high-gain adaptive frameworks. Nussbaum type switching (NTS) functions are widely used to implement UAS [123]. Mittag-Leffler (ML) function, also known as the generalized exponential function, is often used in fractional-order calculus [75]. Although different types of Nussbaum type switching functions are available in the literature [124], the ML function type Nussbaum function has a rapid growth rate when it is implemented in real-time experiments, and it outperforms the other variants of Nussbaum functions [77, 125]. Therefore, the ML function is one of the best candidates to design the NTS function. The ML function is defined in (B.4) below.

$$E_\alpha(s) = \sum_{k=0}^{\infty} \frac{s^k}{\Gamma(k\alpha + 1)}. \quad (\text{B.4})$$

The standard gamma function is denoted by $\Gamma(\cdot)$, and $\alpha > 0$ is a parameter. The ML function has the form $E_\alpha(-\lambda t^\alpha)$, which can be considered a Nussbaum function under certain conditions, such as when $\alpha \in (2, 3]$ and $\lambda > 0$, as shown in [75]. An NTS function can be defined as follows.

Definition II.1 Let $\eta' \in \mathbb{R}$, a piecewise right continuous and locally Lipschitz function $N(\cdot) : [\eta', \infty) \rightarrow \mathbb{R}$ is a Nussbaum function, if it satisfies the following [124]:

$$\sup_{\eta > \eta_0} \frac{1}{\eta - \eta_0} \int_{\eta_0}^{\eta} G(\tau) d\tau = +\infty, \quad (\text{B.5})$$

$$\inf_{\eta > \eta_0} \frac{1}{\eta - \eta_0} \int_{\eta_0}^{\eta} G(\tau) d\tau = -\infty. \quad (\text{B.6})$$

where $\eta_0 \in (\eta', \infty)$. The ML function presented in (B.4) can be implemented as a Nussbaum function in MATLAB by following the implementation provided in [126]. This Nussbaum function is then utilized in 2.1.1 to develop the UAS-based adaptive observer.

Appendix C

List of Publications

Below is a list of publications by the author during doctoral studies.

- [1] Hafiz M. Usman, Ramadan ElShatshat, Ayman H. El-Hag, “Real-Time Energy Management Control System for Smart Residential Homes”, (Under review for journal publication).
- [2] Hafiz M. Usman, Ramadan ElShatshat, Ayman H. El-Hag, “A Novel Non-Intrusive Framework for Real-Time Disaggregation of Behind-the-Meter Solar Generation from Smart Meter Data”, Electric Power System Research, (Accepted for publication).
- [3] Hafiz M. Usman, Ramadan ElShatshat, Ayman H. El-Hag, “Distribution Transformer Remaining Useful Life Estimation Considering Electric Vehicle Penetration”, IEEE Transactions on Power Delivery, (Accepted for publication).
- [4] Hafiz M. Usman, Ramadan ElShatshat, Ayman H. El-Hag, Rabih A. Jabr, “Estimation of Distribution Transformer kVA Load Using Residential Smart Meter Data”, Electric Power System Research, vol. 204, 107663, March 2022.
- [5] Hafiz M. Usman, Ramadan ElShatshat, Ayman H. El-Hag, “A Practical Approach for Distribution Transformer Loss of Life Assessment Considering Electric Vehicles Penetration”, IEEE Power and Energy Society General Meeting (PESGM), 2023, Orlando, Florida, USA.
- [6] Hafiz M. Usman, Ramadan ElShatshat, Ayman H. El-Hag, Behind-the-Meter Solar Generation Disaggregation via Universal Adaptive Stabilization, IEEE Power and Energy Society General Meeting (PESGM), 2022, Denver, Colorado, USA.

- [7] Hafiz M. Usman, Ramadan ElShatshat, Ayman H. El-Hag, “Distribution Transformer kVA Load Estimation Using Smart Meter Data”, IEEE Electrical Power and Energy Conference (EPEC) 2021, Toronto, Canada.