People's Democratic Republic of Algeria

Ministry of Higher Education and Scientific Research

University M'Hamed BOUGARA – Boumerdes

Institute of Electrical and Electronic Engineering

Department of Power and Control Engineering

Final Year Project Report Presented in Partial Fulfilment of the Requirementsfor the Degree of

MASTER

In **Power Engineering**

Option: **Power Engineering**

Title:

Smart Metering System Optimization Using a Global Algorithm

Presented by:

- **Amine BEDJIL**
- **Mustapha HARIR**

Supervisor:

- **Prof. A. RECIOUI**

Abstract

Non-technical losses or electricity theft have been a serious problem in many developing countries for a long time. This study aims to develop a practical method for determining and reducing the non-technical losses in the power grid by detecting where the suspicion of incorrect registration of electricity consumption occurs and reveal the electricity theft. The proposed method summarizes a mathematical optimization method and modeling technique of smart metering system optimization by using a particular algorithm to identify and minimize the measurement errors for increasing the electricity readings accuracy and lowering the electricity losses and related costs.

TABLE OF CONTENTS

Abstract…………………………………………………………………………… I
Table of contents…………………………………………………………………. II
List of figures…………………………………………………………………...…… IV
List of tables…………………………………………………………………………. V
List of symbols……………………………………………………………………… VI
Acknowledgements…………………………………………………………………. VIII
General introduction………………………………………………………………… 1
Chapter1: Generalities…………………………………………………………… 3
Introduction………………………………………………………………………. 4
1. Generalities about Smart Grid………………………………………………… 5
1.1. Definitions…………………………………………………………………… 5
1.2 Components of smart grid and their functions…………………………………… 7
1.3 Characteristics of the Smart Grid ……………………………………………… 9
1.4 Smart Grid benefits……………………………………..…………………… 10
1.5 Difference between Traditional Power Grid and Smart Grid ………………… 11
2. Advanced Metering Infrastructure (AMI) Based on Smart Meters………………… 14
2.1 Main components of AMI……………………………………..………… 14
3. Context Overview of Smart Meters Rollout in Electricity Sector. The Importance of Smart Metering Systems 16
3-1. Losses in the power system ……………………………………..………… 16
3.2 Smart metering implementation……………………………………..……… 19
Conclusion…………………………………..…………………………………… 21
Chapter2: State of the art in NTL Detection & DFO algorithm……………………… 22
1.Introduction……………………………………………………………………. 23
2. State of the art in non-technical losses detection…………………………………. 23
2.1 Grid-oriented methods……………………………………..………… 24
2.2 Hybrid-oriented methods……………………………………...…… 25
2.3 Data-oriented methods…………………………………..…………… 27
2.4 Challenges in data-oriented methods for non-technical losses Detection 30
3.Swarm Intelligence……………………………………..…………………… 31
4.DISPERSIVE FLIES OPTIMISATION…………………………………………… 32

5. Dispersive flies algorithm for Optimized Operation of an Electricity Utility Smart Metering System 37
Conclusion………………………………………..…………………………………… 37
Chapter3: Simulation results and discussion………………………………………… 39
1. Introduction……………………………………..…………………………… 40
2. Problem solving……………………………………..………………………… 40
2.1. Mathematical Model Formulation of the Optimization Problem……………… 41
3. Simulation……………………………………..……………………………… 43
3.1 Results……………………………………..………………………………… 47
3.2 Discussion……………………………………..…………………………… 49
Conclusion……………………………………..…………………………………. 50
General Conclusion……………………………………..………………………… 51
References……………………………………..……………………………………… 53

LIST OF FIGURES

Figure1. 1: Smart grid diagram illustration 6
Figure1. 2: The three main components of an AMI system 14
Figure1. 3: Example of a smart meter and a home display unit 15
Figure1. 4: A typical electricity smart metering system structure 20

Figure2. 1: Sample update of x_i, where i = 3 in a 2D space. 33
Figure2. 2: optimization results of function 1 by using DFO algorithm 36
Figure2. 3: optimization results of function 2 by using DFO algorithm 37
Figure2. 4: Optimization process for Rastrigin function using Dispersive flies algorithm................. 38

Figure3. 1 : The energy outline at the power distribution grid level. 45
Figure3. 2: Unauthorized connection and their scheme (1—main branch, 2—false column,.............. 46
Figure3. 3: OTC evolution for January2019–February 2020 per individual sector. 47
Figure3. 4: Own Technological Consumption (OTC) evolution in the case of the whole smart-meter based... 48
Figure3. 5 : Measured and optimized OTC evolution for whole sector integrating analyzed sector ... 49

Figure3.6: comparison between OTC before and after the use of DFO………………………………50
Figure3.7: comparison between OTC % before and after the use of Blind Sparky Algorithm………….50

LIST OF TABLES

Table1. 1: Comparison between Smart Grid and Traditional Grid.. 12

Table2. 1: Data-driven methodologies for NTL detection. 28

Table3. 1 : The 2020 energy balance for the considered investigated area. 44
Table3. 2: Experimental measured data and optimized results. 48

LIST OF SYMBOLS

PDCs	Power distribution companies
DG	Distributed generation
AMI	Advanced metering infrastructure
PMU	Phasor Measurement Unit
DSM	Demand-Side Management
DERs	Distributed energy sources
RESs	Renewable energy sources
PHEVs	Plugin hybrid electric vehicles
MDMS	Meter data management system
TLs	Technical losses
NTLs	Non-technical losses
OTC	Own Technological Consumption
OBIS	Object Identification System
FRTU	Feeder Remote Terminal Units
SVM	Support Vector Machine
SM	Smart meter
PG & E	Pacific Gas and Electric
RF	Radio Frequency
MV	Medium voltage
LV	Low voltage
DSE	Distribution state estimation

NTRU	Number Theory Research Unit
ANOVA	Analysis of variance
SCADA	Supervisory control and data acquisition
EC	Energy consumption
GUI	Graphical user interface
RD	Research and development
ANEEL	Brazilian Electricity Regulatory Agency
ML	Machine learning
TPR	True positive rate
RCL	Recall
FPR	False positive rate
PRC	Precision
ROC-AUC	Area under the receiver operating characteristic curve
ELM	Extreme Learning Machines
TNB	Tenaga nasional berhad
OS-ELM	Online sequential extreme learning machines
CWR	Credit worthiness rating
MLP	Multi-layer perceptrons
RMSE	Root mean square error
DT	Decision trees
SI	Swarm Intelligence
DFO	Dispersive Flies Optimization

Acknowledgements

In the name of Allah, the Most Gracious and the Most Merciful.

First and for most, we thank Allah for giving us strength and ability to complete this project. Next, we would like to take this opportunity to thank all the people who helped us to complete this project. We would also like to express our sincere gratitude to our supervisor professor A.Recioui for his guidance and support throughout this project. Thanks should also go to Mr.al Rifaie Senior Lecturer in Artificial Intelligence at the University of Greenwich for his help. We would also like to pass our deepest gratitude to all of our families' members.

Finally, we would like to thank all the teachers that taught us and shared their precious knowledge and the staff of the INELEC for assisting us with all our study related concerns throughout these five years.

General introduction

Electricity theft and fraud in energy consumption are two of the major issues for power distribution companies (PDCs) for many years. PDCs around the world are trying different methodologies for detecting electricity theft.
Today's electric power systems engineer is perplexed by the pressure to ``do something'' about wasted energy. He needs to know where losses exist in system components, if he can measure them, what are the theoretical savings, and what he can do about them.

Losses of electrical energy in the power grids at the transmission and distribution level include both technical losses (TL) and non-technical losses (NTLs) [1]. The computation of TL is generally needed for the correct estimation of NTL [2]. TLs are unavoidable as these occur in the equipment during the transmission and distribution (T&D) process, whereas NTLs are labeled as administrative losses that occur because of non-billed electricity, malfunction of the equipment, error in billings, low-quality infrastructure, and illegal usage of electricity [3]. The fraudulent behavior of energy customers is usually associated with electricity theft, regularized corruption, and organized crime [4]. Therefore, such sort of losses cannot be precisely estimated.

In this report, we will explore the capabilities of a particular swarm intelligent (SI) algorithm for NTL detection in a smart metering context, where electricity utilities have access to measurements provided by smart electricity meters (SMs).
The SMs rollout has a positive impact on both power grid planning and operations. As an example, the power grid planning can be improved by using the SMs data to correct topological errors.
Smart metering is hence an enabling technology that will help to address a number of challenges in the move towards smart energy systems.

The work is divided into three chapters. In chapter 1, we give some generalities about the Smart Grid concept, evolution, components and their functions, characteristics and benefits of Smart Grid and then in some details we covers the basic points of smart metering concept and its rollout in electricity sector .the chapter will be helpful in describing the key enabling technologies and thus allowing the reader to play a part in the debate over the future of smart metering and Smart Grid.

In chapter 2, we give a broader overview of all the methodology types that are used in NTLs detection then a particular attention is paid to the optimization technique that we are going to use in order to solve our problem by using the dispersive flies algorithm.

Finally, In Chapter 3, the simulation results in MATLAB are presented and discussed.

Chapter 1

Generalities

Introduction

The ever increasing demand for electricity has caused several problems to power utilities and governments in many countries. The power system expanded rapidly from 1950s mainly in the United States of America and some European countries. A rapid growth of distributed generation (DG) has also been observed. Each day, more renewable energy sources are added to the system apart from the centrally generated ones. Since wind power and solar power are highly variable, more sophisticated control systems are needed to facilitate the grid [5].

Moreover the old grid system is not readily configurable to rapidly changing demand patterns. It suffers from many shortcomings like poor efficiency, lack of reliability, lack of energy buffering, high cost of energy consumption, low fault detection speed, carbon pollution and insufficient interaction between the consumer and the grid company. Transmission and distribution equipments are out of date and should be replaced. Meanwhile the government and regulations are forcing the utilities for more competition, efficiency, low price for electricity, and green energy. Therefore the necessity for an advanced grid system is identified.

Research and developments in power system engineering have contributed in developing of a reliable and highly efficient grid system which supports DG, security, reliability and two-way interaction. The improvements in the electronic communication technology are also used to resolve the limitations of the old grid system [6]. The incorporation of modern telecommunication technologies has established a reliable communication link all over the grid system making it easy to monitor and control. This communication infrastructure is used to monitor and control the power usage at different locations in the grid system. An advanced metering infrastructure (AMI) is also needed to view and analyze the demand patterns on a per-user basis. The replacement of electromechanical meters with smart meters along with domestic load controllers is identified for better energy
conservation at the consumer side.

Ultimately the concept of smart grid is raised concerning the drawbacks of the old grid system and the necessity for a new intelligent grid system that has improved reliability, security, and efficiency.

1. Generalities about Smart Grid:

1.1. Definitions:

Even though there is no exact definition for ‘‘Smart Grid’’, we can say that smart grid is basically an intelligent electricity delivery system combined with modern digital and information technology, which provides efficiency, security, reliability and more benefits for both utilities and consumers.

The Smart Grid can and should be defined by broader characteristics. A selection of definitions for the Smart Grid reported in literature is given below:

The US Department of Energy defines:

A smart grid uses digital technology to improve reliability, security, and efficiency (both economic and energy) of the electric system from large generation, through the delivery systems to electricity consumers and a growing number of distributed-generation and storage resources[7].

The definition of Smart Grid by European technology platform is,

A Smart Grid is an electricity network that can intelligently integrate the actions of all users connected to it-generators, consumers and those that do both-in order to efficiently deliver sustainable, economic and secure electricity supplies[8].

IEEE definition for Smart Grid is,

The smart grid is a revolutionary undertaking-entailing new communications-and control capabilities, energy sources, generation models and adherence to cross jurisdictional regulatory structures [9].

A definition of the Smart Grid proposed by Cisco states:

A Smart grid is the term generally used to describe the integration of all elements connected to the electrical grid with an information infrastructure, offering numerous benefits for both the providers and consumers of electricity [10].

The Department of Environment, Water, Heritage and the Art of Australian Government declares:

Smart grids combine advanced communication and metering infrastructure with existing energy networks to enable a combination of grid-side and customer applications to deliver a more efficient and robust network [11].

The IEC development organization defines the Smart Grid as:

The Smart Grid is integrating the electrical and information technologies in between any point of generation and any point of consumption [12].

In an article published in IET *Engineering and Technology* (*E&T*) magazine, Davies defined the Smart Grid as:

A smart grid is an electricity network that uses digital and other advanced technologies to monitor and manage the transport of electricity from all generation sources to meet the varying electricity demands of end-users.

Smart grids co-ordinate the needs and capabilities of all generators, grid operators, end-users and electricity market stakeholders to operate all parts of the system as efficiently as possible, minimizing costs and environmental impacts while maximizing system reliability, resilience and stability[13].

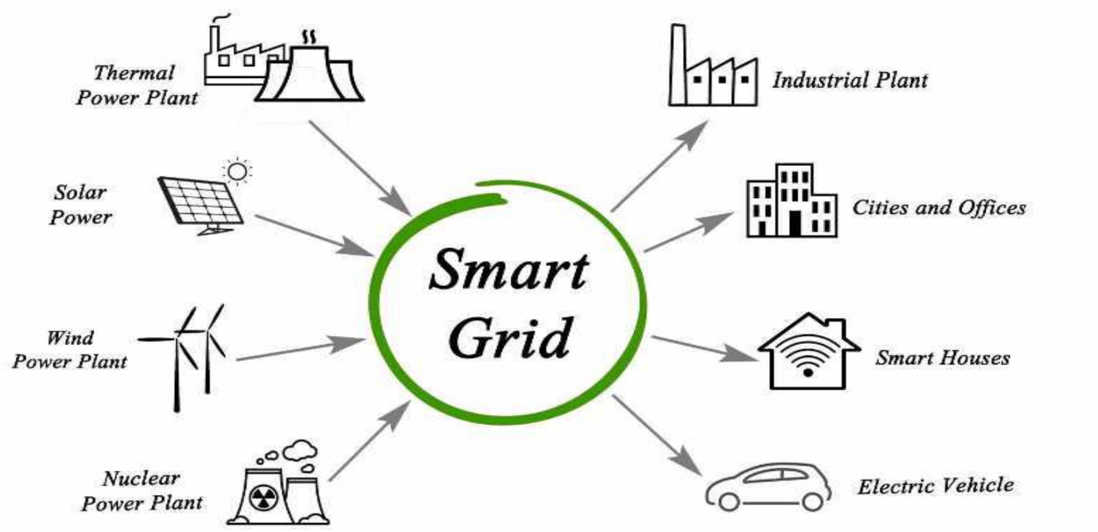


Figure1. 1: Smart grid diagram illustration[48]

1.2 Components of smart grid and their functions [14]:

For the generation level of the power system, smart enhancements will extend from the technologies used to improve the stability and reliability of the generation to intelligent controls and the generation mix consisting of renewable resources.

1.2.1 Smart Devices Interface Component

Smart devices for monitoring and control form part of the generation components' real time information processes. These resources need to be seamlessly integrated in the operation of both centrally distributed and district energy systems.

1.2.2 Storage Component

Due to the variability of renewable energy and the disjoint between peak availability and peak consumption, it is important to find ways to store the generated energy for later use. Options for energy storage technologies include pumped hydro, advance batteries, flow batteries, compressed air, super - conducting magnetic energy storage, super - capacitors, and flywheels. Associated market mechanisms for handling renewable energy resources, distributed generation, environmental impact and pollution are other components necessary at the generation level.

Associated market mechanism for handling renewable energy resources, distributed generation, environmental impact and pollution has to be introduced in the design of smart grid component at the generation level.

1.2.3 Transmission Subsystem Component

The transmission system that interconnects all major substation and load centers is the backbone of an integrated power system. Efficiency and reliability at an affordable cost continue to be the ultimate aims of transmission planners and operators. Transmission lines must tolerate dynamic changes in load and contingency without service disruptions.

To ensure performance, reliability and quality of supply standards are preferred following contingency. Strategies to achieve smart grid performance at the transmission level include the design of analytical tools and advanced technology with intelligence for performance analysis such as dynamic optimal power flow, robust state estimation, real - time stability assessment, and reliability and market simulation tools. Real – time monitoring based on PMU, state estimators sensors, and communication technologies are the transmission subsystem's intelligent enabling tools for developing smart transmission functionality.

1.2.4 Monitoring and Control Technology Component

Intelligent transmission systems/assets include a smart intelligent network, self -monitoring and self - healing, and the adaptability and predictability of generation and demand robust enough to handle congestion, instability, and reliability issues. This new resilient grid has to withstand shock (durability and reliability), and be reliable to provide real - time changes in its use.

1.2.5 Intelligent Grid Distribution Subsystem Component

The distribution system is the final stage in the transmission of power to end users. Primary feeders at this voltage level supply small industrial customers and secondary distribution feeders supply residential and commercial customers. At the distribution level, intelligent support schemes will have monitoring capabilities for automation using smart meters, communication links between consumers and utility control, energy management components, and AMI. The automation function will be equipped with self - learning capability, including modules for fault detection, voltage optimization and load transfer, automatic billing, restoration and feeder reconfiguration, and real – time pricing.

1.2.6 Demand Side Management Component

Demand side management options and energy efficiency options developed for effective means of modifying the consumer demand to cut operating expenses from expensive generators and defer capacity addition.

DSM options provide reduced emissions in fuel production, lower costs, and contribute to reliability of generation. These options have an overall impact on the utility load curve. A standard protocol for customer delivery with two - way information highway technologies as the enabler is needed. Plug - and - play, smart energy buildings and smart homes, demand - side meters, clean air requirements, and customer interfaces for better energy efficiency will be in place.

1.3 Characteristics of the Smart Grid [15]:

Similar to the definition of the Smart Grid, its characteristics have been identified by different organizations/authors using different approaches. However, the widely adopted approaches for identifying Smart Grid characteristics are based on (i) functionality approach and (ii) broad approach.

Smart Grid characteristics based on functionality approach include seven principal characteristics as listed below:

1. ***Optimize*** asset utilization and operating efficiency.
2. ***Accommodate*** all generation and storage options.
3. ***Provide*** power quality for the range of needs in a digital economy.
4. ***Anticipate and respond*** to system disturbances in a self-healing manner.
5. ***Operate resiliently*** against physical and cyber-attacks and natural disasters.
6. ***Enable*** active participation by consumers.
7. ***Enable*** new products, services, and markets.

While those based on the broad approach are as follows:

● ***Adaptive*** and ***self-healing***: Smart Grid being adaptive means it has less reliance on operators, particularly in responding rapidly to changing conditions. However, the Smart Grid being self-healing means it has the capability of automatically repair or remove potentially faulty equipment from service before it fails, and has the ability of reconfiguring the system in such a way to ensure continuity of the energy to all customers.

● ***Flexible***: The Smart Grid has the ability to rapid and safe interconnection of distributed generation and energy storage at any point on the system at any time.

● ***Predictive***: The Smart Grid has the ability to apply operational data to equipment maintenance practices and even identify potential outages before they occur.

This may be achieved with the help of using machine learning, weather impact projections, and stochastic analysis to provide predictions of the next most likely events, so that appropriate actions can be taken to reconfigure the system before the next worst events can happen.

● ***Integrated***: This is particularly important in terms of real-time communications and control functions.

● ***Interactive***: The Smart Grid should have the capability of providing appropriate information regarding the status of the system not only to the operators, but also to the customers, that is, both consumers and prosumers, to allow all key participants in the energy system to play an active role in optimal management of contingencies and also to facilitate the interaction between customers and markets.

● ***Optimized***: This is achieved by knowing the status of every major component in real or near real time and having control equipment to provide optional routing paths that provide the capability for autonomous optimization of the flow of electricity throughout the system with the aim of maximizing reliability, availability, efficiency, and economic performance.

● ***Secure***: Since the two-way communication capability covering the end-to-end system is considered as a fundamental and basic requirement of the Smart Grid, the need for physical as well as cyber-security of all critical assets is essential. This is extremely important to ensure that the Smart Grid is secured from attack and naturally occurring disruptions.

1.4 Smart Grid benefits:

The benefits obtained from the full implementation of the Smart Grid are enormous [16–17]. This includes technical, environmental, and electricity marketing benefits:

(a) Technical benefits:

Full deployment of Smart Grid would result in several technical benefits that include:

(i) **Energy efficiency improvement:** This is achieved through loss reduction, peak shaving, that is, peak demand control, implementation of AMI and automated energy system operation.

(ii) **Grid reliability improvement:** This is achieved by reducing the frequency and duration of power interruptions.

(iii) **Operational efficiency improvement:** Achieved through active control, automation, and management services in distribution grids and by empowering customers through home automation and use of smart appliances.

(iv) **Security and safety improvement:** Security improvement can be achieved by using sensors and automated operations that will reduce the threats of blackouts and by properly coordinating the operation of transmission and distribution with intelligent preventive and emergency control and coordinated restoration. Safety improvement, however, can be achieved by reducing the vulnerability of the grid to unexpected hazards and promoting a safer system for personals whether workers or general public.

(v) **Quality of supply:** Quality of supply in terms of maintaining voltage magnitude within their statutory limits can be achieved by Smart Grid technologies such as censors, two-way information, and communication technologies.

(vi) **Improved connection and access of the grid:** Improved connection and access of the grid is particularly important to distributed energy sources (DERs), including renewable energy sources (RESs) and plugin hybrid electric vehicles (PHEVs).

(b) Environment benefits:

Environment benefits gained from deployment of Smart Grid include:

(i) **Reduction in carbon emissions:** This is achieved due to reduction in grid losses, integration of renewable and distributed generation, and by supporting efficient end-use by plug-in electricity vehicles.

(ii) **Climate change benefits:** Reduction in grid losses resulted from deployment of Smart Grid, as stated above, together with facilitating generation of electricity from renewable energy sources, such as wind, solar, and hydro has major implications on reduction in CO2 emission which in turn improve the prospect of climate change.

(c) Electricity marketing benefits

Under the Smart Grid environment, the electricity price can be reduced compared with that of conventional grid, due to the dynamic interaction of the demand side of the market (consumers) with electricity supply side (suppliers/ providers). The information made available under such an environment about electricity price from different suppliers would naturally let consumers choose the least electricity price supplier. Consequently this creates healthy electricity market competition, which benefits consumers and also plays part in optimizing the operation of the power system network.

1.5 Difference between Traditional Power Grid and Smart Grid [18]:

The traditional power grid is basically the interconnection of various power systems elements such as synchronous machines, power transformers, transmission lines, transmission substations, distribution lines, distribution substations, and different types of loads. They are located far from the power consumption area and electric power is transmitted through long transmission lines.

This table below covers the key differences between the Traditional Power Gird and the Smart Grid on the basis of technology, power distribution & generation, sensors, monitoring, equipment, control, and customer choices.

The smart grid is a modern form of the traditional power grid which provides more secure and dependable electrical service. It is, in fact, a two-way communication between the utility and the electricity consumer.

Table1. 1: Comparison between Smart Grid and Traditional Grid[18]

Characteristics	Traditional Power grid	Smart Grid
Technology	**Electromechanical:** Traditional energy infrastructure is electromechanical. This means that it is of, relating to, or denoting a mechanical device that is electrically operated. The technology of this manner is typically considered to be “dumb” as it has no means of communication between devices and little internal regulation.	**Digital:** The smart grid employs digital technology allowing for increased communication between devices and facilitating remote control and self-regulation.
Distribution	**One-Way Distribution:** Power can only be distributed from the main plant using traditional energy infrastructure.	**Two-Way Distribution:** While power is still distributed from the primary power plant, in a smart grid system, power can also go back up the lines to the main plant from a secondary provider. An individual with access to alternative energy sources, such as solar panels, can actually put energy back on to the grid.
Generation	**Centralized:** With traditional energy infrastructure, all power must be generated from a central location. This eliminates the possibility of easily incorporating alternative energy sources into the grid.	**Distributed:** Using smart grid infrastructure, power can be distributed from multiple plants and substations to aid in balancing the load, decrease peak time strains, and limit the number of power outages.
Sensors	**Few Sensors:** The infrastructure is not equipped to handle many sensors on the lines. This makes it difficult to pinpoint the location	**Sensors Throughout:** In a smart grid infrastructure system, there are multiple sensors placed on the lines. This helps to pinpoint the location

	of a problem and can result in longer downtimes.	of a problem and can help reroute power to where it is needed while limiting the areas affected by the downtime.
Monitoring	**Manual:** Due to limitations in traditional infrastructure, energy distribution must be monitored manually.	**Self:** The smart grid can monitor itself using digital technology. This allows it to balance power loads, troubleshoot outages, and manage distribution without the need for direct intervention from a technician.
Equipment	**Failure & Blackout:** As a result of aging and limitations, traditional energy infrastructure is prone to failures. Failure of infrastructure can lead to blackouts, a condition where the end customer is receiving no power to their unit causing downtime.	**Adaptive & Islanding:** Using a smart grid system, power can be rerouted to go around any problem areas. This limits the area impacted by power outages and can do it on a per residence level.
Control	**Limited:** Using traditional power infrastructure, energy is very difficult to control. After leaving the power plant or substation, companies have no control over the energy distribution	**Pervasive:** With the increased amount of sensors and other smart infrastructure, energy companies have more control than ever over power distribution. Energy and energy consumption can be monitored all the way down the line; from the moment it leaves the power plant, all the way to the consumer.
Customer Choices	**Fewer:** The traditional power grid system infrastructure is not properly equipped to give customers a choice in the way they receive their electricity. Alternative energy sources, for example, have to be separated from power plants and traditional grid infrastructure. This is also part of the reasoning behind the establishment of electric companies as a public utility.	**Many:** Using smart technologies, infrastructure can be shared. This allows more companies and forms of alternative energy to come on to the grid allowing consumers to have more choice in how they receive energy.

2. Advanced Metering Infrastructure (AMI) Based on Smart Meters:

Smart metering has been recognized as a major part of the smart grid system. It has been touted as a great bright hope that will enable residential electric customers to cut their usage and save electricity costs [7]. The AMI is the system that collects and analyzes data from smart meters using two-way communications, and giving intelligent management of various power-related applications and services based on that data. The implementation of AMI is widely seen as the first step in the digitalization of the electric grid control systems. Recently, AMI has gained great attraction in both industry and commerce due to the accurate improvement in online meter reading and control [19].

2.1 Main components of AMI:

An AMI is a system which comprises of a number of technologies and applications that are integrated together to perform as a single system [20]. The three main components of AMI systems are as follows as shown in Figure 2.2 [21,22].

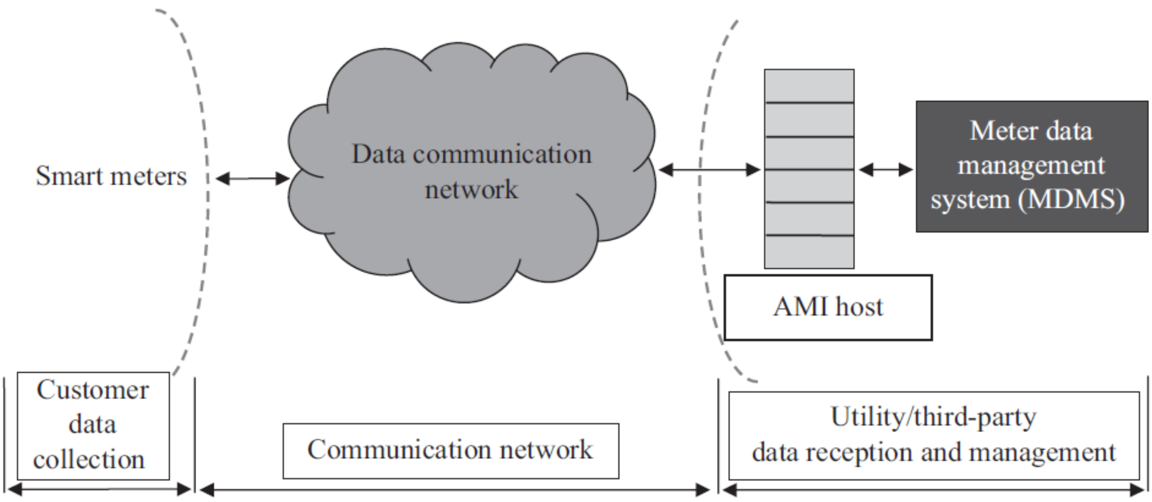


Figure1. 2: The three main components of an AMI system[14]

(i) **Smart meters**

Smart meters are typically digital programmable devices that record customer consumption of electric energy in intervals of an hour or less and communicate that information, daily or more frequent, back to the energy supplier for monitoring and billing purposes. Other functions of smart meters include [23] (i) time-based pricing, (ii) net metering, (iii) loss of power and restoration notification, (iv) remote turn on/turn off operations, (v) load limiting for ‘‘bad pay’’ or demand response purposes, (vi) energy prepayment, (vii) power quality monitoring, (viii) tamper and energy theft detection, and (ix) communications with other intelligent devices in the home.

Figure1. 3: Example of a smart meter and a home display unit[49]

(ii) **Communication network**

Communication network is the second important component of an AMI system. The aim of the communications network employed by AMI is to continuously support the interaction between the energy supplier, the consumer, and the controllable electrical load [20]. Under such environment, open bidirectional communication standards must be employed but at the same time it must be highly secured. With bidirectional communications, utilities can monitor real-time consumption by end-users [21]. It also enables end-users to actively participate in system operation by facilitating receiving price information or control signals from utilities.

(iii) **Data reception and management system**

The meter data transferred over the communication network are received at utility/third party site by the AMI host system [22], which is then sent to the meter data management system (MDMS) as shown in Figure. MDMS plays an important role in realizing the full potential functions of AMI, particularly when implemented prior to a large-scale residential AMI installation [24]. The major functions of MDMS system include (i) automating and streamlining the complex process of collecting meter data from multiple meter data collection technologies,

(ii) evaluating the quality of the collected data and generating estimates where errors and gaps exist, and (iii) delivering the collected data in a format that suits utility billing systems.

3. Context Overview of Smart Meters Rollout in Electricity Sector. The Importance of Smart Metering Systems:

The adoption of smart metering systems is an option that implies both consumers and distributors/suppliers of utilities as stakeholders which are currently based on the interest of reducing costs and losses with these utilities as well as to use and manage these consumptions more efficiently [25].

3-1. Losses in the power system [26]

The percentage of transmission and distribution losses has been quite high and they affect the economy of the Utility. The amount of losses in electrical distribution system is one of the key measures of distribution performance as it has a direct impact on the utility. Distribution losses, refers to the difference between the amount of energy delivered to the distribution system and the amount of energy customers is billed.

Distribution losses are comprised of two types:

- Technical and
- Non-technical losses

These energy losses are defined in terms of the following equation:

$$\sum \text{EnergyLosses} = \sum \text{IncomingEnergy} - \sum \text{EnergySold} \tag{1.1}$$

Where:

$\sum$ EnergyLosses $\longrightarrow$ In the amount of energy lost

$\sum$ IncomingEnergy $\longrightarrow$ Represents the amount of energy delivered

$\sum$ EnergySold $\longrightarrow$ Represents the amount of energy recorded or sold

In general, system losses increase the operating costs of electric utilities and typically result in higher cost of electricity. By default, the electrical energy generated should be equal to the energy registered as consumed. In reality, the situation is different because losses occur as an integral result of energy transmission and distribution

3.1.1 Technical losses (TLs)

Technical losses, according to Davidson et al. are due to the current flowing in a conductor generating heat and affecting resistance, causing electricity loss. In all conductors at least one of the following losses occurs: Copper losses, Dielectric losses, Induction/radiation losses. [51]

The main factors impacting technical losses according to Neetling et al. are: Substations, Circuits, Voltage levels, Type of circuits (air, underground, mixed, i.e. location of cattle), Type of load (residential, commercial, industrial, mixed), Transformation points, Installed capacity, Predicted demand, and Length of the circuits. [52]

Technical losses represent 6-8 % of the cost of generated electricity and 25% of the cost to deliver the electricity to the customer. [51]

3.1.2 Non-technical losses (NTLs)

An ideal electrical energy distribution network will generate electrical power X and distribute the electrical power to the network equal to X. Due to losses in the transmission and distribution sections of the electrical energy network less than X electrical energy is distributed to the network. This loss in electrical energy is the system losses of the electrical distribution network. It is given by:

$$\sum P_{Generated} = \sum P_{Distributed} + \sum P_{Systemlosses} \tag{1.2}$$

Non-technical losses represent electricity that is delivered to customers, but not paid. Mainly those losses caused by consumption of the owner and operator networks, energy lost in fault (short circuit), stealing electricity, unchecked consumption (public lighting), and errors in the measured, the collection and processing of data when reading. Also a mistake can come from the time difference between meter reading and billing of electricity.[51]

A reduction in non-technical losses will have a direct economic benefit in reducing electricity prices paid by the customer and it will increase the income of electrical distribution supply companies as the electrical energy losses decrease and more electrical energy could be sold to the customer. The non-technical losses are almost impossible to calculate from first principles as these losses are depended on human intervention on the electrical energy distribution network. The indirect approach to calculate the non-technical losses of an electrical distribution network is given by Davidson & Odubivi.[52]

$$\sum P_{Non\text{-}technical} = \sum P_{Generated} - \left(\sum P_{Distributed} + \sum P_{TechnicalLosses}\right) \tag{1.3}$$

An important role in reducing the Own Technological Consumption (OTC), which results from the difference between the energy entered in the Commercial Contour and the energy distributed to the consumers by any electricity distributor, is represented by the diminution of the non-technical losses. The non-technical losses can be attenuated by increasing the security of the distribution installations, in particular by frequent checking of the measurement groups both for domestic, but especially for industrial consumers. Electricity theft represents an illegal practice to obtain electricity for different uses, which results in significant losses for electricity distribution companies. A loss of about USD 25 billion is estimated worldwide, of which USD 6 billion is estimated to be in the United States, representing around 3.5% of the electricity consumed, a loss mainly due to unauthorized manipulation of analog meters. Non-Technical Losses (NTLs), which are usually attributed to the theft of electricity before the metering group (through false columns) or by falsifying the energy meter, by measuring or administering errors and unpaid electricity are recorded with predominance in developing countries such as those in South Africa, where losses of up to 50% of the electricity produced are recorded. A significant loss of electricity due to fraudulent consumption is also recorded in India, where if at least 10% of NTL were recovered it would save approximately 83,000 GWh annually. The smallest non-technical losses (below 6%) are registered in countries such as: Finland, Germany, Holland, Japan, etc., where fraudulent electricity consumption is strongly discouraged by prosecuting individuals or organizations involved.

In addition to economic losses, theft of electricity is also a major issue in terms of people safety (people that live in the vicinity of communities where the theft of electricity has a high percentage of occurrences). For example, in an area of eastern Uganda, where an NTL of over 50% is recorded, approximately 50 people are electrocuted every week.

An effective method for stopping unauthorized interventions in electricity distribution facilities is to replace the conventional meters with smart meters that are able to identify electricity consumption in a more detailed way, as well as some events related to the quality of electricity or unauthorized interventions in electrical installations. The smart meters have implemented a number of functions that are beneficial for both the network operator (by assuring an accurate and real-time metering of the delivered electricity), as well as for the consumer (in order to optimize the electricity requirement) [27].

3.2 Smart metering implementation [27]:

Smart meters significantly simplify the process of measuring and collecting data for each consumer but they are also subject to cyber-attacks, as most smart meters are manufactured and programmed to the requirements of the OBIS code, so they have components with low resistance in handling both hardware and software. In case an electricity meter is fraud, it no longer sends to the network operator the actual energy consumption, but sends recordings that are much smaller than the real ones, so the non-invoiced energy registers as OTC of the energy distributor. In order to recover the respective electricity losses, the distribution operator applies a series of measures by which it identifies the consumption points with significant energy losses. The method applied by the distribution operators, in order to identify the defective or fraudulent measurement groups, is to perform annual energy balances on each area of the power distribution substations. After identifying the areas of consumption with a high percentage of losses, each individual consumer in the field has to be checked individually, operation that implies a high expense for the distribution operator and an embarrassing situation for the honest consumers.

In order to narrow the search area of the points where energy is lost, some distribution operators have installed some electronic devices called Feeder Remote Terminal Units (FRTU), which are able to detect the energy consumption of the downstream receivers and send the recorded data in real time to a server where an analysis is made for each receiver separately. The installing of FRTUs narrows the problem groups search area but does not exactly identify the point or points where the power meter erroneously registers or electricity is stolen by other methods. For a most efficient exploitation of FRTUs, a series of algorithms can be implemented in order to restrict the fraudulent consumption points search area. Most electricity distribution operators choose non-hardware solutions for detecting uncontrolled energy leaks, as they are more economically reliable, but they can only be implemented in areas where smart measurement systems are implemented. Of the recent non-hardware methods used in the detection of fraudulent consumption are those related to artificial intelligence; based on previous recorded consumption, a neural network or a decision tree can be created so that the difference between the consumption recorded by the power meter and the estimated one by the algorithm exceeds a certain limit, then at that point exists the possibility of an anomaly. One of the efficient methods for detecting consumers who steal electricity is to classify them using a Support Vector Machine (SVM), based on historical data related to electricity consumption and events recorded by the intelligent measurement system.

The implementation of SM is topical and in process of development; many countries have few localities with intelligent systems of measurement and remote management implemented for at least five years, thus with designed algorithms based on data analysis to detect fraud in distribution systems considerable results cannot yet be achieved.

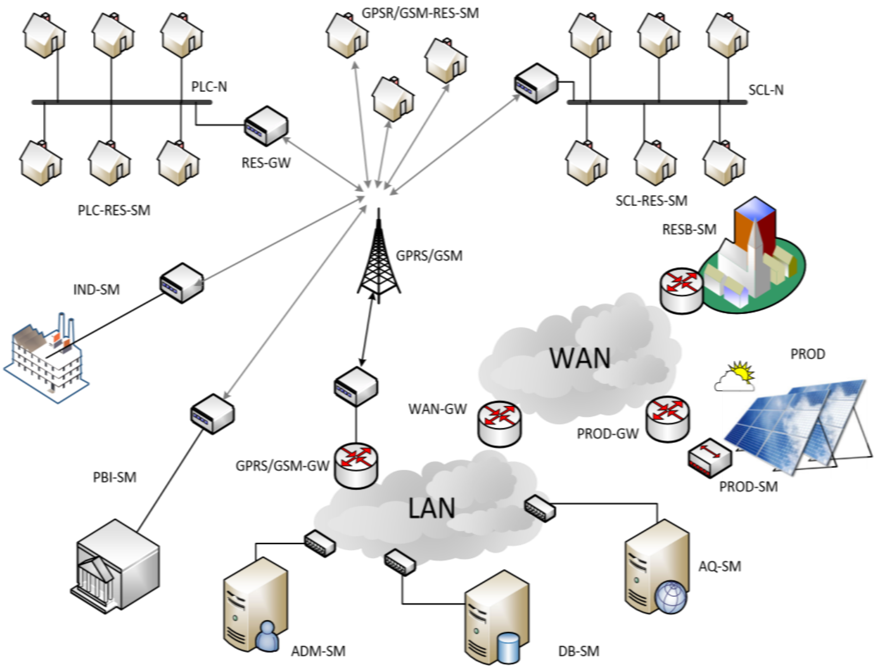


Figure1. 4: A typical electricity smart metering system structure [27]

PLC-N—Power Line Communication Network ;PLC-RES-SM-Power Line Communication Based Residential Smart Metering Group.RES-GW—Residential Communication Smart Metering Gateway; GPRS/GSM-RES-SM—GPRS/GSM based Residential Smart Meters group; SCL-N—Serial Current Loop communication Network; SCL-RES-SM—Serial Current Loop communication Residential Smart Meters; IND-SM—Industrial consumer Smart Meter; PBI-SM—Public Institution Smart Meter; RESB-SM—Residential electricity Balance Smart Meter.

Conclusion:

Now that we have defined Smart grid and smart metering concept and their rollout in electricity sector. we'll move to the theoretical part of the implementation of the proposed evolutionary algorithm for Optimized Operation of Smart Metering System.

Chapter 2

State of the art in NTL detection

&

DFO Algorithm

1.Introduction

Power systems are made up of extensive complex networks governed by physical laws in which unexpected and uncontrolled events can occur. This complexity has increased considerably in recent years due to the increase in distributed generation associated with increased generation capacity from renewable energy sources. Therefore, the analysis, design, and operation of current and future electrical systems require an efficient approach to different problems such as load flow, parameters and position finding, filter designing, fault location, contingency analysis, system restoration after blackout, islanding detection, economic dispatch, unit commitment, etc. The evolution is so frenetic that it is necessary for engineers to have sufficiently updated material to face the new challenges involved in the management of new generation networks (smart grids).

Given the complexity of these problems, the efficient management of electrical systems requires the application of advanced optimization methods for decision-making processes. Electrical power systems have so greatly benefited from scientific and engineering advancements in the use of optimization techniques to the point that these advanced optimization methods are required to manage the analysis, design, and operation of electrical systems. Considering the high complexity of large-scale electrical systems, efficient network planning, operation, or maintenance requires the use of advanced techniques. Accordingly, besides classical optimization techniques such as Linear and Nonlinear Programming or Integer and Mixed-Integer Programming, other advanced techniques have been applied to great effect in the study of electrical systems. Specifically, bio-inspired meta-heuristics have allowed scientists to consider the optimization of problems of great importance and obtain quality solutions in reduced response times thanks to the increasing calculation power of the current computers.

2. State of the art in non-technical losses detection [50]

This part will present the state of the art in NTL detection methodologies and give a broader overview of all the methodology types that are used in this field. Thus, the next sections of this chapter will discuss the following types of methods:

2.1 Grid-oriented methods:

Grid-oriented methods use energy balances, power flows or state estimation to detect where NTL occurs. Besides using the data recorded at the customer level, these methods rely on measurements made throughout the entire distribution grid. Most of these methods also need knowledge of the network topology and parameters.

In [28], the authors propose a method for NTL detection at the MV/LV transformer level, using distribution state estimation (DSE). This methodology needs a single main measurement at the beginning of the distribution substation. Technical and commercial data of the grid, such as the connectivity between the meter of the customer and the transformer, is also needed. The monthly billed energy at the MV/LV transformer level has been used in order to assign a ratio of the total power consumption provided by the main measurement, to each transformer. The main advantage of this methodology is that it has very low metering requirements. Its drawback is that it cannot detect NTL at the customer level.

A method for detecting NTL using SM data has been proposed in [29]. The method has been devised specifically for theft detection. An energy balance is performed in order to detect NTL at the MV/LV transformer level. If an NTL is detected at this level, the method will further detect the NTL location at the customer level, by comparing the estimated and measured voltages of the SMs. This methodology has been tested on a simulated typical LV grid configuration from the Netherlands, with 240 customers, and was shown to be able to detect intermittent NTL cases as well.

Using power flow computations, the authors in [30] estimated NTL at the distribution transformer level. Since it is extremely hard in practice to have an exact knowledge of the network topology and parameters, the authors assumed that the distribution circuit has a simplified topology and connectivity. This assumption allowed to compute the level of technical losses and indirectly the NTL. The method has been tested on a simulation with 10 customers, where one of the customers was committing theft. The simulation has shown that the method is able to detect NTL percentages as low as 10% at the transformer level.

A two-stage method for NTL detection in LV networks using SM data has been proposed in [31]. The first stage of the methodology is detecting NTL at the distribution transformer level by checking the difference between the current measured on the secondary side of the distribution transformer and the sum of all the SMs current measurements. The second stage of the method detects NTL at the branch level in the LV grid, by using the network topology and the lines' impedances. If the impedances are unknown, they can be estimated using historical measurement data, where no NTL was present. The method has been tested on a typical Portuguese LV network and has been shown to obtain a success rate of 85%, even in cases with incomplete data of the network.

The authors in [32] propose a method to detect NTL that occurs due to cyber-attacks to establish the location of NTL, a comparison is made between the measurements received from reliable devices (e.g. phasor measurements units, intelligent electronic devices) and the estimated measurements obtained from state estimation. The exact location of the NTL is then found using the A-Star algorithm. The method has been evaluated on a real distribution network.

A method for NTL detection based on state estimation, that preserves the privacy of the consumers, has been proposed in [33]. The privacy of the consumers has been preserved by encrypting the data using the Number Theory Research Unit (NTRU) algorithm. The experiments show that the proposed method is able to accurately detect NTL whilst attaining data confidentiality and authentication.

As shown above, grid-oriented methods can detect NTL with high accuracy. However, most of them require knowledge of network topology and parameters as well as the installation of additional metering devices in order to increase the observability of the distribution system. Thus, these methods cannot yet be widely used by the utilities as their data and metering requirements are not easily attainable in practice. Grid-oriented methods that are focused on detecting NTL at the distribution transformer level have lower data and metering requirements, hence they can be faster adopted by the utilities in the future.

2.2 Hybrid-oriented methods

Hybrid-oriented methods use, in the first stage, network related data to detect NTL at the distribution transformer level or in several areas of the LV network. The second stage of these methods detect NTL at the customer level, either by employing the use of statistical methods on the energy consumption data of the customers or through the use of machine learning algorithms.

In [34], the authors propose a method for NTL detection using DSE and analysis of variance (ANOVA). The DSE is used to detect distribution transformers with anomalous usage using the normalized residual test. To perform the DSE, the following information was used: customer SM data, historical data from SCADA and network topology information from various sources such as outage management and customer information systems. After identifying transformers with anomalous usage, the NTL is detected at the customer level using ANOVA. This analysis is done by comparing the EC measurements of a customer with its baseline EC profile that has been previously validated.

The authors in [35] use DSE for NTL detection in LV networks. The NTL was considered to occur due to electricity theft. The authors used the semi-definite relaxation method, instead of the standard Newton Raphson method, in order to obtain the global optimal solution for the state estimation. Suspicious users were further investigated with ANOVA. The methodology has been tested on a 8-bus distribution system and has been shown to detect successfully electricity theft.
The authors in [36] proposed a graphical user interface (GUI) platform to detect NTL losses. The method is based on three stages. The first stage detects NTL at the distribution transformer level by comparing the measured current on the secondary side of the transformer with the aggregated current measurements of the SMs connected to it. The second stage detects NTL at the customer level by using fuzzy logic and a SVM classifier. The last stage of the method checks for correlations between anomalous customers and their event logs. The developed method aims to be implemented in a pilot project side with real SM data of customers.

In [37], the authors propose a method which detects areas with high NTL, in the LV network, through the use of SM measurements and energy balances. The second stage of the method detects NTL at the customer level, in the areas identified with high NTL, using a SVM classifier. The classifier uses as an input energy consumption data, clients' registration data and socio-economic indices. The method has been tested as part of a research and development (RD) project of ANEEL (Brazilian Electricity Regulatory Agency). The method to detect areas with high level of NTL has not been developed and tested at that stage of the project.

Hybrid-oriented methods can be more easily adopted by the utilities as they have lower data requirements for network topology, parameters and measurements. Nevertheless, most utilities do not currently have the necessary network data availability to deploy these methodols on a large scale.

2.3 Data-oriented methods

Data-oriented methods are a very popular area of research for NTL detection, due to their low data availability requirements. Generally, these methods are based only on the data collected at the customer level. The data collected at the customer level includes the measurements recorded by the electricity meter as well as some information of the customer (location, meter brand, meter location etc.) that usually resides in auxiliary databases. In the beginning, these methods were based on simple rules extracted from customer consumption data, often relying on expert knowledge. Nowadays, these methods are based exclusively on machine learning (ML) techniques. The ML algorithms that are used for NTL detection are mainly based on supervised learning.

Methods for NTL detection based on supervised learning use the results of previous on-field inspections as labels, in order to create a training dataset. The objective of these algorithms is to classify as accurately as possible whether a customer sample has NTL or not. To train the supervised ML classifier, the data of each customer that had an inspection is collected and used as an input during the training stage. Two types of methods for processing the input, can be found in the literature:

- Input processing based on feature engineering - these methods are using expert and domain knowledge to extract features from raw consumption data recorded by the meter and auxiliary data that provides additional information of the meter (e.g. meter brand, location, contract type).
- Input processing based on raw data - these methods use the raw data recorded by the meter and the auxiliary data without any further processing.

Methods based on feature engineering can achieve great performance as they rely on the insights gathered by on-field inspectors or utility employees, whilst the methods based on raw data have the advantage that they do not have to rely on such expertise and are not constrained to the expert knowledge for the NTL detection task. **Table 2.1** shows the main characteristics of the methods that will be discussed further. As seen in the table, the performance of the models is assessed using various metrics such as the true positive rate (TPR), known also as the recall

(RCL), the false positive rate (FPR), the precision (PRC) and the area under the receiver operating characteristic curve (ROC-AUC).

Table2. 1: Data-driven methods for NTL detection.

Method	**Type of NTL detected**	**Data source for NTL cases**	**# of customers**	**Type of data**	**% samples with NTL**	**ML Algorithms**	**Results (best algorithm)**			
							TPR	FPR	PRC	ROC-AUC
[38]	All	-	1500	half-hourly EC data	-	ELM, OS-ELM, SVM	-	-	-	-
[39]	abrupt changes	real on-field inspections	383	monthly EC & credit worthiness rating	13.83 %	SVM	-	-	77.41 %	-
[40]	Fraud	synthetic	5600	half-hourly EC	-	MLP	93.75 %	25.00 %	78.95 %	-
[41]	Fraud	synthetic	5650	half-hourly EC	-	DT	-	-	-	-
[42]	All	real on-field inspections	≈ 100K	monthly EC	0 % - 100 %	Boolean, Fuzzy and SVM	-	-	-	0.56

In [38], the authors propose a method for NTL detection using Extreme Learning Machines (ELM). The approach has been tested and developed with real data from Malaysia’s Tenaga Nasional Berhad (TNB), the largest electricity utility in Malaysia. For each customer in part, a typical customer profile is created for weekdays, Saturdays, Sundays and public holidays. If outliers are detected on any new load curve, the load curve is further classified for NTL detection, with one of the following algorithms: ELM, Online Sequential ELM (OS-ELM) and Support Vector Machines (SVM). The results showed that the ELM was able to outperform the SVM model.

A method based on a SVM classifier has been proposed in [39], where the authors used the model for classifying customers as having/not having an NTL in their meter. The method has been tested in 3 towns from Malaysia, targeting NTL that occurs as an abrupt change in the customer's consumption pattern. The input for the SVM classifier consisted of 24 daily average EC values, aggregated from monthly measurements. Besides EC data, the classifier uses as an input the credit worthiness rating (CWR) corresponding to a specific customer. Though the input processing does not involve extensive feature engineering, the system uses additional filtering using data from the Customer Information Billing System as well as High Risk data, in order to correlate this information with the output predictions of the SVM.

Another method based on MLP has been presented in [40], where the goal was to detect energy fraud in SMs. The method is based on real SM data belonging to approximately 5000 residential customers and 600 businesses. These data have been collected by the Irish Social Science Data Archive Center. The MLP model's objective is to predict the energy consumption of a customer. Potential energy fraud was detected by checking if the Root Mean Square Error (RMSE) of the predicted energy consumption and the actual energy consumption was higher than 0.5 kWh. The energy fraud samples
have been synthetically generated by introducing random noise in the EC profile. The results show that the MLP model is able to detect successfully energy fraud in 93.75% of the cases. A similar method has been presented in [41], where the authors used decision trees (DT) instead of MLP to detect energy fraud in smart meters. The threshold for the RMSE has been set to 0.4 kWh in this case.

The impact of the imbalance that naturally occurs in NTL datasets has been assessed in [42]. Naturally, the number of customers who have been identified with NTL is much higher compared to the one of customers with no NTL in their meter. The methodology has been developed using real data of a Brazilian electricity utility. The NTL dataset has been subsampled to contain different percentages of samples with NTL, from 0.1% to 90%. Three models were used in the comparison: Boolean logic, fuzzy logic and a SVM classifier. The input features for the models consisted simply of the last 12 months of EC measurements.

As shown above, data-oriented methods for NTL detection have been studied extensively by researchers, as they rely only on the data that it is already available in the electricity utilities. However, it is extremely difficult to have an honest comparison between the performance of these methods. This is due to the fact that there are major differences in these approaches:

different datasets availability, they use either real or synthetic NTL datasets or they monitor for different metrics.

2.4 Challenges in data-oriented methods for non-technical losses Detection

there are several challenges that impede the progress in this research area as well as the performance of NTL algorithms in the real environment. these are the following challenges that can be encountered by researchers who are trying to push forward and make advances in this field:

- Lack of benchmark datasets - Although the authors in [43] provided a benchmark dataset for NTL detection, this dataset consists of only EC data. Its main disadvantage is that it creates synthetical NTL samples that consist either in partial or total load reduction, whilst the non-NTL samples have normal consumption patterns. A benchmark dataset provided by an electricity utility would be the best scenario, as it will provide realistic and more complex NTL cases as well as additional data besides the EC measurements. However, with increased data privacy regulations, it seems to be increasingly difficult for the electricity utilities to share their data with the research community.

- Different metrics of performance - It is difficult to compare the performance of different methods when there isn't a common metric that is reported by all researchers. Moreover, metrics that are inappropriate for imbalanced datasets such as the accuracy, are heavily used, making it difficult to really assess the true performance of one's method. Recent research works have started to acknowledge the importance of choosing the right metric for NTL datasets

Noisy data and labels - Often, the data collected by electricity meters, either come with missing values or anomalous ones. It is difficult for the practitioner to know whether these issues come from NTL/non-NTL reasons. The choice of whether to impute these values with normal estimates or to keep them as they are can be vital to the performance of the model. Another important challenge is the noise in the labels (results of previous on-field inspections). As the customer samples are labeled manually by on-field inspections they are prone to human error.

Introducing misclassified samples makes it more difficult and decreases the performance of NTL models.

3.Swarm Intelligence :

Based on the general concept of Swarm Intelligence (SI) many SI algorithms have been developed up until now. The SI algorithms represent the subfamily of nature inspired global optimization techniques. Other subfamilies are physical algorithms (such as simulated annealing, harmony search, and so on), evolutionary algorithms (such as genetic algorithms, genetic programming, and others), and immune algorithms (such as clonal selection algorithms, negative selection algorithms, and so on). The main advantages of the SI algorithms over traditional optimization techniques are as follows: SI algorithms start with a population of potential solutions not from a single point, SI algorithms do not require the derivative objective function, the solutions can cooperate with each other to share knowledge [44].
Genetic Algorithm , Particle Swarm Optimization and Ant Colony Optimization are only few such techniques belonging to the broader category of swarm intelligence; it investigates collective intelligence and aims at modelling intelligence by looking at individuals in a social context and monitoring their interactions with one another as well as their interactions with the environment [45].

The work presented here aims at proposing a novel nature algorithm inspired by the swarming behavior over food sources and their dispersing behavior when facing a threat. This model – Dispersive Flies Optimization or DFO – The primary aim of the algorithm is numerical optimization, which is effectively adjusting several parameters of a certain problem and getting a better solution over time. One of the strengths of DFO, and swarm intelligence algorithms in general, is that they can deal with noisy environments or dynamically changing environments, where the solutions are non-stationary. While DFO has been applied to discrete problems, it is primarily proposed to deal with continuous search spaces [44].

4.DISPERSIVE FLIES OPTIMISATION [46] [44]

Dispersive Flies Optimization (DFO) is an algorithm inspired by the swarming behavior of flies hovering over food sources. DFO, which is a recently proposed algorithm, is one of the simplest yet robust continuous optimization techniques with only two tunable parameters, which makes it an-easy-to-implement yet strong optimizer. This algorithm has been applied to various fields including optimization, medical imaging and digital art.

To describe this algorithm, the swarming behavior of flies in DFO is determined by several factors and that the presence of threat could disturb their convergence on the marker (or the optimum value). Therefore, having considered the formation of the swarms over the marker, the breaking or weakening of the swarms is also noted in the proposed algorithm.

In other words, the swarming behavior of the flies, in Dispersive Flies Optimization, consist of two tightly connected mechanisms, one is the formation of the swarms and the other is its breaking or weakening.

The algorithm and the mathematical formulation of the update equations are introduced below [46].

As reported in [44] the position vectors of the population are defined as:

$$x^t = x^t_{i0}, x^t_{i1}, \dots, x^t_{i,D-1}, \qquad i = 1, 2, \dots, N-1$$

where i represents the ith individual, t is the current time step,D is the problem dimensionality and N is the population size. For continuous problems, $x_{id} \in \mathbb{R}$ (or a subset of $\mathbb{R}$).

In the first iteration, when t = 0, dth component of ith fly is initialized as:

$$x^0_{id} = U\,(x_{min,d} - x_{max,d}) \tag{2.1}$$

This, effectively generates a random value between the lower ($x_{min,d}$) and upper ($x_{max,d}$) bounds of the respective dimension, d.

On each iteration, dimensions of the position vectors are independently updated, taking into account:

- current fly's position
- current fly's best neighboring individual (consider ring topology, where each fly has a left and a right neighbor)
- and the best fly in the swarm.

Therefore, the update equation is:

$$x^{t+1}_{id} = x^{t}_{in,d} + u\,(x^{t}_{sd} - x^{t}_{id}) \tag{2.2}$$

Where,

- x^{t}_{id}: position of the i^{th} fly in d^{th} dimension at time step t
- $x^{t}_{in,d}$: position of $\vec{x}^{\,t}_{i}$'s best neighboring individual (in ring topology) in d^{th} dimension at time step t

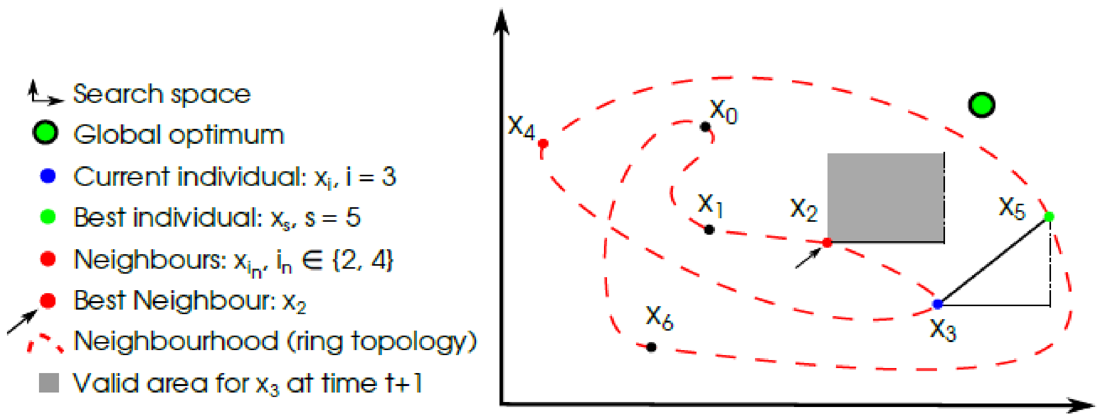


Figure2. 1: Sample update of x_i, where i = 3 in a 2D space. [44]

- x^{t}_{sd} : position of the swarm's best individual in the d^{th} dimension at time step t and
- s Є {0, 1, 2,……. N-1}
- u ~U(0; 1): generated afresh for each dimension update.

The update equation is illustrated in an example in **Fig. 2.1** where $\vec{x}_3$ is to be updated. The algorithm is characterized by two main components: a dynamic rule for updating the population's position (assisted by a social neighboring network that informs this update), and communication of the results of the best found individual to others.

As stated earlier, the position of members of the swarm in DFO can be restarted, with one impact of such restarts being the displacement of the individuals which may lead to discovering better positions. To consider this eventuality, an element of stochasticity is introduced to the update process. Based on this, individual dimensions of the population's position vectors are reset if a random number generated from a uniform distribution on the unit interval U(0; 1) is less than the restart threshold, Δ. This guarantees a restart to the otherwise permanent stagnation over likely local minima.

Algorithm 1 summarizes the DFO algorithm. In this algorithm, each member of the population is assumed to have two neighbors (i.e. ring topology).

Algorithm 1 Dispersive Flies Optimization [44]

---

procedure DFO (N,D, x_{min}, x_{max},f)*
for i = 0 →N - 1 do Initialization: Go through each fly
for d = 0 → D -1 do Initialization: Go through each dimension
$x^0_{id} = U\,(x_{min,d} - x_{max,d})$. Initialize d^{th} dimension of fly i
end for
end for
while ! termination criteria do Main DFO loop
for i = 0 → N - 1 do Evaluation: Go through each fly
$\overrightarrow{xi}$.fitness ←f($\overrightarrow{xi}$)
end for
$\vec{x}_s$ = arg min [f($\overrightarrow{xi}$)], i ∈ {0,1, 2,…..N - 1} Find best fly
for i = 0 → N - 1 and i ≠ s do Update each fly except the best
$\overrightarrow{xin}$= arg min [f($\vec{x}$ (i-1)%N),f($\vec{x}$(i+1)%N)] Find best neighbour
for d = 0 →D - 1 do Update each dimension
if U(0; 1) < Δ then Restart mechanism
$x^{t+1}_{id} \leftarrow U\,(x_{min,d} - x_{max,d})$ Restart within bounds
else
u ←U(0; 1)
$x^{t+1}_{id} \leftarrow x^{t}_{in,d} + u\,(x^{t}_{sd} - x^{t}_{id})$ Update the dimension value
if $x^{t+1}_{id} < x_{min,d}$ or $x^{t+1}_{id} > x_{max,d}$ then Out of bounds
$x^{t+1}_{id} \leftarrow U(x_{min,d}; x_{max,d})$ Restart within bounds
end if
end if
end for
end for
end while
return $\vec{x}_s$
end procedure

* INPUT: swarm size, dimensions, lower/upper bounds, fitness function.

The Flowchart of DFO

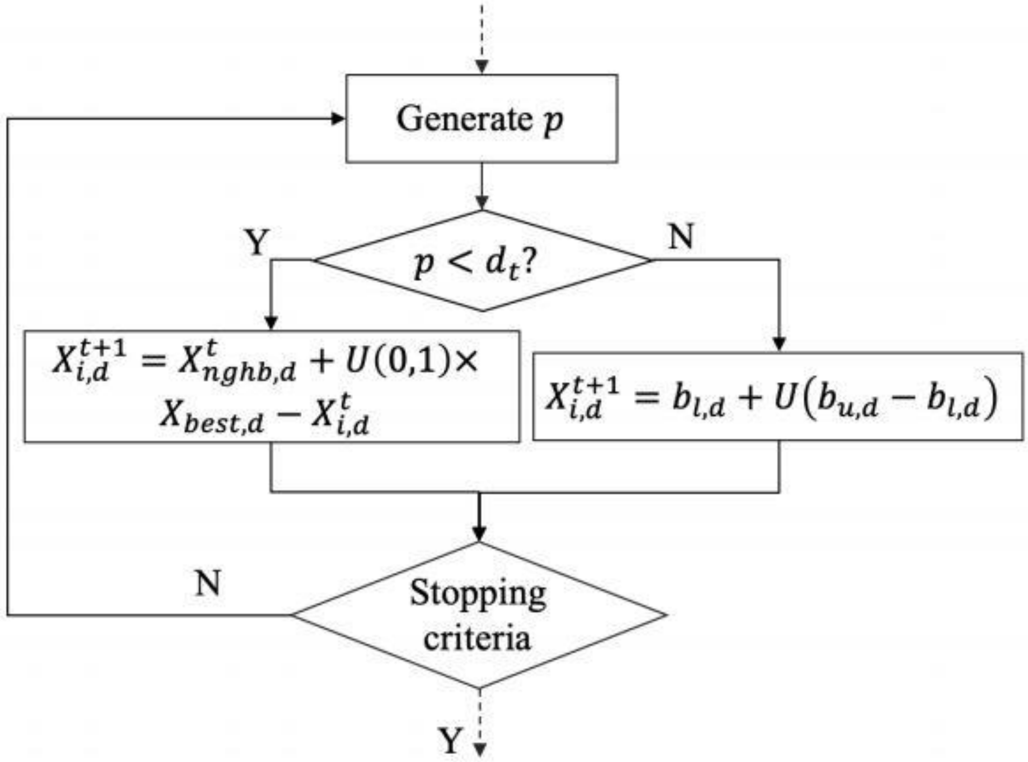


Figure2.2: The Flowchart of DFO[53]

Tested functions with using DFO algorithm:

a-The fitness function used in the code is the Sphere function which is defined below in Eq. 11.4. The fitness function f takes a D-dimensional vector (i.e. one fly, or ~xi) and returns a single value (i.e. fitness value). DFO is tasked to find the optimal value for each parameter or dimension.

$$f(\vec{x}_i) = \sum_{d=1}^{D} x^2_{id} \qquad \text{where} \quad -5.12 \leq x_{id} \leq 5.12 \qquad (2.3)$$

Implementation of the fitness function (Sphere) in MATLAB:

```
function [sum]=f(X)
   [N,D]=size(X);
   sum=zeros(N,1);
   for i=1:N
      for d=1:D
         sum(i,1)=sum(i,1)+X(i,d)^2;
      end
   end
end
```

The simulation results :

```
Command Window
  Iteration: 979     Best fly index: 71     Fitness value: 1.1983e-19
  Iteration: 980     Best fly index: 57     Fitness value: 1.1463e-19
  Iteration: 981     Best fly index: 73     Fitness value: 1.1398e-19
  Iteration: 982     Best fly index: 18     Fitness value: 1.1291e-19
  Iteration: 983     Best fly index: 80     Fitness value: 1.1279e-19
  Iteration: 984     Best fly index: 36     Fitness value: 1.1275e-19
  Iteration: 985     Best fly index: 82     Fitness value: 1.1264e-19
  Iteration: 986     Best fly index: 52     Fitness value: 1.113e-19
  Iteration: 987     Best fly index: 16     Fitness value: 1.1041e-19
  Iteration: 988     Best fly index: 89     Fitness value: 1.1011e-19
  Iteration: 989     Best fly index: 73     Fitness value: 1.0966e-19
  Iteration: 990     Best fly index: 90     Fitness value: 1.096e-19
  Iteration: 991     Best fly index: 55     Fitness value: 1.0953e-19
  Iteration: 992     Best fly index: 37     Fitness value: 1.0941e-19
  Iteration: 993     Best fly index: 20     Fitness value: 1.0934e-19
  Iteration: 994     Best fly index: 70     Fitness value: 1.0313e-19
  Iteration: 995     Best fly index: 82     Fitness value: 1.0173e-19
  Iteration: 996     Best fly index: 19     Fitness value: 9.5486e-20
  Iteration: 997     Best fly index: 16     Fitness value: 9.2784e-20
  Iteration: 998     Best fly index: 82     Fitness value: 8.9983e-20
  Iteration: 999     Best fly index: 19     Fitness value: 8.8408e-20
  Iteration: 1000     Best fly index: 70     Fitness value: 8.7524e-20
  Final best fitness=8.6952e-20
```

Figure2. 2: optimization results of function 1 by using DFO algorithm

b-Another function tested with the DFO algorithm is in the following:

$$f(\vec{x}_i)=\sum_{d=1}^{D} x^2_{id} -10\sum_{d=1}^{D} \cos(2\pi x^2_{id})+10 \quad \text{where} \quad -10\leq x_{id}\leq 10 \qquad (2.4)$$

Implementation of the fitness function in Matlab:

```
function [sum]=fi(X)
  [N,D]=size(X);
  sum=zeros(N,1);
  for i=1:N
     for d=1:D
        sum(i,1)=sum(i,1)+X(i,d)^2-10*cos(2*pi*X(i,d))+10;
     end
  end
end
```

The simulation results:

```
Command Window
  Iteration: 979    Best fly index: 7    Fitness value: 4.2306e-09
  Iteration: 980    Best fly index: 28    Fitness value: 4.207e-09
  Iteration: 981    Best fly index: 28    Fitness value: 4.207e-09
  Iteration: 982    Best fly index: 15    Fitness value: 4.2068e-09
  Iteration: 983    Best fly index: 17    Fitness value: 3.8929e-09
  Iteration: 984    Best fly index: 14    Fitness value: 3.6301e-09
  Iteration: 985    Best fly index: 92    Fitness value: 3.4812e-09
  Iteration: 986    Best fly index: 28    Fitness value: 3.2082e-09
  Iteration: 987    Best fly index: 24    Fitness value: 2.8922e-09
  Iteration: 988    Best fly index: 7    Fitness value: 2.8332e-09
  Iteration: 989    Best fly index: 40    Fitness value: 2.7343e-09
  Iteration: 990    Best fly index: 40    Fitness value: 2.7343e-09
  Iteration: 991    Best fly index: 28    Fitness value: 2.7212e-09
  Iteration: 992    Best fly index: 27    Fitness value: 2.7159e-09
  Iteration: 993    Best fly index: 78    Fitness value: 2.6852e-09
  Iteration: 994    Best fly index: 44    Fitness value: 2.6721e-09
  Iteration: 995    Best fly index: 25    Fitness value: 2.6598e-09
  Iteration: 996    Best fly index: 93    Fitness value: 2.6109e-09
  Iteration: 997    Best fly index: 92    Fitness value: 2.5588e-09
  Iteration: 998    Best fly index: 95    Fitness value: 2.4938e-09
  Iteration: 999    Best fly index: 49    Fitness value: 2.2334e-09
  Iteration: 1000    Best fly index: 46    Fitness value: 2.1407e-09
  Final best fitness=2.1407e-09
```

Figure2. 3: optimization results of function 2 by using DFO algorithm

c- Rastrigin function:

$$f(\mathbf{x}) = 10d + \sum^{d} \left[x_i^2 - 10\cos(2\pi x_i)\right] \qquad (2.5)$$

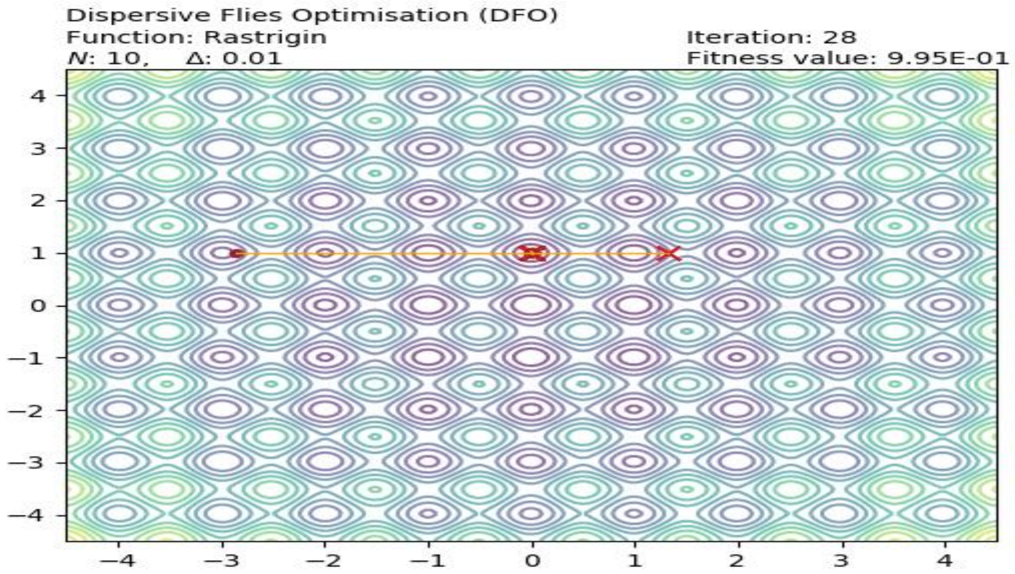


Figure2. 4: Optimization process for Rastrigin function using Dispersive flies algorithm

5. Dispersive flies algorithm for Optimized Operation of an Electricity Utility Smart Metering System:

Currently, the identification and correction of OTC is performed by manual analysis consisting in the differences between the energy delivered to the consumer and the one entered identification. This procedure based on the identification of inconsistencies in the energy balance indicates the existence of measurement errors that must be examined and identified individually and manually.

This procedure involves high costs and long time, as well as discomfort for the consumers.

In order to eliminate these shortcomings, therefore, the dispersive flies algorithm and based on the data provided by the smart metering system and a consumption model, will identify the nodes in which problems with the energy consumption or recording are registered.

Conclusion:

Now that we have finished presenting the methodology types that are used in NTLs detection and the optimization algorithm used to develop an optimization solution for identifying the nodes in a system of electricity distribution, in which the consumed energy is not recorded correctly, we'll see in the next chapter the results of the optimization of real-time energy consumption records from each node, comparing them to general measurement group records. by simulating the algorithms in MATLAB.

Chapter 3

Simulation Results

&

Discussion

1. Introduction

MATLAB is a platform for scientific calculation and high-level programming, which uses an interactive environment that allows you to conduct complex calculation tasks more efficiently than with traditional languages, such as C, C++ and FORTRAN. It is the one of the most popular platforms currently used in the sciences and engineering.

MATLAB is an interactive high-level technical computing environment for algorithm development, data visualization, data analysis and numerical analysis. MATLAB is suitable for solving problems involving technical calculations using optimized algorithms that are incorporated into easy to use commands.

It is possible to use MATLAB for a wide range of applications, including calculus, algebra, statistics, econometrics, quality control, time series, signal and image processing, communications, control system design, testing and measuring systems, financial modeling, computational biology, etc. The complementary toolsets, called *toolboxes* (collections of MATLAB functions for special purposes, which are available separately), extend the MATLAB environment, allowing you to solve special problems in different areas of application.

In addition, MATLAB contains a number of functions, which allow you to document and share your work. It is possible to integrate MATLAB code with other languages and applications, and to distribute algorithms and applications that are developed using MATLAB.
[47].

In this chapter, MATLAB is used to develop an optimization solution for identifying the nodes in a system of electricity distribution, in which the consumed energy is not recorded correctly by using the DFO algorithm discussed in the previous chapter.

2. Objective function:

To solve our problem, we will use the Dispersive Flies Optimization (DFO) is population based, global optimizer which has been introduced in 2014. It takes inspiration from the observation of flies and their behavior when swarming around a food source. In summary, DFO is a simple numerical optimizer over continuous search spaces.

2.1. Mathematical Model Formulation of the Optimization Problem:

Our problem consists of one objective function proposed by the author in [25] and its aim is to develop an optimization solution for identifying the nodes in a system of electricity distribution, in which the consumed energy is not recorded correctly. In this sense, the objective is to develop and solve an optimization model, which is composed of: smart meters, gateways and the physical power support that is used as a communication medium. A series of factors such as: voltage drops in the nodes, data history, anomalies in the remote management systems, the existence of sporadic consumers, differences between the active energy and the reactive energy consumed, which can lead to the identification of the nodes with erroneous energy records were considered in developing the optimization model. Thus the resulting optimization model proposed given by the following function:

$$F\,(\boldsymbol{\epsilon r}, \boldsymbol{\alpha\Delta u}, \boldsymbol{\beta W}, \boldsymbol{\tau Wr}) = Mp\,(\boldsymbol{\varepsilon r}) + Vp\,(\Delta\mathbf{u}) + ERPp\,(\boldsymbol{\beta W}) + ED_{WhVARh}\,(\boldsymbol{\tau Wr})$$

$$= \sum_{j=1}^{n} \Big(\sum_{i=1}^{m} (ki \cdot ci \cdot \boldsymbol{\epsilon rij} \cdot Wi) + \Delta ETj - Wsj \Big)^2 + \sum_{n=1}^{k} (\boldsymbol{\alpha\Delta u} \cdot (\Delta Ui + Ui) - Un)^2 +$$

$$+ (\boldsymbol{\beta W}i(t) \cdot W_i(t) - W_{ierp}(t))^2 + (\boldsymbol{\tau Wr}i \cdot W_{ir}(T) - W_i(T))^2. \qquad (3.1)$$

Subject to:

$$\alpha\Delta ui, \beta Wi \geq 1.$$

$$\Delta U_i \leq \frac{1}{100} \cdot U_n.$$

$$Wi, Wisap \leq 0.$$

$$|\boldsymbol{\epsilon}ri| \leq \epsilon SMCi \cdot W_i.$$

$$\boldsymbol{\epsilon}ri \neq 0.$$

n—number of transformation stations.

m—number of consumers from j transformation station area.

k—total number of consumers from the analyzed consumption area;

M_p (ϵ_r)—the metering function precision expressed as ε_r optimization vector variable dependence.

$V_p(\Delta_u)$—the power failure, term expressed as Δ_u optimization vector variable dependence.

$ERP_p(\beta_W)$—the difference between measured electricity and registered in database, term expressed as β_W optimization vector variable dependence;

$ED_{WhVARh}(\tau_{Wr})$—the energy difference between reactive and active power.

k_i—coefficient determined based on previous experiences.

c_i—coefficient describing node i degree of connection (connected or disconnected).

ϵ_{ri}—describes a measuring error of power meter between −0.5% and +0.5% in the case of household consumers.

ϵ_{SMCi}—represents the value indicated by the precision class of the smart meter.

W_i—node i measured energy.

ΔE_{Tj}—estimated technical energy loss.

W_s—electricity measured by the general power meter from the transformation station.

$\alpha\Delta_u$—coefficient determined by the voltage drop registration error on each node.

$\Delta Ui = \frac{\sum_{i=1}^{n}(Ri \cdot Pi + Xi \cdot Qi)}{Un}$ (3.2) —represents the calculation of the voltage drop in the electrical connection for each node.

P_i—the active power of consumer related to node i.

R_i—the electrical resistance of the electrical connection corresponding to the consumer i.

X_i—the electrical reactance corresponding to the connection of each node separately.

Q_i—the reactive energy recorded by each power meter.

U_n—nominal voltage.

β_{Wi}—error coefficient of data transfer between the telecommunication system and the data storage system.

$W_i(t)$—the active energy recorded in node i at time t energia.

$W_{isap}(t)$—the energy registered in the database of the billing information system reported at time t.

τ_{Wri}—error coefficient, difference between the active energy and the reactive inductive energy in an analysed time interval T.

W_{ir}—the reactive energy consumed, read at time t.

The optimization problem has been modeled starting from synthetic data based on data package contains measured time series data for several small businesses and residential households relevant for household- or low-voltage-level power system modeling.
The data includes power generation as well as electricity consumption (load) in a resolution up to single household consumption.

The proposed objective is to track real-time energy consumption records from each node, comparing them to general measurement group records.
The DFO algorithm **works** by iteratively trying to improve a candidate solution with regard to a numerical measure that is calculated by a fitness function. Each member of the population, a **fly** or an agent, holds a candidate solution whose suitability can be evaluated by their fitness value.

3. Simulation:

The first step in detecting non-technical losses in a particular area is to foresee an energy balance for that area. If the respective balance is below a theoretical threshold calculated by the distribution operator taking into account the characteristics of the consumption area, then a series of technical measures should be taken in order to reduce the OTC.

Table 3.1 summarizes the energy balance data for a community of 30 households in southern Germany. for the year of operation 2020, before applying the optimization algorithm proposed in the previous chapter.

Table3. 1 : The 2020 energy balance for the considered investigated area.

Analysed period	Electricity input [Kwh]	Distributed Electricity [KWh]	OTC Electricity [KWh]	OTC Achieved percentage [%]
Jan,2020	181,4476	162,468181	18,97941896	11,6819
Feb,2020	175,2986	158,1018073	17,19679266	10,877
Mars,2020	170,4612	144,5851898	25,87601016	17,8967
Apr,2020	169,0758	148,1611235	20,91467646	14,1162
May,2020	164,231	150,7969042	13,4340958	8,9087
Juin,2020	162,9178	145,6973885	17,22041146	11,8193
Jul,2020	150,3792	130,9502074	19,42899264	14,8369
Aug,2020	160,2362	137,3865179	22,84968212	16,6317
Sep,2020	167,5586	141,9724018	25,58619822	18,022
Oct,2020	174,9734	151,5969538	23,37644624	15,4201
Nov,2020	187,2674	164,9076724	22,35972756	13,5589
Dec,2020	228,7776	199,8372336	28,9403664	14,482
year 2020	2092,6244	1636,624348	227,2224523	13,9487

The data are processed by an application developed in the MATLAB programming environment based on the dispersive flies algorithm. The application provides for each node the values of the 4th coefficients described in the mathematical model: $\boldsymbol{\epsilon r}, \boldsymbol{\alpha\Delta u}, \boldsymbol{\beta W}, \boldsymbol{\tau Wr}$.

If no anomaly is registered in a node, then the coefficients and the objective function will have the following values:

$$\boldsymbol{\epsilon r}, \boldsymbol{\alpha\Delta u}, \boldsymbol{\beta W} = 1.$$

$$\boldsymbol{\tau Wr} \geq 1$$

$$F(\boldsymbol{\epsilon_r}, \boldsymbol{\alpha\Delta_u}, \boldsymbol{\beta_W}, \boldsymbol{\tau_{Wr}}) \rightarrow 0$$

In **Figure 3.1** is synthesized the concept of energy contour of an electricity distribution operator, containing the input energy (sections B, C and D, the energy distributed to the consumers (section A), the energy delivered to another distribution operator (section F) and the energy losses (OTC) (section G). Part of the OTC energy can be recovered by identifying the defective measurement groups, this quantity being invoiced according to the legal provisions (section H). Each distribution operator monitors daily the evolution of the energy contour, establishing the forecast of the energy exchanges for the next day and trying by using the methods described in [27] to reduce the technical losses, but especially the non-technical losses.

An important element in balancing the energy contour is to increase the amount of recovered energy and to stop the losses of electricity from unauthorized interventions [27].

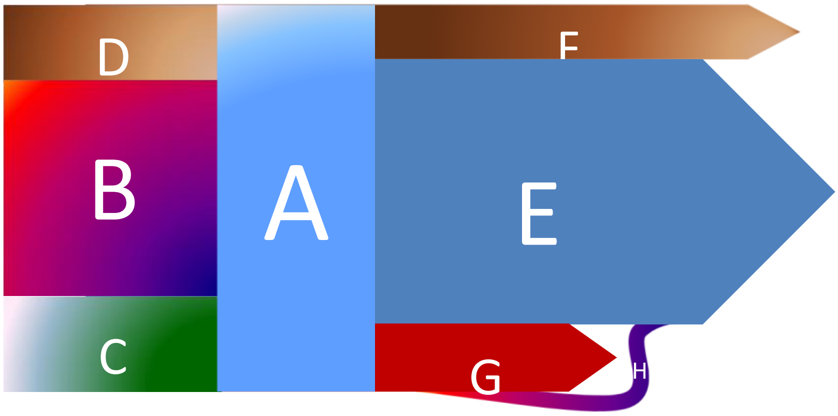


Figure3. 1 : The energy outline at the power distribution grid level. [27]

A—Available Energy, F—Output exchange energy, E—Net energy delivered to consumers, D—Distribution grid interconnection, B—Electric power transmission interconnection, C—Local produced energy, G—OTC, H—Recovered component.

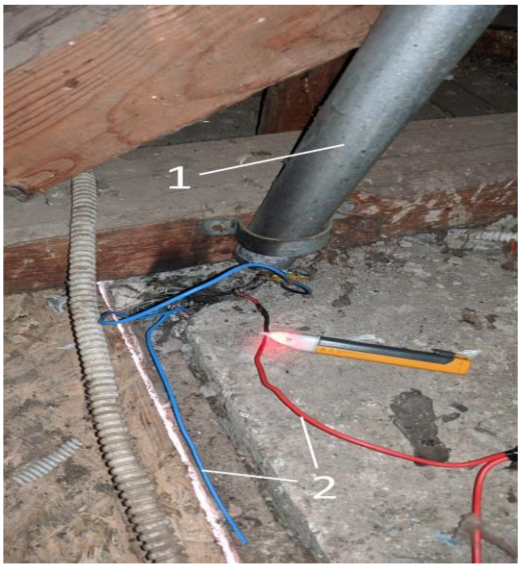
In the case of an energy meter corresponding to a node with a measurement error greater than the threshold imposed by the legal measurement rules, then the value of the coefficient ***Єr***, will be greater than the unit and the value of the objective function will be greater than zero. There are many situations, especially in the disadvantaged areas, where certain consumers, after being disconnected from the electricity network, will connect themselves back illegally. In these situations, the consumed energy can't be invoiced and the index from the telemetering system will be different from the index registered in the billing system

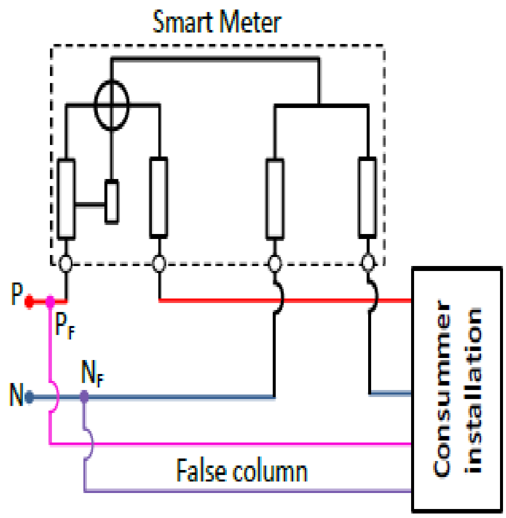
(**betaW** > 1). The classic methods used to bypass the electricity meter,

by false columns or shunts made under the terminal cap of the meter, will be detected by following the

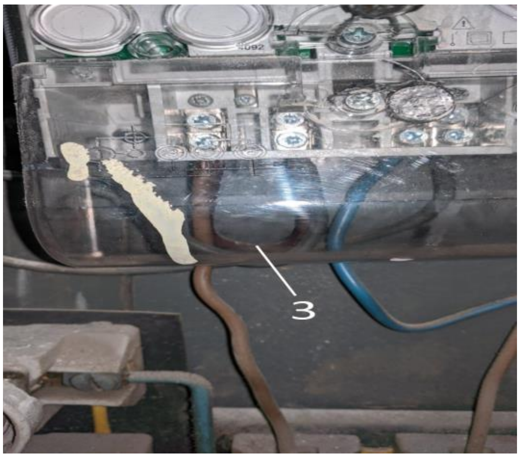
changing values of the coefficients **alphaDu, tauWr**.

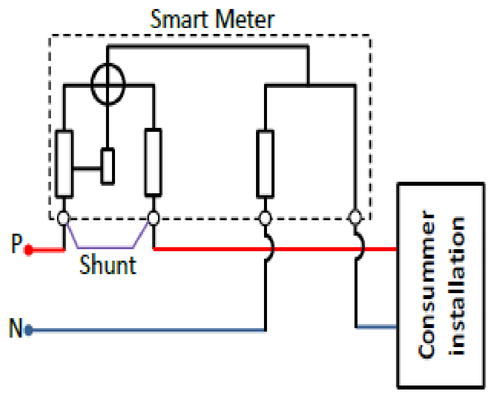
By applying the Dispersive flies algorithm on the analyzed measurement area, a series of irregularities were detected in some measurement groups such as well masked illegal installations mounted before the electricity meter, as presented in the **Figure 3.2** a,b which are dangerous for both the distribution operator and the consumer. Unauthorized installations do not comply with any norms from the point of view of fire prevention and extinction, as well as from the safety of the operating personnel. A more subtle method of stealing electricity is the one shown in the Figure c,d which consists of inserting a shunt between the input and output terminals of the electricity meter.





(a) (b)





(c) (d)

Figure3. 2: Unauthorized connection and their scheme [27]

(1—main branch, 2—false column,3—shunt connection).(-- (**a**) at the main branch--(**b**) main branch connection with false column--(**c**) at the measurement group--(**d**) shunt at the measurement group)

In the **Figure 3.3** is represented the evolution of the OTC in the analyzed measurement area.

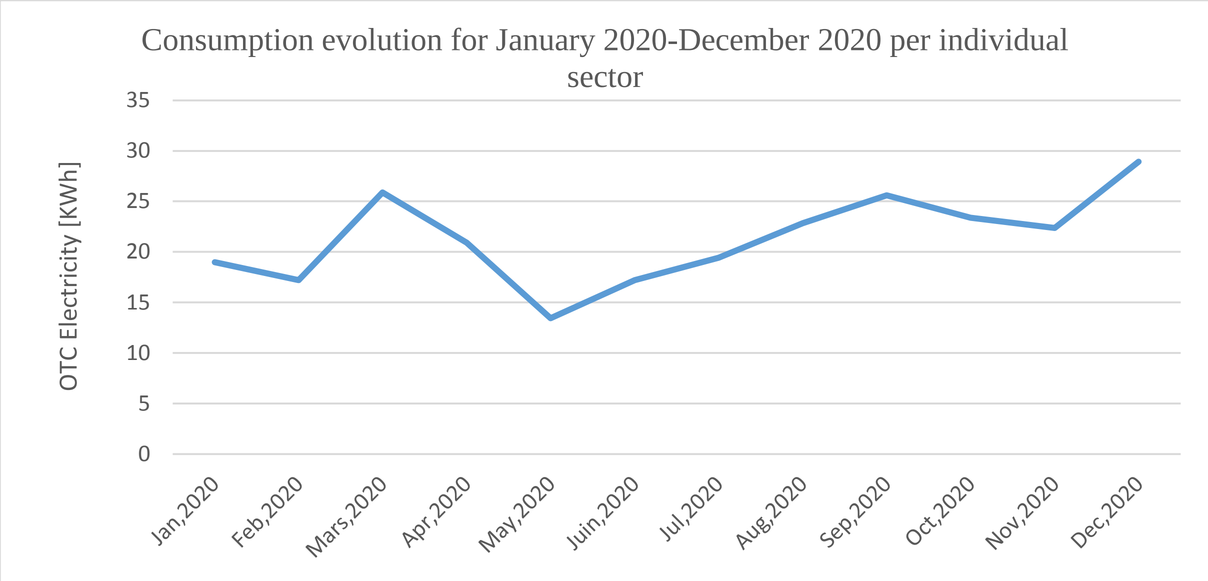


Figure3. 3: OTC evolution for January2019–February 2020 per individual sector.

3.1Results:

After the implementation of the Dispersive flies algorithm on the analyzed measurement area, a significant decrease can be observed in the amount of OTC. The implemented algorithm uses all the facilities offered by the electricity measurement sensors in each node, thus any anomaly related to the precise measurement of the electrical energy is instantly detected.

The overall experimental measured data and the results of optimization after using the Dispersive flies algorithm are summarized in Table 3.2.

Table3. 2: Experimental measured data and optimized results.

Analysed period	Electricity input [Kwh]	Distributed Electricity [KWh]	OTC Electricity [KWh]	OTC Achieved percentage [%]	**Forecasted OTC after dispersive flies algorithm [%]**	**Forecasted OTC after dispersive flies algorithm [KWh]**
Jan,2020	181,4476	162,468181	18,97941896	11,6819	**7,8188**	**12,70309461**
Feb,2020	175,2986	158,1018073	17,19679266	10,877	**7,6153**	**12,03996829**
Mars,2020	170,4612	144,5851898	25,87601016	17,8967	**15,7873**	**22,82612634**
Apr,2020	169,0758	148,1611235	20,91467646	14,1162	**12.95**	**19,18682508**
May,2020	164,231	150,7969042	13,4340958	8,9087	**7,5972**	**11,45638675**
Juin,2020	162,9178	145,6973885	17,22041146	11,8193	**9,7363**	**14,18553485**
Jul,2020	150,3792	130,9502074	19,42899264	14,8369	**12,4227**	**16,26758601**
Aug,2020	160,2362	137,3865179	22,84968212	16,6317	**14,6317**	**20,10195554**
Sep,2020	167,5586	141,9724018	25,58619822	18,022	**15,8613**	**22,51860869**
Oct,2020	174,9734	151,5969538	23,37644624	15,4201	**12,6191**	**19,1302075**
Nov,2020	187,2674	164,9076724	22,35972756	13,5589	**10,2372**	**16,88197442**
Dec,2020	228,7776	199,8372336	28,9403664	14,482	**10,9315**	**21,84516056**
year 2020	2092,6244	1636,624348	227,2224523	13,9487	**11,38**	**185,37867**

The graph in the Figure 3.4 shows a decrease in the percentage of the OTC for the entire measurement analysis area, related to the total amount of distributed energy.

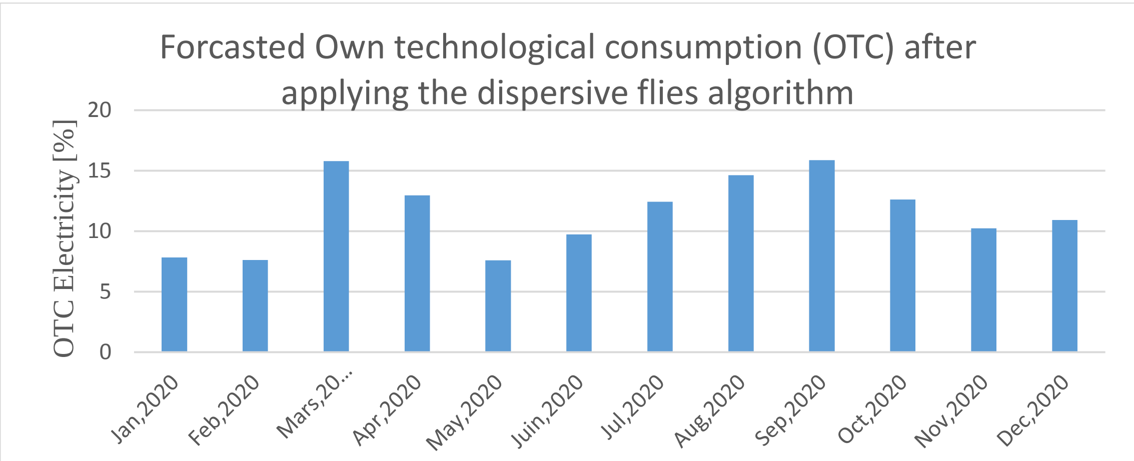


Figure3. 4: Own Technological Consumption (OTC) evolution in the case of the whole smart-meter based energy measurement analyzed sector.

Figure 3.5 presents the comparative evolution of the recorded losses and of the losses resulted after optimization as a result of the sources of losses identification through the proposed algorithm.

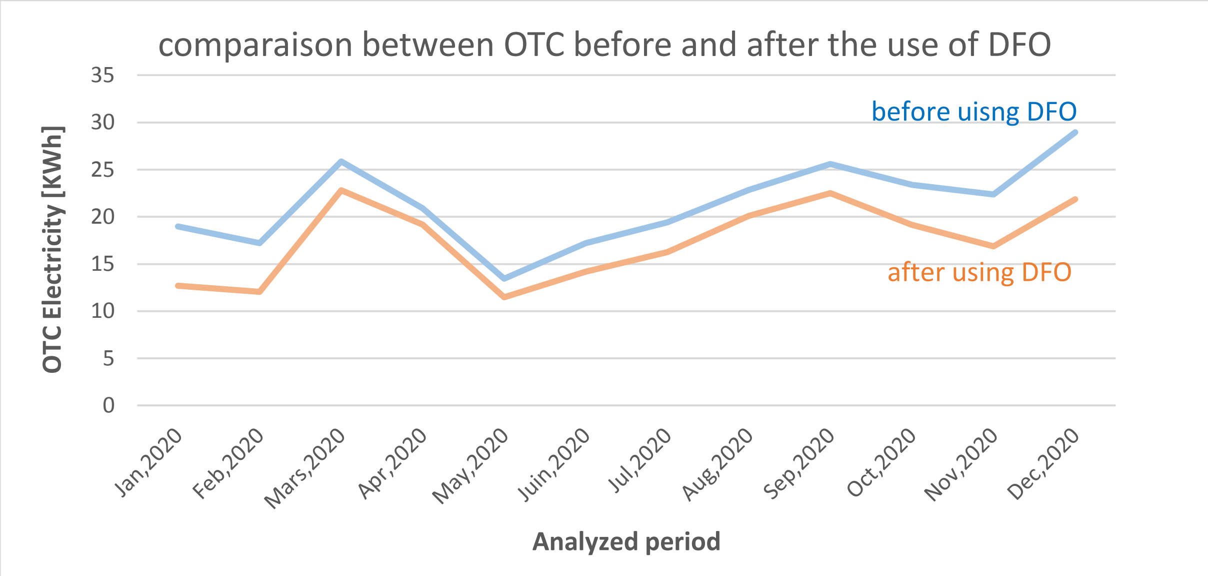


Figure3. 5 : Measured and optimized OTC evolution for whole sector integrating analyzed sector

3.2Discussion:

The result shows that the proposed optimization technique reduces the own technological consumption energy in the analyzed measurement area to a certain level when compared to normal execution. Before optimization the OTC generally is in the range [13.43, 28.9] KWh then after applying the DFO algorithm the OTC is in the range [11.45, 22.82] KWh.

Comparative Study:

The graphs bellow show a comparative study of the OTC percentage improvement using two different optimization techniques where in our study we have used the dispersive flies optimization and in a study done in Mures-County Romania the blind sparky optimization is used.

When we compare the OTC improvement in the two graphs, we can conclude that the DFO algorithm is a powerful optimizer**.**

Our Experimental Case study

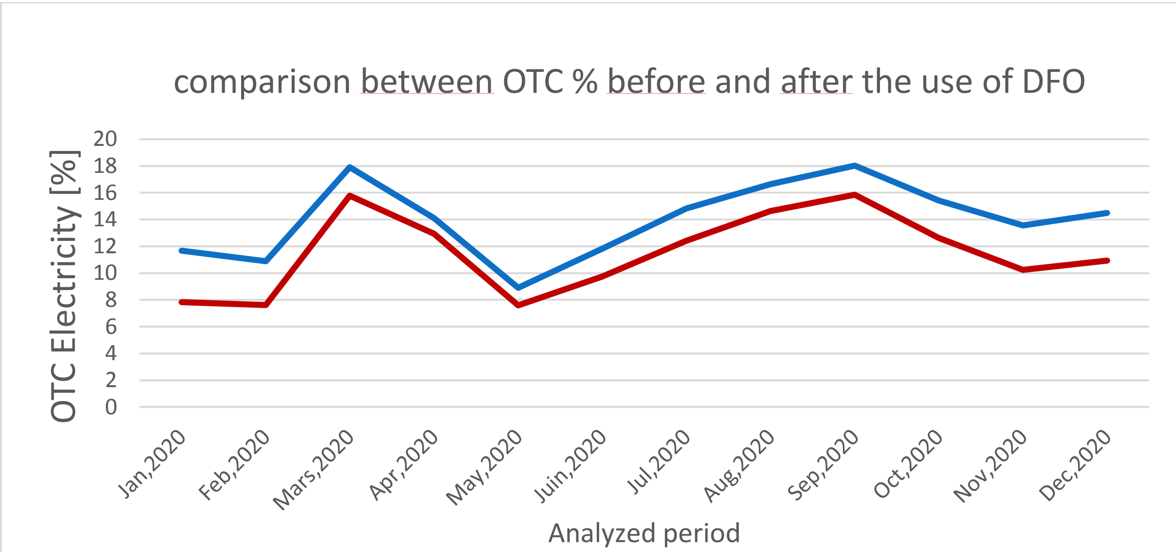


Figure3.6: comparison between OTC before and after the use of DFO

Mures-County Romania

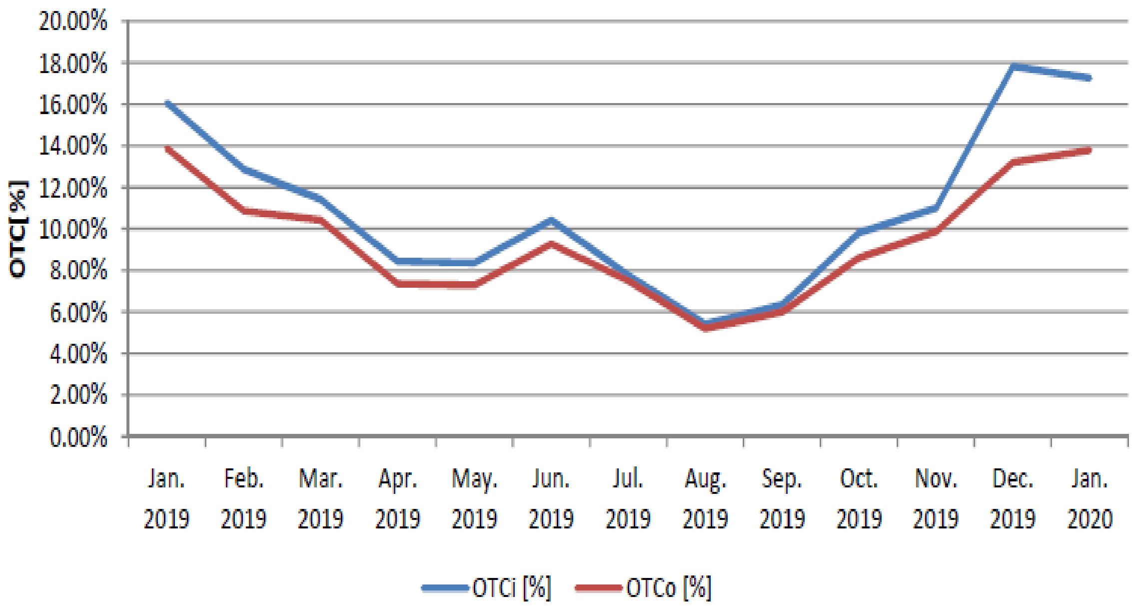


Figure3.7: comparison between OTC % before and after the use of Blind Sparky Algorithm

Conclusion:

After applying the Dispersive flies algorithm on the analyzed measurement area a remarkable improvement of the OTC can be noticed. The analysis and simulation indicate that the non-technical losses can be significantly reduced since the results are satisfactorily and are a good enough approximation to the results we tried to reproduce.

General Conclusion

This report explored the capabilities of smart metering system using a swarm intelligent algorithm for the detection of non-technical losses in electricity utilities. It has reproduced the results of the practical methodology for NTL detection proposed in paper [25] by using a new solution called Dispersive flies optimization algorithm used for identifying locations with significant non-technical losses in a power distribution grid manifested in the form of incorrectly counted electricity. The methodology has been developed and tested on synthetic datasets with real non-technical losses based on datasets for a community of 30 households in southern Germany.

The final obtained results reveals that by applying the proposed optimization algorithm the non-technical losses can be significantly reduced, which leads to a significant improvement of the OTC. However, testing the algorithm lead to different results and it is normal that results are different in each run knowing that the task of an optimiser is to get you as close as possible to the optimal value. Swarm optimisers are called "guided-stochastic optimisers", which means they use both guided approach, as well as stochastic approach (randomisation), in order to get closer to the optimal solution. Therefore, because of the stochastic part, the solution is different each time. That is why researchers run the experiment, on average, 30 times and then report the mean, standard deviation, as well as the min and max values.

Some of the variables and instructions used in mathematical model were somewhat ambiguous and left to our interpretation and may affect the accuracy of results such as the values of parameters ki, ci, and ЄSMCi

ki—coefficient determined based on previous experiences.

ci—coefficient describing node i degree of connection (connected or disconnected).

$Є_{SMCi}$—represents the value indicated by the precision class of the smart meter.

In our country Algeria advanced electricity metering is seen as a developing market but with restrictions, such as low levels of liberalization in the power sector and high corruption.

I hope this new technology will be implemented in our country, because it contains all the necessary means for the integration of smart metering systems and smart grid: the financial side, scientific side, environmental side ... etc. especially in the south of Algeria, where all the resources are available.

Lastly, the Implementations of the smart metering systems brings many benefits and could be a remedy to reduce NTL for the electricity distribution sector. From the consumer point of view, smart metering systems provide more precise billing, flexible billing program or awareness of the electricity consumption. However, significant benefits arise also for electricity distribution companies towards improving the quality of service and, if evaluated from the current work goal point of view, smart metering systems constitute base framework support for real-time monitoring solutions needed for high quality of the electricity delivery along identification of the non-technical losses sources.

References:

[1]. Depuru, S.S.S.R.; Wang, L.; Devabhaktuni, V.; Nelapati, P. A hybrid neural network model and encoding technique for enhanced classification of energy consumption data. In Proceedings of the 2011 IEEE Power and Energy Society General Meeting, Detroit, MI, USA, 24–28 July 2011; pp. 1–8.

[2]. Costa, B.C.; Alberto, B.L.A.; Portela, A.M.; Maduro, W.; Eler, E.O. Fraud Detection in Electric Power Distribution Networks using an Ann-Based Knowledge-Discovery Process. Int. J. Artif. Intell. Appl. 2013, 4, pp.17–23.

[3]. Sharma, T.; Pandey, K.K.; Punia, D.K.; Rao, J. Of pilferers and poachers: Combating electricity theft in India. Energy Res. Soc. Sci. 2016, 11,pp. 40–52.

[4]. Dos Angelos, E.W.S.; Saavedra, O.R.; Cortés, O.A.C.; De Souza, A.N. Detection and identification of abnormalities in customer consumptions in power distribution systems. IEEE Trans. Power Delivery Vol. 26.2011.pp. 2436–2442.

[5]. Ekanayaka J, Liyanage K, Jianzhong W, Yokoyama A, Jenkins N (2012) The smart grid "Smart grid technology and applications", 1st ed. Wiley, UK, pp. 1–15

[6]. Smart Grid (2012) http://en.wikipedia.org/wiki/Smart_grid. [Accessed 25 June 2021]

[7]. K.S.K Weranga, Sisil Kumarawadu, D. P. Chandima. Smart Metering Design and Applications." Smart Grid and Smart Metering", Sri Lanka.2014.pp.1–15.

[8].European Technology Platform. SmartGrids: strategic deployment document for Europe's electricity networks of the future [Online]. EuropeanCommission; 2010. Available from http://www.smartgrids.eu/documents/ SmartGrids_SDD_FINAL_APRIL2010.pdf [Accessed 25 June 2021].

[9].Dileep, G. A survey on smart grid technologies and applications. Renewable Energy, 2020.pp. 2589-2625.

[10]. Cisco. Why Cisco and Smart Grid? [Online]. 2009. Available from http:// www.cisco.com/cisco/web/UK/solutions/strategy/energy/pdfs/sGrid_qa_c67_532319. pdf [Accessed 21 June 2021]

[11]. Utility Standard board. Smart Grid: interoperability and standards – an introductory review[Online].2008.Availablefromhttp://xanthusconsulting.Com/Publications/documents/Smart_Grid_Interoperability_and_Standards_White_Paper.pdf [Accessed 25 June 2021]

[12]. IEC. IEC Smart Grid standardization roadmap [Online]. IEC; 2010. Available from http://www.iec.ch/smartgrid/downloads/sg3_roadmap.pdf [Accessed 25 June 2021]

[13]. Davies S. ‘Network evolution: developing a modern, intelligent power grid’.E&T Magazine. 2012:pp.5-52

[14]. James Momoh. Smart Grid Fundamentals of Design and Analysis” SMART GRID ARCHITECTURAL DESIGNS”, Canada, 2012.pp.12-15

[15]. Salman K. Salman. Introduction to the Smart Grid Concepts, Technologies and Evolution” Introduction to the Smart Grid concept”. London, United Kingdom, 2017. pp.5-10.

[16]. Council of European Energy Regulators (CEER). Smart grids scope, history and prospects update on smart metering activities – note to the GA [Online]. Europe: CEER; 2009. Available from www.ure.gov.pl/download.php? s¼1&id¼2456 [Accessed 21june 2021]

[17]. Center for Neighborhood Technology (CNT). Illinois smart grid initiative: summary of smart grid benefits and issues [Online]. Available from http://www.cnt.org/news/media/isgi-summary-of-benefits-and-issues-6-08.pdf [Accessed 21 June 2021]

[18]. Difference between Traditional Power Grid and Smart Grid [Online]. Available from https://electricalacademia.com/electricpower/differencetraditionalpowergridsmartgrid/[Accessed 21 June 2021].

[19]. Trong Nghia Le, Wen-Long Chin,Dang Khoa Truong and Tran Hiep Nguyen Smart Metering Technology and Services – Inspirations for Energy Utilities.pp.5--12

[20]. National Energy Technology Laboratory (NETL). Advanced metering infrastructure [Online] .USA:Report;2008. Available from https://www.netl.doe.gov/File%20Library/research/energy%20efficiency/smart%20grid/whitepapers/AMI-White-paper-final-021108–2–APPROVED_2008_02_12. pdf [Accessed 25 June 2021]

[21]. Bian B., Kuzlu M., Pipattanasomporn M., and Rahman S. ‘Analysis of communication schemes for advanced metering infrastructure (AMI)’. IEEE PES General Meeting Conference and Exposition; National Harbor, MD, USA, 2014, pp. 1–5

[22]. Electric Power Research Institute (EPRI). Advanced metering infrastructure (AMI) [Online]. February 2007. Available from http://www.ferc.gov/eventcalendar/Files/20070423091846-EPRI%20 %20Advanced%20Metering.pdf [Accessed 25 June 2021]

[23]. European Commission (European Technology Platform). Smart Grids: vision and strategy for Europe’s electricity networks of the future [Online]. 2006. Available from http://ec.europa.eu/research/energy/pdf/smartgrids_en.pdf. [Accessed 25 June 2021]

[24]. Moore S. Key features of meter data management systems [online]. 2008. Available from https://www.itron.com/na/PublishedContent/Key%20MDM %20Features%20Whitepaper_FINAL.pdf [Accessed 25 June 2021]

[25]. Ilie Vlasa, Adrian Gligor, Cristian-Dragos Dumitru, and Laszlo Barna Iantovics. SmartMetering Systems Optimization for Non-Technical Losses Reduction and Consumption Recording Operation Improvement in Electricity Sector.Sensors.2020.pp.7--11

[26]. Ines Bula, Valmir Hoxha, Muzafer Shala, Edmond, Hajrizi.Minimizing non-technical losses with point-to-point measurement of voltage drop between "SMART" meters

[27]. Ilie Vlasa , Adrian Gligor , Cristian-Dragos Dumitru , and Laszlo Barna Iantovics. Smart Metering Systems Optimization for Non-Technical Losses Reduction and Consumption Recording Operation Improvement in Electricity Sector.Sensors.2020.pp.10--13

[28] R. V. Cruz, C. V. Quintero, and F. Pérez, "Detecting non-technical losses in radial distribution system transformation point through the real time state estimation method," .2006 IEEE/PES Transmission & Distribution Conference and Exposition: Latin America, 2006, pp. 1–5.

[29] P. Kadurek, J. Blom, J. F. Cobben, and W. L. Kling, "Theft detection and smart metering practices and expectations in the Netherlands," in 2010 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT Europe). IEEE, 2010, pp. 1–6.

[30] D. N. Nikovski, Z. Wang, A. Esenther, H. Sun, K. Sugiura, T. Muso, and K. Tsuru, "Smart meter data analysis for power theft detection," in International Workshop on Machine Learning and Data Mining in Pattern Recognition. Springer, Berlin, Heidelberg, 2013, pp. 379–389.

[31] L. Marques, N. Silva, I. Miranda, E. Rodriges, and H. Leite, "Detection and localization of nontechnical losses in low voltage distribution networks," in Mediterranean Conference on Power Generation, Transmission, Distribution and Energy Conversion (MedPower 2016). IEEE, 2016.

[32] J. B. Leite and J. R. S. Mantovani, "Detecting and locating non-technical losses in modern distribution networks," IEEE Transactions on Smart Grid, vol. 9, no. 2, pp. 1023–1032, 2018.

[33] M. Wen, D. Yao, B. Li, and R. Lu, "State Estimation Based Energy Theft Detection Scheme with Privacy Preservation in Smart Grid," in 2018 IEEE International Conference on Communications (ICC). IEEE, 2018, pp. 1–6.

[34] S. C. Huang, Y. L. Lo, and C. N. Lu, "Non-Technical Loss Detection Using State Estimation and Analysis of Variance," IEEE Transactions on Power Systems, vol. 28, no. 3, pp. 2959–2966, 2013.

[35] C. L. Su, W. H. Lee, and C. K. Wen, "Electricity theft detection in low voltage networks with smart meters using state estimation," in 2016 IEEE International
Conference on Industrial Technology (ICIT). IEEE, 2016, pp. 493–498.
[36] K. Kee, S. Shahab, and C. Loh, "Design and development of an innovative smart metering system with GUI-based NTL detection platform," in 4th IET Clean Energy and Technology Conference (CEAT 2016). IEEE, 2016.
[37] J. Pulz, R. B. Muller, F. Romero, A. Meffe, F. Garcez Neto, and A. S. Jesus, "Fraud detection in low-voltage electricity consumers using socio-economic indicators and billing profile in smart grids," CIRED - Open Access Proceedings Journal, vol. 2017, no. 1, pp. 2300–2303, 2017.
[38] A. H. Nizar, Z. Y. Dong, and Y. Wang, "Power utility nontechnical loss analysis with extreme learning machine method," IEEE Transactions on Power Systems, vol. 23, no. 3, pp. 946–955, 2008.
[39] J. Nagi, K. S. Yap, S. K. Tiong, S. K. Ahmed, and M. Mohamad, "Nontechnical loss detection for metered customers in power utility using support vector machines," IEEE Transactions on Power Delivery, vol. 25, no. 2, pp. 1162–1171, 2010.
[40] V. Ford, A. Siraj, and W. Eberle, "Smart Grid Energy Fraud Detection Using Artificial Neural Networks," in 2014 IEEE Symposium on Computational Intelligence Applications in Smart Grid (CIASG). IEEE, 2014, pp. 1–6.
[41] C. Cody, V. Ford, and A. Siraj, "Decision tree learning for fraud detection in consumer energy consumption," in 2015 IEEE 14th International Conference on Machine Learning and Applications (ICMLA). IEEE, 2015, pp. 1175–1179.
[42] P. O. Glauner, A. Boechat, L. Dolberg, R. State, F. Bettinger, Y. Rangoni, and D. Duarte, "Large-Scale Detection of Non-Technical Losses in Imbalanced Data Sets," in 2016 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT). IEEE, 2016, pp. 1–5.
[43] R. D. Trevizan, A. S. Bretas, and A. Rossoni, "Distribution Test System for Nontechnical Loss Detection," in 2018 North American Power Symposium (NAPS). IEEE, 2018, pp. 1–6.
[44] Adam Slowik. Swarm Intelligence Algorithms A Tutorial" Dispersive Flies Optimization A Tutorial" London.2017 pp.135--145
[45] Mohammad Majid al-Rifaie. Dispersive Flies Optimization.London.2014
[46] Mohammad Majid al-Rifaie, Anna Ursyn, Robert Zimmer, and Mohammad Ali Javaheri Javid On Symmetry, Aesthetics and Quantifying Symmetrical Complexity" Dispersive Flies Optimization".London.2017.pp6-7

[47] Cesar Lopez. MATLAB Optimization Techniques. 2014. Springer .pp. 1-23

[48]Getting ready to operate the smarter grid. [Online].2019. Available from https://www.smart-energy.com/features-analysis/getting-ready-to-operate-the-smarter grid/[Accessed 29 June 2021]

[49] Could energy smart meters also deliver smarter health? [Online].Available from https://www.augmentedinsights.co.uk/author/admin//[Accessed 29 June 2021]

[50] Madalina-Mihaela Buzau. Machine learning algorithms for the detection of non-technical losses in electrical distribution networks. Sevilla, 2019.pp.9-19

[51] Davidson I.E., April 2002.

[52]Deepak Madan, 2012

[53] Newly Emerging Nature-Inspired Optimization -Algorithm Review, Unified Framework, Evaluation, and Behavioral Parameter Optimization HUI LI , (Member, IEEE), XIAO LIU , ZHIGUO HUANG , CHENBO ZENG , PENG ZOU ,ZHAOYI CHU , AND JUNKAI YI .2020.CHINA. pp.8

1