Zonal Energy Management and Optimization System (ZEMOS) for Smart Grid Applications

By

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AUTHOR'S DECLARATION

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

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Abstract

In the context of implementing the smart grid, electric energy consumption, generation resources, should be managed and optimized in a way that saves energy, improves efficiency, enhances reliability and maintains security while meeting the increasing demand at minimum operating cost. In order to achieve these objectives, there is a need to implement an efficient Zonal Energy Management and Optimization Systems (ZEMOS) that address both existing and future challenges possibly imposed by the use of renewable energy generators that lead to bi-directional power flow instead of unidirectional as in the traditional grids while operate in a coordinated way for the benefit of the whole electric grid. The proposed ZEMOS contains custom defined built-in functions in modular form, which could easily be integrated with other existing energy monitoring systems in the zone of interest (i.e. industrial facility, commercial centers, testing facility, sub-system of the utility service area, educational institutions, power plant, etc.). The proposed ZEMOS provides functions that ensure energy saving, improved reliability, increased efficiency and enhanced utilization of distributed resources: generation energy storage and loads without compromising the tasks carried within that zone. Those module-based systems are characterized by their scalability and flexibility, since more functions can be added down the road as needed. This is necessary in order to accommodate the constant changes imposed by the smart grid and avoid the need to change the whole infrastructure. The proposed ZEMOS performance was investigated for study zones that involve single and multi-objective operations. Besides, study zones with more than single decision makers were also considered in this thesis. Accordingly, the implementation of ZEMOS satisfies the outlined objectives for specific study zone which leads to a reduction in greenhouse gas emission, the improvement of the energy generation portfolio, a reliance on the optimized renewable energy source and a reduction in the energy losses while ensuring high power quality. Furthermore, managing the energy consumption and optimizing the operation of such sizable zones (at Mega Watts scale) ensures significant economic benefits in terms of energy saving, better utilization of available resources, improving the efficiency of energy systems, and exporting novel smart grid technologies, which will lay the foundation to meet future challenges using existing infrastructure.

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Acronyms

ZEMOS	Zonal Energy Management and Optimization System
EPA	Environmental Protection Agency
OPA	Ontario Power Authority
EMS	Energy Management Systems
DEMS	Decentralized Energy Management System
GHG	Greenhouse Gas
PHEV	Plug-in Hybrid Electric Vehicle
CEMS	Centralized Energy Management System
ESS	Energy Storage Systems
DG	Distributed Generation
PV	Photovoltaic
SEMS	Smart Energy Management System
MAS	Multi-Agent Systems
CMO	Central Microgrid Operator
DIEMS	Distributed Intelligent Energy Management System
DMS	Distribution Management Systems
AMI	Advanced Metering Infrastructure
DSM	Demand Side Management
EE	Energy Efficiency
TOU	Time of Use
DR	Demand Response
DLC	Direct Load Control
RTP	Real-Time Pricing
ADR	Automated Demand Response
VPP	Virtual Power Plant
BEMS	Building Energy Management Systems
WSEMS	Whole System Energy Management Systems
SUEMS	Single Unit Energy Management Systems
OM	Objectives Module
RTM	Resources and Tools Module
SMM	Smart Matching Module
CM	Control Module
DMM	Decision Making Module
DBM	Data Bank Module
DM	Decision Maker
FIT	Feed In Tariff
SEP	Smart Energy Profile
PLC	Power Line Carrier
DSL	Digital Subscriber Lines
COE	CO_2 Emissions
CUI	Current Unbalance Index
CVI	Voltage Unbalance Index
ELI	Energy Loss Index
GA	Genetic Algorithm
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
OpenDSS	Open Distribution System Simulator
SMS	Smart Matching Scheme
SI	Sensitivity Index
RTS	Reliability Test System
LDC	Line Drop Compensator
TIP	Theoretical Ideal Point
DBIP	Data Based Ideal Point
CE	Correlated Equilibrium
CS	Case Study
DS	Distribution System
PAR	Peak to Average Power Ratio

Chapter 1 Introduction

1.1 General Overview

Greenhouse gas emissions reduction has become essential due to global warming in the last few decades. Therefore, governments around the world are taking actions to minimize climate change. Accordingly, over 140 countries agreed on the implementation of the Kyoto protocol for reducing emissions [1]. The US EPA [2] presented the U.S. greenhouse gas emissions in commonly used economic categories: agriculture, commercial, electricity generation, industry, residential and transportation. According to this classification, emissions from electricity generation produce the largest portion of U.S. greenhouse gas emissions in 2009. According to [2], electrical power industry contributes to 33% of CO_2 emissions.

In addition, the trend in transmission systems indicates steady disinvestments for new transmission lines [3, 4]. Hence, the increasing load demand makes the entire electrical grid more fragile due operating system components closer to their limits. Meanwhile, the appliances used at the customers' side are getting more sensitive to electrical variations. As a result, new approaches that significantly increase the efficiency of the entire electrical delivery system is required. These approaches will not only increase reliability, but they should also improve energy efficiency in the delivery process and thereby reduce greenhouse gas emissions. In other words, a smarter grid is expected to be introduced by the aforementioned approaches.

In the context of implementing the smart grid, electric energy consumption, generation resources, energy storage, and plug-in electric vehicles, should be managed and optimized in a way that saves energy, improves efficiency, enhances reliability and maintains security, while meeting the increasing demand at minimum operating cost. Moreover, Smart Grids are expected to address the major deficiencies of the existing grid. According to [5], the main features of Smart Grid are:

- The automated healthy restoration of the network after a fault without operator interference (Self-Healing).
- The ability to monitor and control the quality of the power delivered to the customers.
- The ability of integrating distributed resources (renewable generations and storage devices).
- The use of grid resources in order to minimize the network losses.
- Advanced energy management in order to minimize the system operational costs and minimize carbon and greenhouse gasses emissions.
- Minimize manual interactions with the network.

- Provide secure real time energy management to customers at secure levels in terms of the cyber physical infrastructure

In the view of the previous discussion, energy management systems are receiving more attention from researchers, electricity consumers, and electric utilities. For example, a five-utility pilot project commissioned by the Ontario power authority (OPA) in 2010, for 130 homes and small businesses in Ontario equipped with smart thermostats, smart plugs and in-home displays to allow the participants to monitor and manage their energy use inside or remotely via access to an online portal [6]. The technologies also enabled participation in demand-response programs, which represent a future opportunity for home and business owners. The small and large utilities involved in the project – Cambridge and North Dumfries Hydro, Hydro One (Owen Sound), Kitchener-Wilmot Hydro, Toronto Hydro and Waterloo North Hydro – will use the information collected from the pilot to design future energy-management offerings for their customers.

Accordingly, the main concern of this research work is to develop an efficient energy management and optimization system which is targeting distribution system subdivision or zones (at Mega Watts scale). The proposed Zonal Energy Management and Optimization System (ZEMOS) consists of modular custom built-in functions to manage energy consumption, increase efficiency, optimize the operation of energy systems and ensure reliable and safe grid integration. The proposed ZEMOS contributes to the reduction of carbon footprints, the optimization of the utilization of renewable energy sources and the reduction of the daily demand peak periods. Moreover, managing the energy consumption and optimizing the operation of such sizable zones will ensure significant economic benefits in terms of energy saving, better utilization of available resources, and exporting novel smart grid technologies.

1.2 Research Motivations

In the market, there are many Energy Management Systems (EMS) exists which can monitor energy consumption and attempt to regulate it. These products can be grouped into two main types:

- EMS designed to operate on the whole system, including generation, transmission and distribution, such as the Decentralized Energy Management System (DEMS®)[7] or energy management systems developed for microgrids;
- EMS designed to operate on a single unit (home, commercial building, etc.).

Large industrial facilities, educational institutions, residential subdivisions, distribution system sub-division, etc. are typical zones that are not yet served efficiently by any of the available energy management products in the market to the best of the author's knowledge. This segment of the market has unique characteristics; that is, it is relatively large in size, to be handled by single unit EMS and at the same time it has many customer specific features and requirements to be served by the whole system EMS. This niche market is the main motivation for proposing this research work.

The energy management products that exist in the market mostly tackle two main objectives separately: minimum operational costs and minimum emissions and they did not efficiently address multi-objectives problems. This is due to the fact that the multi-objectives problem was normally converted into a single weighted objective function which might not generate an acceptable solution. In addition, only the aforementioned objectives are tackled by those multi-objectives products. This might be incompatible with a decision maker (operator or zone owner) who would seek alternative objectives and needs. In other words, for different operating conditions, typical zones might require different objectives over specific time periods rather than only reducing emissions or minimizing the operational cost.

Furthermore, those EMS products find difficulty in dealing with conflicts between objectives that would rise if more than one decision maker exists within the same area. Finally, present products lack the capability to integrate additional system tools or controlled resources.

1.3 Research Objectives

The main objective of this research is to develop an efficient energy management system that can monitor and manage the power of a zonal segment of the power system, while taking into account the nature and characteristics of the zone and which can be easily integrated with the existing single unit and the whole system EMS.

The implementation of ZEMOS assists the zone owner (who can be easily identified, e.g. industrial facility, commercial centers, testing facility, sub-system of the utility service area, educational institutions, power plant, etc.) to save energy and improve the utilization of his own resources, with the minimum compromise of tasks.

Moreover, ZEMOS is based on the idea of *modular structure* which will best fit into the zone concept. The proposed ZEMOS custom defined modular built-in functions can be easily integrated with existing monitoring and controlling systems in the defined zone (s). Each of these modules can be updated and expanded separately. By adding extra modules, additional functions could be provided to enhance the capabilities of the proposed ZEMOS; hence, there would be no need to change the whole system infrastructure. In addition, ZEMOS has the ability to fulfill and maintain multiple objectives by enabling the use of the same system controlled resource or tool by more than one objective. Moreover, if more than one decision maker is present in the zone, ZEMOS has the ability to investigate conflicts of interests between decision makers and generate an acceptable solution by all peers.

From a utility perspective, ZEMOS is installed at a distribution system sub-division. Consequently, ZEMOS utilizes the sub-division controlled resources in order to efficiently operate the system, reduce utility operational cost and defer zonal system components upgrades. For example, if a sub-division suffers from a shortage of electrical energy, ZEMOS would manage the sub-division controlled resources and tools in order to defer upgrades, thus, it avoids critical (undesired) loads shedding.

From a customer perspective, ZEMOS is able to fulfill many objectives over different time periods. For example, a zone owner could be a large industrial facility that has a painting stage during its production line. Thus, the zone owner objective during the painting stage will be avoiding supply interruption (supply continuity); however, during a different time period, the objective will be to save energy. On the other hand, another industrial load might require scheduling of its electrical demand activities to minimize the waiting time for production.

This research focuses on developing an energy management system that monitors and manages zone energy flow in conjunction with fulfilling the aforementioned features through two main objectives. These objectives are outlined as follows:

1.3.1 Objective 1

The first objective of this research is to develop the proposed zonal management system basic structure and to develop the basic system modules. It is worth noting that each module represents a function that is employed by ZEMOS operation. Next, the role of each module is clearly identified. In addition, a coordination scheme is developed between the system modules in order to develop the link between each module and the rest of the system. This process involves developing zone objectives functions, controlled tools and resources, optimization and control techniques, data processing module, data forecasting module.

1.3.2 Objective 2

The second objective of this research is to build a system framework to cope with different system operating conditions. This is achieved by selecting the efficient optimization and control techniques that are utilized in order to optimize the system according to the number of objectives and the number of decision makers. A decision making criteria is developed in accordance with the nature of each decision maker's objectives to optimize the system for multi-objectives operation.

Many system objectives functions and controlled resources are selected to reflect a typical study zone in order to evaluate the proposed ZEMOS performance. Pareto optimality is introduced to solve multi-objectives problems in this research. A Data forecasting is developed to maintain decision makers' objectives for specific and predetermined time periods. A selective smart matching scheme is developed in order to match the operator's objective function with the most appropriate and efficient controlled resources/tools that can be optimally controlled to fulfill the operator's objectives from the zone side. Finally, a game theoretic multiple decision makers' algorithm is presented to be utilized for resolving conflicts of interests that may rise in distribution systems that have more than only one decision maker.

1.4 Conclusions

The proposed work focuses on developing a custom based and extendable zonal energy management system. In the meantime, the proposed research introduces the application of multiple objective optimization or multi-criteria decision making for electrical distribution system. Furthermore, the proposed research investigates the performance of the energy management systems in the presence of multiple decision makers. The research aims to develop and integrate the proposed ZEMOS into existing electrical distribution systems sub-divisions (zones).

In general, zone owners or zone operators will have a good motive to use this system because it will provide them with their energy consumption profile, help them reduce their energy consumption and better utilize their energy resources based on their system characteristics, system configurations, objectives, policies and their business plan. In conclusion, ZEMOS can provide electric utilities with efficient means of increasing their profit.

1.5 Thesis Outline

The rest of this thesis is organized as follows: Chapter 2 provides a brief review of the background topics and associated literature relevant to this research. Chapter 3 presents the detailed description of the proposed ZEMOS. Chapter 4 presents the modelling of the proposed ZEMOS for single decision maker with single and multiple objectives. Chapter 4 also introduces the modelling of the proposed smart matching scheme that increases the efficiency of ZEMOS. The performance of the proposed modelling techniques and algorithms is presented, with the related results, in chapter 5. A multi-participant decision making algorithm is presented along with ZEMOS performance, in the presence of more than a single decision maker, in chapter 6. Summary, Contributions, and Future Work are presented in chapter 7.

Chapter 2 Background and Literature Review

2.1 Introduction

The use and production of electricity are changing. Meanwhile, consumers are becoming more aware of the environmental impacts of the electricity system and are seeking greater ability to manage their electricity use to control energy costs and help protect the environment from the greenhouse gas emissions. Renewable energy resources such as solar, wind and storage support lowering greenhouse gases emission, and allow consumers to produce their own electricity and sell the excess. In addition, widespread use of plug-in electric vehicles will bring even greater change as consumers look to conveniently charge their cars at home or on the road. These changes will require a significant change in the electricity system. Today, the electricity grid is mainly a pathway for moving electricity from generators to consumers. Under the smart grid umbrella, the grid will enable two-way flows of electricity and information which will facilitate the implementation of new technologies of electricity production, delivery, and use. Furthermore, the trend in transmission systems indicates steady disinvestments for new transmission lines [3, 4]. Hence, with the increasing size of supply and demand growth, system components are expected to operate closer to their limits. As a result, the need for developing smarter distribution systems becomes a necessity. Moreover, due to the limited capabilities of centralized computing on large-scale distributed systems, decentralized or semi-centralized decision-making processes are presented as a suitable option for use in distributed energy systems.

Energy management is one of the most important and novel approaches to enable smart grid operation. The term Energy Management has a number of meanings and one of these is the process of monitoring, controlling and conserving energy in a building, organization or distribution system. Energy management system (EMS) is also viewed as a system of tools used to monitor, control and optimize the generation, delivery and/or consumption of energy [8]. According to [9], energy management is defined as "*The judicious and effective use of energy to maximize profits (minimize costs) and enhance competitive positions*".

A typical energy management system involves the following steps:

1. Metering energy consumption and collecting data.
2. Finding techniques to save energy and estimating *how much* energy each technique could save.

3. Taking actions to target the opportunities to fulfill organization's objectives.
4. Tracking the progress by analyzing the meters data to see how well energy-saving efforts have worked.

(And then back to step 2, and the cycle continues...)

In this section, the literature related to developing and optimizing energy management systems are presented. According to the literature, energy management systems are classified into two different areas. The first area is related to building and organizational energy management systems. Therefore, these small scale EMS (single unit EMS) studies are introduced in section (2.2). The second research area, described in section (2.3), investigates medium and large scale EMS (whole system EMS), such as micro-grid energy management or utility owned EMS, respectively.

2.2 Single unit Energy Management Systems:

In this section, literature related to buildings single unit energy management systems are introduced. Building Energy Management Systems has the following benefits[10]:

Building occupants

- Good control of internal comfort conditions
- Possibility of individual room control
- Increased staff productivity
- Effective monitoring and targeting of energy consumption
- Improved plant reliability
- Save time and money during maintenance

Building owner

- Higher rental value
- Flexibility on change of building use
- Individual tenant billing for services facilities manager
- Central or remote control and monitoring of building
- Increased level of comfort and time saving

Maintenance Companies

- Ease of information availability
- Computerized maintenance scheduling
- Effective use of maintenance staff
- Early detection of problems

To illustrate, optimization of energy efficiency in buildings [11] means:

- Only use energy when it is required
- Apply the energy that is used with the highest possible efficiency

Building structures consume significant levels of energy (particularly electricity) [12]. In addition, household energy consumption contributes to 27% of overall CO_2 emissions [13]. According to [14], heating, ventilation and air-conditioning systems consumes more than 50% of the energy of a typical commercial building (Figure 2.1).

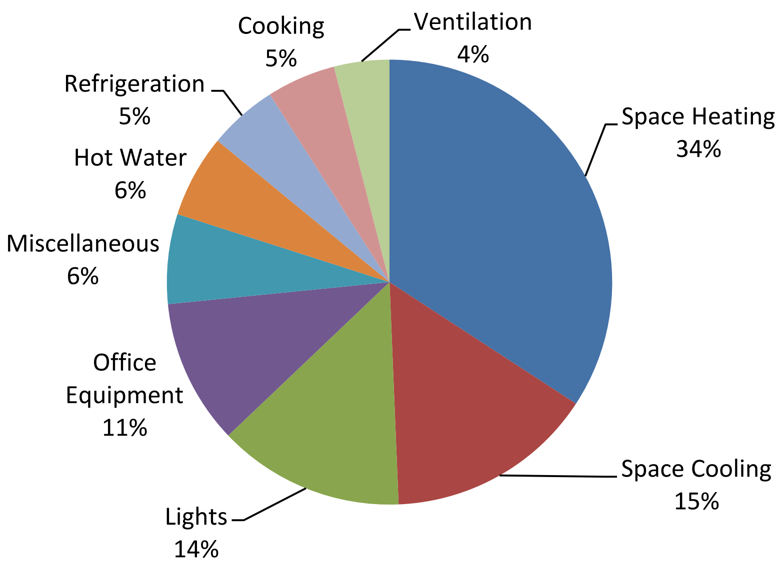


Figure 2.1 Commercial building energy use

As a consequence, most of the EMS designs are focused on energy-saving and individual space controls for heating, ventilation and air-conditioning. Besides, buildings' EMS should work on optimizing the lighting system which includes developing an intelligent control for making use of daylight and the sun's energy. Heating and lighting controls are achieved by the optimization of energy consumption via monitoring, collection, and evaluation of operational data from the building. In commercial and residential buildings, it is only expected that rooms change their use with time. Consequently, it is necessary that the designed EMS be easily adaptable to the needs of the user with the minimum cost during this time [15].

Energy saving techniques, and habits such as, natural day lighting, LED light bulbs, "Energy Star" certified appliances, etc., are being used in the energy efficient building industry.

Building Energy Management techniques:

Many techniques have been introduced and studied in the literature. For instance, the authors of [16] recommend an energy management system for private and business buildings by utilizing building automation systems. The main purpose of the proposed system is to provide an intelligent system that can help the occupants to *monitor* and *control* their energy consumption and also to notice their energy saving options. The introduced EMS is based on knowledge-driven energy analysis. As a result, it offers a more intelligent mechanism as improvement of classical data-driven analysis, which is commonly used by existing energy analysis solutions.

In [17], the authors state that most of the currently available energy management systems in domestic environment are concerned with real-time energy consumption monitoring and the display of statistical and real time data of energy consumption. Although these systems play an important role in providing a detailed overview of energy consumption in home environment, they all leave it to households to take appropriate actions to reduce their energy consumption. Some energy management systems provide general energy saving recommendations, but they do not consider the household energy profiles and energy consumption profiles of home appliances. Consequently, [17] proposes an EMS that addresses this issue by taking into account the household energy consumption profiles of electrical appliances. Therefore, it is expected to provide the households with effective advice on their energy consumption by enabling them to take focused and effective actions towards efficient energy use.

The author of [18] proposes a building energy management system with the following objectives:

- Increased energy efficiency
- Decreased cost of energy
- Decreased greenhouse gas (GHG) emissions.

In [19] a semi-centralized decision making methodology, using multi-agent systems for building energy management system, is presented. The system main objective is the minimization of the energy cost. The authors of [20] focus on Energy Management System (EMS) applied to the residential loads. The proposed EMS consists of three layers:

- Equipment layer, with local and fast control mechanism;
- Reactive layer, which is triggered when energy constraints are violated;
- Anticipative (forecasting) control layer, which adjusts devices set-points in order to tackle expected energy events.

The work in [20] deals mainly with an anticipation layer that allocates energy by taking into account predicted events. The proposed EMS system is solved as a weighted multi-objective optimization problem, where the anticipation control layer tries to maximize the total satisfaction of services and, at the same time, minimize the total energy cost. However, the authors did not treat both objectives with the same importance. With that being said, two scenarios were used in [20]. The first scenario is where the energy cost has a higher priority than the comfort level, in which, inhabitants accept to decrease their comfort level in order to reduce their energy bill. In the second scenario, the comfortable mode is preferred by the EMS, which leads to a search for a solution based only on the comfort objective. So, the EMS system then selects the best solution according to the consumer's preferences. Similar EMS system, based on the same three layers (anticipation, reactive and equipment layers), was also proposed in [21] which operates with the same criteria, i.e. maximum comfort and minimum energy cost. The main difference is that Tabu search is used in [21] as the optimization control algorithm in order to solve the weighted multiple objectives problem.

2.3 Whole system Energy Management Systems

Energy management is not only about saving energy in buildings. It is also used in other fields:

- It is what utility companies do to ensure that their energy sources generate enough energy to meet the demand.
- It also refers to techniques for managing and controlling customer's energy levels.
- It is a major part of controlling and optimizing microgrids operation.

Whole system EMS refers to managing system generation, transmission, distribution, and loads in order to fulfill an operator's needs. It is important to realize that energy management systems can be both installed and managed by either customers or utilities. In this section, literatures related to both technologies are presented in detail.

2.3.1 Customer owned EMS

Most customers' owned whole system energy management systems are mainly developed and designed for microgrids. The problem of energy management in microgrids is finding the optimal energy output of the available generators and storage systems so that particular operational objectives are fulfilled. A common objective for stand-alone modes is to minimize the operational costs required for supplying the microgrid local loads [22] or to minimize the total cost for charging the PHEV [23]. On the other hand, when the microgrid is operated under the grid-connected mode of operation, the maximization of profits is the typical objective [24]. In [25], the authors investigates the real-time operation of a hybrid DC microgrid by addressing the technical challenges that faces the implementation and monitoring of the DC microgrid.

In [22, 26], additional objectives such as the minimization of greenhouse gas emissions of the microgrid have also been proposed by applying heuristic and multi-objective optimization techniques. The authors of [27] propose the development of CEMS (Centralized Energy Management System). Figure 2.2 shows a typical CEMS architecture as viewed in [28]. In the CEMS a central unit collects all the relevant information from the different microgrid elements in order to optimally evaluate the inputs of the control system for the next period. CEMS input variables can be:

- Forecasted power output of the non-dispatchable generators.
- Forecasted local load.
- State of charge of the storage system.
- Operational limits of dispatchable generators and storage system.
- Security and reliability constraints of the microgrid.
- Interconnection status of the microgrid.
- Main grid energy price forecasting.

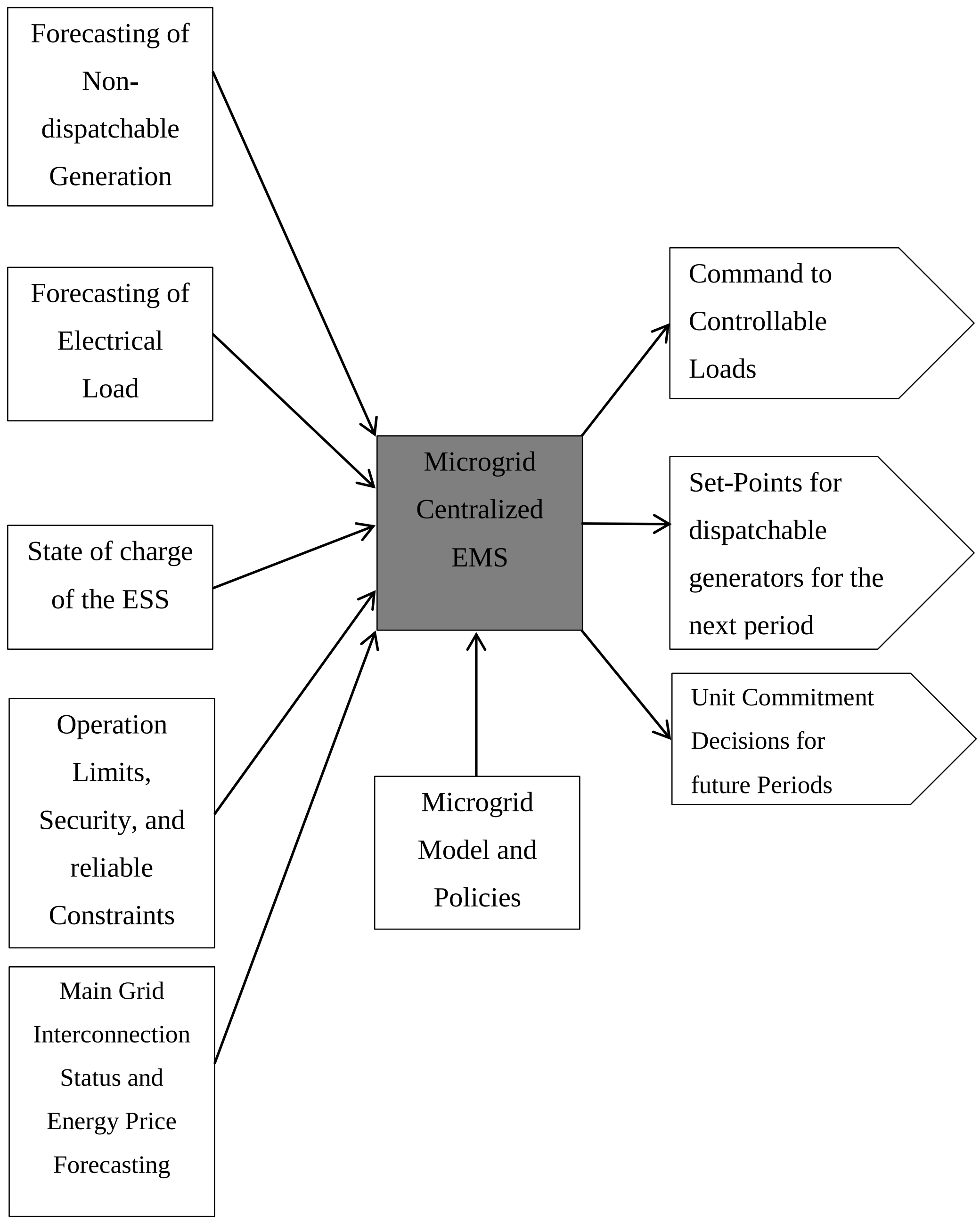


Figure 2.2 Centralized Energy Management System (CEMS)

Once all the input variables are collected, optimization is executed in order to determine the optimal operating set points to fulfill a selected objective over a pre-specified time frame. Typical output variables of the CEMS are the binary decision variables for connecting or disconnecting loads for load shifting and reference values of the control system (e.g., output power and/or terminal voltage) for each dispatchable DG.

Many CEMS were introduced in the literature. For instance, a CEMS for a microgrid composed of an ESS and wind power generator, using a dynamic linear programming (LP) formulation, is presented in [29]. On the other hand, a CEMS for a PV and storage microgrid is implemented in [30] by using a linear programming solution technique combined with heuristics. In [31, 32], a different evolutionary algorithms for optimization were applied to the CEMS problem.

A smart energy management system (SEMS) which is used to optimize the operation of the microgrid was presented in [33]. The SEMS proposed by [33] consists of three main modules (power forecasting module, energy storage system [ESS] management module and optimization module). The forecasting module is responsible for predicting the photovoltaic (PV) output power. It is also responsible for predicting the load demand behavior. The main goal of the ESS management module is to optimize the storage system operation in order to fulfill the recommended energy flow. In the meantime, economic load dispatch and operation optimizations of distributed generation (DG) were simplified into a *single-objective* optimization problem in the SEMS. This optimization process was performed for three different operation policies. The objective function of the optimization problem is changed according to the operation policy in order to maximize the operational profit and to minimize operation costs of the microgrid.

The authors of [34] proposes a rule-based energy management system for a collection of energy sources and users. The introduced EMS main objective was to maximize energy utilization efficiency of the sources while satisfying the demand of users. The EMS output is a signal sent to the energy delivery network in order to turn on/off switches and deliver the power to energy users or storage units.

For the most part, the CEMS main advantage is that it allows for a wide observability of the microgrid which makes CEMS suitable for the systems that require a strong cooperation between system resources.

On the other hand, CEMS has many drawbacks as follows:

- Reduced operational flexibility, as modifications are needed for each additional resource or tool (generators, storage systems, etc.)
- Extensive computational requirements to perform the optimization.

Another popular type of energy management system is the distributed energy management system (DEMS) which is based on multi-agent systems (MAS). It was first proposed for microgrids in [35] for optimally coordinating a competitive market environment and with multiple generator owners. The main microgrid resources are represented by different agents that communicate with a central microgrid operator (CMO) in order to control the operation of the microgrid. In other words, consumers, generators and storage systems send buying and selling bids to the Central Microgrid Operator (CMO) according to their requirements, availability, cost functions, technical limitations, and forecasts. The CMO matches buying and selling bids in order to maximize the microgrid profit or minimize the operating costs. In addition, the CMO ensures the feasibility of the recommended operational plan. To allow demand response , reference [36] proposes additional agents which are assigned to additional tools such as load shifting and load curtailment.

The multi-agent based DEMS reduces the amounts of the required data, thus reducing computation time. Additionally, DEMS main advantage is its flexibility, as it provides the plug-and-play feature. However, DEMS based on MAS show deficiencies compared to CEMS when applied to microgrids that require strong cooperation between different system elements [28] in order to reliably operate the microgrid. This is due to the fact that there is not enough information traded between different components and the CMO. Besides, DEMS are not flexible with respect to changing the operator’s objectives or multi-objective based systems. A typical DEMS model based on MAS for a microgrid operation in grid-connected mode is shown in Figure 2.3.

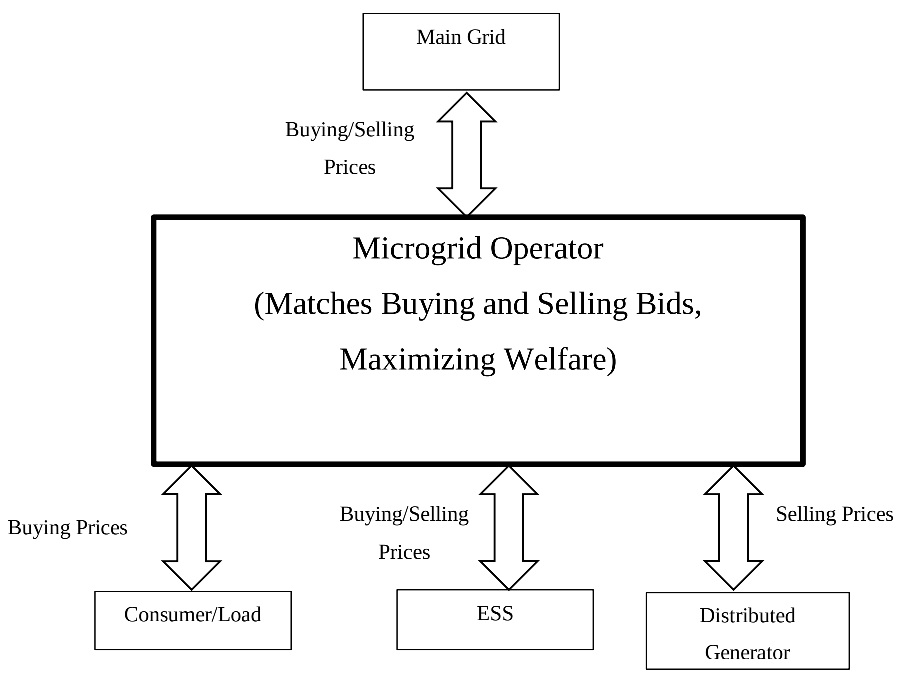


Figure 2.3 Distributed Energy Management System (DEMS)

In [37], a distributed intelligent energy management system (DIEMS) is implemented to optimize operating costs. The function of the DIEMS is to generate set points for all the sources and storages in such a way that economically optimized power dispatch will be maintained to meet certain load demands. The proposed DIEMS features forecasting of power generation for DIEMS in order to simulate the dependency of the optimization on generation and the power output from renewable sources, which strongly depends on the weather. The developed optimization schemes utilize linear programming along with heuristics.

In addition, the authors of [38] propose a multi-agent based decentralized energy management system. The introduced system is applied to a distribution grid for the purpose of voltage stability improvement. The proposed EMS use the reactive power reserves of inverter based DG in order to fulfill the system objective.

2.3.2 Electric utility owned systems

Management and coordination of large numbers of distributed and demand response resources are the most important concerns that need to be tackled by a utility owned energy management systems. In the meantime, a high degree of grid reliability with minimum operational cost must be maintained. When addressing utility owned EMS systems, it is necessary to comprehend and investigate a similar control system which is called Distribution Management Systems (DMS).

A) Distribution management systems (DMS)

There are many definitions for the distribution management systems functions, according to [39] *"Distribution Management System (DMS) is a computer control system for a distribution control center that contains traditional SCADA functions and also contains functions that analyze present and future conditions on the distribution system to support distribution operations".* In other words, DMS should monitor & control the entire distribution network efficiently and reliably. It acts as a decision support system that assists the control room with the monitoring and control of the electric distribution system. As a result, DMS leads to improving the reliability and quality of service by reducing outages, minimizing outage time, maintaining acceptable frequency and voltage levels.

The author of [39] compared distribution management systems with energy management systems as follows:

- Both collect power system status and measurement information via remotely-located data collection terminals**.**

- Both process the collected information and present it to operators.
- Both contain analytical functions to help operators analyze future situations.
- Both store information for later retrieval and analysis of historical events.
- Both are typically connected to other computer systems for sharing data and analytical results.

The authors of [40] introduce the Centralized Model-Based Distribution Management System, which is implemented by Detroit Edison. The introduced DMS supports the following functions:

- Unbalanced load flow (UBLF)
- Line unloading
- Restoration switching and analysis (RSA)
- Fault locating
- Simulation
- Switching plans
- Increased visualization of the distribution network
- Integration with transmission systems energy management system
- Volt/Var optimization
- Integrated outage management system (OMS)
- Integration with Advanced Metering Infrastructure (AMI)

The authors of [40] applied the proposed DMS on a distribution network model to find the optimal settings for the transformer taps and decide whether the capacitors should be switched on or off. However, integrating additional functions, in the introduced DMS in [40], is not a simple action. Moreover, it does not provide demand side management and control which reduce the control capabilities of the system.

In conclusion, DMS offers many functions to support the distribution grid reliability and operation. However, according to [41], distribution management systems fail to offer scalability, functionality and operational capabilities required for managing a large number of *distributed* and *demand-side resources.* As a result, it will be difficult for the DMS to provide the necessary processing support required by end-use consumers and their operational requirements. This is due to the fact that DMS's are more centralized in nature and do not cope with the modern distributed trend distribution systems.

B) *Demand Side Management:*

Utility owned EMS implementations normally require coordination with demand resources management and controls. Hence, research related to demand side and recourses management are investigated and presented in this section.

Demand Side Management (DSM) is used to improve the energy system performance at the side of consumption. DSM could be performed by:

- Improving energy efficiency by using energy saving products.
- Smart energy tariffs with incentives for certain consumption patterns.
- Real-time control of distributed energy resources.

The authors of [42] classify the DSM into four categories according to their timing and impact on the customer process :

- Energy Efficiency (EE)

  Energy efficiency measures include all permanent changes on equipment (e.g., exchanging an inefficient ventilation system with a better one) or improvements on the physical properties of the system (e.g., investing in the building shell by adding additional insulation). In addition, Energy Conservation habits are sometimes considered part of Energy Efficiency [43].
- Time of Use (TOU)

  Time of use tariffs means that customers are penalized for electricity usage during certain periods of time (e.g. peak hours) with a higher price. Consequently, customers will reschedule their consumption in order to minimize their costs. However, TOU is not a flexible technique for DSM because a change in the TOU price-schedule means a change in a supply contract/tariff which does not happen frequently.
- Demand Response (DR)

  Demand Response techniques are classified as dynamic demand side management. Demand response might not only reduce the customer's energy consumption but it manages it too. For example, a water pump is a load type that can be easily shaved or shifted for a specific period due to the presence of its storage tanks. However, when the water pump is allowed to operate again, it has to fill up the tanks which were drained during the shedding period. Eventually, this means that energy is not saved and a new peak may be generated. Such an effect is called payback or rebound effect (figure 2.4).

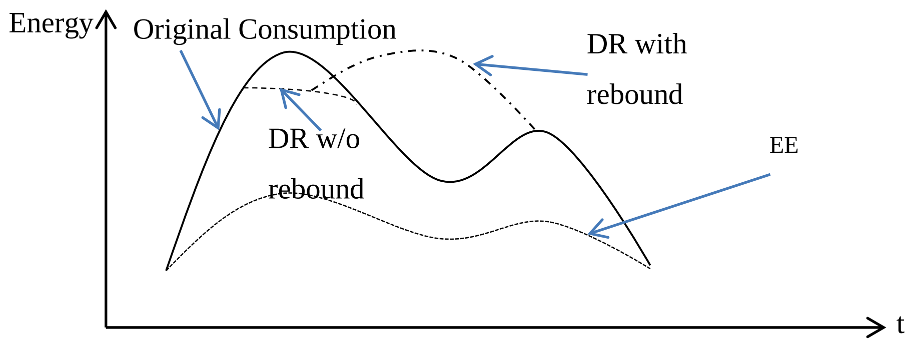


Figure 2.4 Impact of improved energy efficiency versus demand response

Loads are motivated to contribute to DR as follows [44]:

- *Incentive-Based DR:*
    - i- **Direct load control (DLC)**: utility or grid operator gets free access to customer processes.
    - ii- **Interruptible/Curtailable rates**: customers get special contract with a limited number of sheds.
    - iii- **Emergency demand response programs**: voluntary response to emergency signals.
    - *iv*- **Demand bidding programs**: customers can bid for curtailing at attractive prices
- *Time-Based Rates DR:*
    - i- **Critical peak pricing**: a less predetermined variant of TOU.
    - ii- **Real-time pricing (RTP)**: wholesale market prices are forwarded to end customers.

- Spinning Reserve (SR)

  This means that loads can act as "virtual" (or negative) spinning reserve if their power consumption is correlated to the grid state in a "droop control" or some other smart manner. For example, devices use less power if frequency drops [45].

Generally, demand response is the most useful technique that can be utilized by EMS during system operation. Typically, a signal, which contains a price or a command for load curtailments/shifting, is sent by the distribution system operator. The deadline for satisfying the command is not necessarily instantaneous. It might be in the next hour or even in the next day.

In Direct Load Control (DLC) it is assumed that loads are fully under control. Meanwhile, all intelligence is assumed to be in the decision making system. A stochastic model for loads is used in [46] for the purpose of saving energy costs and system losses. In [47, 48] a modern system for automated demand response, OpenADR, is introduced. In OpenADR, a message is sent from the operator to a server. The server then forwards the message to the subscribed clients (loads) in order to react to the operator's message.

In addition, demand shifting could be achieved by using load models. If a grid emergency is predicted to take place at a specific time, intelligent consumers can plan ahead and do their tasks earlier (if applicable) or later. For example:

- Precooling
- Producing for the stock
- Filling water tanks
- Industrial load rescheduling

Load peaks should be moved before the shed time in order to avoid any trouble during the shedding time. In order to achieve this, load models are needed to predict how long things can be turned off, how much it takes to fill the "virtual storage" and what it costs [49]. The "virtual storage" of Demand Shifting can be enhanced by special means, such as increasing the thermal isolation of a structure [50].

A commercial *decentralized energy management* system was developed by Siemens [7]. DEMS® offers intelligent solutions for central control of decentralized systems for power supply companies, industrial companies, operators of functional buildings and energy service providers in deregulated markets. DEMS® overcomes the power fluctuations of renewable DGs by utilizing a controllable and switchable load to compensate these continuous changes. However, DEMS® mainly focuses only on reducing the operational costs and increasing the customer's profit. In addition, DEMS® controls the distribution system energy using the so called Virtual Power Plants (VPPs). VPPs are a community of typically smaller generation units (often renewable energy sources) that appear as one power plant to the grid management [51]. DEMS® is the centralized management that controls the typically distributed equipment from a central dispatch and management node.

Loads in VPPs are considered special cases. As loads cannot generate power, they can only act as virtual storage by using demand shifting. Aggregating many loads leads to considerable sizes that can participate on power markets and compete with traditional electric storage [52].

The most important benefit of VPPs is the guaranteed availability. This means that if the grid operator requires a specific amount of power, it must be delivered. However, the main drawback of this technique is the need for a large number of intelligent loads which are capable of shifting its virtual storage ahead in order to avoid any troubles during the emergency time as described before.

2.4 Conclusions and Discussions

In conclusion, according to the literature, the main role of *single unit EMS*, or BEMS (Building Energy Management Systems), is to manage the energy flow through the building in order to fulfill the decision maker's objectives. BEMS must be an adaptive system in order to cope with building changes and updates which is not the case in most of the surveyed literature. Besides, the surveyed BEMS address the energy management problem from two perspectives. The first perspective is by specifying different decision makers' limits (such as electricity bill value, specific energy consumptions, etc.). Meanwhile, BEMS monitors the energy usage. Once a specific limit is reached, BEMS starts to manage or shed the system loads and energy usage in order to avoid violating the system specified limits.

The second perspective is that BEMS is designed in such a way that is solves the multiple objectives optimization problem related to comfort maximization and energy costs minimization. Most of the literature tackled this multi-objectives problem *only* by identifying objective priorities, and consequently, the problem is converted into a single objective problem with different weights for each objective.

Weighted multi-objectives technique has a major difficulty with the criterion that would be used for identifying the weights values. A priori selection of weights does not necessarily guarantee that the final solution will be acceptable [53]; thus, the optimization problem should be resolved with new weights. In fact, weights must be functions of the original objectives, not constants, in order for a weighted sum to mimic a decision maker preference function accurately. The second drawback with the weighted sum approach is that it is impossible to obtain points on non-convex portions of the optimum feasible space boundaries [54-56]. Finally, the authors of [54] indicate that varying the weights consistently and continuously may not necessarily result in an even distribution of Pareto optimal points and an accurate and complete representation of the Pareto optimal set.

In case of whole system EMS, most of the energy management systems that were surveyed do not provide sufficient flexibility in case of system structural variations or objectives changes. In other words, each EMS is designed to be applied only on their corresponding distribution systems for which they were primarily designed for.

Furthermore, most of the proposed systems are commonly developed to only fulfill a single objective which is either operational costs minimization or profit maximization. Few researches introduced multi-objectives optimization by taking into consideration the minimization of greenhouse gases emission. However, multiple objectives problems were tackled by using weighted sum optimization techniques. In addition, they are operated only from a single decision maker's perspective.

Some of the investigated EMS features flexibility of upgrading the controlled system by using multi agents systems which also reduces the computational analysis. However, using multi-agents, full control of different components will be difficult due to the lack of relevant information which leads to reduced cooperation between different elements and the centralized controller.

In order to develop efficient energy management systems, it is necessary to utilize demand side management. *Demand-side management* may operate based on an agreement between the utility and resource owner, e.g., a fixed demand-response or feed-in tariff, or based on a pricing scheme that combines wholesale market, transmission, distribution, and retail charges. New methods, tools and procedures are needed for the end-to-end management of such complex system. These methods and procedures should economically schedule, dispatch and control the demand-side resources while ensuring the reliability of distribution grid and the quality of power supply to retail customers.

Chapter 3 Proposed Zonal Energy Management System

3.1 Introduction

The objective of this research is to develop a Zonal Energy Management System (ZEMOS) that adopts modular built-in functions. According to the literature, present energy management systems can be classified according to their applications into three layers as shown in Figure 3.1.

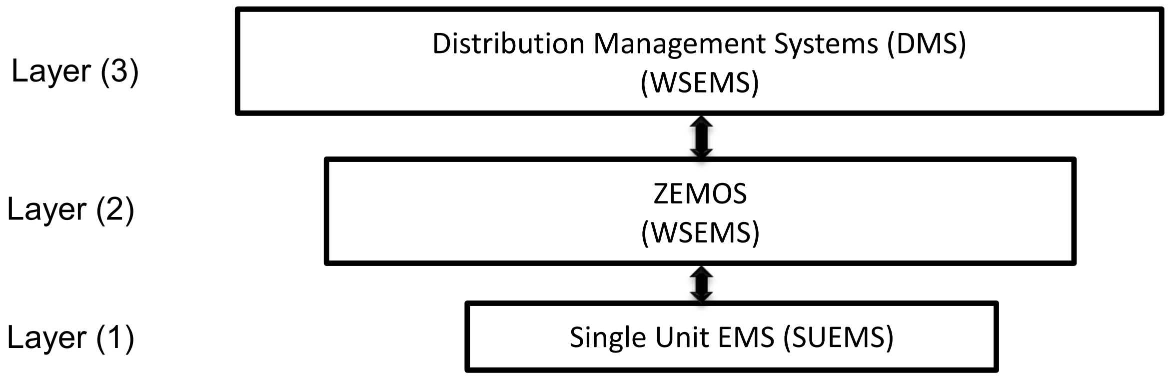


Figure 3.1 The Layers of the Energy Management Systems

The proposed ZEMOS is targeting the middle layer that links the whole system EMS and the single unit EMS as shown in Figure 3.1. The proposed ZEMOS controls, optimizes, and manages the energy between sources and loads of a particular zone. The proposed ZEMOS tackles the deficiencies of the existing energy management systems that were mentioned in the previous chapter. This is achieved by developing custom built-in functions in modular forms that enables the expansion of zonal resources and facilitates the integration of ZEMOS in different zones. As a matter of fact, module-based systems are characterized by their scalability and flexibility since more functions can be added down the road as needed, which is a necessity to accommodate the constant changes imposed by the smart grid. Therefore, the need to change the whole infrastructure of the system is no longer necessary. In this thesis, ZEMOS addresses the zonal problems from an operational planning viewpoint. That is, ZEMOS analysis is performed hours ahead from the desired optimization period. Therefore, security analysis are not taken into consideration within the scope of this thesis.

Besides, the proposed ZEMOS has the ability to control a study zone if multiple decision makers exists in the zone under-study. ZEMOS forecasts the zonal behavior during a specific study period and, consequently, ZEMOS recommends a possible energy flow that fulfills the operator’s, or zone owner’s (decision maker), objectives during the predetermined study period.

3.2 Basic system characteristics and description:

The main role of the proposed ZEMOS is to fulfill the decision maker’s objectives during a predetermined time period. The types of the fulfilled objectives are dependent on the decision maker’s nature and purposes. To illustrate, the decision maker might be an operator who controls a particular sub-division of the distribution system from utility perspective. Consequently, the proposed ZEMOS recommends an energy flow that minimizes the CO_2 emissions or reduce the energy costs in the controlled zone. In addition, this sub-division might suffer from a shortage of electricity due to the increasing load demand during a specific period of time. In this case, ZEMOS utilizes all the zonal possible controlled tools and resources to overcome this problem. Such action results in a deferral in the distribution system necessary upgrades within the controlled zone which will lead to increasing the utility savings. Meanwhile, if the system upgrades are necessary and cannot be avoided, ZEMOS reduces the size and the capacity of the upgraded components.

On the other hand, ZEMOS will be able to serve customer owned zones which might require objectives that are usually different from the utility objectives. For example, the customer might require supply continuity during a predetermined period of time. Favourably, the customer would need to increase the comfort on the account of the cost. As an alternative, another customer might require economic operation in his zone in order to maximize his profit and reduce the operational costs.

On the whole, the proposed ZEMOS uses all the possible zonal controlled resources and tools in order to fulfill the decision makers’ objectives, such as:

- Minimizing CO_2 emissions
- Minimizing energy costs
- Minimizing Zonal losses
- Reducing the installation cost of new equipment (capacitors / reactors)
- Scheduling of the zonal loads
- Improving the power quality

The proposed ZEMOS is a custom built-in energy management system that is composed of a set of extendable modules. Each module activates predetermined functions to achieve specific goals. Eight modules are used to construct the basic structure of the proposed system in order to fulfill the aforementioned objectives.

The first module is the objectives module (OM) which is dedicated to identify and determine the operators' objectives and the corresponding objective functions. The second module is the resources and tools module (RTM) which will determine and collect all the possible zonal controlled resources such as demand side management, controlled components (i.e. capacitors, regulators, reconfiguration switches, etc.), and distributed generation. A smart matching module (SMM) is developed in order to select the most efficient zonal controlled resources that will economically fulfill the operator's objectives. Two modules are developed to generate the optimum states for the system resources that will fulfill the required objective. Those modules are the control module (CM), and the decision making module (DMM). The CM generates the optimum solution sets while the DMM assists the decision makers to select the best solutions set among the generated non-dominated optimal points for multi-objectives operation.

In order to successfully operate the proposed ZEMOS, data storage, forecasting, and processing functions are required. Therefore, a Data Bank module is developed which stores, forecasts, and processes the necessary data for ZEMOS operation. Finally, input and output modules are included in order to collect the ZEMOS inputs and to accommodate the ZEMOS outputs, respectively.

In the next sections, a detailed system description is presented which includes identifying possible system inputs and outputs. Furthermore, a detailed structure of the proposed system modules will be introduced.

3.3 Proposed ZEMOS Basic Structure:

The main achievement of the proposed ZEMOS is its modular based structure. That is, ZEMOS consists of a set of modules; each has its own function. Combined together, ZEMOS modules are expected to fulfill the desired zone owner objectives and needs. Furthermore, each module size could be separately extended in order to enhance the system capabilities. An illustrative block diagram of basic structure of the proposed ZEMOS is shown in Figure 3.2.

In addition to the input and output interfacing modules, a particular module is assigned for identifying the decision maker's (i.e. zone owner or operator) objectives. Once an objective is selected, it will consequently be matched to the most efficient and economical controlled tools, or resources, from the resources and tools module. The most efficient and economic resources, or controlled, are matched to the required operator's objective using the smart matching module. The selected controlled resources/tools are used to fulfill the desired objective. Besides, the proposed system features overlapping between different tools which means that different objectives could use the same tool to satisfy customer requirements that involves multiple objectives.

The control module (CM) is responsible for identifying the optimal values of the tools and resources states that fulfill the operator's objectives while adhering to the zoonal operational constraints.

The proposed ZEMOS is a multi-objective, multi-decision maker system. Such a feature requires the presence of a conflict resolution algorithm. As a result, the CM investigates the presence of conflicts between objectives and between decision makers. Combined with the decision making module, the CM identifies decision maker's preferences and selects the best solution algorithm that generates optimum non-dominated solutions sets. These generated solutions sets will be reduced to a single solutions set by the decision making module.

A data bank module is necessary for data storage, data forecasting and data processing. The data bank module is also needed for identifying the system status (normal, emergency, restoration, loading conditions, DG states, etc.).

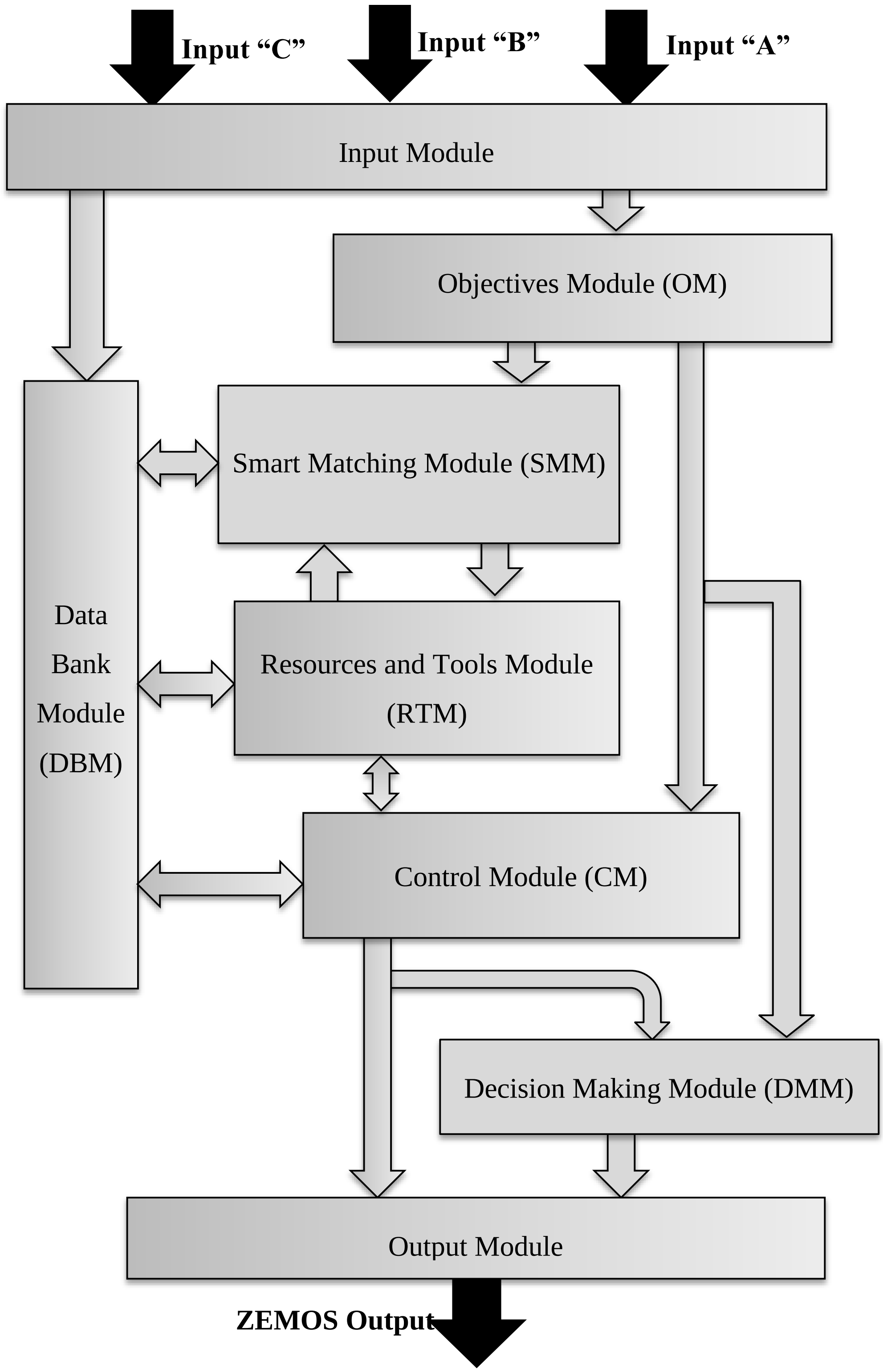


Figure 3.2 Basic structure of the proposed Zonal Energy Management and Optimization System (ZEMOS)

3.3.1 Input Module:

The proposed ZEMOS requires a set of input data that will be collected by the input module during the system operation. ZEMOS inputs are divided into three main groups.

A) *Decision inputs:*

Decision inputs are the variables that should be specified by each decision maker (zone operator /zone owner) in order to control the operation of the proposed ZEMOS. The main decision inputs are:

- **Objectives selector**

  This is the main input which determines the main objectives required by the decision maker. This input will raise two flags: the first flag is used to determine the number of objectives requested by the decision maker. The second flag is used to indicate the type of the problem that is handled by ZEMOS (i.e. single or multiple decision makers problem). Consequently, the control module will be able to identify, through this input, the appropriate control algorithm that corresponds to the nature of the problem.

- **Objectives priorities**

  This input indicates whether the objectives have equal priorities or not. Those objective functions of unequal priorities should be ranked according to the decision maker's preferences. This input is used by the control module and the decision making module in order to determine the adequate technique which will be used to maintain the decision maker's objectives for the purpose of multi-objective operation.

- **Objective functions magnitudes acceptable limits:**

  This input is used by the decision making module to specify which solution point of the ZEMOS set of solutions should be excluded from the generated optimal set. If not supplied by the operator, the acceptable limits are set, by default, to be equal to the base-case values.

- **Constraints**

  This input indicates different decision maker constrains. They are adjusted by each decision maker only once and they are stored in the CM. The stored constraints will not be changed unless the decision makers wish to readjust them.

- **Objectives duration**

  The proposed ZEMOS includes a stochastic data forecasting technique. Consequently, these forecasting functions require a time duration that is used as a forecasting time limit.

- **Decision maker's time limit**

  This is the time duration between the decision maker first interaction with ZEMOS and the time at which the decision maker's objectives will be fulfilled. This time limit is the stopping criteria for the ZEMOS calculations and operation until the ZEMOS output is provided.

B) System information:

System information includes all the data that identifies the system and components status, such as:

- System state (normal, emergency, and restoration)
- Distributed generators (number of DGs, types of DGs, number of dispatchable DGs and their info, such as ratings, historical solar irradiance and/or wind speed data)
- Loads (ex., types of loads and load models [constant current, constant voltage, constant power, etc.], and historical load data)
- Transmission lines (parameters, and transmission lines capacities).
- Utility energy prices… etc.

C) Measurements and online data:

The measurements input represent the online data (readings, notifications) collected from different system meters such as:

- Smart meters data.
- Decision maker selected strategies in case of multi-decision making multi participants operation (e.g. selected demand response reductions, selected DG owners' output power…etc.)
- Voltages
- Main feeder currents
- Present loading conditions (peak, light loads, load demand etc.)

3.3.2 Objectives Module (OM)

The main purpose of this module is to store all the possible objective functions that are modelled according to the decision maker (DM) requirements. The objective functions are then to be selected by the decision maker under different operating conditions. It is worth noting that the objectives module is extendable in terms the number of objectives functions that can be stored. That is, mathematical models of the stored objective functions can be updated independently regardless of the controlled resources, control algorithm, and system status. The basic structure of the objectives module is shown in Figure 3.3.

The inputs of the objectives module are based on the decision maker's (i.e. system operator) needs, which are represented by ZEMOS input "A" (described previously in section 3.3.1).

The objectives module has two output groups. The *first output group* includes the objectives duration, selected system constraints, objectives priorities, processing time limit, objectives functions magnitudes acceptable limits, and the number of objectives selected by the decision maker. This output group will be useful for the control module (CM), which will be explained later.

The *second output group* of the objectives module is the types of objectives functions selected by the decision maker (operator/zone owner). The second output group is used by the SMM as explained in the next section. Besides, the second output group is sent to the CM in order to optimize the selected objectives functions.

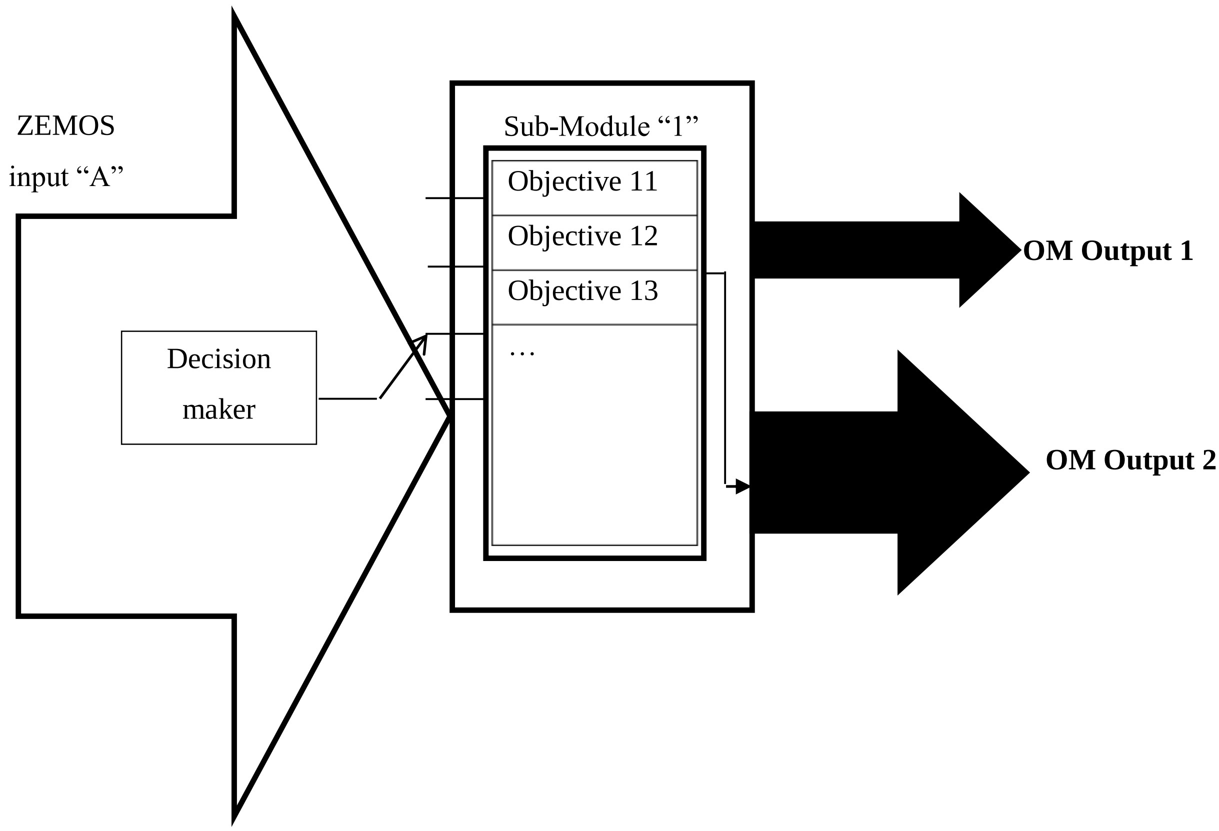


Figure 3.3 Objectives Module (OM)

3.3.3 Smart Matching Module

The smart matching module (SMM) determines the most economical and efficient controlled system resources or tools. Thus, SMM reduces the amount of calculations and the operational costs required to optimally operate the zone under-study. The purpose of the SMM is to reduce the optimization process computational requirements by decreasing the number of decision variables. That is, the algorithm avoids the utilization of the controlled resources that produces results that would have a negative impact on the operator’s objective.

Besides, the SMM reduces the possibility of utilizing the controlled resources that requires a high operational costs related to controlling that resource, and, in the meantime, those controlled resources have an insignificant effect with respect to the operator’s objective; thus, decreasing the overall operational costs associated with the system optimization process. The proposed SMM can be applied with any kind of controlled resource or any type of objective functions. As a result, the SMM will facilitate the potential variations of the operator’s needs.

The SMM requires the identification of the selected objectives functions from the OM. In addition, the SMM needs to recognize the current system conditions, system information, and historical data which are supplied by the data bank module. Furthermore, the SMM needs to exchange information with the data bank module in order to be able to evaluate the impacts of changing each system controlled resource on the selected objective functions. In the meantime, for all the controlled tools and controlled resources, the decision variables upper limits, lower limits, and states needs to be identified by the SMM. Consequently, these information will be collected from the Resources and Tools Module (RTM).

The SMM output is a vector that is sent to the Resources and tools module (RTM). The SMM output matches the operator's objectives with the system resources. In other words, the SMM selects the most efficient resources and tools that fulfill the operator's objectives.

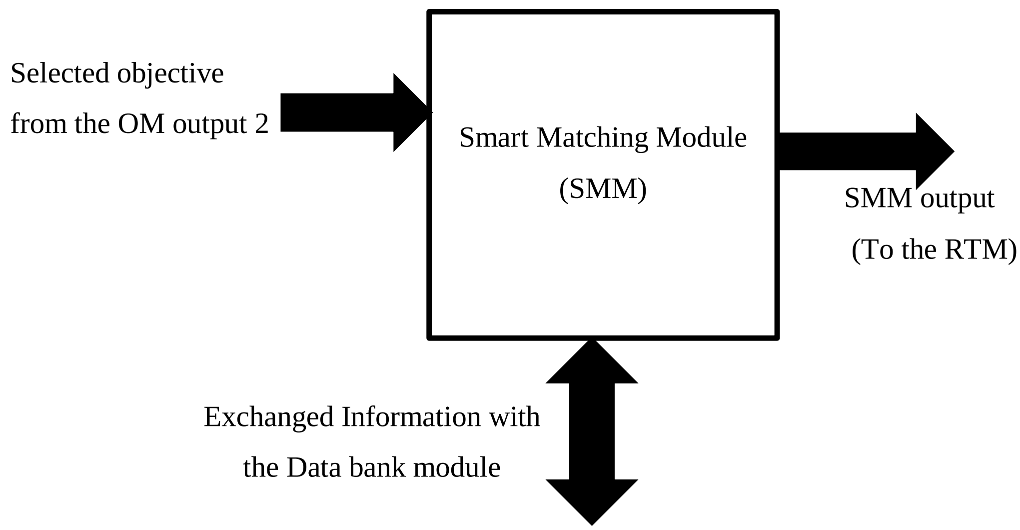


Figure 3.4 Smart Matching Module (SMM)

3.3.4 Resources and Tools Module (RTM)

The RTM module consists of a set of sub-modules; each represents a possible zonal controlled tool or resource. A controlled tool/resource is a possible zonal means that can be utilized to fulfill a specific objective function. A system resource might be a contracted demand response participant, DG set points, capacitors switching states, voltage regulator taps, etc. All the possible zonal tools and resources in the controlled zone are mathematically modelled and stored in the RTM.

There is one variable and two vectors attached to each tool, as follows:

- *Nvar:* indicates the number of input variables (states) required by each controlled resources (e.g. amount of loads reduced, voltage regulator tap position, etc….).
- *Lbound :* vector indicating the lower bounds of all the controlled resources decision variables or states.
- *Ubound :* vector indicating the upper bounds of all the controlled resources decision variables or states.

The selected resources or tools are determined by the SMM output. For instance, according to Figure 3.5, it is predetermined using the SMM that objective 11 is efficiently fulfilled by controlling resources no. "1" & "2"; hence, a signal is sent to the RTM to activate the controlled no. "1" and "2". As a result, the set points of both resources (1 & 2) are recognized as unknowns and will be defined as decision variables that need to be optimally evaluated by the control module in order to fulfill objective "11".

On the other hand, Resource "3" has not been activated by any objective; thus, its inputs will remain as in the base-case values, which are identified by in the data bank module.

Generally, RTM has two inputs groups and two output groups:

- *Inputs group "1":*

  This input is the SMM output which includes information about the controlled tools/resources that must be activated.

- *Inputs group "2":*

  This input is received from the data bank module, which determines the base-case values that represent the states of the inactivated controlled tools/resources or the selected strategies for the multiple decision makers operation.

- *Outputs group "1":*

  This is the RTM output that is sent to the control module(CM), which specifies the number of unknown variables (*Nvar*), and their lower and upper bounds for each activated controlled tool/resource. These values will then become the decision variables of the optimization problem or the control algorithm.

- *Outputs group "2":*

  The second RTM output represents the values for controlled tools/resources that are not activated by the objectives module but are evaluated according to their base-case states.

To illustrate, according to Figure 3.5, the outputs group of the RTM will be as follows:

i. *Nvar1*, *Lbound1*, *Ubound1* (output 1)

ii. *Nvar2, Lbound2, Ubound2* (output1)

iii. Base case values of Resource *"3"* (output 2)

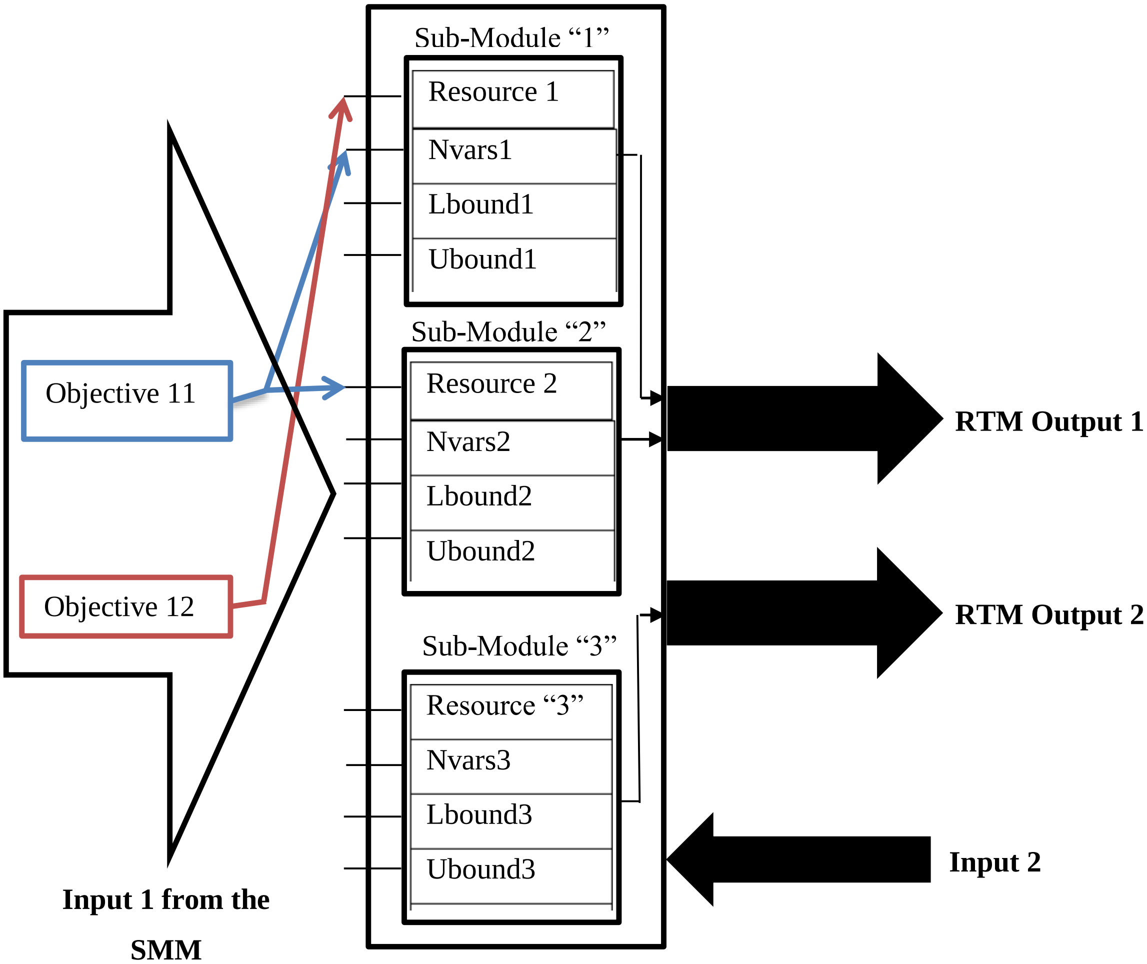


Figure 3.5 Resources and Tools Module (RTM)

3.3.5 Control Module (CM)

A number of optimization and conflict resolution algorithms are stored in the CM. The optimization/control algorithm is selected according to the number of decision makers, and the number of objectives per DM and the nature of the problem, both of which are determined from the objectives module (output "1"). The current ZEMOS implementation involves classification based on two possible cases:

- **Single decision maker:**

  For a single decision maker operation, ZEMOS operation can be classified into two possible cases:

1. *Single decision maker with single objective:*

   In this case, the CM generates a solution that is a single set of decision variables that meets the DM's objective.

2. *Single decision maker with multiple objectives:*

   In contrast, the CM in this case does not offer a single solution but must determine a set of points that all fit a predetermined definition for an optimum solution. For such a set of solutions, one solution cannot be said to be preferable (i.e. dominates) to another. This concept for defining optimal solutions is recognized as Pareto optimality [57]. The main goal of the CM is to find as many Pareto-optimal and feasible solutions as possible.

- **Multiple decision makers:**

  For multi-decision makers (DMs) operation, necessary conflicts resolution control algorithm is developed and stored in the CM. In conflict resolution, the control algorithm is used in order to perform a stability analysis which is defined as the study of possible moves and counter moves by all the decision makers in order to determine the most likely and acceptable solution. Consequently, a solution point is said to be a stable point and acceptable for a specific decision maker (DM), if the DM has no incentive or motivation to deviate from it "independently" under a specific stability definition. An equilibrium set of points means that all decision makers consider this set of points as a stable set of points. As a result, the main goal of the CM is to determine the equilibrium set of points for a study system.

Upon the selection of the appropriate algorithm, CM starts the process of generating the solution points set while adhering to all the decision makers' constraints.

The CM (Figure 3.6) inputs are:

- OM outputs (output 1 &2)
- Number of decision variables along with their upper and lower bounds (RTM output 1)
- Base-case states and values for the inactivated tools and resources (RTM output 2)

Coordination, via CM output "2," is also required between the CM and the data-processing sub-module for the necessary parameters and electrical quantities to be evaluated (e.g. load flow analysis). The optimal set of solution points, generated by the CM, is stored in the output module and also communicated to the decision-making module through CM output "1".

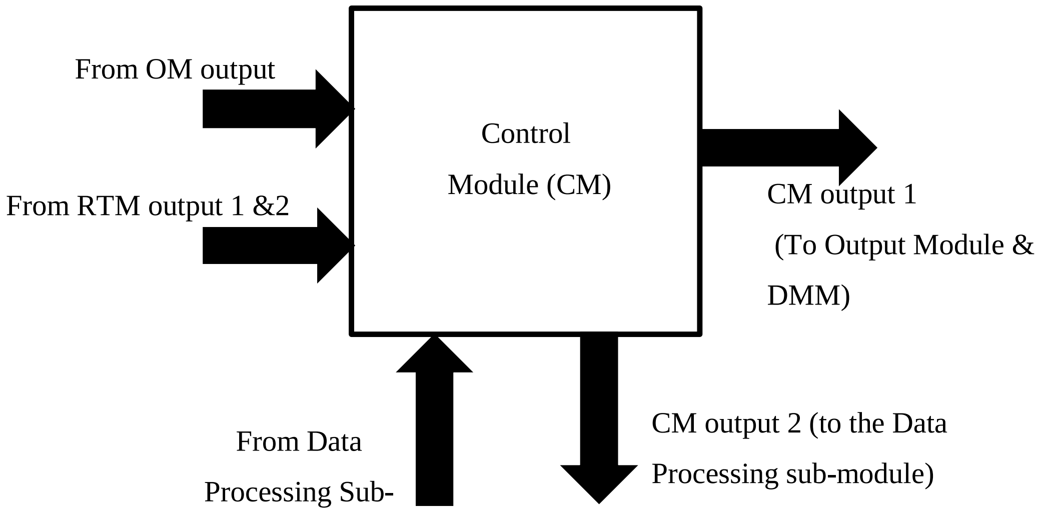


Figure 3.6 Control Module (CM)

3.3.6 Decision making module (DMM)

The main purpose of the decision-making module is to adopt a predetermined decision-making approach for recommending a single solution that will meet all the DM's objectives as well as satisfying all the DM's operational constraints. Generally, decision making approaches can be classified into three main types [58]:

a. ***Priori Approach*** [58]: in which a decision is made before searching for the solutions (Decide⇒Search).

   Generally, a priori approach is combined with the representation of the problem as a weighted sum of objectives. Priori approaches require a decision maker (DM) to define the objectives' priorities prior to search. This is usually reflected in the weights associated with the weighted sum of the objectives. In this case, the preferences of the DM are modeled to evaluate and compare solutions ([59],[60]). Accordingly, the decision making module will send a signal to the CM in order to select the appropriate algorithm and its corresponding settings (such as the values of the weights in weighted global optimization technique). Such a technique requires low computational time which results in a quick single solution.

   However, the main problem with this approach is that it limits the search space, as it will not be able to find all the possible optimal solutions (which is called Pareto Front). Moreover, weights (no matter how they are defined) could be greater or smaller than necessary. As a result, a more preferable solution could be missed.

b. ***Interactive approach*** [58]: in which decision making is integrated with search (Decide⇔Search).

   An interactive approach requires the interaction of the decision maker during the search process. Therefore, the decision maker's preferences are changed according to the present situation. This approach will increase the efficiency of the generated solution. However, interactive approaches also have some drawbacks, mainly related to the preference information that the DM has to provide during the search. For example, the DM can be asked to rank a set of solutions to estimate weights. Usually, a decision maker finds difficulties in providing answers that can guide the search in a systematic way towards a better solution [61]. As a result, the preference of a DM tends to be so inconsistent that it might be even ignored without significantly affecting the results of the decision-making algorithm. Interactive approaches that adopt a simple trial-and-error procedure tend to be highly competitive [62]. Thereby, an interactive approach is time costly from the DM's perspective.

c. ***Posteriori Approach*** [58]: in which a decision is made after searching for a solution set (Search ⇒ Decide).

Posteriori approach executes the decision making process after completing the search process. In other words, a Pareto optimal set is generated and then a posteriori approach will start the process of searching within the generated points in order to find the best point. Consequently, the flow of the information will be from the CM module towards the DMM. The use of a posteriori approaches is popular in operation research field[59, 63].

Any of these approaches could be used in the proposed ZEMOS, or they could be combined in order to come up with a more efficient approach. In this research, a Decision Making Model that is based on a combination between posteriori and interactive approaches is developed and stored in the DMM. The DMM has two main inputs:

- Set of optimum or equilibrium solutions points generated by the CM (CM output 1)
- Decision maker's objectives limits and objectives priorities (OM output 1)

The DMM main output is a single set of optimal decision variables that results in a single solution point, which is stored in the output module. That is, the final recommended output of the ZEMOS.

3.3.7 Data bank Module (DBM)

The data bank module (Figure 3.7) is divided into three sub-modules: data storage sub-module, data forecasting sub-module and data processing sub-module.

A) Data storage sub-module:

The main goal of the data storage sub-module is to store the necessary data for the ZEMOS operation, such as:

- Base-case values of zonal controlled resources and tools (loads values, capacitor's switching states, storage systems charging status, etc.).
- Present system demand values, and distributed generations states.
- System status (emergency, normal, restoration).
- Historical data (solar and wind DGs power levels, loading, etc.).

B) Data Forecasting Sub-module:

Typical distribution systems consist of a large number of elements that are stochastic in nature, such as electrical loads and renewable energy sources. In addition, many countries introduced the Feed in Tariff [64] (FIT) program which is considered as a straightforward way to contract for renewable energy generation. Such a program encourages the installation and the implementation of renewable energy generation projects. Under the umbrella of the FIT program lies the microFIT program [65] which is originated for very small renewable generators (rated less than 10kW). Hence, a typical distribution system sub-division (Zone) might include a large number of renewable distributed generators due to the deployment of the FIT and microFIT programs. Consequently, the number of stochastic elements in the distribution systems is significantly increasing.

Accordingly, in order to fulfill and maintain a particular decision maker's objective during a specified period, the proposed ZEMOS is expected to forecast the future behavior of the study system within the specified period by predicting the power output of renewable sources and the load demands. This task is the main function of the data forecasting sub-module.

In general, a data forecasting model is developed and stored in this sub-module. As with the remainder of the ZEMOS modules, different forecasting models can be developed and stored in the data forecasting sub-module down the road as long as ZEMOS is being utilized.

C) Data processing sub-module:

Data processing sub-module is necessary to process the data used for the CM analysis and operation. Data processing normally entails the evaluation of system objectives functions such as energy loss, unbalance, energy costs, and emissions rate, etc. This sub-module is used for simulating the system load flow based on the stored data, system resources states, optimal decision variables magnitudes and predicted stochastic data. The data processing sub-module has the following inputs:

- Data storage sub-module output
- Data forecasting sub-module output
- Decision variables optimal states (CM output 2)

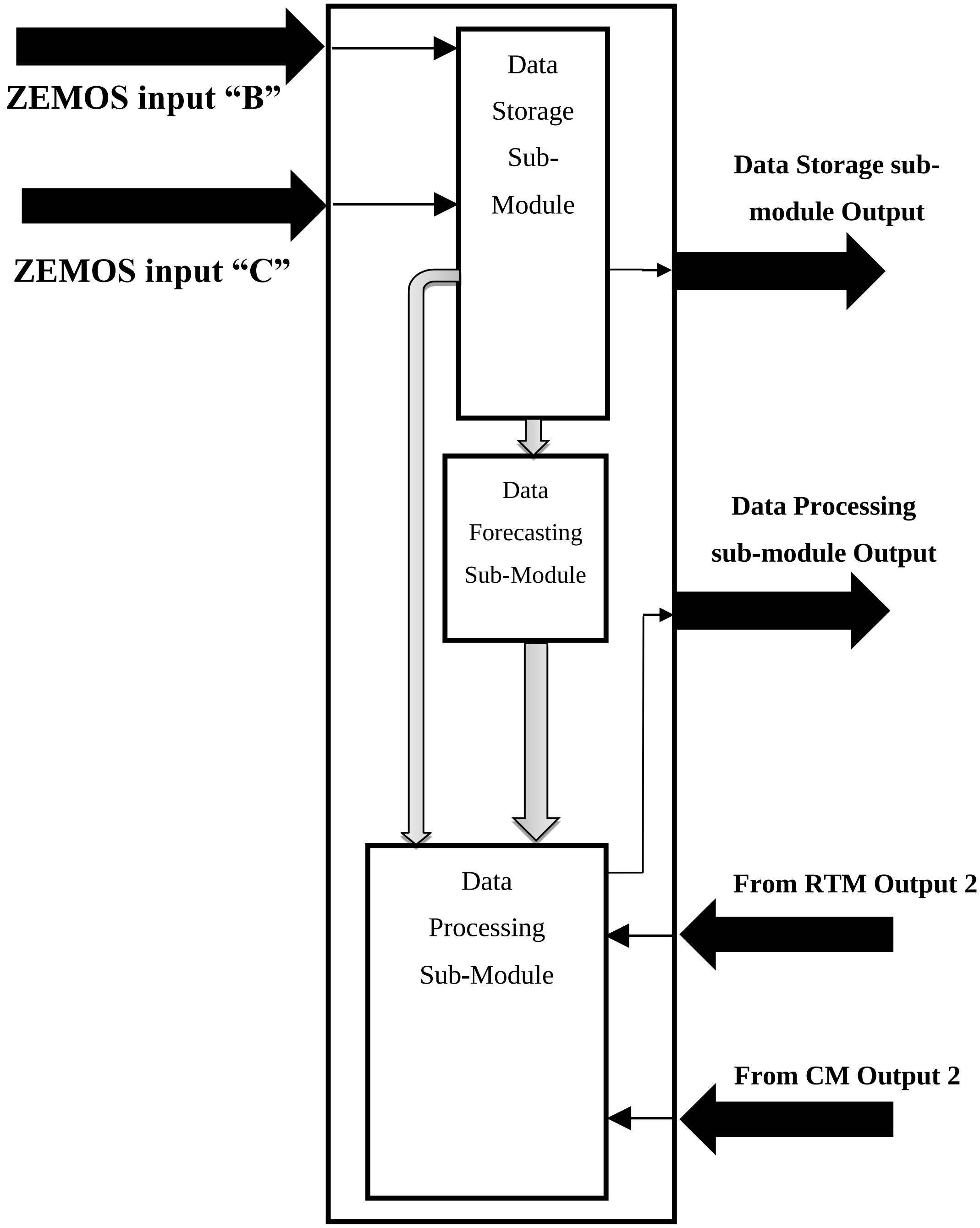


Figure 3.7 Data Bank Module (DBM)

3.3.8 Output module:

In order to fulfill the decision makers' objectives, the proposed ZEMOS is expected to generate an optimal set of solution points for the controlled zonal resources and tools that will fulfill the decision makers' objectives. The expected system outputs are:

A) The controlled systems tools and resources that needs to be optimized.

B) The recommended optimal states of the controlled resources and tools, such as

- Amount of load demands that will be curtailed, or shifted.
- Amount of DGs output powers.
- Capacitors switching states.
- Voltage regulators tap settings.
- Reference values for control systems.
- Reconfiguration switches states

C) The time instant and the duration of the recommended states.

3.4 Communications layer:

Although the development of the communications layer is out of the scope of this research, a brief description of the necessary communications technologies is presented in this section. A two-way communications platform is essential to the operation of the proposed ZEMOS. Communications media are classified into two main media wired and wireless, that can be used for data transmission between smart meters, tools and resources controls, SUEMS, WSEMS, electric utilities and ZEMOS. There are several possible communication technologies that might be utilized for communication between ZEMOS and necessary system components[66]:

3.4.1 Dedicated Wireless networks:

A) ZigBee:

ZigBee is a wireless communications technology that is relatively low in power rating, low data rate, low complexity, low bandwidth requirements, easy network implementation, being a standardized protocol based on the IEEE 802.15.4 standard [67] and low implementation cost. It is ideal for smart lightning, energy monitoring, home automation, and automatic meter reading, etc. According to [68], ZigBee is recognized as a good option for metering, energy management, and for smart grid implementations.

ZigBee Smart Energy Profile (SEP) also has some advantages for electricity utilities, such as load control and reduction, demand response, real-time pricing programs, real-time system monitoring, and advanced metering support[68, 69].

On the other hand, there are some limitations on ZigBee such as low processing capabilities, small memory size, and interference with other appliances, which share the same transmission medium [68]. Consequently, interference detection schemes, interference avoidance schemes and energy-efficient routing protocols, should be implemented to extend the network life time and provide a reliable and energy-efficient performance.

B) Wireless Mesh

A mesh network is a flexible network consisting of a group of active nodes, where each node can act as an independent router. If any node should drop out of the network, wireless mesh network enables the communication signals to find another route via the active nodes, In North America, RF mesh-based systems are very popular [66]. In addition, Mesh networking is a cost effective solution with dynamic self-organization, self-healing, self-configuration, high scalability services, which provide many advantages, such as improving the network performance, balancing the load on the network, extending the network coverage range[70]. On the other hand, Network capacity, and interference can be considered as the major drawbacks of wireless mesh networking systems. Since the metering information passes through every access point, some encryption techniques are needed for security purposes which mean that a third party company is required to manage the network.

3.4.2 Cellular Network Communication

Existing cellular networks can be used for communicating between ZEMOS and the far nodes. The existing communications infrastructure is cost effective in terms of reducing operational costs and additional time requirements for building a dedicated communications system. GPRS, 2G, 2.5G, 3G, WiMAX, and GSM are the main solutions provided by cellular networks.

Lower cost, better coverage, lower maintenance costs, and fast installation features are the main advantages of utilizing cellular network smart grids applications[66], such as demand response management, advanced metering infrastructures, outage management, etc.

On the other hand, some critical situations need continuous availability of communications. The services of cellular networks are shared by customer market and this may result in a decrease in network performance in emergency situations. Hence, these considerations can drive utilities to build their own private communications network.

3.4.3 Power line communication or power line carrier (PLC):

Power lines were originally designed to transmit electric power in the frequency range of 50-60 Hz. PLC technology can be well suited to urban areas for smart grid applications, such as smart metering, energy monitoring and control applications, since the PLC infrastructure is already covering the areas that are in the range of the service of utility companies.

However, there are some technical challenges with the PLC due to the nature of the power line networks. Furthermore, the network topology, the number and type of the devices connected to the power lines, wiring distance between transmitter and receiver, all, significantly affect the quality of signal being transmitted over the power lines and increase the noise level [71].

3.4.4 Digital Subscriber Lines

Digital Subscriber Lines (DSL) is a high-speed digital data transmission technology that uses the wires of the voice telephone network. The already existing infrastructure of DSL lines reduces installation cost. Therefore, DSL technology is a good option for implementing communications between ZEMOS and different system elements.

However, there are some drawbacks such as the problems caused by the distance dependence. Moreover, the wired DSL-based communications systems require communications cables to be installed and regularly maintained, and thus, cannot be implemented in rural areas due to the high cost of installing fixed infrastructure for low-density areas.

On the whole, wireless communications have some advantages over wired technologies, such as low-cost infrastructure and ease of connection to difficult or unreachable areas. However, transmitted signals may suffer from interference and attenuation due to the nature of the transmission path.

On the other hand, wired solutions do not have interference problems and they have the ability to increase the communications capacity, reliability and security. Moreover, their functions are not dependent on batteries, as wireless solutions often do. However, they are costly in case of wide area deployments[66].

3.5 Conclusions

In this chapter, the proposed ZEMOS basic functions were introduced, indicating the main system goals and benefits. In addition, a detailed system structure was presented which includes ZEMOS required inputs and expected outputs. Furthermore, different system modules were described in details, showing the purpose, construction, inputs, and outputs of each module. In addition, a detailed description of necessary coordination between ZEMOS modules is presented.

In the next Chapters, detailed mathematical models and analysis of the proposed ZEMOS will be presented accompanied with the supporting simulation results.

Chapter 4 Zonal Energy Management System with Single Decision Maker (Modelling)

4.1 Introduction

In this chapter, the proposed ZEMOS is mathematically developed for a single decision maker with both single and multi-objectives. Three objectives are introduced as potential applications of ZEMOS that reflects different distribution system practical areas, and accordingly, objective functions are mathematically formulated and stored in the objective module. Besides, typical distribution system operational constraints are presented.

In addition, possible zonal controlled resources, which will be employed by ZEMOS according to the operator's selected objectives, are mathematically modelled. In this research, the controlled resources and tools are assumed to be installed in the study system prior to the application of the proposed ZEMOS. Thereby, the role of the proposed ZEMOS is to control the tools/resources states (set points) only, not to allocate or size them.

As presented in Chapter (3), the proposed ZEMOS is a modular based system that consists of eight modules. Therefore, different algorithms are developed and formulated for data forecasting, smart matching module and decision making module.

4.2 Objectives Module (OM)

The main purpose of this module is to determine the objectives according to the requirements specified by the decision maker (DM). The objectives are initially stored in the objectives module and selected by the DM. It should be mentioned here that the objectives module is extendable in terms of the number of objectives. The input to the objectives module is determined by the DM (input A).

In this research, initially, the main objectives are stored in the objectives module which is related to: the minimization of the energy losses, the phase unbalance minimization, and the minimization of the total amount of CO_2 emissions (COE). These objectives were to be achieved on an operational planning basis (i.e., hourly). On the whole, ZEMOS can minimize the current unbalance, the energy loss, and/or the total amount of COE during a period specified by the operator/DM.

The objectives module input will be assigned to a variable X_j^{obj} , where

$$X_j^{obj} = \begin{cases} 0 & \text{Objective j is not selected by the decision maker} \\ 1 & \text{Objective j is selected by the decision maker} \end{cases}$$

Three objectives are selected for the sake of validating the proposed system. In addition, the system is simulated with three objectives per decision maker. Each objective will be described in the next subsections.

A) Phase unbalance minimization:

The unbalanced currents in the distribution system may lead to excessive neutral currents that result in a tripping of distribution feeders. Meanwhile, three-phase balance affects motors and other devices that depend upon a well-balanced three-phase voltage source. Phase balancing enhances the system performance by improving reliability, quality, and reducing operation costs. In general, the system voltage profile will be improved with balancing the system phases as well as the system energy losses.

Therefore, the first objective in the OM is to minimize the current unbalance in the main feeder of the electric distribution zone. The magnitude of the current at each phase of the main feeder $I^{\Phi}{}_{h}$ is first determined. The current unbalance can then be calculated for each phase and at each hour h of the specified period, as follows:

$$I^{\phi}_{h_{unbalance}} = 100 \times \left\| I^{\phi}_{h} \right| - I_{h_{ave}} \left| / I_{h_{ave}},\ \forall \phi \in \{a, b, c\} \qquad (4.1)$$

where,

$$I_{h_{ave}} = \left(\left| I^{a}_{h} \right| + \left| I^{b}_{h} \right| + \left| I^{c}_{h} \right| \right) / 3,\ \forall h \in \{1, 2, 3.......h_{tot}\} \qquad (4.2)$$

The next step is the calculation of the current unbalance index (CUI) $U_{I,}$ which is based on the identification of the maximum value of the current unbalance for all phases and for all hours simulated during the specified period. A reduction in the value of the CUI that brings it below the acceptable limit indicates that the DS is balanced [72].

$$CUI = U_{I} = \max \left\{ U^{1}_{I}, U^{2}_{I}, U^{3}_{I} ... U^{h}_{I}, ... U^{h_{tot}}_{I} \right\} \qquad (4.3)$$

where,

$$U^{h}_{I} = \max \left\{ I^{a}_{h_{unbalance}}, I^{b}_{h_{unbalance}}, I^{c}_{h_{unbalance}} \right\}, \forall h = 1, 2, ... h_{tot}$$

The first objective function is thus

$$F_{1} = \min(CUI) \qquad (4.4)$$

In case of selecting the phase balancing objective, there will be a constraint on the voltage unbalance at the end point of the study system. The voltage unbalance index U_{V} (VUI) is generated based on the same criteria used for calculating the current unbalance index. The only difference, in this case, is that phase voltages are measured for every bus *i* voltage at every hour *h* of the study period, followed by the calculation of the voltage unbalance for all of the system busses:

$$\forall h \in \{1,2,3,...h_{total}\}, \forall \phi \in \{a,b,c\}, \& \forall i \in \{1,2,...N\}$$

$$V^{i\phi}_{h_{unbalance}} = 100 \times \left| \left| V^{i\phi}_{h} \right| - V^{i}_{h_{ave}} \right| / V^{i}_{h_{ave}} \tag{4.5}$$

$$V^{i}_{h_{ave}} = \left(\left| V^{ia}_{h} \right| + \left| V^{ib}_{h} \right| + \left| V^{ic}_{h} \right| \right) / 3 \tag{4.6}$$

The voltage unbalance index U_V is thus defined as the maximum voltage unbalance value for all the system busses. The voltage unbalance should be limited as follows [73]:

$$U^{h}_{V} \leq 3\% \tag{4.7}$$

where

$$U^{h}_{V} = \max \left\{ V^{a}_{h_{unbalance}}, \mathrm{V}^{b}_{h_{unbalance}}, \mathrm{V}^{c}_{h_{unbalance}} \right\}, \forall h = 1,2,...h_{tot} \tag{4.8}$$

B) Energy Loss minimization:

The second objective is the minimization of the system energy loss during the study period. The total system energy loss can be calculated during the specified study period using the total number of hours h_{tot}, as follows:

$$E_{loss} = 0.5 \times \sum_{h=1}^{h_{tot}} \sum_{i=1}^{N} \sum_{j=1}^{N} \left(G^{h}_{ij} \times [(V^{h}_{i})^2 + (V^{h}_{j})^2 - 2 \times V^{h}_{i} \times V^{h}_{j} \times \cos(\delta^{h}_{j} - \delta^{h}_{i})] \right) \tag{4.9}$$

where V_i is the Voltage at bus *i; G_{ij}* is the conductance of the line connected between buses *i* and *j; δ_i* is the power angle of the bus *i* voltage; *n* is the total number of buses in the system; *h* is the current hour under study; and h_{tot} is the total number of hours during the study period.

In this case, the objective function is:

$$F_2 = \min(ELI) \tag{4.10}$$

where *ELI*: energy loss index

$$ELI = 100 \times E_{loss} / \left(\sum_{h_{tot}} E_{generated} \right) \tag{4.11}$$

C) Amount of CO2 emissions minimization:

The third objective is the minimization of the zonal CO_2 emissions. The total zonal emissions are given by:

$$\psi_{CO_2} = (E_{loss} + E_{Load} - E_{DG}) \times \psi_{grid} + \sum_{i=1}^{N_{DG}} E_{DG}^{i} \times \psi_{DG}^{i} \qquad (4.12)$$

where ψ_{CO2} is the overall amount of zonal emissions (COE) in kg, ψ_{grid} is the specific amount of the CO_2 emissions from the transmission grid (kg/kWh), E_{loss} is the total energy loss in the study zone, E_{load} is the total amount of energy absorbed by the study zone loads, E_{DG} is the total energy supplied by the DGs, N_{DG} is the total number of DGs connected to the study zone, E^{i}_{DG} the total energy supplied by DG*i*, and ψ^{i}_{DG} is the specific amount of CO_2 emissions from DG*i*(kg/kWh). The values of ψ^{i}_{DG} and ψ_{grid} are as set out in [74].

The objective function is:

$$F_2 = \min(COE) \qquad (4.13)$$

4.3 Resources and Tools Module (RTM):

In this study, a variety of models for controlled resources/tools were developed, such as: switched capacitors, demand response, voltage regulators, reconfiguration switches and dispatchable distributed DG power. Controlled tools and resources are assumed to be previously built into the study system before the application of the proposed ZEMOS. The role of the proposed ZEMOS is to control the built-in tools/resources in order to fulfill the decision maker’s objectives. In this section, the system built-in tools are described in detail. In addition, controlled tools and resources mathematical modeling and states definitions are presented in details.

A) Switched Capacitors controls:

A decision variable $X_{c_l}^{h}$ is assigned to each capacitor switch, where

$$X_{c_l}^{h} = \begin{cases} 0 & \text{if capacitor } l \text{ is switched OFF} \\ 1 & \text{if capacitor } l \text{ is switched ON} \end{cases} \quad \text{and } X_{c_l}^{h} \in \{0,1\}$$

If capacitor *l* is connected to bus *i*, the injected reactive power at bus *i* is given by the following*:*

$$Q_i^h = X_{c_l}^{h} \times Q_{c_l}^{h} - Q_{load_i}^{h} \qquad (4.14)$$

where Q_i^h is the injected kVAr at bus *i* during hour *h*, Q_{ci}^h is the injected kVAr of capacitor *l* at bus *i* during hour *h*, and $Q^h_{load\ i}$ is the kVAr requirement of load *i* during hour *h*.

B) Voltage Regulators:

A decision variable T_i^h is selected for each regulator. For each voltage regulator *i*, the output voltage at each hour is given by the following:

$$V_{reg_i}^h = V_{input_i}^h + T_i^h \times V_{tap} \tag{4.15}$$

$$T_i^h \in Z \text{, and } T_{\min_i} < T_i^h < T_{\max_i} \tag{4.16}$$

where $V_{input_i}^h$ is the input voltage of regulator *i* at hour *h*, T_i^h is the tap position of regulator *i* at hour *h*, T_{min} is the minimum tap position of regulator *i*, T_{max} is the maximum tap position of regulator *i*, and V_{tap} is the voltage that corresponds to one tap step (p.u.).

C) Reconfiguration Switches:

A decision variable $X_{s_i}^h$ is assigned to each switch *l* during hour *h*, where

$X_{s_l}^h \in \{0,1\}$ and

$$X_{s_l}^h = \begin{cases} 0 & \text{if switch } l \text{ is switched OFF} \\ 1 & \text{if switch } l \text{ is switched ON} \end{cases}$$

If switch *l* is connected between buses *i* and *j*,

$$Y_{ij}^h = \frac{X_{s_l}^h}{(1 - X_{s_l}^h)} \tag{4.17}$$

where Y_{ij}^h*:* admittance of the line connecting busses *i* and *j*.

D) *Demand* response(DR)controls (load curtailment)

Load curtailment is a mean of reducing demand usage in a facility which will consequently reduce energy usage. This makes load curtailment a very attractive option to reduce operating costs. Normally [75], load curtailment is used to reduce demand peaks in a facility. This is done by monitoring the main utility meter in the facility and by measuring the demand usage every five minutes. Hence, automatic load curtailment takes place when it notices a demand peak is coming. In addition, load-curtailment switches could be activated by either a low voltage limit [76] or by a signal sent from an energy management system as proposed in this research. In this research, load curtailment will be used to fulfill the decision maker's objectives, instead of only reducing the peak demand. Some load types that can be controlled are:

1. Compressors

2. Fan motors (with variable speed systems)
3. Electric Heaters
4. Pumps
5. Air conditioners & others.

In this chapter, it is assumed that the operator can control the demand response through an Incentive-Based demand response program which is called Direct load control (DLC) [44]. In such a program, the utility or grid operator gets free access to customer processes).

The power levels of different loads are as follows:

$$P_i = (1 - 0.01 \times c_i)P \tag{4.18}$$

$$Q_i = (1 - 0.01 \times c_i)Q \tag{4.19}$$

$$c_i \leq c_{\max}$$

where P,Q are the present load kW, kVAr, respectively; P_i, Q_i are the proposed load kW, kVAr at instant i, respectively; c_i is the amount of load reduction as a percentage of the nominal load; and c_{max} is the upper limit of c_i. The load curtailment factor c_i is the controlled variable that is optimally determined.

E) *Distributed* Generation controls

In this research, dispatchable DGs are controlled by selecting a set point of the desired value of the DG output active power. The DG output power levels are expressed by:

$$P_{DGi} = 0.01 \times c_{DGi} \times P_{DGo} \tag{4.20}$$

where P_{DGo} is the DG rated kW, P_{DGi} is the DG kW at instant i, and c_{DGi} is the percentage factor. c_{DGi} is the controlled variable that is optimally determined.

4.4 Control Module (CM)

In this chapter, the system is studied for a single decision maker with single and multiple objectives. In the next chapters, mathematical model of the CM in the presence of more than a single decision maker is presented in details. A number of optimization and conflict resolution algorithms are stored in the CM. The optimization algorithm is selected based on the number of selected objectives, which are determined from the objectives module. Besides, Decision maker’s constraints are stored in the CM module to ensure the feasibility of the generated solutions. The CM requires collecting the number of decision variables along with their upper and lower bounds, and the base-case states of the inactivated tools from the RTM. Coordination is also required between the CM and the data-processing sub-module for the necessary parameters and electrical quantities to be evaluated.

4.4.1 Optimization Algorithm

In the case of a single decision maker with single objective, the CM generates a single solution set (i.e. set of states) which fulfill the decision maker objective. Meanwhile, the CM assures that the proposed solution set must not violate the system operation and the decision maker's constraints.

On the other hand, for a multiple objectives decision maker, the CM generates sets of non-dominated solutions. The generated sets could be provided to the decision maker in order to select the best set or could be sent to the decision making module in order to recommend a single set of states.

Different optimization techniques were used for energy management systems as described in chapter (2). In this study, Genetic Algorithm is used to generate the required sets of solutions. GA is a heuristic search algorithm based on the mechanism of natural selection and genetic engineering and, has several properties as follows [77]:

- GA works with a set of coded variables that is called population of strings.
- GA searches from a population of points separately.
- GA uses only payoff (objective function) information, not derivatives or others.
- GA uses probabilistic transition rules.

GA is an efficient tool to solve optimization problems and which follows an evolutionary strategy. GA can easily determine a good solution of any objective function, even if discrete or if its derivatives are not defined.

A) Single objective decision maker

In the case of a single decision maker with a single objective, each chromosome will be a proposed solution set (tools' states) such as a re-phasing schedule for loads, capacitors switching status or load curtailment schedule. With encoding the chromosome, the new tools' states are determined and then if all of constraints were considered, the system objective is calculated and that is the fitness value. This algorithm is repeated until a stopping criterion is achieved. In this research, the stopping criterion is usually a time limit provided by the decision maker.

B) Multiple objectives decision maker

In case of multiple objectives decision maker, GA can be efficiently used in order to identify the optimal non-dominated Pareto Front. To illustrate, given F(x) is a vector of objective functions, while H(x) and G(x) represent equality and inequality constraints, respectively. A multi-objective optimization problem can be formulated as follows:

$$\min(F(X))$$
$$F(X) = [f_1(X), ..., f_{N_o}(X)]$$

Subject to:

$$\{G(X) = 0, H(X) \leq 0\} \tag{4.21}$$
$$X = [X_1, ..., X_m]$$

Assume X_1, X_2 belong to the solution space. X_1 dominates X_2 iff:

$$\begin{aligned} &\forall k \in \{1...N_o\},\ f_k(X_1) \leq f_k(X_2) \\ &\exists k' \in \{1...N_o\},\ f_{k'}(X_1) < f_{k'}(X_2) \end{aligned} \tag{4.22}$$

Any solution which is not dominated by any other belongs to Pareto front, optimal front or non-dominated front. All Pareto optimal points lie on the boundary of the feasible criterion space (Figure 4.1) [78, 79]. Hence, the role of the CM in this case is to generate the Pareto optimal set of points.

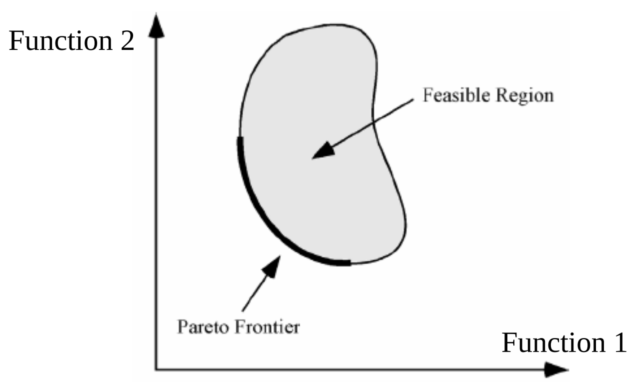


Figure 4.1 Pareto Optimality Concept for two objective functions

When developing genetic algorithms for multi-objective problems, the main questions are how to evaluate the fitness function and how to form the Pareto optimality concept. The solutions set after each generation are ranked into a set of non-dominated fronts according to NSGA II (Non-dominated Sorting Genetic Algorithm II) [80]. NSGA-II has a low level of computational complexity but is an elitist algorithm and also preserves diversity in the final Pareto non-dominated front solutions [80]. NSGA II is described in detail in appendix (A)

In conclusion, Genetics Algorithm was selected due to the following advantages:

- Supports multi-objective optimization
- Because genetic algorithms do not require gradient information, they can be effective regardless of the nature of the objective functions and constraints.
- Always generates an answer, which becomes better with time
- Can run in parallel operations
- Fitness function can be changed from iteration to iteration, which allows incorporating new data in the model whenever they are available.
- Can solve every optimization problem which can be described with the chromosome encoding
- For large scale complex problem, GA can offer close to global optimum solution in a very short time compared to conventional gradient techniques

4.4.2 Constraints:

A study system operation under any of the decision maker's objectives will be subject to the following constraints:

A) Power Flow Constraint:

In this Thesis, Load flow analysis is performed by using the OpenDSS (Open distribution system simulator)[81] software in order to make sure that the proposed ZEMOS recommendations does not violate the power and load flow constraints.

B) Voltage Magnitude Limits:

$$V_{\min} \leq \left|V_{i_a}^h\right|, \left|V_{i_b}^h\right|, \left|V_{i_c}^h\right| \leq V_{\max}, \ \forall i \in \{1,2,...N\} \,\&\, h \in \{1,2,...h_{tot}\}$$

C) Distribution Lines Capacity Limits

$$\left|S_j^h\right| < \left|S_{j\max}^h\right| \qquad \forall j \in \{1,2,3\ldots N_L\}$$

where N_L is the total number of system transmission lines.

4.5 Decision Making Module (DMM)

As mentioned in chapter (3), the main role of this module is to generate the most appropriate solution from the decision maker's perspective. In this study, a decision making approach is developed, mainly based on a Posteriori approach. However, some steps require the interaction of the DM prior to or during the decision making process.

The proposed decision making technique uses an L_p-metrics family as a measure of how close a solution to an ideal point. L_p-metrics family is defined as follows [82]:

$$L_p(x) = \left[\sum_{i=1}^{k} \left(w_i \right)^p \left| \frac{f_i(x) - f_i^0}{f_{i\max} - f_i^0} \right|^p \right]^{\frac{1}{p}} \tag{4.23}$$

Where,

k	total number of objectives
f_i^0	Value of objective *i* at the ideal point
$f_i(x)$	Results of objective *i* corresponding to decision *x*
$f_{i\max}$	Worst value obtainable for objective *i (maximum value of objective i in a minimization problem)*
w_i	Objective *i* weight

L_p is defined as the metric distance between the current solution point and the ideal point of the system objectives. In fact, L_p is a measure of the deviation of all objectives, corresponding to decision *x*, from the ideal value. The value of *p* defines the type of the distance measure used. If $p=1$, this means that all deviations from ideal point are taken into consideration in a direct proportion to their magnitude which is called a "group utility"[83, 84]. If $2\leq p\leq \infty$, large deviations are much more effective in the distance calculation which means that large deviations are having more interest than small deviations. For $p=\infty$, only the maximum deviation will be taken into consideration by the L_p metrics. This is called the "individual utility" or the min-max criterion. The distance function of all objectives is normalized, hence the distance value will be limited to the range of [0,1]. Weighted L_p [82] takes into consideration the relevance of specific objectives over the other by selecting the weights value according to decision makers' priorities.

In this work, deviation is considered a measure of dissatisfaction; hence, three dissatisfaction criteria are used.

Criterion (1) Group dissatisfaction

This indicates that there is no specific DM's objective dissatisfaction is given a larger influence in the decision making process (*p=1*). This means that all deviations from ideal point are taken into consideration in a direct proportion to their magnitude. The objective function of the DMM will be:

$$\min(L_p) \tag{4.24}$$

Criterion (2) Large dissatisfactions influence

This indicates that objectives with large dissatisfaction are given a higher influence in the decision making process (*p=2*). This means that all deviations from ideal point are taken into consideration in a direct proportion to the square of their magnitude. The objective function of the DMM will be:

$$\min(L_p) \tag{4.25}$$

Criterion (3) Maximum dissatisfaction influence

This indicates that the maximum dissatisfaction is the only interest in the decision making process (*p*=∞). This means that only maximum deviations from ideal point are taken into consideration. The objective function of the DMM will be:

$$\min(L_p) \tag{4.26}$$

$$L_p = \max\left(w_1 \left| \frac{f_1(x) - f_1^0}{f_{1\max} - f_1^0} \right|, w_2 \left| \frac{f_2(x) - f_2^0}{f_{2\max} - f_2^0} \right|, \ldots w_k \left| \frac{f_k(x) - f_k^0}{f_{k\max} - f_k^0} \right| \right) \tag{4.27}$$

Proposed decision making algorithm Procedures:

The proposed decision making algorithm should follow the following steps:

Step (1) Identify the DM's preferences prior to the search process

- **Objectives priorities** (if applicable):

  Priorities are used for selecting the weights of different objectives' deviations. If there are no particular decision maker's priorities then all objectives will be assumed to have equal priorities. Hence, all the weights will be adjusted to unity.

- **Objectives desired limits:**

  Desired limits of each objective will be specified by the decision maker in order to be used as a threshold. Thus, an objectives threshold will eliminate all the unacceptable solutions among the Pareto Front Set. Preselected limits will be stored in the data storage sub-module for future use, unless different values are specified by the decision maker

- **Satisfaction criterion:**

  b. Criterion (1) Group dissatisfaction

c. Criterion (2) Large dissatisfactions influence

d. Criterion (3) Maximum dissatisfaction influence

If a satisfaction criterion is not selected by the decision maker, by default large dissatisfaction influence criterion will be automatically selected.

Step (2) Calculate the ideal point

Ideal point can be identified after or before the search process depending on the type of the ideal point used:

- **Theoretical ideal point**

  The theoretical ideal point, if identified, is a historically known ideal value of the objective function. For example, the theoretical ideal value of the percentage power losses is zero percent which might not be a feasible value. However, no one disagrees that it is desirable to make the losses as close as possible to zero percent. A theoretical ideal point is normally specified by the decision maker.

- **Previously stored ideal point**

  Previously stored ideal point is defined as a historical ideal value (min or max) that was previously used by the DMM and lead to an acceptable solution.

- **Data Based ideal point**

  In a minimization problem, data based ideal point is the minimum value of each objective among the current generated Pareto front (Figure 4.2).

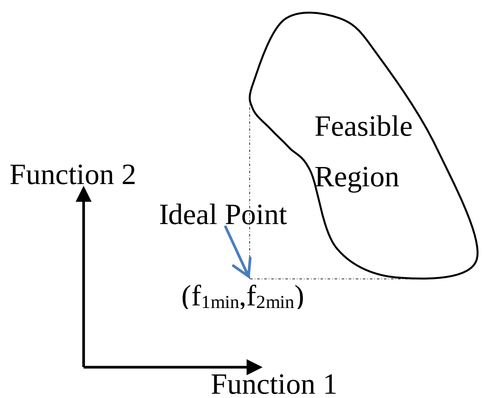


Figure 4.2 Data Based Ideal Point

Step (3) Eliminate all the unacceptable solution points according to each objective threshold (determined in step (1))

Step (4) The deviation of all the solution point will be calculated as described in equation (4.23) or equation (4.27) according to the selected dissatisfaction criterion

Step (5) Apply the selected dissatisfaction technique in step (1) to generate the final decision.

Step (6) Notify the DM with the results. If the recommended solution is approved by the decision maker then the recommended controlled tools/resources' states are executed. However, if the recommended solution is not accepted, the decision maker will have the possibility of selecting a different satisfaction criterion and steps (4, 5) are repeated.

4.6 Data Bank Module (DBM)

The role of the data bank module has been introduced in chapter (3). It consists of three sub-modules, i.e. data storage, data processing, and data forecasting sub-modules.

4.6.1 Data Storage and Processing sub-modules:

Data storage sub-module is used to store the following data:

a. Transmission lines data (admittance, thermal limits)
b. System load data at the study instant
c. Base case states of system tools and resources (switched capacitors, switched filters, phase swapping, load curtailments)
d. DMM and CM outputs.

The data processing sub-module will do the necessary calculations and simulations required by the different modules, i.e. power flow calculations, system voltages, VUI, etc.

4.6.2 Data forecasting sub-modules:

For this research, a stochastic data model was developed based on discrete first order Markov chain analysis. Markov chain is used to imitate a Markov process, which has a discrete state-space [85]. A Markov process simulates system behavior using a set of transitional probabilities. The Markov process depends on three main assumptions:

- The future state depends only on the current state of the system.
- The transitional probabilities are independent of time.
- Time can be discretized such that the system may change state only once per time interval.

Solar irradiance and load data are time-dependent data classified as nonhomogeneous Markov chain processes, so the proposed model therefore includes a technique that generates multiple transition matrices. The time dependency of the data is thus inherently included in the proposed model. The proposed model is described by the following steps:

1- First, each month's historical data are divided into *n* fixed width states.

2- The data are clustered into *m* clusters using a K-means clustering technique [86].

3- A set of daily groups is next created by assigning to the same group the data for each consecutive hour that corresponds to the same data cluster.

4- A probability transition matrix is then generated for each daily group of hours so that cumulative probability transition matrices can be constructed.

5- The next hour is estimated by utilizing the cumulative probability transition matrix of the corresponding group of hours. Given the value of the present hour, the estimation process begins with the generation of a random uniform number between zero and one. The value of the random number is then compared with the cumulative probability matrix row that corresponds to the state of the present hour.

   For instance, if the solar irradiance value for the present hour is at state 1, then the random number is compared with the values of the first row in the cumulative probability transition matrix. The first column, which has a cumulative probability value equal to or greater than the value of the random number, represents the state of the irradiance for the next hour.

6- The estimated value of the next hour is then used in order to predict the value of the subsequent hour, as in step 5. This process is repeated until all the data for an entire day or the specified study period are estimated. Each hour is estimated using the cumulative transition matrix that corresponds to the predicted hour group. Steps 5 and 6 are considered to be a single scenario.

7- Scenarios are generated until the maximum value of the ratio of the standard deviation *σ(X)* of the value of each hourly solar irradiance *X* to the expected value *E(X)* for the same hourly solar irradiance satisfies equation (4.28).

$$\frac{\sigma(X)}{E(X)} \leq \varepsilon \tag{4.28}$$

where ε is a selected small tolerance.

It worth noting that the number of clusters and, accordingly, the number of transition matrices generated are based mainly on the accuracy required by the operator.

4.7 Smart Matching Module:

This section describes the development of the proposed smart matching scheme that will be stored in and utilized by the smart matching module. SMS is used to match the existing controlled resources with the corresponding operator's selected objectives. The generated matching recommendations are stored and then utilized every time a specific objective is required to be optimized. Figure 4.3 shows how a typical multi-objectives optimization problem can be handled with and without the use of the SMS.

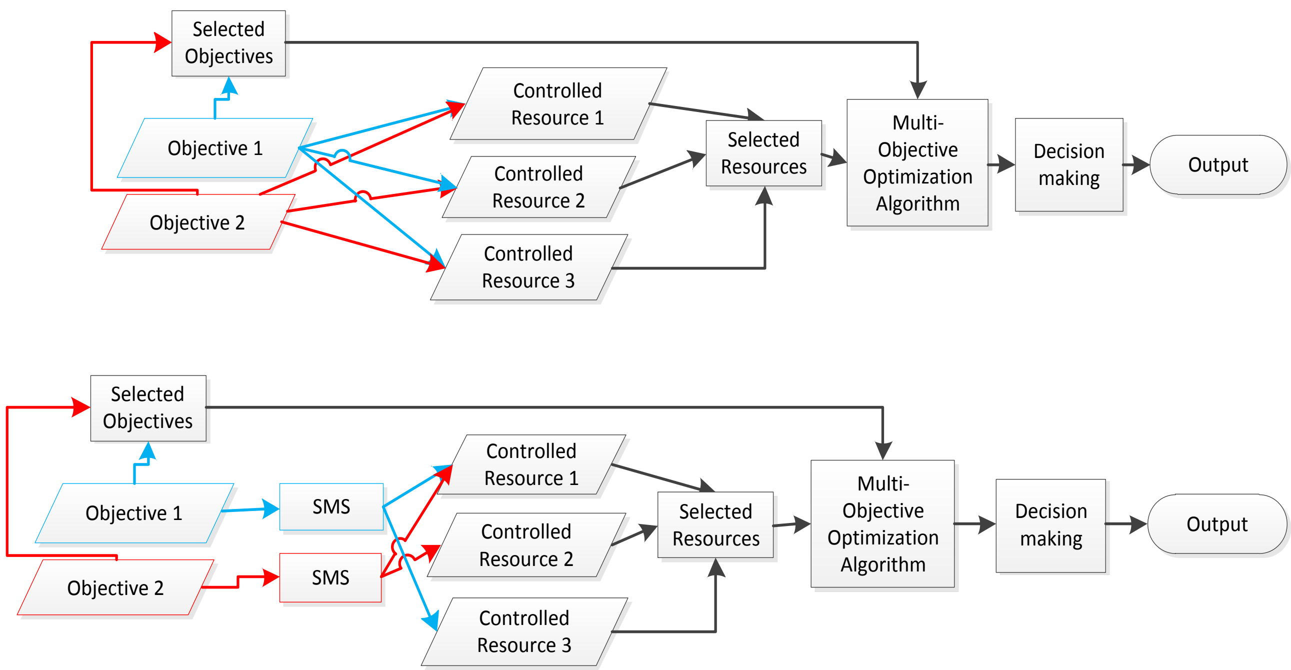


Figure 4.3 Typical multi-objective Optimization problems (a) without using the SMS (b) Using the proposed SMS

SMS is a onetime process that is initially performed offline. It can be repeated for any of the following cases: the installation of additional controlled resources, and an extension of the number of operator's objectives. The algorithm consists of two main stages: a stage that generates a sensitivity index (SI) and estimates the cost of controlled resources operation, plus a matching stage. Figure 4.4 shows the simplified flow chart that illustrates the proposed SMS.

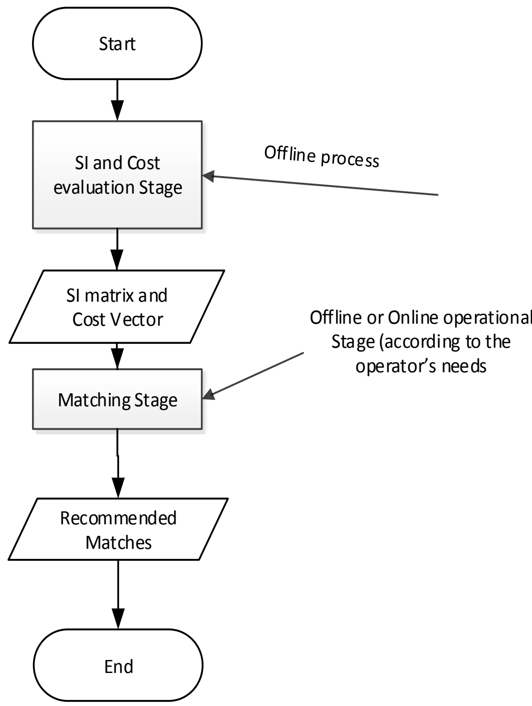


Figure 4.4 Smart Matching Scheme Stages

4.7.1 Sensitivity Index and Cost-Evaluation Stage:

The purpose of this stage is to evaluate the effect of varying each existing controlled resource decision variable on each operator objective function magnitude. In other words, the proposed algorithm calculates the percentage change, in each objective function magnitude, caused by a step change in each controlled resources decision variable regardless of the values of other decision variables. A step change, in the controlled resources, is: a small percentage of a DG output power with respect to the rated output, a small percentage of a DR demand reduction with respect to the rated load, or a single switching action for each switched capacitor.

In addition, the operational cost per step change per hour of utilizing that controlled resources is estimated. The following steps generate the SI matrix:

1) Select an operator objective.
2) Select a controlled resource *i*, identify the lower and the upper bounds for that controlled resource decision variable, and then divide the decision variable range of values into *N* fixed

states.

3) Select random values for the remaining unselected controlled resources decision variables.
4) Begin with the lower bound state of the selected controlled resource decision variable.
5) Estimate the expected value of the desired operator objective function magnitude for the current controlled resource decision variable state, as described in the next chapter.
6) If the current controlled resource decision variable state is the lower bound, increment that decision variable state to the next state and repeat step 5, else go to step 7.
7) Calculate the sensitivity of each controlled resource, decision variable, step change as follows:

$$D^i_{jk} = (Obj^i_k - Obj^i_j) / (S^i_k - S^i_j) \tag{4.29}$$

where D^i_{jk} is the deviation from the operator's objective when controlled resource *i*, decision variable, is changed from state *j* to state *k; Obj^i_k* is the value of the operator's objective when controlled resource *i*, , decision variable, is at state *k*, Obj^i_j is the value of the operator's objective when controlled resource *i*, , decision variable, is at state *j*, S^i_k is the value of controlled resource *i*, decision variable, at state *k*, and S^i_j is the value of controlled resource *i*, , decision variable, at state *j*.

8) Estimate the cost C^i_{jk} of changing controlled resource *i* decision variable from state *j* to *k*.
9) If the current controlled resource decision variable state is at the upper bound go to step 10, else increment the state of the selected controlled resource decision variable and repeat steps 5 through 8.
10) Calculate the sensitivity index SI for controlled resource *i* decision variable as follows:

$$SI_i = \left(D^i_{12} + D^i_{23} + \cdots D^i_{jk} \cdots + D^i_{(N-1)N}\right) / \left(N_R - 1\right) \tag{4.30}$$

where, *N* is the total number of controlled resource states.

11) Estimate the expected cost of a step change for controlled resource *i* decision variable by:

$$C_i = \left(C^i_{12} + C^i_{23} + \cdots C^i_{jk} \cdots + C^i_{(N-1)N}\right) / \left(N_R - 1\right) \tag{4.31}$$

where, N_R is the total number of controlled resource states.

12) Steps 3 through 11 are considered to be a single scenario of the Monte-Carlo simulation (MCS) and are repeated until the following stopping criterion is satisfied:

$$\sigma(SI_i) / E(SI_i) \le \varepsilon \tag{4.32}$$

where $\sigma(SI_i)$ is the standard deviation of the SI for controlled resource *i*, $E(SI_i)$ is the expected value of the SI for controlled resource *i* decision variable; and ε is a selected small tolerance.

13) Repeat steps 2 through 12 for each existing controlled resource until a vector of the SI for all controlled resources is generated for the current operator selected objective function.

14) Repeat steps 1 to 13 for all of the operator's objectives.

By the end of this stage, an SI matrix, of size $N_R xm$ where N_R is the number of controlled resources and m is the number of objectives, is generated which shows the controlled resources impact on each objective magnitude, Table 4.1. A cost vector ($N_R x1$) is generated that indicates the cost associated with the step change for each controlled resource decision variable, Table 4.2. It is necessary to stress that this stage is an offline process so that time is not an issue at this point. The Sensitivity index and cost evaluation stage is summarized in the flow chart shown in Figure 4.5.

Table 4.1 Controlled Resources Sensitivity Index Matrix

	Objective 1	*Objective 2*	…	*Objective m*
Controlled resource *1*	SI_{11}	SI_{12}		SI_{1m}
Controlled resource *2*	SI_{21}	SI_{22}		SI_{2m}
.	.	.		.
.	.	.		.
Controlled resource N_R	SI_{n1}	SI_{n2}		SI_{nm}

Table 4.2 Controlled Resources Cost Vector

Controlled resource 1	C_1
Controlled resource *2*	C_2
.	.
.	.
Controlled resource N_R	C_n

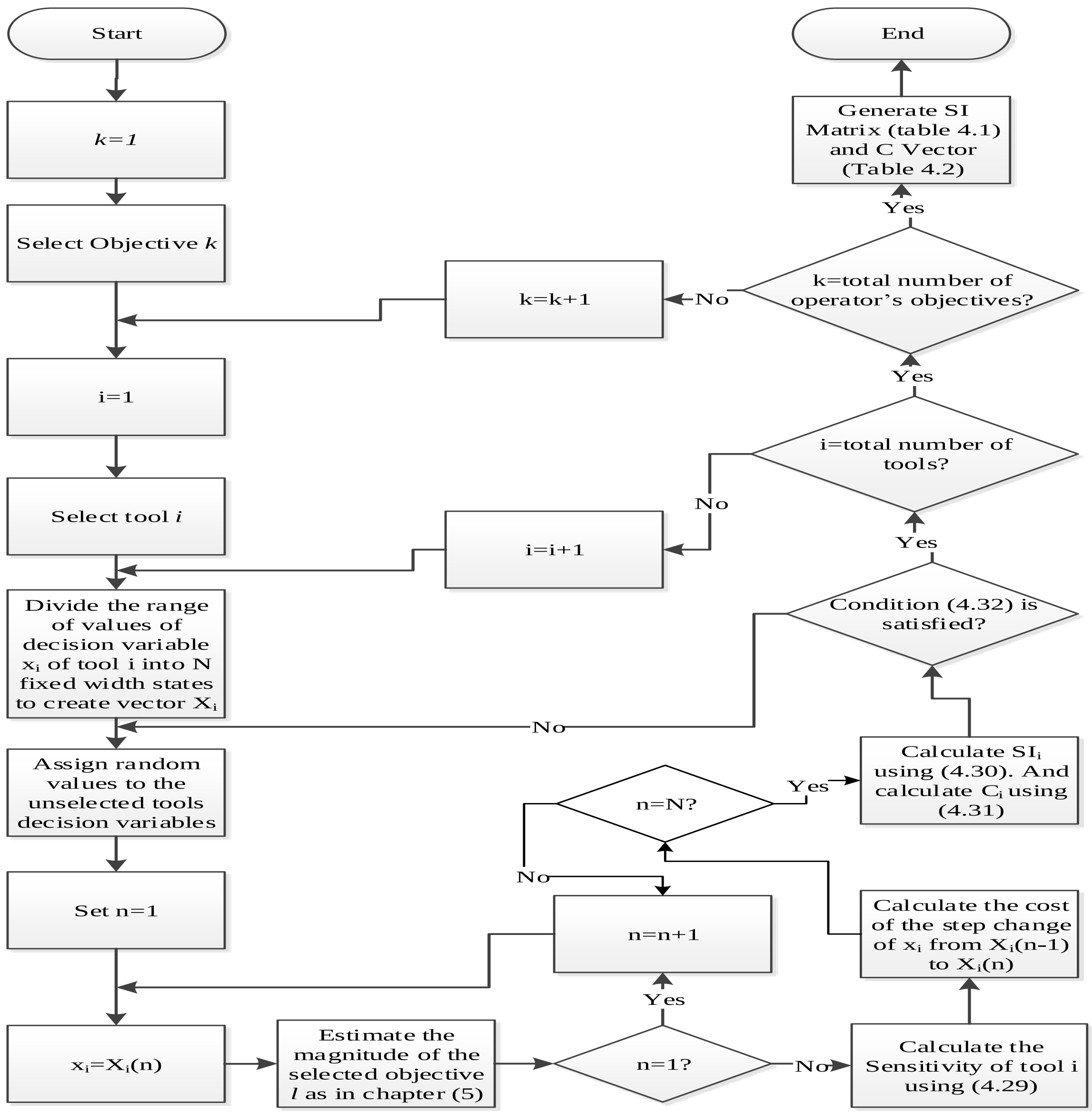


Figure 4.5 Sensitivity matrix and cost evaluation stage

4.7.2 Matching Stage

In this stage, controlled resources are matched with the operator's objective functions using the SI matrix and the cost vectors that were developed during the previous stage; each objective is matched with single or several controlled resources. The matching process is a multi-objective optimization problem that is solved to maximize the total SI while minimizing the operational cost. The matching problem can be formulated as follows:

Objective function:

min(F)

$$F = [-\sum_{i=1}^{N}(x_i^+ - x_i^-)SI_{i,j} \quad \sum_{i=1}^{N}(x_i^+ - x_i^-)C_i] \tag{4.33}$$

subject to

$$x_i^+ + x_i^- \le 1 \quad \forall i = 1,2,3 \ldots N \tag{4.34}$$

$$x_i^+, x_i^- \in \{0,1\} \tag{4.35}$$

where $SI_{i,j}$ is the value of the SI of objective j that corresponds to a step change in the controlled resource i decision variable; C_i is the operational cost of a step change in controlled resource i variable; x^+_i, x^-_i are the decision variables for selecting a step increase or a step reduction for controlled resource i variable, respectively; and N_R is the total number of controlled resources.

A Pareto front is generated, using NSGAII, for the proposed matching multi-objective problem. The set of solutions generated is then reduced to a single solution point using the decision-making algorithm described in decision making module.

4.7.3 Benefits of the proposed SMS

The proposed smart matching scheme is expected to provide the following advantages:

1) Unidirectional controlled resources that can be changed in only one direction (e.g., load shedding can only be decreased) will not be selected if they produce results that have a negative effect on the objective function magnitude (i.e. controlled resources with negative SI values).
2) In the case of bidirectional controlled resources that can be changed in two directions (i.e., DG output power that can be reduced/increased, or a switched capacitor that can be switched on/off); the SMS avoids the use of controlled resources with low sensitivity indices and high operational costs.
3) Because the SI evaluation occurs prior to the solving of the main optimization problem, the optimization process is faster because the number of controlled resources utilized is reduced along with the consequent number of decision variables that must be incorporated in the main optimization problem.
4) The SMS is independent on the type of operator objective functions and the type of the controlled resources and resources. Thus if an operator decides to select different objectives or

additional controlled resources are installed in the system, SMS can be utilized to provide the most efficient control options.

5) The developed SI takes into account the variability with respect to how much the objective functions are dependent on the reduction in the value for a controlled resource, as discussed in [87].
6) The SMS takes system conditions into account and then adapts to different preferences related to cost and sensitivity. In other words, the matching stage problem is normally solved based on the assignment of similar preferences to cost and the SI, with equal weights thus being selected in the decision-making algorithm, as expressed in equation (4.23). On the other hand, in an emergency condition, the SI might be assigned a preference level higher than the one allocated to cost, which means that more controlled resources are matched to the operator's objective regardless of their operational costs.

4.8 Conclusions

In this chapter, mathematical modelling of the proposed ZEMOS is developed and presented in details. The proposed system manages the available zonal tools and resources in order to fulfill the decision maker's objectives. In this chapter, the system is developed for the use with a zone that has a single decision maker with single and multiple objectives. Different decision making criteria were tested and compared in order to develop an efficient decision making algorithm for multi-objective optimization operation.

A set of operator's objectives functions were mathematically developed and stored in the objectives module. The selected objectives involve the minimization of the energy losses, the minimization of phase unbalance, and the minimization of CO_2 emissions. In addition, distribution system constraints were mathematically modeled based on practical distribution system practice.

A number of controlled resources and tools were mathematically developed and stored in the RTM and presented as potential decision variables that can be employed by ZEMOS for zonal optimal operation.

A stochastic data forecasting module is developed that is based on discrete first order Markov chain analysis and generates multiple transition matrices, which ensure that the time dependency of the stochastic data is inherently included in the model.

A decision making algorithm is proposed for being implemented by the decision making module for the sake of supporting the system operator's decisions for multi-objective optimization problems.

Finally, a smart matching scheme (SMS) is developed and utilized to match a distribution system controlled resources or tools with the operator's objectives, based on controlled resources or tools sensitivities and operational costs. The reduction of the number of controlled resources or tools, during the same time limit, reduces the computation complexity of the optimization problem, which provides great advantage for online energy management application.

Chapter 5 Zonal Energy Management System with Single Decision Maker (Simulation results)

The objective of this chapter is to evaluate the performance of ZEMOS when applied to a typical study zone with a single decision maker. In this chapter, simulation results of many case studies are presented in detail. The analysis is performed on the IEEE 123 test feeder. All the system analysis and results were validated using MATLAB and OpenDSS (Open distribution system simulator)[81].

First, the ZEMOS evaluation process starts by validating the proposed data forecasting model. Second, the study of the system performance, in case of single decision maker with a single objective, is presented utilizing all the possible zonal controlled resources/tools. Next, the role of the proposed decision making module (DMM) is verified by applying ZEMOS to a typical multi-objectives study zone. Afterwards, the significance of the smart matching module (SMM) is presented. That is, the performance of ZEMOS, using all modules, is evaluated with and without using the proposed SMS in order to reach the realized accomplishments and benefits of using ZEMOS. It is worth noting that the proposed ZEMOS is *only* employed to control the controlled resources/tool states (set points), not to reallocate or resize them.

For each case study, different types of optimization problems were taken into consideration which involves both single and multi-objective optimization. Different kinds of controlled tools and resources were utilized to optimize the study zone according to the operator's objective(s).

5.1 Study System

The IEEE 123-bus (Figure 5.1) three phase unbalanced test system was used in this study [88]. The system data is shown in appendix (B)

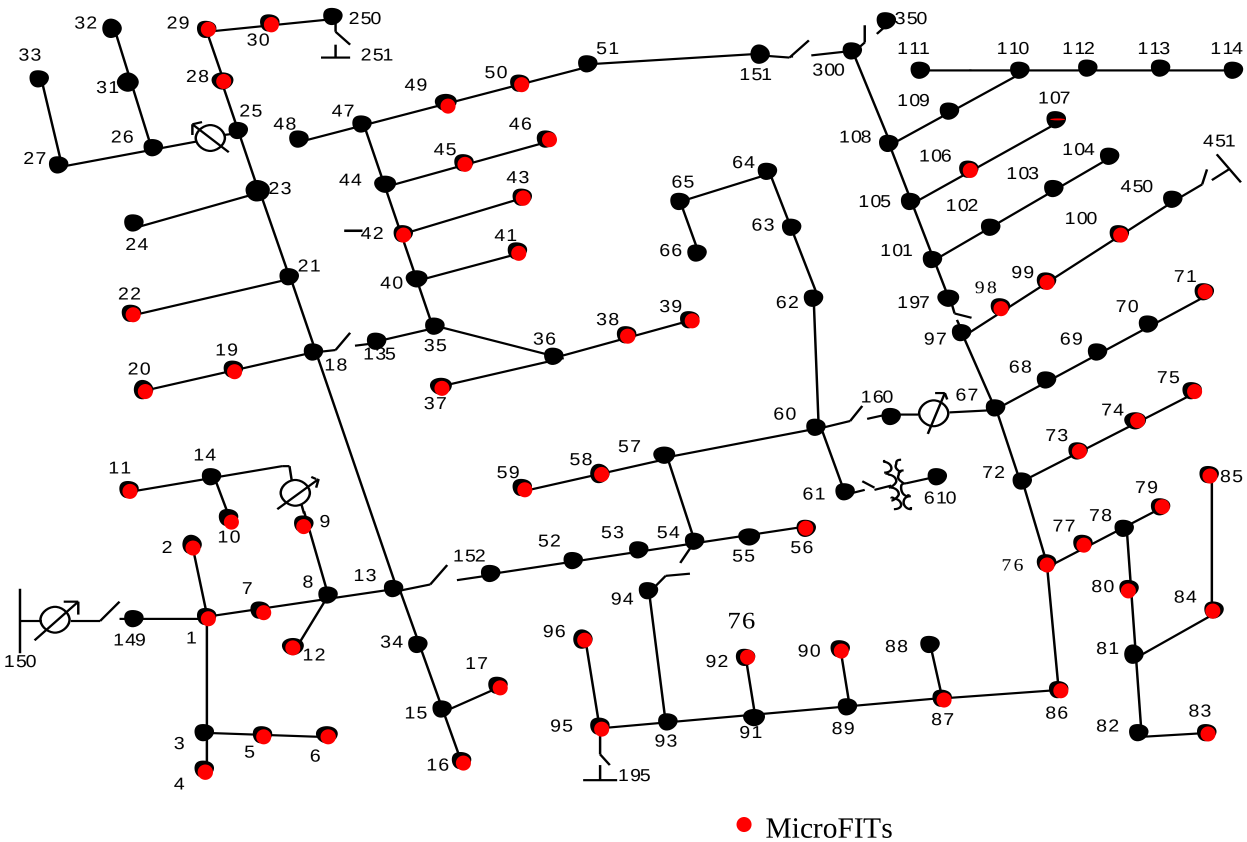


Figure 5.1 IEEE 123 bus test feeder

In the meantime, many countries have introduced a feed-in tariff [64] (FIT) program, which is considered a straightforward method of contracting for renewable energy generation. Such a program encourages the installation and implementation of renewable energy generation projects. Included under the umbrella of the FIT program is the microFIT program [65], which was initiated for integrating very small renewable generators, rated at less than 10kW. As a result of this program, a typical distribution system might include a large number of renewable distributed generators. Therefore, the study system is modified by installing a large number solar based microFITs [65], at different *random* locations on the system as shown in Figure 5.1. In Ontario, the most economical microFITs are solar-based generators [89]. For that reason, in this study, it is assumed that all installed microFITs are 10 kW rated solar generators. This implementation of the microFITs, in the system under study will demonstrate the efficiency of the proposed ZEMOS in the presence of a large number of stochastic renewable distributed generations. Meanwhile, this study will illustrate the important role played by ZEMOS to mitigate the side-effects of the extensive use of the microFITs.

5.2 Data Estimation (Forecasting) Model Validation:

In this thesis, a data forecasting model is developed as a means of estimating stochastic data (e.g. solar irradiance), which were mainly used in order to model the power output of the microFITs.

ELI, CUI, and COE magnitudes were evaluated in order to validate the proposed data forecasting model. The proposed data estimation model was used to forecast the hourly electrical load demand and the hourly solar output power in the study zone. Next, the study system was then simulated in order to estimate the energy loss index (ELI), the current unbalance index (CUI), and the CO_2 using the forecasted data.

The ELI, CUI, and COE were evaluated again by simulating the system using the actual historical data. The proposed model outcomes had thus been validated through a comparison of the actual values with the estimated values of the ELI, CUI, and COE, allowing for an estimation of the level of error in the evaluation of the ELI, CUI, and COE. Two case studies were selected in order to validate the proposed data-forecasting model that represents two different seasons.

5.2.1 Historical Data

The proposed model was developed based on 15 years of solar irradiance historical data [90]. Each month is represented by one day. In other words, each year is divided into 12 d: the equivalent of 288 h (12 days x 24 hours). Consequently, each daily averaged hour in the model represents the same hour for the entire month. Given 15 years of historical data, each simulated day has 450 data points (30 day x 15 year).

5.2.2 Load modeling

In this study, the load profile is assumed to follow the IEEE Reliability Test System (RTS) [91]. This system provides the weekly peak load as a percentage of the annual peak load, the daily peak load cycle as a percentage of the weekly peak load, and the hourly peak load as a percentage of the daily peak.

5.2.3 Solar (PV) generators modeling

Once the hourly solar irradiance has been estimated, the output power of the photovoltaic (PV) array can be calculated using equations (5.1)-(5.5) [92]:

$$T_C = T_A + Ir\left(\frac{T_o - 20}{0.8}\right) \tag{5.1}$$

$$I = Ir\left(I_{sc} + K_i(T_C - 25)\right) \tag{5.2}$$

$$V = V_{OC} - K_v * T_C \tag{5.3}$$

$$P_{Ir} = N * FF * V * I \tag{5.4}$$

$$FF = \frac{V_{Mpp} * I_{Mpp}}{V_{oc} * I_{sc}} \tag{5.5}$$

where Ir is the solar irradiance (kW/m^2), T_C is the cell temperature at Ir (^{o}C), T_A is the ambient temperature (^{o}C), T_o is the nominal cell operating temperature (^{o}C), K_i is the current temperature coefficient (A/ ^{o}C), K_v is the voltage temperature coefficient (V/ ^{o}C), FF is the fill factor, I_{sc} is the short circuit current (A), V_{oc} is the open circuit voltage (V), I_{MPP} is the current at the maximum power point (A), V_{MPP} is the voltage at the maximum power point (V), and P_{Ir} is the output power of the PV array at Ir (kW).

5.2.4 Data Forecasting Validation Results

By means of the proposed model procedures, as described in chapter (4), the historical hourly data were divided into 100 states. Thus, for an irradiance range of 0-1000 W/m^2, each state has a size of 10 W/m^2. In the second step, the data were clustered into three clusters using K-means clustering technique. Accordingly, three groups of data were created by assigning the data that corresponds to the same cluster to the same group, for each consecutive hour.

After grouping the daily hours, a probability transition matrix (100x100) was generated for each of the three groups. Consequently, three cumulative probability transition matrices were constructed. Next, the process of estimating the daily irradiance start with the irradiance value of the present hour.

Two case studies were considered for validating the proposed data forecasting model as follows:

Case study (1): In this case study, stochastic data (load demand and solar output power) were estimated for the winter season. In this section, the data simulation starts immediately after sunrise. For instance, in the winter season, sunrise occurs at 8:00 a.m. Hence, referring to the historical data, the solar irradiance value at 8:00 a.m. is 0 W/m^2 (state 1), which is recognized as the value for the first hour in the estimated day. Next, the proposed forecasting model was used to forecast the subsequent values for the hourly solar irradiance until the end of the day time (i.e., 5:00 p.m., which represents sunset).

Figure 5.2 shows a comparison of a forecasted day in the winter compared with the actual data for two typical days in the same season. Obviously, it can be noted that the daily trend in solar irradiance variation has been successfully captured by the proposed algorithm.

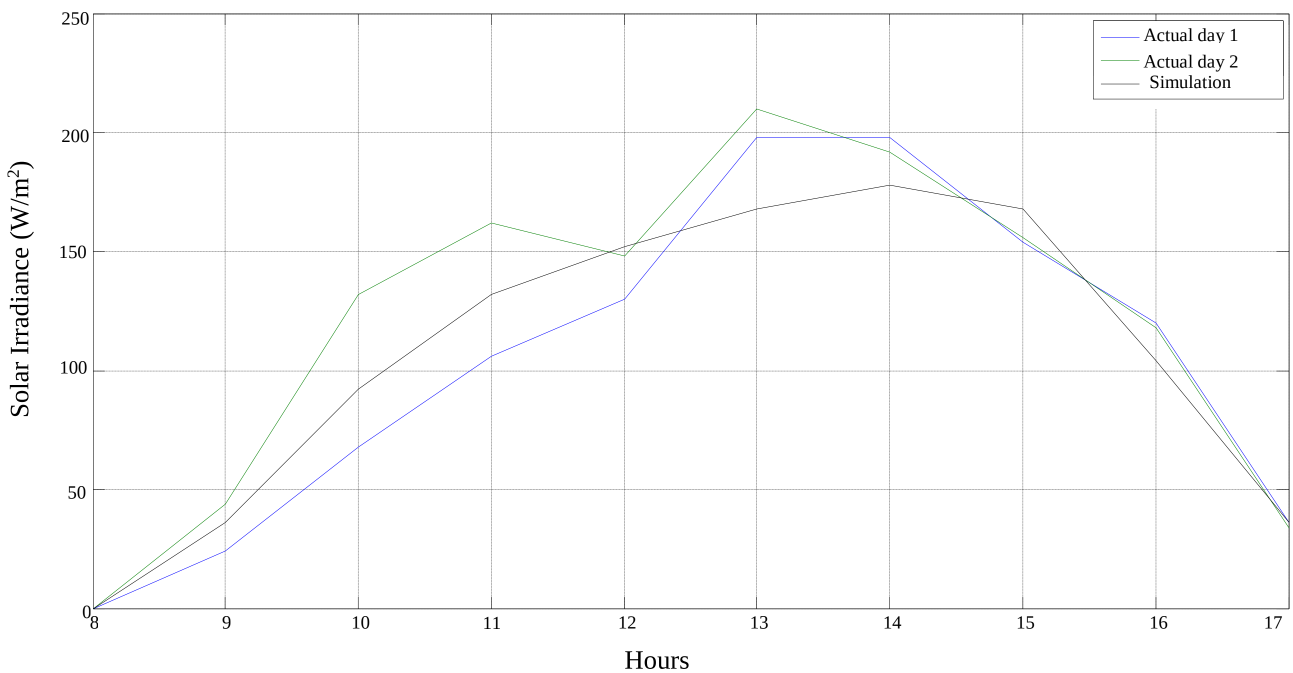


Figure 5.2 Solar irradiance data for a full day in the Winter Season

Case study (2): In the second case study, data are estimated for the summer season. The number of states (and accordingly, step size) is selected to be identical to their corresponding values in case study (1). The main difference in this case is that sunrise takes place at 5:00 a.m, as shown Figure 5.3; hence, the value for solar irradiance equals 0 W/m^2 (state 1) at 5:00 a.m., and sunset is delayed to 8:00 p.m.

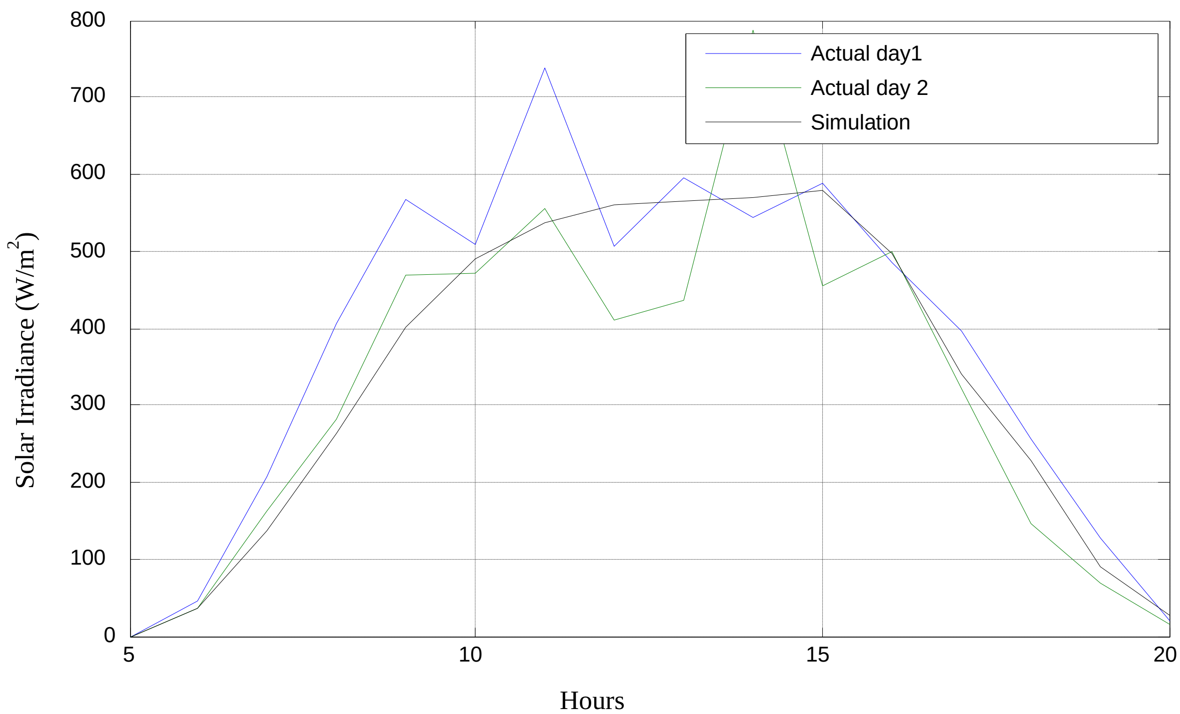


Figure 5.3 Solar irradiance data for a full day in the Summer Season

The forecast data were used to simulate the system under study in order to estimate The ELI, CUI, and COE during the selected periods (i.e. 8:00 to 17:00 in the Winter season, or 5:00 to 20:00 in the summer season), using both the forecast and the actual data sets.

Table 5.1 shows the estimated and actual ranges of the energy loss index (ELI) in the study system for both case studies. The results show that the absolute mean error in estimating the ELI is 0.7% in the winter season and that the absolute error range is less than 3.17%. On the other hand, the absolute error range in estimating the ELI during the summer season is less than 4.6 %.

Table 5.2 shows the estimated and actual ranges of the CUI for both case studies. The results show that the absolute error range in estimating the CUI in the winter season is less than 8.9 % and that the error in estimating the CUI in the summer season is less than 12.9 %. For the COE, Table 5.3 shows the mean and the maximum absolute errors in estimating the COE using the proposed forecasted model. The maximum errors are 5.5% and 6.9% for winter and summer seasons, respectively.

It is worth noting that the estimated errors for both the ELI and the COE were significantly less than the estimated error for the CUI, such discrepancy occurs because the estimation of the both the ELI and the COE depend on the aggregation of the microFIT output power and the electric load demands over the whole forecasted period. On the other hand, the CUI is estimated according to only the maximum unbalance in the main feeder (i.e. only a single reading from the whole forecasted period). Furthermore, the error rate increases in the summer season because the daylight lasts longer and the number of solar irradiance data points forecast is consequently larger than the corresponding number of points for the winter season; that is, randomness is increased during the simulation of the summer season data.

Table 5.1 Estimation of ELI using the proposed data estimation technique

	Winter	Summer
Estimated ELI	1.95%	1.66%
Actual ELI range of values	1.89%-1.97%	1.61%-1.74%
Absolute mean Energy Loss Error	0.7%	1.5%
Maximum Energy Loss Error	3.17%	4.6%

Table 5.2 Estimation of the CUI using the proposed data estimation technique

	Winter	Summer
Estimated CUI	13.87%	16.04%
Actual CUI range of magnitudes	13.42%-15.23%	14.23%-18.4%
Absolute mean CUI Error	3.25%	7.45%
Maximum CUI Error	8.9%	12.9%

Table 5.3 Estimation of the COE using the proposed data estimation technique

	Winter	Summer
Estimated COE (Ton)	4.51	17.4
Actual COE range of magnitudes (Ton)	4.36-4.54	16.3-18.7
Absolute mean COE Error	1.15%	2.82%
Maximum COE Error	5.5%	6.9%

To sum up, the proposed data forecasting model has successfully captured the trend in the stochastic data variations. Meanwhile, the proposed algorithm estimates all the stored ZEMOS objective functions successfully with acceptable estimation mean errors and for two different seasons. The test results showed that as long as the estimated duration of the estimate is reduced, the maximum absolute errors would also be reduced. As a matter of fact, using the proposed algorithm, the forecast accuracy can be improved further by increasing the number of clusters and consequently increasing the number of cumulative transition matrices.

5.3 Single Decision maker with Single objectives

In single objective case studies, ZEMOS is utilized to optimize all the built-in objectives independently. As a result, three independent single objective optimization problems were studied. These single objective functions are related to minimization of the current unbalance Index (CUI), minimization of the energy loss index (ELI), or minimization of the total amount of CO_2 emissions (COE). Each problem was solved for two case studies: one representing a typical day in January (winter) and the other, a typical day in July (summer). The operator specified time limit is selected to be 10 minutes.

The study system was modified by installing a large number microFITs, each rated at 10 kW, at different *random* system locations as shown in Figure 5.1. The study system consists of the following controlled resources or tools: four voltage regulators, 6 controlled switches, three single phase shunt capacitors, and one three phase capacitor. Decision variables are assigned to each controlled resource/tool in order to optimize the system operation, and accordingly, a gene is assigned for each decision variable.

It is worth noting that the reconfiguration switches are important components of distribution networks and already exist in the test system (IEEE 123 test feeder) that is used to evaluate and validate the performance of ZEMOS. In this research, it is assumed that the planning and design engineers had reliably designed the system, in the planning and design stages, regardless the state of the switches. Also, it is assumed that necessary protection system and precautions were designed taking into consideration all possible switching states.

To identify a base case (benchmark), initial capacitors switches states were determined as given in [88]. In addition, for the base case, the demand response participants were assumed to have a zero amount of load curtailment, voltage regulators were controlled automatically using line drop compensator (LDC) techniques, the settings for which are presented in [88].

Significant improvements, in objective functions magnitudes, were realized for different case studies when optimizing the study system operation utilizing ZEMOS. Figure 5.4 compares the base case CUI magnitudes with the optimized ZEMOS output. Minimizing the CUI using ZEMOS results in more than 46.76% reductions of the CUI magnitude compared with the base case. For the ELI case study, Figure 5.5, shows that at least a 8.09% reduction in the ELI was realized using ZEMOS. Finally, using ZEMOS, a 4.7% and 11.33% reduction in the COE magnitude during both months of July and January, respectively, as shown in Figure 5.6.

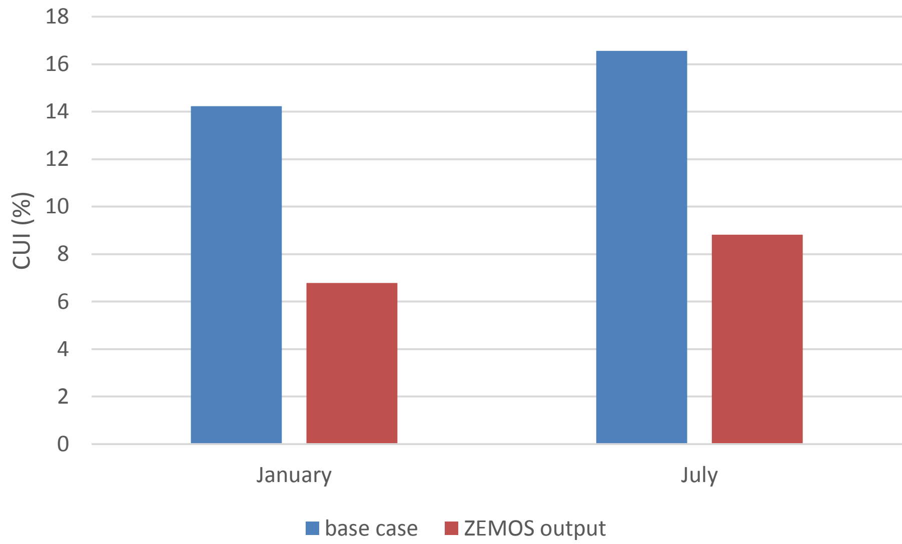


Figure 5.4 Base case and ZEMOS output of CUI

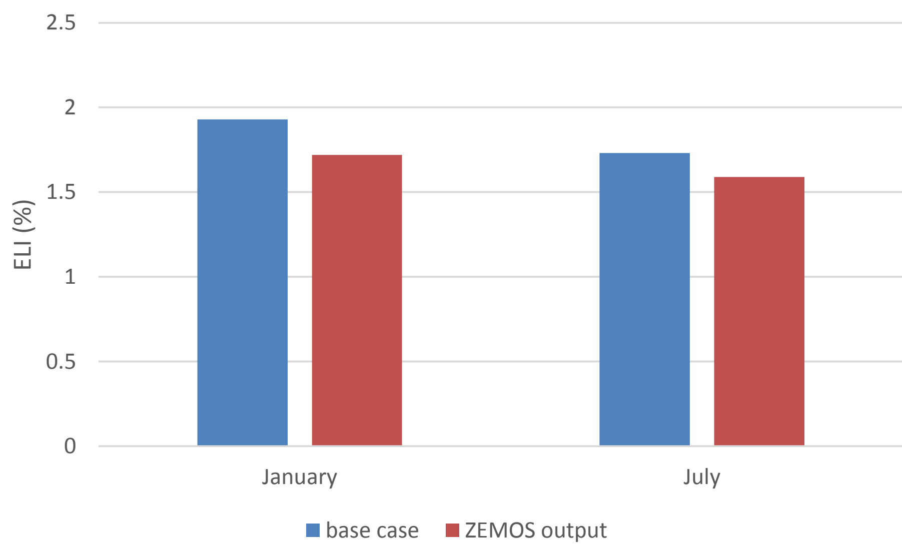


Figure 5.5 Base case and ZEMOS output of ELI

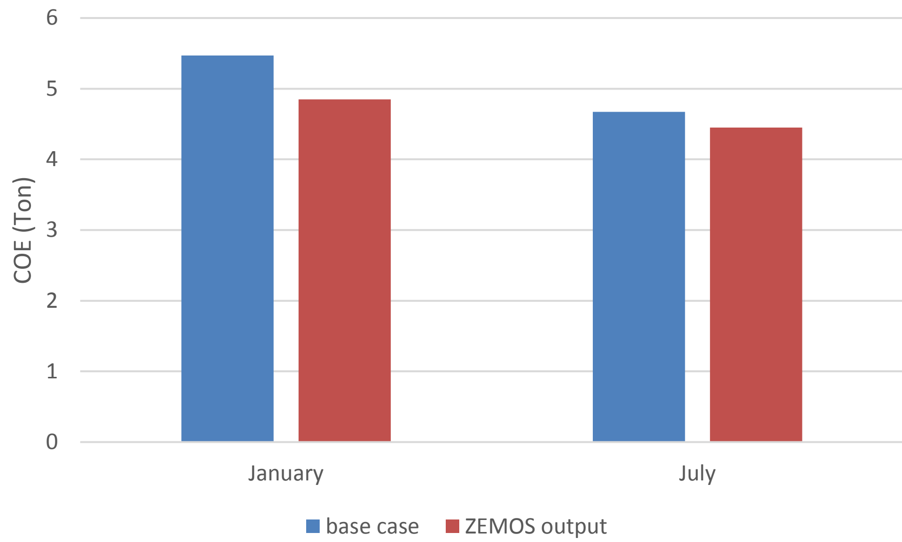


Figure 5.6 Base case and ZEMOS output of COE

5.4 Multi objective optimization and Decision Making Module performance evaluation

Utilizing the decision making module, the proposed ZEMOS supports optimal operation of the study system in the case of multiple objectives. Four different problems were solved to reflect ZEMOS operation in multiple objectives mode as outlined in Table 5.4. All the multi-objective case were compared with the base case values as described in the previous section.

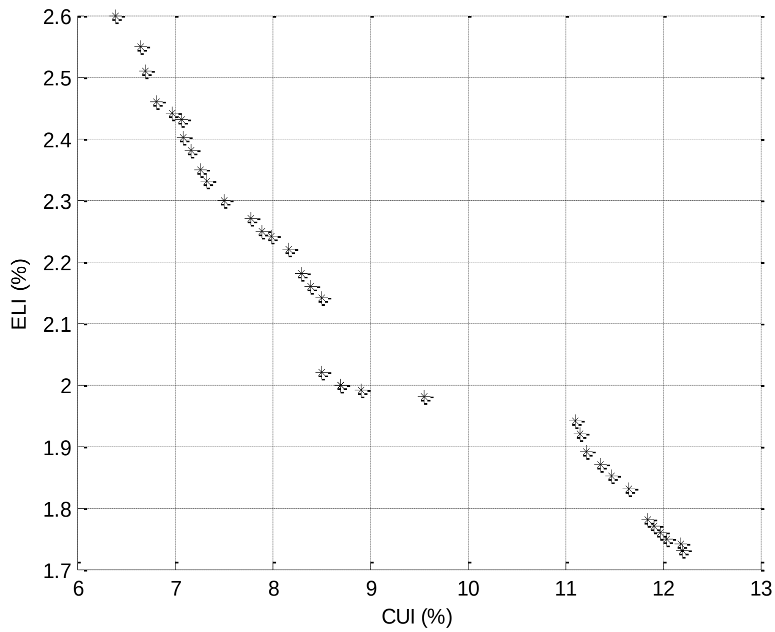
Table 5.4 Different multi-objective optimization problems

Multi-objective Optimization Problem (P1)	Min([CUI ELI])
Multi-objective Optimization Problem (P2)	Min([CUI COE])
Multi-objective Optimization Problem (P3)	Min([ELI COE])
Multi-objective Optimization Problem (P4)	Min([CUI ELI COE])

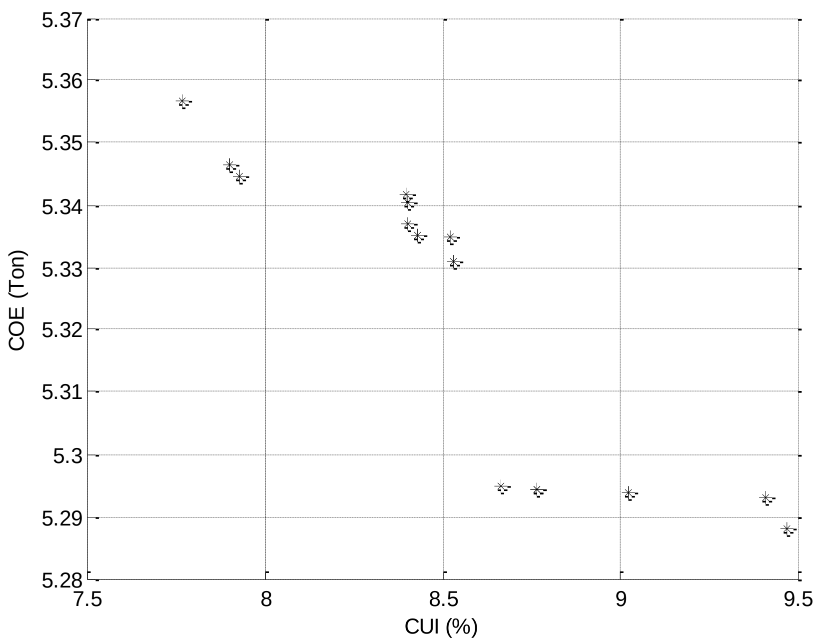
All objective functions were optimized for each case study using both seasons, July and January. The results were simulated with an operator-specified time limit of 10 minutes.

The simulation results are compared using different types of dissatisfaction criteria. This is done in order to compare the final decisions generated by each criterion. In addition, system decisions are compared using two different types of ideal points (theoretical and data based ideal points).

Figure 5.7 to Figure 5.10 show the Pareto fronts which were generated by the CM for all the multiple objective case studies for both seasons. Obviously, the proposed framework had successfully generated acceptable non-dominated Pareto Fronts for all of the introduced case studies, which satisfy the Pareto front definition given in [57]. However, the number of solution points in each Pareto Front is in the range of 14-34 points, which complicates the decision making process from the operator's view point. This concludes that the CM has successfully generated a non-dominated Pareto Front within the specified time bound, while adhering to the system constraints. It comes to the attention that some solution points might be worse than the base case values which is an unacceptable situation. For those reasons, in order to facilitate the operator's decision making process, the presence of a decision making system becomes a necessity which is the role of the DMM. In fact, decision making module (DMM) saves efforts and time for the operator, which would be wasted for selecting the best decision from the generated Pareto front.

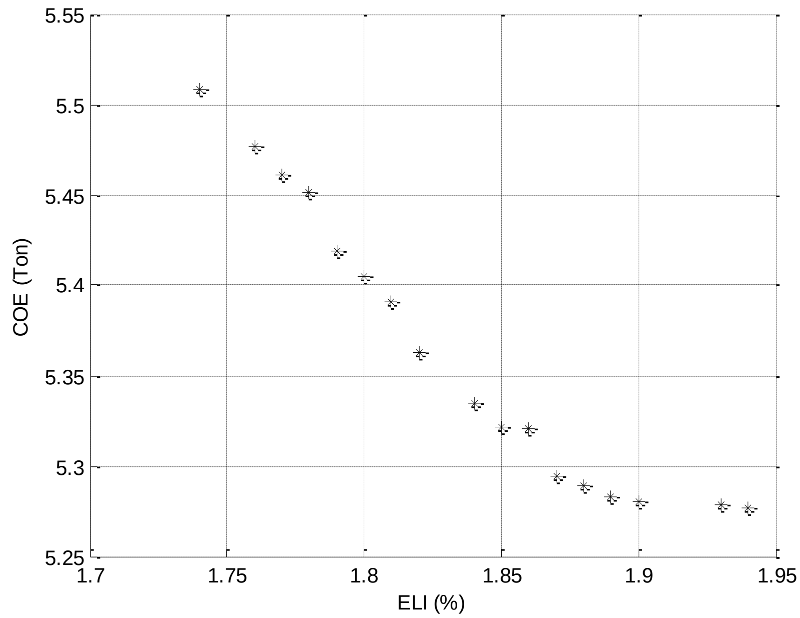


(a)

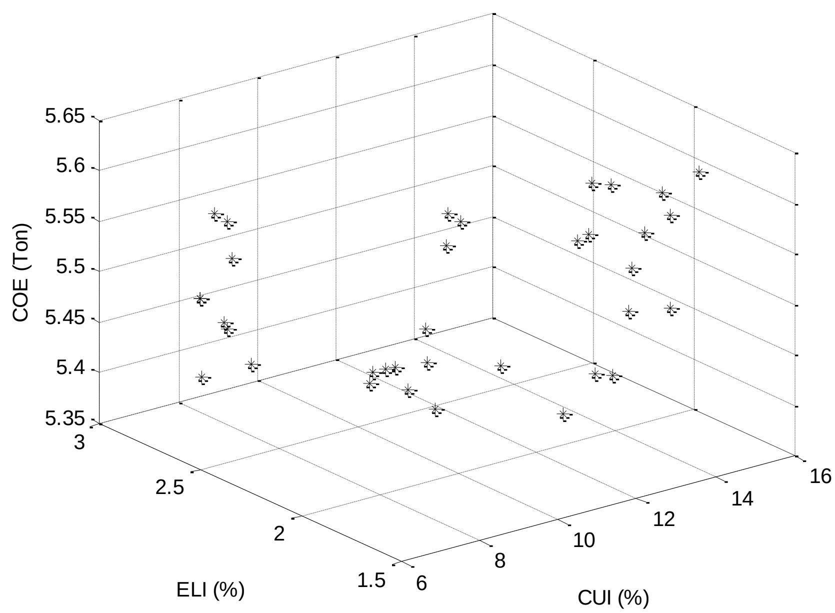


(b)

Figure 5.7 Pareto Front for multi-objective optimization problems in January a) Problem P1 (CUI and ELI) b) Problem P2 (CUI and COE)

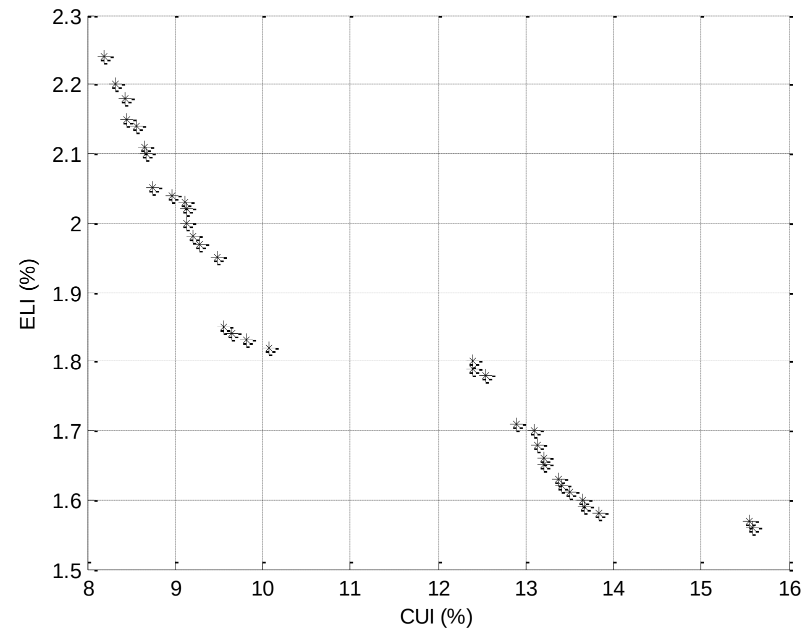


(a)

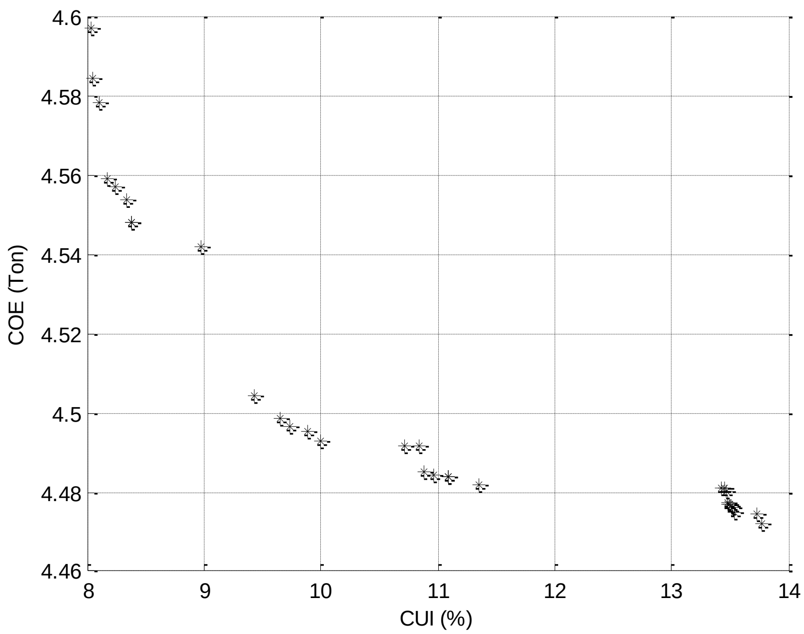


(b)

Figure 5.8 Pareto Front for multi-objective optimization problems in January (a) Problem P3 (ELI and COE) (b) Problem P4 (CUI, ELI, and COE)

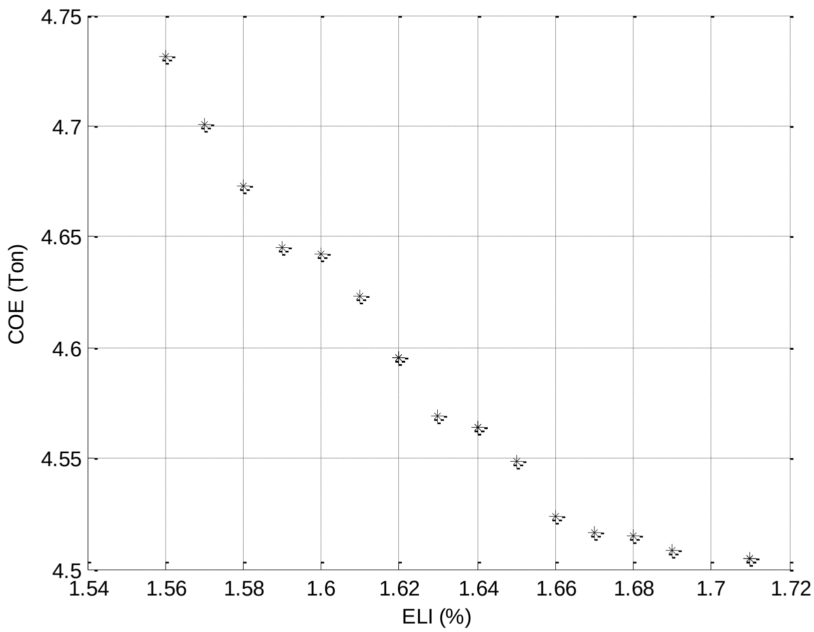


(a)

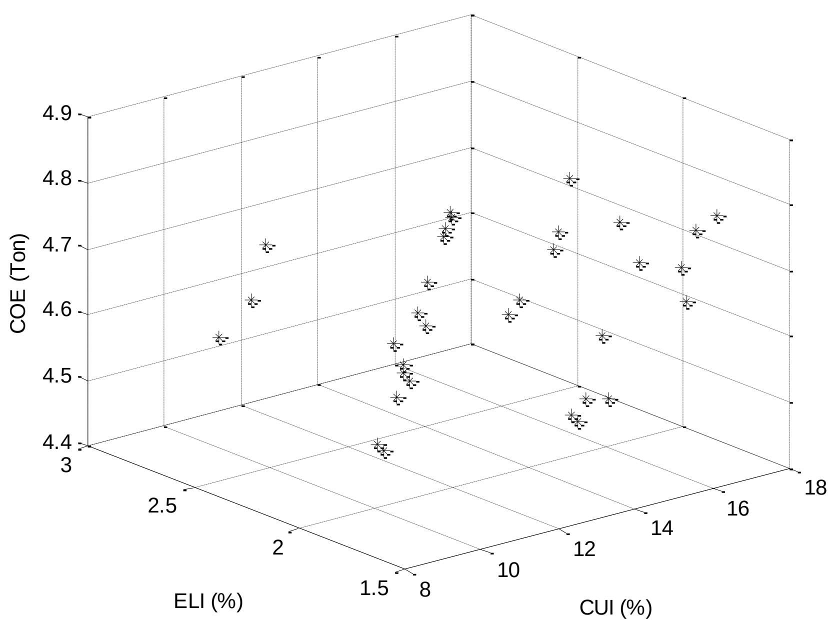


(b)

Figure 5.9 Pareto Front for multi-objective optimization problems in July a) Problem P1 (CUI and ELI) b) Problem P2 (CUI and COE)



(a)



(b)

Figure 5.10 Pareto Front for multi-objective optimization problems in July (a) Problem P3 (ELI and COE) (b) Problem P4 (CUI, ELI, and COE)

The decision making process starts with opting out all the points that violate the decision maker's specified limits for the system objectives i.e. base case values. This step will reduce the number of points to 14-32 points in all case studies. Next, the selected satisfaction criterion is used to select the best decision. Satisfaction criterion selection is normally left to the decision maker. However, it could be confusing for the decision maker to select the most appropriate criterion. Hence, the point that is recommended by the most number of satisfaction criteria will be advised by the proposed ZEMOS.

For all multi-objective optimization problems, the theoretical ideal point (TIP) for CUI, ELI, and COE are 0%, 0%, 0 Ton, respectively. On the other hand, the data based ideal point (DBIP) is calculated from the generated Pareto Fronts which is case study dependent. Table 5.5 to Table 5.8 show the final decisions obtained by using all the proposed satisfaction criteria for different problems and for both seasons.

Table 5.5 Recommended optimum decisions for multi-objective optimization problem P1 (CUI and ELI) using different satisfaction criteria

Decision-Making Criterion	Ideal Point Type	Objectives Optimums Value (Jan)		Objectives Optimums Value (Jul)	
		CUI (%)	ELI(%)	CUI (%)	ELI(%)
Group Dissatisfaction	TIP	12.2	1.73	13.83	1.58
	DBIP	11.8397	1.78	13.49	1.61
Large Dissatisfaction Influence	TIP	11.8297	1.78	13.49	1.61
	DBIP	11.91	1.77	13.66	1.59
Maximum Dissatisfaction Influence	TIP	11.66	1.83	13.22	1.65
	DBIP	11.2	1.89	13.13	1.68

Table 5.6 Recommended optimum decisions for multi-objective optimization problem P2 (CUI and COE) using different satisfaction criteria

Decision-Making Criterion	Ideal Point Type	Objectives Optimum Values (Jan)		Objectives Optimum Values (Jul)	
		CUI (%)	COE (Ton)	CUI (%)	COE (Ton)
Group Dissatisfaction	TIP	8.67	5.3	9.43	4.5
	DBIP	7.76	5.36	8.05	4.58
Large Dissatisfaction Influence	TIP	7.76	5.36	8.17	4.56
	DBIP	8.67	5.3	9.43	4.5
Maximum Dissatisfaction Influence	TIP	9.02	5.29	11.35	4.48
	DBIP	8.67	5.3	9.43	4.5

Table 5.7 Recommended optimum decisions for multi-objective optimization problem P3 (ELI and COE) using different satisfaction criteria

Decision-Making Criterion	Ideal Point Type	Objectives Optimum Values		Objectives Optimum Values	
		ELI (%)	COE (Ton)	ELI (%)	COE (Ton)
Group Dissatisfaction	TIP	1.87	5.29	1.66	4.52
	DBIP	1.79	5.42	1.59	4.65
Large Dissatisfaction Influence	TIP	1.79	5.42	1.59	4.65
	DBIP	1.84	5.33	1.63	4.57
Maximum Dissatisfaction Influence	TIP	1.86	5.32	1.66	4.52
	DBIP	1.82	5.36	1.63	4.57

Table 5.8 Recommended optimum decisions for multi-objective optimization problem P4 (CUI, ELI, and COE) using different satisfaction criteria

Decision-Making Criterion	Ideal Point Type	Objectives Optimums Values (Jan)			Objectives Optimums Values (Jul)		
		CUI (%)	ELI (%)	COE (Ton)	CUI (%)	ELI (%)	COE (Ton)
Group Dissatisfaction	TIP	12.25	1.92	5.39	13.914	1.64	4.64
	DBIP	12.25	1.92	5.39	13.914	1.64	4.64
Large Dissatisfaction Influence	TIP	12.25	1.92	5.39	13.914	1.64	4.64
	DBIP	12.25	1.92	5.39	13.914	1.64	4.64
Maximum Dissatisfaction Influence	TIP	12.25	1.92	5.39	13.84	1.7	4.54
	DBIP	12.25	1.92	5.39	13.84	1.7	4.54

Based on the completed decision-making process for all case studies, the final optimum decisions that will be recommended by the DMM are the decisions that had been generated the maximum number of times using different dissatisfaction criteria, i.e. the highlighted values in each table. Consequently, the final decisions selected for all case studies are the decisions that generate the objective functions values shown in Table 5.9.

Table 5.9 Final optimum values for all case studies

Optimization Problem	Season	Objectives Optimums Values		
		CUI (%)	ELI (%)	COE (Ton)
Problem P1	January	11.8397	1.78	
	July	13.49	1.61	
Problem P2	January	8.67		5.3
	July	9.43		4.5
Problem P3	January		1.79	5.42
	July		1.59	4.65
Problem P4	January	12.25	1.92	5.39
	July	13.914	1.64	4.64

Figure 5.11, Figure 5.12, and Figure 5.13 show the final recommended optimal values of all system objectives, for all case studies, compared with the corresponding base case values. Using ZEMOS, the CUI, ELI, and COE magnitudes were reduced by 43.1%, 8.1%, and 3.6%, respectively, for multi-objective case studies. The accomplished improvements verify the effectiveness of the proposed ZEMOS and the important role that was recognized using the proposed decision making algorithm.

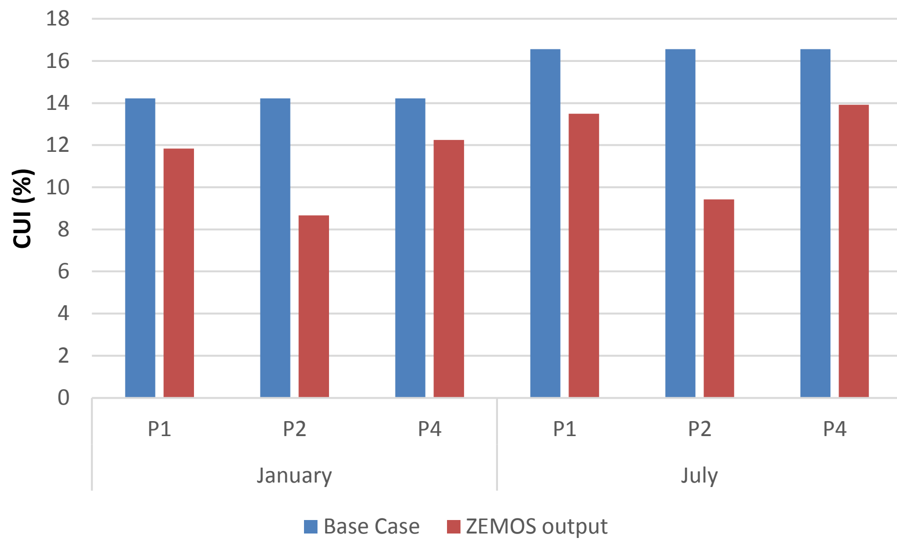


Figure 5.11 CUI Magnitudes for all multi-objectives case studies

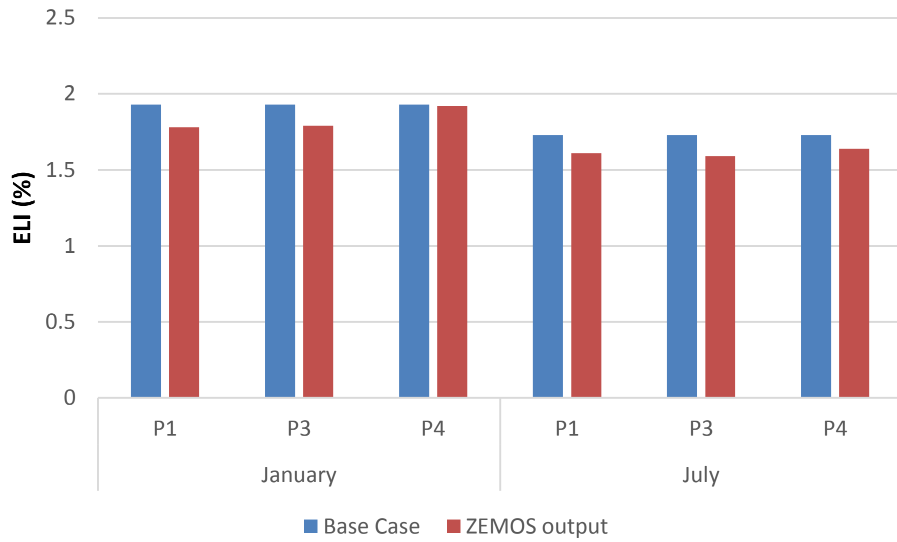


Figure 5.12 ELI Magnitudes for all multi-objectives case studies

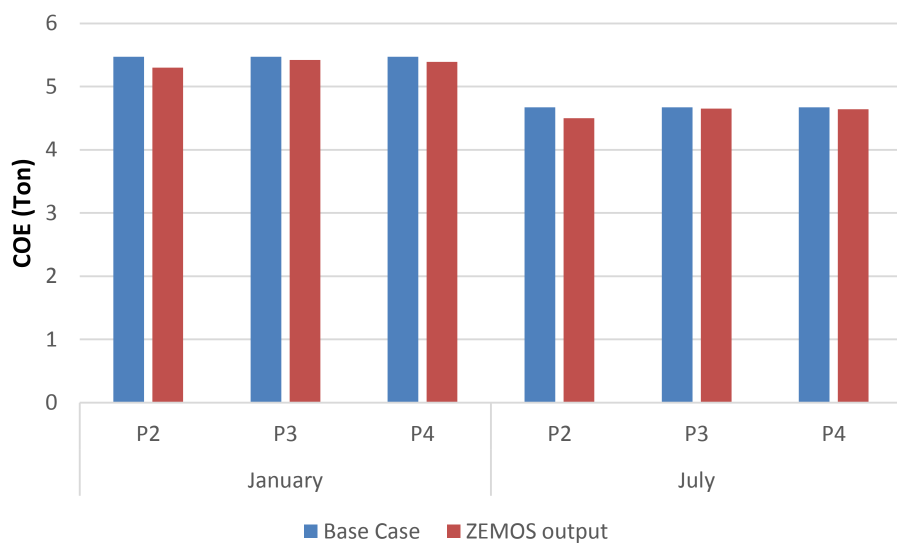


Figure 5.13 COE Magnitudes for all multi-objectives case studies

5.5 ZEMOS performance using the smart matching module (SMM):

This section is dedicated to validate the effectiveness of the proposed smart matching scheme (SMS). The smart matching scheme is utilized by the smart matching module. This section starts with the mathematical models that were utilized to evaluate the operator's objective functions for the purpose of the SMS process. Next, sample results that show the SMS process are presented, followed by the presentation of all the case studies results with related discussion. The test results were conducted both with and without the SMS.

In this section, two case study scenarios were solved representing the peak hours (11 am: 15 pm) of a typical day in the winter and a typical day in the summer. For each season, the system is analyzed for seven cases: three single-objective optimization problems and four multi-objective optimization problems.

Unlike the previous case studies, voltage regulators are controlled using the LDC while reconfiguration switches are assumed to remain uncontrolled by ZEMOS to avoid any negative impact on the protection system or the system voltage profile.

On the other hand, demand response participants and DG owners were introduced as possible controlled tools and resources that can be optimally controlled by ZEMOS. Therefore, the test system shown in Figure 5.1, was modified to include the installation of two conventional three-phase DGs, each rated at 250 kW, at two different locations, nodes 25 and 47.

Nine demand response participants are controlled by ZEMOS each rated 50 kW or more [93]. The controlled Loads are located at nodes 47, 48, 49, 64, 65, 66, and 76(a,b and c).

As a result, the study zone is currently equipped with 15 controlled resources as follows: nine demand response (DR) controls; two three-phase conventional DGs, output power controls; three single-phase shunt capacitors control switches; and one three-phase capacitor control switch. Capacitors locations are as shown in [88];.

To identify a base case (benchmark), initial capacitors switches states were determined as given in [88]. In addition, for the base case, the demand response participants are assumed to have a zero amount of load curtailment, and the output power values of the DGs are randomly selected. Therefore, the base case values might be different from the previous case studies.

5.5.1 Long term Objective Functions estimation

Sensitivity Index evaluation is a long-term offline study that will be used for different system operations. This section describes the evaluation of the operator's objective functions for long term studies as in the SI evaluation. The system under study consists of stochastic elements such as loads and microFITs. Due to the random nature of those elements, the estimation of the system objective functions, for long term studies, requires detailed modelling of those elements. Consequently, this section presents the proposed modeling of the stochastic elements (e.g. MicroFITs and load demand).

Next, the proposed models will be utilized to evaluate the expected value of the operator's objective functions for long term studies.

5.5.1.1 Modeling of MicroFITs and Load Data

The main purpose of this model is to generate probability density functions for each stochastic element, which will be used to estimate the hourly solar irradiance and the hourly load demand, respectively.

A) Historical Data Processing

For the solar irradiance, the proposed models were developed based on 15 years of historical data [90]. For both types, each season is represented by one day. The year is divided into four seasons, with each season represented by one day. In other words, each year is divided into four days, equivalent to 96 hours (4 d x 24 h). Each daily hour in the model thus represents the same hour for the entire season. Given 15 years of historical data, each simulated day has 1350 data points (30 d x 3 m x 15 yr). As for the loads , the load profile is assumed to follow the IEEE Reliability Test System (RTS) [91].

From the historical data, the mean and standard deviation for each hour segment are calculated, and from them, the probability density functions are generated for each hour, and each element as described below.

B) MicroFITs data modeling

Examining the historical irradiance data reveals that for the same hour of the typical day in any season [94], the solar irradiance data normally have a bimodal distribution function. Hence, the data are divided into two groups, each group having a unimodal distribution function; a beta pdf is then developed for each unimodal [94]. Next, the beta cumulative distribution function (CDF) is calculated for each value of the solar irradiance for the same hour of the typical day in a season, as follows:

$$F_{\beta}(I_{nor} \mid a,b) = \frac{1}{B(a,b)} \int_{0}^{I_{nor}} x^{a-1}(1-x)^{b-1}dx \tag{5.6}$$

$$b = (1-\mu_{irr}) \times \left(\left((1+\mu_{irr})\mu_{irr} / \sigma_{irr}^{2} \right) - 1 \right) \tag{5.7}$$

$$a = \mu_{irr} \times b / (1-\mu_{irr}) \tag{5.8}$$

$$I_{nor} = \left(I - I_{\min} \right) / \left(I_{\max} - I_{\min} \right) \tag{5.9}$$

Where, I is the solar irradiance (kW/m^2); I_{min}, I_{max} are the solar minimum and maximum recorded historical solar irradiance at the current hour, respectively; $F_{\beta}(I_{nor}|a,b)$ is the Beta CDF of I_{nor} ; a,b are the parameters of the Beta distribution function; and μ_{irr} ,σ_{irr} are the mean and the standard deviation of the solar irradiance data, respectively.

C) Load data modeling

Examining the load data shows that for the same hour of the typical day in each season, the load levels are found to follow a normal distribution function. The normal cumulative distribution function (CDF) is calculated for each load level for the same hour of a typical day, as follows:

$$F_{norm}(L \mid \mu_{load}, \sigma_{load}) = \frac{1}{\sigma_{load}\sqrt{2\pi}} \int_{-\infty}^{L} e^{-\frac{1}{2}\left(\frac{x-\mu_{load}}{\sigma_{load}}\right)^2} dx \tag{5.10}$$

Where, L is the load level as a percentage of the peak load; $F_{nor}(L \mid \mu_{load}, \sigma_{load})$ is the normal CDF of L; and μ_{load} ,σ_{load} are the mean and the standard deviation of the load data, respectively.

5.5.1.2 Objectives evaluation process

Monte-Carlo simulation (MCS) is used to estimate the expected value of the operator's objectives, as follows:

1) Random uniform numbers (p_{load}, p_{solar}) between 0 and 1 is generated for each hour.
2) The inverse cumulative density functions CDF are used for each hour, based on the random numbers generated in step (a) to generate values for the power levels of the loads and microFITs by utilizing the corresponding CDF, as follows:
   - For the microFITs:

$$I_{nor} = F_{\beta}^{-1}(p_{solar} \mid a,b) = \left\{ I_{nor} : F_{\beta}(I_{nor} \mid a,b) = p_{solar} \right\} \tag{5.11}$$

   The hourly solar irradiance is given by:

$$I = I_{\min} + I_{nor} \times \left(I_{\max} - I_{\min} \right) \tag{5.12}$$

   Where, I is the solar irradiance value which cumulative probability under the beta CDF is specified by the corresponding value in p_{solar}. Next, The microFITs output power $P(I)$ is then evaluated as given in [95].

   - For the loads:

$$L = F_{norm}^{-1}(p_{load} \mid \mu_{load}, \sigma_{load}) = \left\{ L : F_{norm}(L \mid \mu_{load}, \sigma_{load}) = p_{load} \right\} \tag{5.13}$$

   Where, L is the load level as a percentage of the peak load which cumulative probability under the normal CDF is specified by the corresponding value in p_{load}.
3) The generated load levels and microFITs powers are used to simulate the system under study and

hence to evaluate the value of the current operator objective function.

4) Steps (1) →(3) are considered to be one scenario, which is repeated until the following stopping criterion is satisfied:

$$\sigma(Obj_i) / E(Obj_i) \le \varepsilon \quad (5.14)$$

where $\sigma(Obj_i)$ is the standard deviation of objective I, $E(Obj_i)$ is the expected value of objective I; and ε is a selected small tolerance. The estimated long term operator's objective is the expected value $E(Obj_i)$.

5.5.2 Smart Matching Scheme

First, sensitivity indices were evaluated to estimate the effect of each controlled resource on the different objectives function magnitude, as shown in Table 5.10. A preliminary step was to evaluate the hourly costs of the step changes for each controlled resource variable, based on consideration of the demand response payments, as set out in [96]; payments to the DG owners, as given in [97]; and capacitor kVAr prices, as indicated in [98].

Table 5.10 SI for all existing system controlled resource and resources

	CUI SI (%)	ELI SI (%)	COE SI (%)
Load 1	-0.4191	0.173459	-0.04911
Load 2	-0.83193	0.40814	0.667866
Load 3	-1.68406	0.05604	0.225704
Load 4	-1.78581	0.10991	0.248495
Load 5	0.330038	0.274247	0.234324
Load 6	-0.25614	0.155399	0.235888
Load 7	-0.04937	0.403604	0.340651
Load 8	-1.0419	0.20005	0.239537
Load 9	0.433572	0.308661	0.232745
DG1	-0.74168	0.077242	-0.09247
DG2	-0.78802	0.08605	-0.08167
Capacitor 1	-8.57864	11.23376	0.343
Capacitor 2	6.347553	2.493459	0.077533
Capacitor 3	-7.07814	0.17462	0.003123
Capacitor 4	-2.14794	1.136032	-0.05527

Next, the matching process is conducted by solving the optimization problem described by equations ((4.33) to(4.35)). This process is executed for the objectives related to minimizing CUI, ELI, and COE. A single solution set for each problem is then selected based on the decision-making algorithm developed in the DMM.

Table 5.11 shows the results of the matching process. Load curtailments (demand response) are considered to be unidirectional controlled resources because operators can send signals only to reduce the controlled loads. Thus, if the SI of a load has a negative value, it is not matched to the corresponding objective (i.e., loads 1, 2, 3, 4, 6, 7, and 8 are not matched with the objective related to min(CUI)). In addition, most DR related resources involve higher payments per step change than other existing controlled resources/tools [96]. For this reason, they are not recognized as the best option during the matching process (e.g. loads 1, 2, and 3 are not selected for any given objective).

Table 5.11 Relations between system objectives and tools

Objecti	**Load1**	**Load2**	**Load3**	**Load4**	**Load5**	**Load6**	**Load7**	**Load8**	**Load9**	**DG1**	**DG1**	**Cap1**	**Cap2**	**Cap3**	**Cap4**
CUI					X				X	X	X	X	X	X	X
ELI					X		X		X	X	X	X	X	X	X
COE				X	X	X	X	X	X	X	X	X	X	X	X

5.5.3 Results of ZEMOS operation using SMS

In single-objective case studies, denoted as *S*, three single objective problems were solved independently (i.e. *S1=min(CUI), S2=min(ELI)* or *S3=min(COE)*). Four different problems were solved to reflect the system operation in multiple objectives mode as outlined in Table 5.12.

Table 5.12 Different multi-objective optimization problems

Optimization Problem (P1)	Min([CUI ELI])
Optimization Problem (P2)	Min([CUI COE])
Optimization Problem (P3)	Min([ELI COE])
Optimization Problem (P4)	Min([CUI ELI COE])

All objectives were optimized for each case study using the SMS recommended matches, as given in Table 5.11. For both seasons, the results were simulated with an operator-specified time limit of 50s. The optimization problems were solved a second time without using the SMS; that is to say, all the controlled resources/tools were matched to each objective to validate the SMS.

In case of single-objective optimization, the simulation results show that, using the proposed SMS produces a significant improvement with respect to each objective compared with the base case values shown in figures 5.14, 5.15 & 5.16. Meanwhile, during the same operational time limit (50s), the use of the SMS results in better values of the CUI for both seasons. On the other hand, using the SMS may not provide superior values for the cases of improving the ELI and COE because not all of the existing tools were utilized. However, the differences in magnitude between the results generated with and without the SMS lie within a range that does not exceed 4.06%.

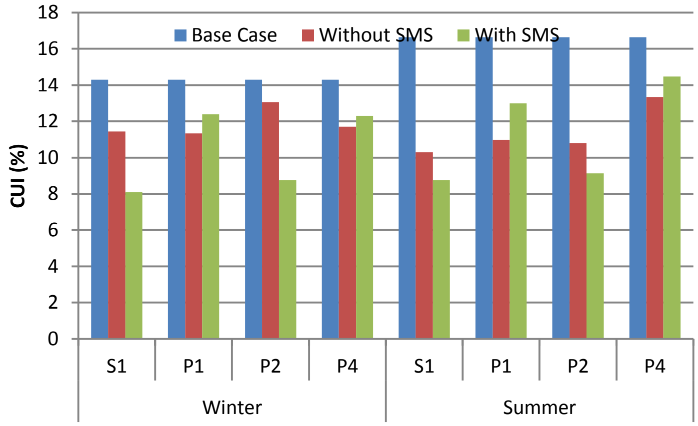


Figure 5.14 CUI magnitudes for all case studies

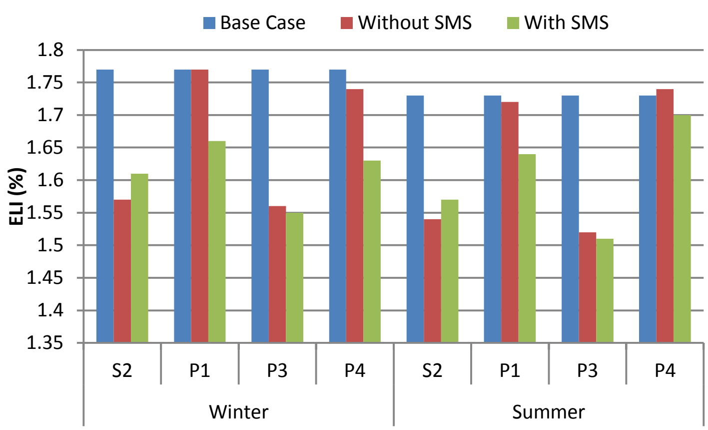


Figure 5.15 ELI magnitudes for all case studies

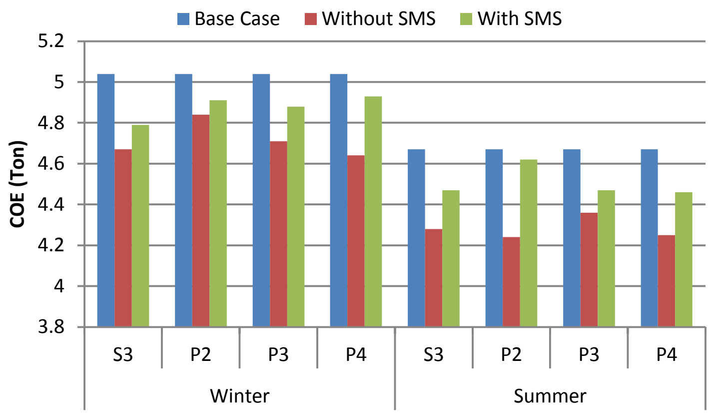


Figure 5.16 COE magnitudes for all case studies

In case of multi-objectives optimization, compared with the base case, using the SMS, the following improvements were realized: up to a 45.13% reduction in the CUI, up to a 12.72% reduction in the ELI, and up to a 4.5% reduction of the COE.

For the optimization problem P2, utilizing the SMS provides a better value of the CUI. However, without using the SMS, a better COE value is obtained. As a result, one solution cannot be said to be preferable to another. In other words, no solution is considered as a dominant solution. In fact, for all multi-objective optimization problems results, solving without the use of the SMS does not provide any solution that dominates the solutions provided using the SMS.

On the other hand, the operational costs were reduced when the SMS is utilized. For any optimization problems that involve the minimization of the ELI, the cost savings were evaluated and can be calculated as follows:

$$S = C_o - C_{oSMS} - C_{loss} \tag{5.15}$$

where S represents the total savings; C_{loss} is the cost of the difference in energy loss between the two cases, based on IESO prices from [99] for the energy loss; and C_o , C_{oSMS} are the total optimal operational costs (i.e., capacitor kVAr costs, DG utility payments, and demand response payments) during the study period with and without the SMS, respectively.

On the contrary, for any optimization problem that does not involve the minimization of the ELI, the cost savings were evaluated and can be calculated as follows:

$$S = C_o - C_{oSMS} \tag{5.16}$$

The test results show that, compared with the ZEMOS operation without the SMS, optimization using the SMS provides cost savings of from 23.27% up to 66.25% for the winter case study and cost savings of from 24.51% up to 57.82% for the summer as shown in Figure.5.17.

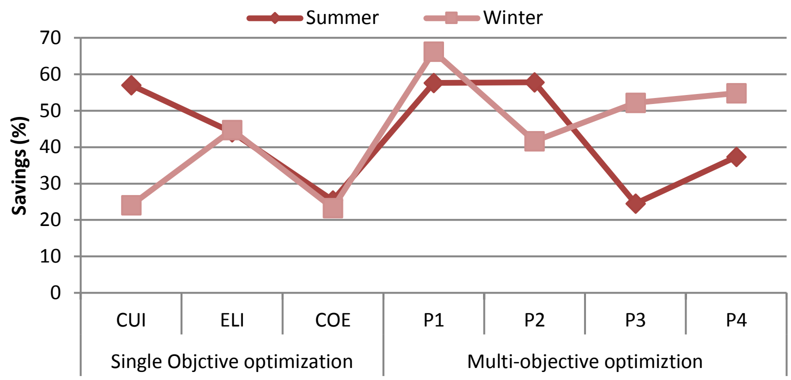


Figure.5.17 Percentage optimal operational costs savings using the proposed SMS for different kinds of optimization problems and both seasons

5.6 Conclusions

In this chapter, ZEMOS was applied on a study zone with a single decision maker. The analysis was done for different single and multi-objective optimization case studies.

The proposed data forecasting model was applied on the study system to validate the model. It has been shown that the proposed forecasting model can be used to successfully capture the stochastic data variations trend. In addition, the proposed algorithm estimates the CUI, ELI, and COE in a satisfactory manner with an acceptable error range. Obviously, the less the estimated duration, the less the maximum objective functions estimation errors.

For the multi-objective optimization case studies, simulation results showed that the control module (CM) has successfully generated optimum and acceptable Pareto Front. Besides, the proposed decision making algorithm has proven to be useful and efficient in assisting the decision maker to select an efficient and optimal decision.

On the other hand, the proposed smart matching scheme (SMS) is used to solve different kinds of optimization problems, either single or multi-objectives problems within shorter time frames. The results of using SMS, for the zone under study, reveal consistent improvements in the system objectives functions magnitudes for all of the case studies, compared with the base case.

The performance of different optimization problems solutions using the SMS is compared with the tradition optimization which does not use the SMS, within the same operator’s required time frame.

For single objective optimization, the simulation results demonstrate that the proposed SMS either generates superior solutions, within the operator’s time limit or it reduces the operational costs if no significant changes are introduced compared with ZEMOS operation without the SMS.

For multi-objective optimization, the generated solutions without the SMS did not dominate the solutions generated using the SMS, for all types of problems and case studies. Yet, using the proposed SMS, a significant savings associated with the optimal operational costs are realized.

The investigated case studies showed that there were significant and consistent improvements in the CUI, the ELI, and COE magnitudes compared with the base case without the need for installing additional components or upgrading the existing zonal components. The simulation results showed that there is always an acceptable solution within the specified time frame regardless of the number of objectives, types of objectives, or the number of the controlled system resources or tools which supports the proposed modularity concept adopted by ZEMOS.

Chapter 6 Zonal Energy Management System with multiple Decision Makers (Modeling and Simulation results)

Implementing a smart grid allows generators and loads to interact in an automated fashion to improve the distribution system (DS) performance. Therefore, modern smart distribution systems are viewed as common systems which includes many rational individuals, or decision makers, (e.g. system operator, loads, and generators). In this chapter, we investigate the possibility of having controlled resources/tools owners that are rational and are able to make their own decisions. Under different system circumstances, each decision maker will select a set of specific actions, or strategies, that will improves his own payoff function. As a result, conflicts of interests between different individuals might take place. Social impact between, different decision makers, is one of the most important challenges that face the smart grid implementation. Consequently, the *efficient* and *fair* management of the energy of such systems will be a complicated task for utilities.

Therefore, this chapter introduces the utilization of ZEMOS for distribution system operation with more than a single decision maker each has its own *single*, and independent, objective which is called multi-decision makers analysis or multiple participant decision making [100].

Game theory is one of the most vital mathematical branches that explore the conflicts and collaborations between different rational players within such a common system. According to [101], game-theoretic based approaches are considered one of the most promising tools for the study and the control of smart grid systems. Several researches utilized game theory to control the operation of the DS [102-107].

The first research area discusses the several control problems in microgrids that can be solved using game theory. A non-cooperative game theory framework that controls both the loads and energy sources in a small-scale power system (e.g. microgrids) were presented in [102, 103]. The proposed algorithm in [103] was based on evaluating the Nash equilibrium [104] using the best response algorithm. It is worth noting that the authors in [103] have simplified the problem by not integrating transmission line losses.

The authors in [105] present a distributed demand-side energy management system that utilizes a two-way digital communication infrastructure to evaluate the Nash equilibrium. The proposed algorithm optimizes the energy consumption costs by recommending an optimal energy schedule for each demand response participant.

The authors in [106], propose a demand side method based on a day ahead optimization process. The main objective of these users is to minimize the energy expenses. A Nash equilibrium game theoretical approach is used to determine optimal production and storage strategies of each user.

In [107], the authors presented a method for the users to optimize their storage devices and when to buy energy from the grid. In other words, the consumers make strategic storage decisions in order to maximize their own utility function (e.g. revenue). The authors in [107], utilize Nash equilibrium in order to evaluate the optimum operating conditions for all players.

The authors in [108] use the concept of Nash equilibrium to introduce two market models that match the supply and the demand in a smart grid system.

Most of the existing game theoretic research works rely only on optimizing the players' utility functions by utilizing the concept of Nash equilibrium [109]. Using Nash equilibrium, each player only takes into consideration his own strategy to selfishly maximize his own payoff. Nash equilibrium is normally reached using the best response algorithm [103, 105, 107]. Best response algorithm has a main advantage; explicitly, it's simple implementation. On the other hand, best response has two major drawbacks [110]. First, convergence to equilibrium is not guaranteed for all types of utility functions [110]; second, it does not always guarantee the convergence to an efficient equilibrium which is fair to all players [110], this is due to the fact that all players are selfish. With that in mind, there are always greedy players, with best performance whose actions dominate the game, leading to a significant reduction on other players' performance or payoff. Therefore, the game outcome might require further improvement.

For those reasons, the concept of correlated equilibrium (CE) [111] is adopted in this research work as an alternative to control the system under study. CE is considered more general than the Nash equilibrium (i.e. Nash equilibrium is a sub-set of the set of Correlated equilibria).

The CE concept has many benefits. First, negative (undesirable) payoff actions are completely avoided. Second, fairness is achieved by allowing each player to consider joint distribution of all players' actions. In CE, each player considers others' actions to explore the existence of any mutual benefits between the players. Besides, each player takes into account his historical actions during the game in order to reach the correlated equilibrium[112]. Such considerations will lead to a better performance than using the concept of Nash equilibrium and maximize the social welfare of all players [112, 113] (i.e. fairness between participants is maximized). As a result, customers are motivated to participate in such a scheme that increases fairness between different game players in addition to the incentive payments paid by the electric distribution utility through a demand response program.

In this research work, we propose a control algorithm that can be employed in ZEMOS combined with a demand response program, in which, participants' incentive payments will increase if their actions improve the global system objective (i.e. social welfare). Therefore, each user, who will willingly participate in a game, will embrace actions that will satisfy the DS operator needs. Due to the decentralized nature of the proposed algorithm, the amount of information exchanged between participants is reduced[105]. The proposed algorithm is based on CE which provides a wider range of applications than best response techniques. The proposed algorithm addresses the major drawbacks of the traditional best response algorithm.

This chapter covers the detailed problem description and formulation related to multiple participants' decision making operation. Proposed utility functions for the different system decision makers are presented. The chapter also provides a detailed description of the proposed CE based algorithm that is stored in the control module (CM). Results of the simulation accompanied with the related discussion of the findings are also presented followed by the conclusions and discussions.

6.1 Problem Description and Formulation

In this section, a detailed description of the zone under-study is presented. This system has different decision makers (DMs), each has specific utility functions (payoff function). Therefore, mathematical formulations of the utility functions, associated with each DM, are introduced. Next, a mathematical formulation, that represents each DM's strategies or control options is presented. Finally, the present system performance is evaluated to formulate the problem under study.

6.1.1 System Description

The IEEE 123-bus (Figure 6.1) test system was used again in this chapter [88]. The test system was modified by installing a large number of solar based microFITs, each rated at 10 kW, at different *random* locations on the system as shown in figure 6.1. This implementation of the microFITs, in the system under study will demonstrate the efficiency of the proposed algorithm in the presence of a large number of stochastic renewable generations. In addition, the test system was modified to include the installation of only one conventional three-phase DG rated at 250 kW located at node 47.

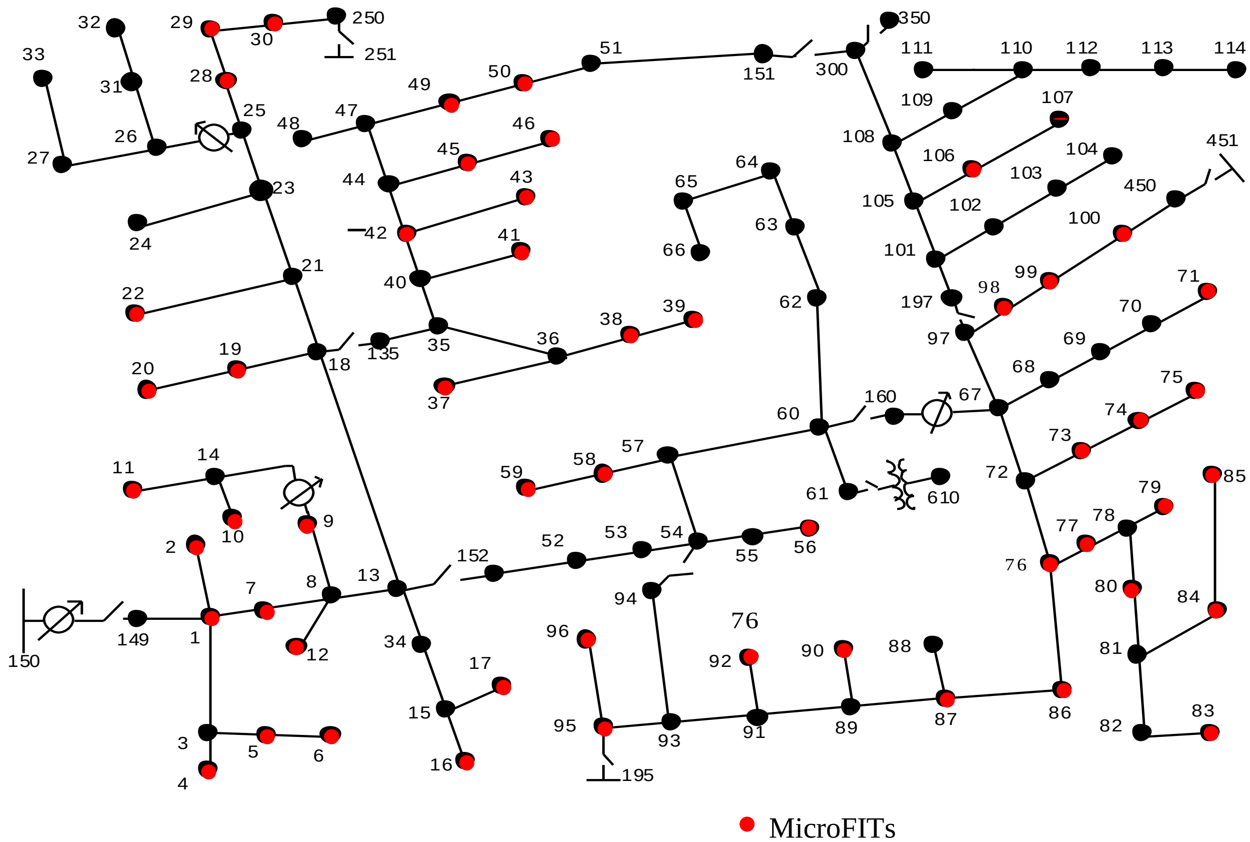


Figure 6.1 IEEE 123 bus test feeder

The study system has seven decision makers: the electric DS operator , five demand response (DR) participants each rated above 50 kW [96], and one conventional DG owner. The demand response participants are located at nodes 47, 48, 65, and 76 (a, and b).

6.1.2 Utility functions evaluation

The system under study includes seven different decision makers (DMs); each has his own utility function or payoff. The DMs involved in this system can be classified as: the DS operator and DS customers (i.e. DR participants and DG owner)

6.1.2.1 Distribution system operator:

The DS operator is represented as a decision maker whose needs, or objectives, change according to the system operating conditions. DS operator objectives are stored in the objectives module (OM). Two objectives, that are stored in the OM, are utilized to generate two case studies that are analyzed in this chapter: the first case study (CS1) is related to the minimization of the system energy losses over a specified period of time. The second case study (CS2) is related to the minimization of the system phase unbalance over a specified period of time.

The utility function of the system operator for CS1 is:

$$U_1 = -\overline{ELI} \tag{6.1}$$

The utility function of the system operator for CS2 is:

$$U_1 = -\overline{CUI} \tag{6.2}$$

6.1.2.2 Distribution system customers:

Six DMs customers exist in the system under study. Five DMs represent demand response loads, and one conventional DG owner. For each DM, the utility function is modeled in accordance with the incentive based demand response programs, wherein each DM receives incentive payments for their participation in the improvement of the DS performance [114].

It is worth noting that the utility functions of distribution system customers are not stored in ZEMOS for privacy protections. However, DMs will notify ZEMOS only with the magnitude of their utility functions. As a result, ZEMOS will determine the worst off decision maker in order to maximize the social welfare.

For demand response DMs, the utility function is as set out in [96]; wherein, two components are included (availability payment *Av*, and the utilization payment *Uti*). The availability payment corresponds to the average kW confirmed load reduction per month. On the other hand, the utilization payment corresponds to the amount kWh curtailed load during the current operator's specified period. Subsequently, the local utility function of a specific DR player/participant is given by:

$$U_{i_{local}} = Av_i + Uti_i \,,\ \forall i = 2,3,4,5,6 \tag{6.3}$$

$$Av_i = \frac{\sum_{month} kWh_i}{\text{Total Activation hours in a month}} \times \text{Av}_{\text{rate}} (\$/\text{kW}) \tag{6.4}$$

$$Uti_i = E(A_i^n)(kWh) \times Uti_{rate} (\$/\text{kWh}) \tag{6.5}$$

Where A_i^n is the selected action,strategy, of DM i for the time interval n; $E(A_i^n)$ is the energy supplied by DM i for the time interval n.

For the DG owner, the utility function is formulated based on two components (capacity payment *C*, and the Energy payment *EP*) [115]. The capacity payment corresponds to the average kW confirmed supplied power per month. On the other hand, the energy payment corresponds to the kWh supplied during the present operator's specified period. Therefore, the local utility function of a specific DG owner is given by:

$$U_{i_{local}} = C_i + EP_i, \forall i = 7 \tag{6.6}$$

$$C_i = \frac{\sum_{month} E_i}{\text{Total operating hours in a month}} \times \mathrm{C}_{\mathrm{rate}} (\$/\mathrm{kW}) \tag{6.7}$$

$$EP_i = E(A_i^n)(kWh) \times E_{\mathrm{rate}} (\$/\mathrm{kWh}) \tag{6.8}$$

Where A_i^n is the selected action,strategy, of DM *i* for interval *n;* and $E(A_i^n)$ is the energy supplied by the DG owner for interval *n*, $\mathrm{E}_{\mathrm{rate}}$ is the kWh rate as set out by the system operator

6.1.3 Decision makers Strategies:

In this research work, each decision maker has a set of strategies *S,* which can be adopted by each decision maker to maximize his own payoff. The DS operator strategies are selected using ZEMOS. Otherwise, each customer DM notifies ZEMOS with the adopted strategy for processing and simulation. In other words, the selected strategy replaces the controlled tools/resources decision variables that were previously evaluated by ZEMOS.

For the DS operator, the potential strategies are the switching status of three single-phase shunt capacitors control switches; and one three-phase capacitor control switch.

A decision variable $X_{c_l}^h$ is assigned to each capacitor switch, where

$$X_{c_l}^h = \begin{cases} 0 & \text{if capacitor } l \text{ is switched OFF} \\ 1 & \text{if capacitor } l \text{ is switched ON} \end{cases} \quad \text{and } X_{c_l}^h \in \{0,1\}$$

If capacitor *l* is connected to bus *i*, the injected reactive power at bus *i* is given by the following*:*

$$Q_i^h = X_{c_l}^h \times Q_{c_l}^h - Q_{load_i}^h \tag{6.9}$$

where Q_i^h is the injected kVAr at bus *i* during hour *h, Q_{ci}^h* is the injected kVAr of capacitor *l* at bus *i* during hour *h,* and $Q^h_{load\ i}$ is the kVAr requirement of load *i* during hour *h.* $X_{c_l}^h$ is the controlled variable that is optimally determined.

For the demand response (DR) decision makers, the potential strategies are the amount of energy curtailed. The power levels of different loads are calculated as follows:

$$P_i = (1 - 0.01 \times c_i) P \tag{6.10}$$

$$Q_i = (1 - 0.01 \times c_i)Q \tag{6.11}$$

$$c_i \le c_{\max}$$

where P,Q are the present load kW, kVAr, respectively; P_i, Q_i are the proposed load kW, kVAr at instant i, respectively; c_i is the amount of load reduction as a percentage of the nominal load; and c_{max} is the upper limit of c_i. The load curtailment factor c_i is the controlled variable that is optimally determined.

In this thesis, dispatchable DGs owner strategies are controlled by selecting a set point of the desired value of the DG output active power. The DG output power levels are expressed by:

$$P_{DGi} = 0.01 \times c_{DGi} \times P_{DGo} \tag{6.12}$$

where P_{DGo} is the DG rated kW, P_{DGi} is the DG kW at instant i, and c_{DGi} is the percentage factor. c_{DGi} is the controlled variable that is optimally determined.

6.1.4 Problem formulation and System Performance

Typically, the operator follows an activation protocol when initiating an energy management process, as set out the demand response protocol used in [96]. For an operator's specified period, the system operator will issue a standby notification to all the participants. In response, the participants, i.e. decision makers, will be required to respond with a Confirmation, specifying both the confirmed selected strategy (e.g. amount of load curtailed kW, or DG injected kW), and Confirmed Hours (even if the Confirmed kW and/or the Confirmed Hours will be zero). The operator can either issue a standby notification one day ahead, or few hours ahead of the required optimization period. Accordingly, each decision maker will independently adopt the strategies that will selfishly maximize his local payoff, utility function, while adhering to his own operational constraints (e.g. non-shiftable loads [105]).

Under such circumstances, the process is continuously repeated during the peak period for typical days and in different seasons. The selfish actions adopted by the decision makers lead to an increasing trend in the ELI expected values from the initial condition, as shown in Figure 6.2. This situation refers to the existence of a conflict of interest between the system decision makers and the operator's needs, leading to worse operating conditions. For the second case study, the average CUI also follows an increasing trend which converges to 15.4%, as shown in Figure 6.3. Thus, the conflicts of interests between the system decision makers arise in both case studies. Obviously, there is a need for an efficient algorithm that handles and resolves conflicts between DS decision makers. Therefore, the main purpose of this chapter is to develop such an algorithm that resolves the aforementioned conflicts.

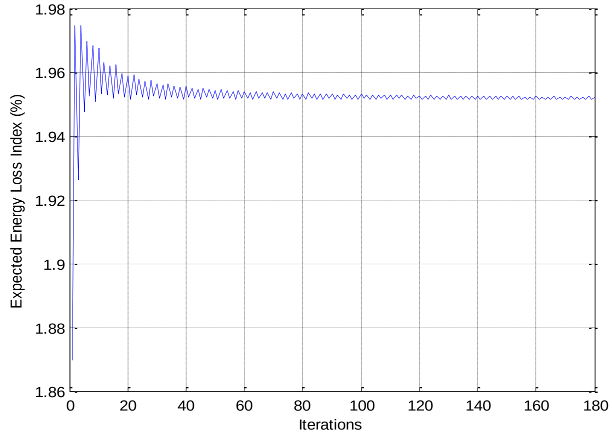


Figure 6.2 Average ELI for a repeated optimization process

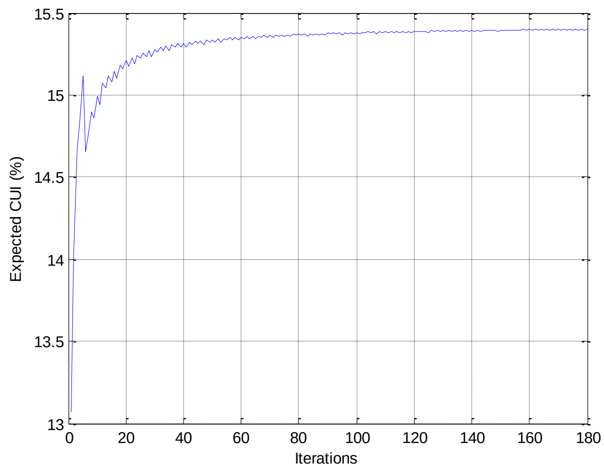


Figure 6.3 Average CUI for a repeated optimization process

6.2 Proposed Utility Functions

With the existence of conflicts between zonal decision makers, the development of a cooperative algorithm that will efficiently manage the system becomes a necessity. The proposed algorithm should achieve fairness between different system participants by increasing the social welfare which is realized by improving the performance of the worst-off decision maker.

In this research, a modification is proposed to the utility function of each decision maker in order to introduce a global objective related to the social welfare improvement. Therefore, each decision maker tends to maximize his own payoff along with the system global objective. Next, a correlated equilibrium game theoretic based approach is developed to optimize the system operation during the operator's specified time frame. This proposed algorithm aims to maximize the minimum satisfaction level among all the decision makers (DMs) by maximizing the worst-off decision maker. Therefore, the global utility function can be described as follows:

$$U_{global} = \max(\min(U_i)) \tag{6.13}$$

Where, U_i is the utility function, payoff, of DM *i*.

To denote the problem, participants/DMs payments are penalized if they tend to worsen the predefined global objective as in the classical curtailable programs [114]. The utility function of each decision maker is modified by including an additional term that reflects the global objective, as follows:

$$U_i = \omega_1 \bar{U}_{i_{local}} + \omega_2 F \tag{6.14}$$

Where,

$$F = \min(U) \tag{6.15}$$

$$U = [U_1, U_2, U_3, U_4, U_5, U_6, U_7] \tag{6.16}$$

$$\bar{U}_{i_{local}} = \frac{U_{i_{local}} - U_{i\min_{local}}}{U_{i\max_{local}} - U_{i\min_{local}}} \tag{6.17}$$

$$\omega_1 + \omega_2 = 1 \tag{6.18}$$

$\bar{U}_{i_{local}}$ is the normalized local utility function, payoff, of DM$_i$. $U_{i\max_{local}}$, $U_{i\min_{local}}$ are the maximum and minimum recorded payoffs of DM$_i$ during the history of the system operation, respectively.

ω_1 and ω_2 are the weighting factors introduced to combine the local and global utility components. By carefully adjusting the values of ω_1 and ω_2, the effect of each component can be changed. Consequently, the selfish and cooperative behaviours of each DM are adjusted. Thus, the question remains to be how to choose ω_1 and ω_2 which lead to the best overall system performance. This work does not provide a closed form solution to this question. Instead, the weighting factors are selected to provide an equal priority to each component of the DM's utility function. In other words, it is assumed that each DM will maximize his own local utility function and, in the meantime, will contribute to the maximization of the social welfare with the same priority. Therefore, ω_1 *and* ω_2 are assigned with equal values.

The proposed utility functions design will motivate DS customers to participate in such a process for two reasons:

- Fairness between different decision makers is attained by maximizing the payoff function of the worst-off DM who cannot be identified prior to the initiation of the energy management process.
- Each DM tends to maximize its own payoff. However, each player might slightly decrease its self-earnings, local payoff, to increase his chances on being selected, by the SMS, for this process in the future by maximizing the global system objective.

In the simulation results section, it will be proved that the development of a cooperative policy, based only on the utility functions modifications, is not enough. In fact, the outcomes of the process depend on the algorithm that is used to handle the problem. For that reason, a correlated equilibrium game theoretic approach had to be developed to solve the problem that was presented above.

6.3 ZEMOS Modelling for multi-participant decision making:

This section describes the correlated equilibrium game-theoretic approach that is used to optimize the performance of the zone under study. Each decision maker will be modeled as a game player aiming to maximize his utility function described in section 6.2.

Although Nash equilibrium implementation is simple using best response [103, 105, 107], it has many draw backs as follows:

- First, convergence to equilibrium is not guaranteed for all types of utility functions [110] or games, even in power system applications as shown in [103].
- Second, it does not always guarantee the convergence to an efficient equilibrium which is fair to all players [110], this is due to the fact that all players are selfish. In fact, there are always greedy players which actions will lead to a significant reduction on other players' performance or payoff. Therefore, the game outcome might require further improvement.

On the other hand, the correlated equilibrium (CE) concept has many benefits.

- Unlike the pure Nash Equilibrium, or Best Response algorithm, a correlated equilibrium always exists [116]; that is, convergence to correlated equilibrium is always guaranteed regardless of the shape of the game [116].
- The negative (undesirable) payoff actions are completely avoided as shown in the next section.
- Fairness is achieved by allowing each player to consider joint distribution of all players' actions. That is, each player considers others' actions to explore the existence of any mutual benefits

between the players. Besides, each player takes into account his historical actions during the game in order to reach the correlated equilibrium [112] (i.e. fairness between participants is maximized).

- CE converges to a social welfare which exceeds that of any Nash equilibrium [112, 113].

For those reasons, correlated equilibrium (CE) is introduced as an efficient solution to the multiple participants decision making problem. Correlated equilibrium is presented as an efficient solution to the problem. Correlated equilibrium between different system players is computed via an adaptive learning algorithm of the regret matching procedure of [117]. Besides, this section explains how the multi-decision making process can be handled by ZEMOS.

6.3.1 Definition of Correlated equilibrium

In an *N*-players game *G*, each player *i* ($i \in N$) is a selfish game player aiming to select a rule for selecting an action S_i^n at each time slot to maximize his utility function $U_i(S_i)$. The utility function of each player is calculated using equation (6.14) since each player only has control over his own actions, so the optimal action selections policy depends on the rational consideration of the action policies from other users. The *correlated equilibrium* [111] is an important generalization of the Nash equilibrium. In fact, Nash equilibrium corresponds to a special case wherein players select strategies independently. Besides, a correlated equilibrium always exists in any finite game[118], and is defined as follows.

For the proposed game *G*, a probability distribution *P* over a set of strategies $K = \Omega_1 \times \Omega_2 \times \Omega_3 \ldots \Omega_N$ is a correlated equilibrium, if and only if, for all $i \in N, S_i \in \Omega_i, and\ S_{-i} \in \Omega_{-i},\ \ \forall S'_i \in \Omega_i$

$$\sum_{S_{-i} \in \Omega_{-i}} P(S_i, S_{-i})\left(U_i(S'_i, S_{-i}) - U_i(S_i, S_{-i})\right) \leq 0 \qquad (6.19)$$

This means that: when player *i* selects action S_i, then choosing any other action S'_i instead, will not lead to a higher utility, or payoff. Where, Ω_i represents the set of strategies that can be adopted by player *i*

6.3.2 Regret Matching Algorithm

The regret matching algorithm is a learning algorithm that will converge to a correlated set of equilibria [117]. In this section, the proposed regret matching learning algorithm is presented in detail. In this algorithm, each player will depart from the present strategy to different strategies using a probability distribution which depends on the measures of regret for not playing this new strategy in the history of the game.

The algorithm can be explained as follows:

Let G be a game, with a set of players N, that is played repeatedly, through turns (e.g. times or iterations): $n=1,2,3,\ldots$. Each game player $i \in N$ has a set of strategies $\Omega_i = \{A_i, B_i, C_i, \ldots\}$. The process has two major steps, as follows:

Regret update:

At each time slot n, i.e. iteration, each player i calculates the utility function $U_i(S_i^n, S_{-i}^n)$, using(6.14), of playing the current strategy $S_i^n = A_i$, $A_i \in \Omega_i$ while all other players play S_{-i}^n.Besides, player i calculates the utility function of playing a different strategy $S_i^n = B_i$, $B_i \in \Omega_i$.

At the next iteration $n+1$, each player i will select a new strategy S_i^{n+1} based on the average regret measure R_i^n.

$$R_i^n(A_i, B_i) = \max\{D_i^n(A_i, B_i), 0\} \tag{6.20}$$

Where, $R_i^n(A_i, B_i)$ represents the average regret measure at iteration n when player i did not play strategy B_i each time strategy A_i was played in the history of the game (e.g. previous iterations). And $D_i^n(A_i, B_i)$ is the utility difference every time B_i replaces strategy A_i in the history of the game up to iteration n, and given by.

$$D_i^n(A_i, B_i) = D_i^{n-1}(A_i, B_i) + \Delta D_i^n(A_i, B_i) \tag{6.21}$$

$$\Delta D_i^n(A_i, B_i) = \alpha_n \left(\left(U_i(B_i, S_{-i}^n) - U_i(A_i, S_{-i}^n) \right) - D_i^{n-1}(A_i, B_i) \right) \tag{6.22}$$

$\Delta D_i^n(A_i, B_i)$ is the step size of the utility difference change.

According to [117], $\alpha_n = 1/n$, which will lead to a reduced step size in calculating the utility difference with respect to time. With that in mind, the average utility difference each time B_i replaces A_i is given by:

$$D_i^n(A_i, B_i) = \frac{1}{n} \sum_{j=1}^{n} \left[U_i(B_i, S_{-i}^j) - U_i(A_i, S_{-i}^j) \right] \tag{6.23}$$

However, this reduced step size assumes that the system parameters do not change with time [119]. This does not agree with the nature of the electric distribution systems due to the stochastic inherent variations in the system loads demands and renewable sources output powers. For that reason, the utility difference should be updated with a constant step size [119]. Therefore, the set of correlated equilibrium is captured in the presence of time dependent system parameters. Consequently, α_n is represented by a constant value *k*, where $0<k\leq 1$, that depends on the nature of the game. The utility difference is then given by:

$$D_i^n(A_i, B_i) = \sum_{j=1}^{n} k(1-k)^{n-j}\left[U_i(B_i, S_{-i}^j) - U_i(A_i, S_{-i}^j)\right] \qquad (6.24)$$

The regret update process is repeated for all player *i* strategies

Decision:

At iteration $n+1$, each player *i* decides to select a new strategy $S_i^{n+1} \in \{A_i, S'_i\}$ according to the probability distribution Γ:

$$\Gamma = \begin{cases} p_i^{n+1}(S'_i) = \dfrac{R_i^n(A_i, S'_i)}{\mu}, & \forall S'_i \neq A_i \\ p_i^{n+1}(A_i) = 1 - \sum\limits_{S'_i \neq A_i} p_i^{n+1}(S'_i) \end{cases} \qquad (6.25)$$

$$S'_i = \{B_i, C_i, \ldots\}$$

Where, μ is a predetermined constant which guarantees that the summation of all strategies probabilities is unity.

In this research, the outcomes of the proposed algorithm are compared with the traditional Best Response (BR) that converges to Nash equilibrium. The best response algorithm matches exactly the behavior of typical distribution customers; wherein, each player selfishly and independently selects the strategies that will only result in a maximum payoff, in a deterministic way. Meanwhile, the strategy selection process, in the best response, does not take into account the history of the game or the other players' actions. Accordingly, the strategy selection process, using the BR, is as follows:

$$\max(D_i^n(S_i, S'_i)) \qquad (6.26)$$

$$D_i^n(S_i, S'_i) = \left(U_i(S'_i, S_{-i}^n) - U_i(S_i, S_{-i}^n)\right) \qquad (6.27)$$

It should be noted that $D_i^n(A_i, B_i)$, is a special case of the utility difference calculated in (6.24), with $k=1$. For that reason, correlated equilibrium is considered a generalized form of the traditional Nash equilibrium.

6.3.3 The proposed Algorithm

A regret matching based algorithm is proposed to compute the correlated equilibrium for managing a distribution (DS) using ZEMOS as follows:

1. The SMS will select the controlled resources and determine which participant qualifies for the game according to the zonal operator's selected objectives.
2. A control signal is sent to the CM to initiate a game and follow the procedures of the proposed regret matching algorithm. Consequently, a notification signal sent to the selected participants, i.e. controlled resources or tools that are customer owned, to announce the game initiation.
3. Initially, $n=0$, each player i , independently, selects a random strategy S_i^o . Operator's strategies will be selected internally through ZEMOS by the control module (CM).
4. Next, the players notify ZEMOS with selected strategies and the utility function magnitude $U_i^{(0)}$. Selected strategies will be passed through the input and data bank modules to the RTM. On the other hand, all the $U_i^{(0)}$ magnitudes will be sent to the CM through the input and data bank modules for to be processed.
5. The CM simulates the system for the selected strategies, and evaluates the operator utility function $U_1^{(0)}$. Meanwhile, the CM estimates the initial worst-off utility function and evaluates $F^{(0)}$ as in (6.15) and send it to the output module.
6. Next, ZEMOS broadcasts the present value of $F^{(0)}$ to all players.
7. Accordingly, each player will update the value of its utility function that corresponds to the present selected strategy using (6.14) and calculates the updated regret using (6.20).
8. In the next iteration n, i.e. the next time the game is played, each players selects a new strategy S_i^n according to (6.25).
9. The players notify ZEMOS operator with their selected strategies S_i^n and their utility functions magnitude $U_i^{(n)}$ which will be processed by ZEMOS as explained in step 3.
10. The CM simulates the system for the selected strategies, and evaluates the operator's utility function. Consequently, the CM estimates the worst-off utility function and evaluates $F^{(n)}$ as follows:

$$F^{(n)} = \begin{cases} 1 & if \quad U_{worst-off}^{(n)} > U_{worst-off}^{(n-1)} \\ U_{worst-off}^{(n)} & if \quad U_{worst-off}^{(n)} < U_{worst-off}^{(n-1)} \end{cases} \tag{6.28}$$

11. ZEMOS broadcasts the current value of $F^{(n)}$ to all players.

12. Accordingly, each player will update its utility function that corresponds to the present selected strategy S_i^n , using (6.14) and calculates the updated regret using (6.20).
13. Steps 8 to 13 are repeated for every iteration, i.e. every time the game is repeated.

Each iteration represents a time interval during which the game is played. It could be an hour, or number of hours which are specified by the system operator.

6.4 Simulation results

In this section, two games were studied to validate the proposed regret matching algorithm. The first game (first case study or CS1) is related to minimizing the system total energy losses during a predetermined time period. In the second game (second case study or CS2), the operator's needs are the minimization of system phase unbalance. All games were studied at different random periods and were repeated for typical days that correspond to different seasons of the year. In this thesis, it is assumed that all the system players confirmed the participation in the game, each time the operator initiate a game.

The outcomes of the proposed algorithm were compared with the traditional best response algorithm using the same proposed utility functions that were introduced in section 6.2. As a result, the examined games were solved a second time, during the same study periods, using the best response algorithm, which converges to traditional Nash equilibrium.

For each game, two necessary parameters, k and μ in equations (6.24) and(6.25), must be determined prior to playing a game. In this research, a GA based offline exhaustive search is performed to determine the parameters values. The parameters were selected for the purpose of maximizing the magnitude of the worst-off player utility function. k is selected to be 0.9, since μ guarantees that the summation of all strategies probabilities is unity , therefore μ is given by:

$$\mu = \left(\sum_{S'_i \neq A_i} p_i^{n+1}(S'_i) \right) + 0.001 \tag{6.29}$$

Figure 6.4 shows the variation of the expected values of all players' utility functions, using best response for the ELI minimization game (CS1). In this thesis, social welfare is considered to be improved by increasing the utility function of the worst-off player; thus the worst off player must be identified by ZEMOS. Using the best response algorithm, *player 4* is the worst-off player during the whole game play. On the other hand, *player 7* (i.e. the DG Owner) is the greedy player whose actions dominate the game which leads to reducing the other players' utilities.

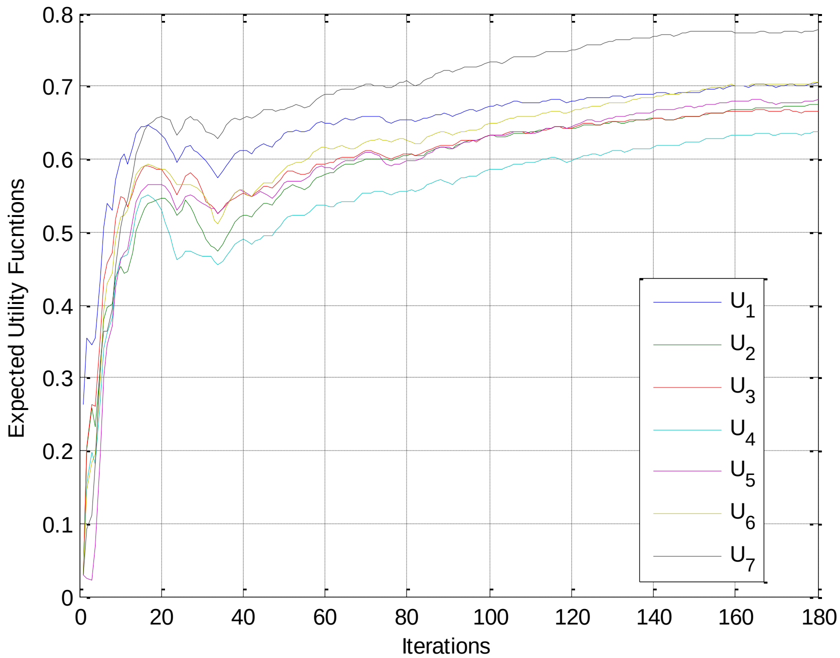


Figure 6.4 Expected Utility Functions of all players for the ELI minimization game (CS1) using the Best Response Algorithm

Figure 6.5 shows the utility functions of all the system players when the game is played using the proposed regret matching algorithm. Player 4 is still considered the worst off player of the game. However, using the proposed regret matching algorithm, the utility function of the worst-off player (i.e. *player 4)* is improved, as shown in Figure 6.6, by an average improvement of 9.2%. As well, as the social welfare which is measured by the improvements realized in the worst off player utility function.

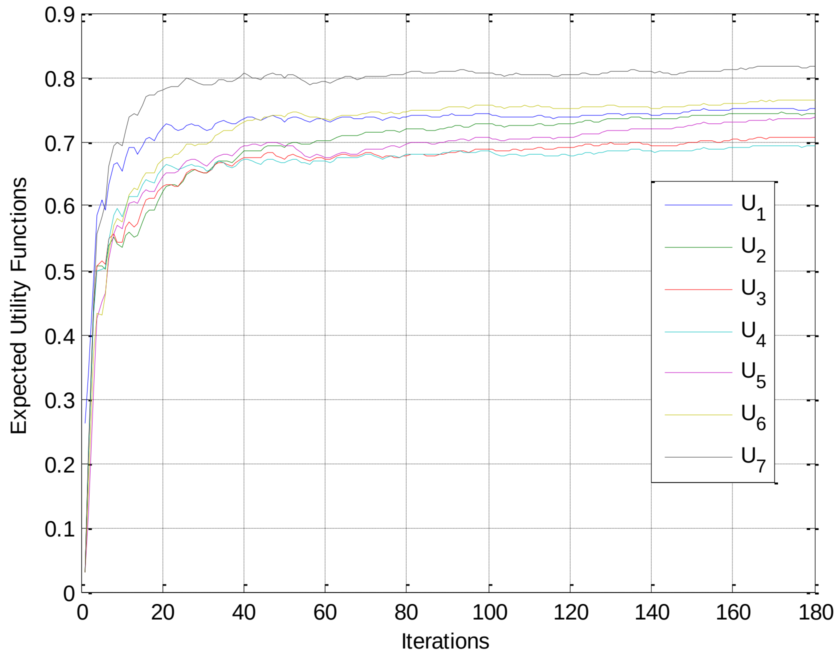


Figure 6.5 Expected Utility Functions of all players for the ELI minimization game (CS1) using the proposed Regret Matching Algorithm

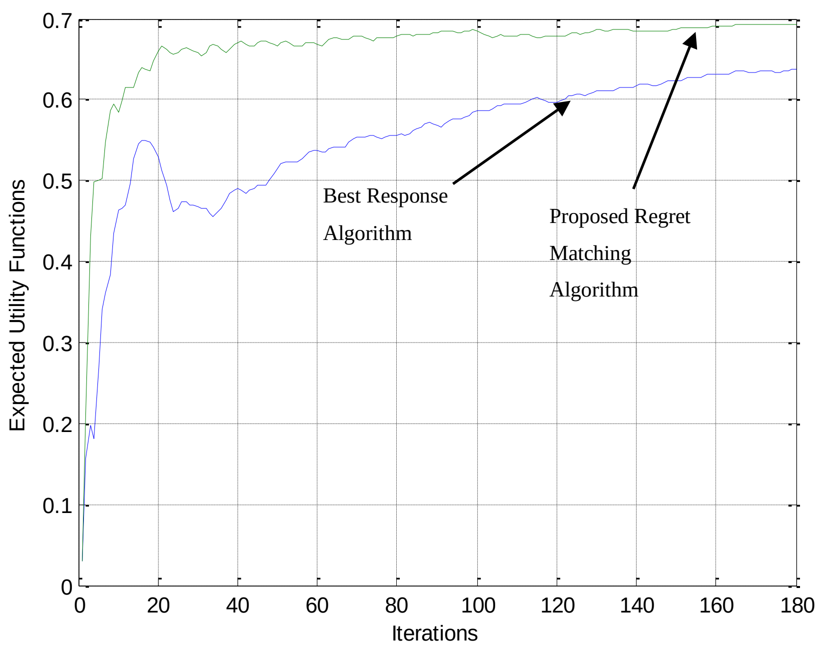


Figure 6.6 Expected Utility Functions of the worst-off player for the ELI minimization game (CS1) using Best Response and the proposed Regret Matching Algorithm

In the meantime, the expected energy loss is reduced during the game play as shown in Figure 6.7. The best response algorithm results in up to 2.55% reduction in the system energy loss compared to the outcomes of the traditional algorithm, shown in Figure 6.2. Additional up to 2.2% reductions in the energy loss realized using the proposed regret matching algorithm compared to the best response algorithm; After running 180 scenarios, where each scenario might represent an hour or more per day, the total achieved saving using the proposed regret matching algorithm

$$S=C_b-C_r+C_l \tag{6.30}$$

Where, S is the total average saving for CS1 using the proposed regret matching algorithm in dollars; C_b is the total kWh incentive payments for the DGs and the DR participants using Best response in dollars; C_r is the total kWh incentive payments for the DGs and the DR participants using regret matching in dollars; and C_l is the total savings for the energy loss cost reduction in dollars based on IESO prices from [99].

The test results show that, compared with the best response algorithm, the total average saving *"S"* are $13,302 for CS1. It worth noting that the total incentive payments for the DR participants and the DG owner for all the 180 iterations is $12,799 for the best response algorithm. Therefore, the realized savings due to energy loss, using the proposed regret matching algorithm is paying off most of the incentive payments. This introduces a significant improvement using the regret matching algorithm over the best response algorithm. In fact, the amount energy cost savings are eventually increasing as long as the game continues to be played. In the meantime, according to the authors of [120], a reduction in the peak to average power levels (PAR) is realized if a system is operated with the objective of energy saving.

Consequently, although the PAR (peak to average ratio) was not selected as the main objective of this case study; yet, it was found that the PAR has been reduced from 1.37 to 1.21 (i.e. 13.22% improvement compared with the best response algorithm). In addition, it was found that the diversified main feeder peak power is reduced by 13.03%. The peak to average power level (PAR) in the study system main feeder is evaluated as follows:

$$PAR=\frac{P_{peak}}{P_{ave}}=\frac{\max_{h\in 1:h_{tot}} P_h}{\frac{1}{h_{tot}}\sum_{h=1}^{h_{tot}} P_h} \tag{6.31}$$

Where, P_h is the total diversified power supplied to the study system through the main feeder at hour h.

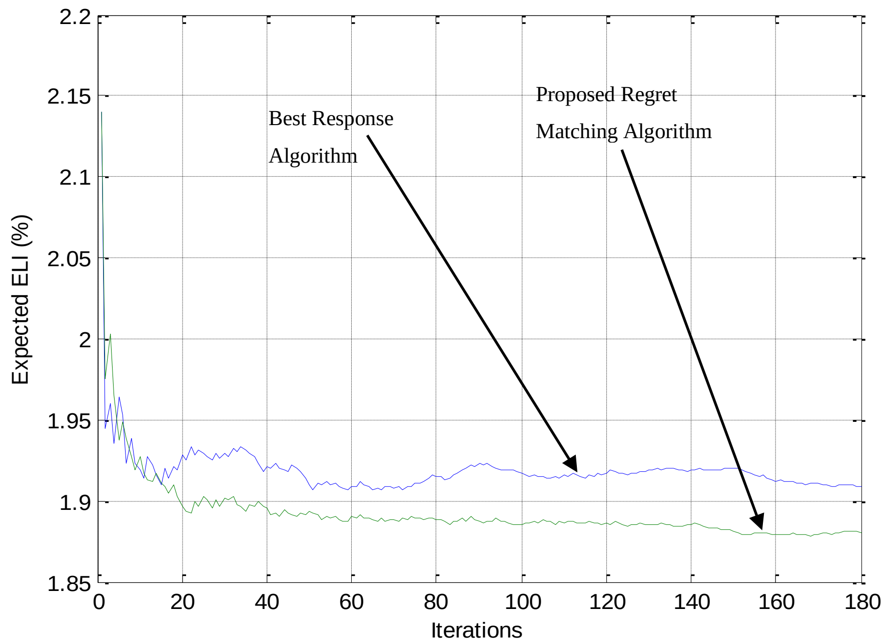


Figure 6.7 Expected Energy Loss for the ELI minimization game (CS1) using the Best Response and the proposed Regret Matching Algorithms

For the CUI minimization game (CS2), *player 1* is considered the worst-off player as shown in Figure 6.8. It is necessary to mention that *player 1* represents the system operator. On the other hand, Figure 6.9 shows the utility functions of all the system players when the game is played using the proposed regret matching algorithm. Using the proposed algorithm, the worst-off player utility function converges to 0.6, which is approximately 17% better than the corresponding value using the best response algorithm as shown in Figure 6.10.

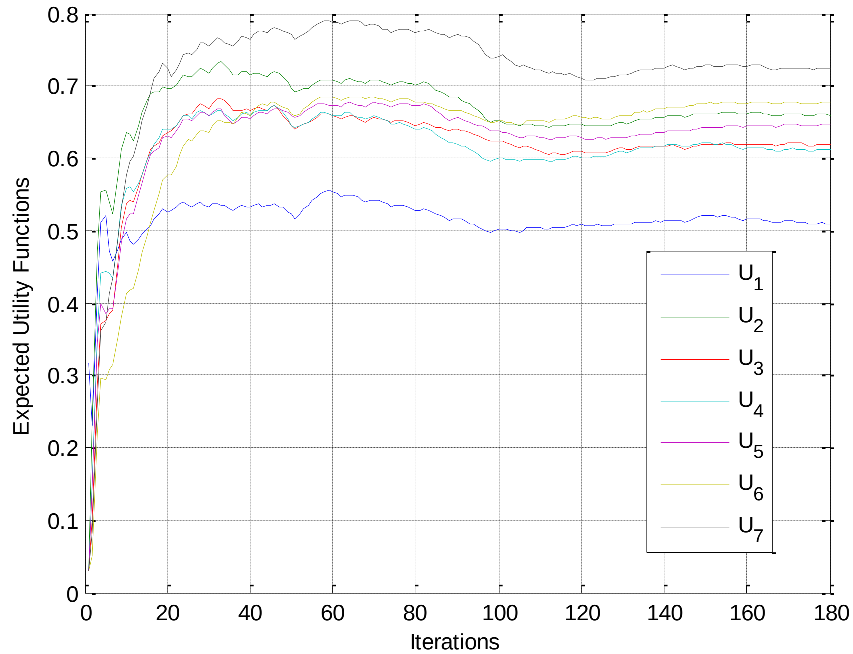


Figure 6.8. Expected Utility Functions of all players for the CUI minimization game (CS2) using the Best Response Algorithm

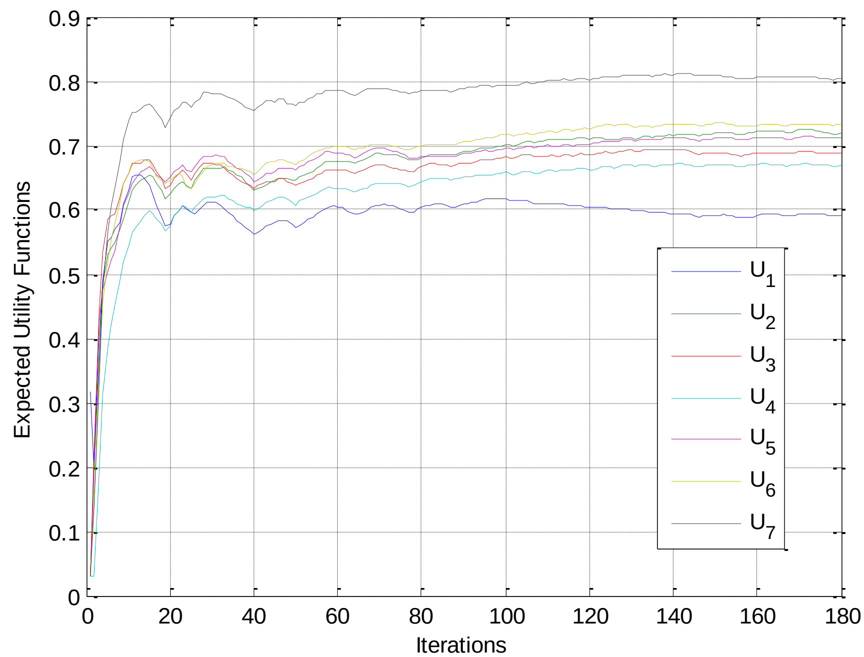


Figure 6.9. Expected Utility Functions of all players for the CUI minimization game (CS2) using the proposed Regret Algorithm

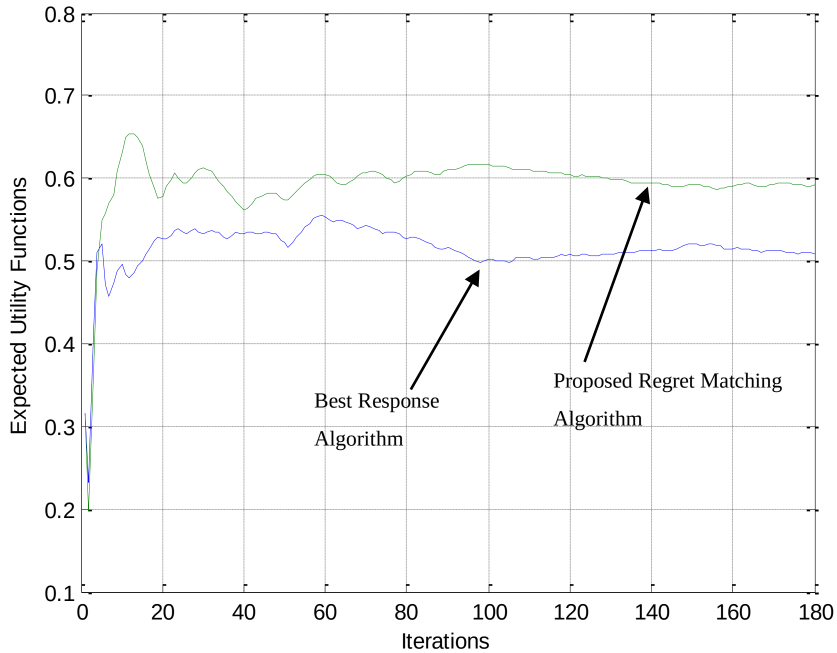


Figure 6.10 Expected Utility Functions of the worst-off player for the CUI minimization game (CS2) using the Best Response and the proposed Regret Matching Algorithm

Using the best response algorithm, the expected CUI increases and converges to 15.1% which indicates that the phase unbalance is increased. On the other hand, the proposed algorithm reduces the expected CUI magnitude to 14.25%, as shown in Figure 6.11. The proposed algorithm generates superior results than either using the best response algorithm or the traditional algorithms presented in section 6.1, as shown in Figure 6.3

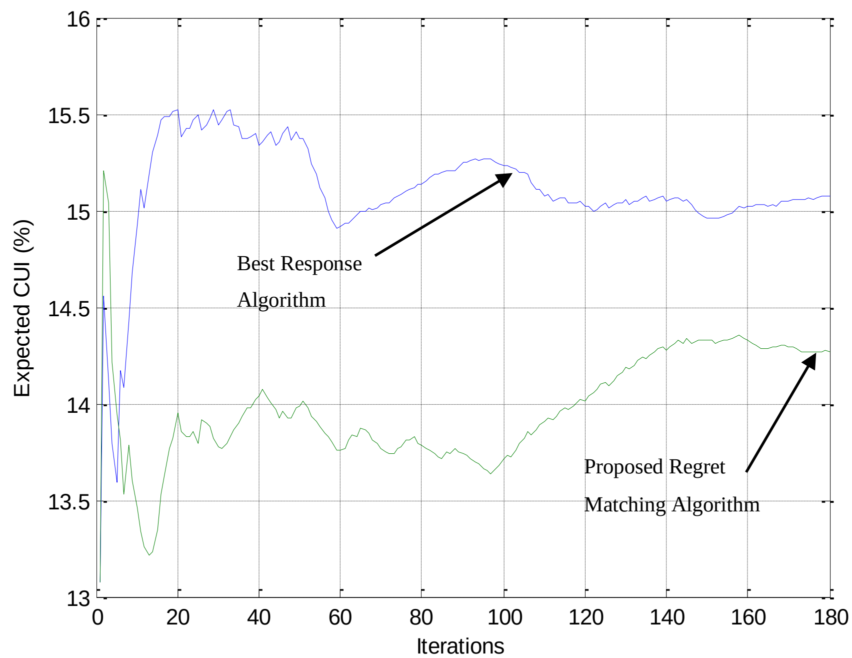


Figure 6.11. Expected CUI for the CUI minimization game (CS2) using the Best Response and the proposed Regret Matching Algorithms

With the realized improvements in the worst-off player utility function, social welfare is improved or fairness is achieved between system decision makers or players.

6.5 Conclusions

The main goal of using ZEMOS in this chapter was to resolve conflicts between different typical distribution system decision makers for optimal zonal operation. A cooperative correlated equilibrium game theoretic approach is developed. The set of correlated equilibrium is computed using a regret matching learning algorithm. The proposed algorithm is applied to a typical zone with seven decision makers each is modelled as a game player.

Two case studies were simulated and tested to verify the efficiency of the proposed multiple participants decision making algorithm. The first case study is related to minimizing the system energy loss every time the game is played. The second case study is related to minimizing the system phase unbalance which takes places due to the presence of a large number of single phase microFITs.

The performance of the proposed algorithm is compared to the traditional best response algorithm which was used in many zonal operation problems related to multi-decision making with multiple participants.

The simulation results demonstrate that the ZEMOS generates superior solutions within the operator's selected game duration. That is, the proposed algorithm consistently improves the worst-off player utility function which increases fairness between players, improves the social welfare.

In addition, the proposed algorithm reduces the energy losses along with the peak to average ratio during all the simulated iterations for the first case study. Besides, the proposed algorithm provides a significant savings associated with the energy loss costs for the first case study. For the second case study, the CUI was improved using the proposed algorithm compared with the best response algorithm.

Chapter 7 Summary, Contribution and Future Work

7.1 Summary

The main objective of this thesis is to develop a zonal energy management and optimization system (ZEMOS) to manage, and control the distribution system operation. The developed ZEMOS is a multiple decision makers and multiple objectives energy management system which consists of modular custom built-in functions to manage zonal energy flow. Thanks to ZEMOS modular structure, different functions can be easily implemented to enhance the potential capabilities of ZEMOS. Two novel functions, were developed, implemented, and tested to assist the application of ZEMOS for multiple decision makers operation, and single decision makers multi-objectives, i.e. Regret matching algorithm and decision making module. Furthermore, an efficient smart matching scheme was developed to enhance the economical and the effective implementation of the proposed ZEMOS.

In chapter (2), a general overview of the literature related to energy management systems is presented in details accompanied with the classification of different energy management systems. Demand side management is reviewed and presented as a potential resource that can be controlled to optimize the distribution system operation. Drawbacks and deficiencies of the surveyed energy management systems were identified and emphasized to clarify the motivations behind the proposed ZEMOS that is expected to tackle these deficiencies.

In chapter (3), the proposed ZEMOS basic functions were introduced, indicating the main system goals and benefits. Each ZEMOS module serves a function that is utilized by ZEMOS. A general framework of the modular structure and the coordination layout between modules were presented in details.

Chapter (4) and (5), presents ZEMOS operation for a single decision maker (i.e. distribution system operator or zone owner). Developed algorithms, that were utilized and stored in the corresponding modules, were mathematically modelled in chapter (4). Next, ZEMOS is tested and simulated in chapter (5) for three different objectives that were selected to reflect operation of ZEMOS for typical areas of distribution system applications. That is, energy savings, CO_2 emissions reduction, and service quality improvement represented by phase unbalance reduction. In this part of the thesis, the study zone was optimized for single and multi-objectives optimization operation. The efficiency of the proposed smart matching scheme (SMS) is introduced as a potential function that can match the operator objectives to the most economical and efficient controlled resources. ZEMOS performance was compared with and without the proposed SMS.

The main objective of chapter (6) was to investigate the application of the proposed ZEMOS as a means to optimally and efficiently manage/control the distribution system operation whenever conflicts arise between decision makers regardless of the operator's objective. Therefore, a game theoretic approach is developed, mathematically formulated, and simulated. The proposed algorithm was stored in the control module to be utilized every time ZEMOS is operated in the presence of multiple decision makers zones.

7.2 Main Contributions of the Research

The main contributions of the research presented in this thesis can be summarized in the following:

1- A modular structure was successfully incorporated in the proposed zonal energy management system. The basic modular structure lay down the road to potential enhancements in the functions and capabilities of ZEMOS. In addition, novel algorithms can be developed and stored in the system modules to enhance the area of applications of each module as well as improving the efficiency of each module and consequently ZEMOS as a whole. That is, the number of objective functions, the number of controlled resources and tools, control algorithms, data forecasting techniques, etc…

2- A decision making algorithm is developed for the purpose of mutli-objectives optimization. The main purpose of the decision-making process is to determine from a generated Pareto non-dominated front a single solution for recommendation as one that will fulfill all the operator's objectives. In other words, a Pareto optimal set is generated, and then, based on the control module, a quick search process is begun within the points generated in order to determine the best point. The proposed algorithm does not rely on the weighted multi-objectives search techniques that were commonly used in the existing EMS and have many drawbacks as reported in chapter (2). The developed algorithm is an interactive algorithm that can interact with the decision maker, when needed, to improve the recommended ZEMOS output.

3- A smart matching scheme (SMS) is developed as a generalized framework that optimally and efficiently selects the proper controlled resources (e.g. capacitors banks, distributed generation power output, demand response participants…etc.) to manage, and control the distribution system operation. The SMS evaluates the impacts of the controlled resources (offline process) first, and then matches the resources to the operator's objectives, regardless of the control algorithm used (e.g. Optimization, and Game Theory). The SMS is mainly used to enhance the performance of the control algorithm that is used, by ZEMOS, to solve the distribution system problems. The proposed SMS can be used by a distribution system operator prior to the application of the main control or optimization process to achieve the following benefits:

- Reduction of the control algorithm computational burden. Specifically, it decreases the number of decision variables by avoiding the utilization of the controlled resources that would have negative impacts on the operator's objective. The realized reductions in computational requirements are essential feature for active distribution system applications.

- Minimization of the overall operational costs associated with the system control process by reducing the possibility of utilizing resources that exhibit a high operational cost and an insignificant impact on the operator's objective.

4- A generalized game theoretic algorithm is developed and simulated for multiple participants decision making operation. The proposed game theoretic approach can optimally and efficiently manage and control the distribution system operation whenever conflicts arise between decision makers regardless of the type operator's objectives. The proposed algorithm is stored in the control module as a means that simply be integrated in ZEMOS for the purpose of conflict resolution analysis. Therefore, it is not limited to specific system resources, strategies, or operator's objectives. Meanwhile, the proposed algorithm was established to enhance the fairness between different zonal decision makers by implementing the maximization of the social welfare within the algorithm. The social welfare is maximized by maximizing the payoff function of the worst off participant/player during operation.

7.3 Future Work

The following items have been identified for future work based on the findings of this thesis:

- Design and develop a coordination module that will be used to link the proposed ZEMOS with the existing single unit, and whole system energy management systems. In addition, it will also have communication capabilities with other zones in its neighborhood, thereby ensuring coherent optimal operation for the whole system.
- Use ZEMOS for a study zone with high penetration of plugin hybrid electric vehicles (PHEV) to facilitate the integration of the PHEV into the distribution system.

- Develop a prototype model of the proposed ZEMOS in order to physically implement the introduced concepts. The developed prototype involves the investigation of the possible communication protocols between ZEMOS modules. As well as, the communication protocols between ZEMOS and different zonal participants (i.e. demand response participants, DGs,…etc.). In addition, the prototype shall investigate the market analysis and practical evaluation of the proposed ZEMOS in real life applications. Furthermore, real-time implementation of the proposed ZEMOS will be investigated to address zonal security related issues along with post contingency analysis.

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Journal Papers:

- **H.A.Mostafa**, Ramadan El Shatshat, and M.M.A.Salama "Multi-Objective Optimization for the Operation of an Electric Distribution System with a Large Number of Single Phase Generators", IEEE Transactions on Smart Grid, 2013, Vol. 4, issue 2.
- **H.A.Mostafa**, Ramadan El Shatshat, and M.M.A.Salama "Optimal Distribution Systems Operation using Smart Matching Scheme (SMS) for Smart Grid Applications", IEEE Transactions on Smart Grid, 2014, Vol. 5, issue 4.
- **H.A.Mostafa**, Ramadan El Shatshat, and M.M.A.Salama "A Correlated Equilibrium (CE) Game-Theoretic Approach for Multiple Participants Electric Distribution Systems Operation", IEEE Transactions on Smart Grid, 2014. (under review)

Conference Papers:

- **H.A.Mostafa**, Ramadan El Shatshat, and M.M.A.Salama "Phase Balancing of a 3-phase Distribution System with a Considerable Penetration of Single Phase Solar Generators", IEEE PES Transmission and Distribution, Chicago, IL, USA, 2014.
- **H.A.Mostafa**, Ramadan El Shatshat, and M.M.A.Salama "A Review on Energy Management Systems", IEEE PES Transmission and Distribution, Chicago, IL, USA,2014.

Appendix A Non-dominated Sorting Genetic Algorithm II (NSGA II)

NSGAII is developed by[80] , it starts by calculating the following variables for each solution:

1) Domination count n_p , which indicates the number of solutions that dominate the solution p
2) S_p this is a set of solutions that the solution p dominates.

In order to identify a solutions set of the first non-dominated front (*First Ranked solutions set*) in a population of size M, each solution is compared with every other solution in the population to identify whether it is dominated or not. Consequently, if solution p dominates solution q thus n_p=0 and n_q=1. Meanwhile, solution q will be a member of the set S_p. This process is repeated for the rest of the population set (*M-1* times). Consequently, all solutions in the first non-dominated front will have a zero domination count n_p.

Now, for each solution p with zero n_p, each member q of its set S_p will be visited and reduce its domination count by one. As a result, any member q with zero domination count will be placed in a separate list Q. These members belong to the second non-dominated front (*Ranked second*). The above procedure is continued with each member of Q and the third front is determined. This process continues until all fronts are determined.

All first rank (non-dominated) solutions are assigned the best fitness, whereas second rank solutions are assigned fitness worse than first rank solutions. Similarly, third rank solutions are assigned fitness worse than second rank solutions and so on for all Pareto front sets. Therefore, this assignment of fitness makes sure that the search is directed toward the non-dominated solutions.

In addition, it is desired that a multi-objective optimization technique maintains a good spread of solutions in the obtained set of solutions (diversity). NSGA II guides the selection process at the different stages of the algorithm toward a uniformly spread-out Pareto optimal front. This is done by sorting the solutions that belongs to the same front (same rank) according to their diversity. As an illustration, solutions located in low crowded regions are more preferable than solutions located in highly crowded regions.

On the whole, NSGA II has a low computational complexity. Meanwhile, it is an elitist algorithm. Moreover, it preserves diversity between final Pareto non-dominated front solutions.

Appendix B IEEE 123 Node Test Feeder Data

Table B.1 IEEE 123 Load Data

Node	Load Model	Ph-1 kW	Ph-1 kVAr	Ph-2 kW	Ph-2 kVAr	Ph-3 kW	Ph-3 kVAr
1	Y-PQ	40	20	0	0	0	0
2	Y-PQ	0	0	20	10	0	0
4	Y-PR	0	0	0	0	40	20
5	Y-I	0	0	0	0	20	10
6	Y-Z	0	0	0	0	40	20
7	Y-PQ	20	10	0	0	0	0
9	Y-PQ	40	20	0	0	0	0
10	Y-I	20	10	0	0	0	0
11	Y-Z	40	20	0	0	0	0
12	Y-PQ	0	0	20	10	0	0
16	Y-PQ	0	0	0	0	40	20
17	Y-PQ	0	0	0	0	20	10
19	Y-PQ	40	20	0	0	0	0
20	Y-I	40	20	0	0	0	0
22	Y-Z	0	0	40	20	0	0
24	Y-PQ	0	0	0	0	40	20
28	Y-I	40	20	0	0	0	0
29	Y-Z	40	20	0	0	0	0
30	Y-PQ	0	0	0	0	40	20
31	Y-PQ	0	0	0	0	20	10
32	Y-PQ	0	0	0	0	20	10
33	Y-I	40	20	0	0	0	0
34	Y-Z	0	0	0	0	40	20
35	D-PQ	40	20	0	0	0	0
37	Y-Z	40	20	0	0	0	0
38	Y-I	0	0	20	10	0	0
39	Y-PQ	0	0	20	10	0	0
41	Y-PQ	0	0	0	0	20	10
42	Y-PQ	20	10	0	0	0	0
43	Y-Z	0	0	40	20	0	0
45	Y-I	20	10	0	0	0	0
46	Y-PQ	20	10	0	0	0	0
47	Y-I	35	25	35	25	35	25
48	Y-Z	70	50	70	50	70	50
49	Y-PQ	35	25	70	50	35	20

Table B.2 IEEE 123 Load Data

Node	Load Model	Ph-1 kW	Ph-1 kVAr	Ph-2 kW	Ph-2 kVAr	Ph-3 kW	Ph-3 kVAr
50	Y-PQ	0	0	0	0	40	20
51	Y-PQ	20	10	0	0	0	0
52	Y-PQ	40	20	0	0	0	0
53	Y-PQ	40	20	0	0	0	0
55	Y-Z	20	10	0	0	0	0
56	Y-PQ	0	0	20	10	0	0
58	Y-I	0	0	20	10	0	0
59	Y-PQ	0	0	20	10	0	0
60	Y-PQ	20	10	0	0	0	0
62	Y-Z	0	0	0	0	40	20
63	Y-PQ	40	20	0	0	0	0
64	Y-I	0	0	75	35	0	0
65	D-Z	35	25	35	25	70	50
66	Y-PQ	0	0	0	0	75	35
68	Y-PQ	20	10	0	0	0	0
69	Y-PQ	40	20	0	0	0	0
70	Y-PQ	20	10	0	0	0	0
71	Y-PQ	40	20	0	0	0	0
73	Y-PQ	0	0	0	0	40	20
74	Y-Z	0	0	0	0	40	20
75	Y-PQ	0	0	0	0	40	20
76	D-I	105	80	70	50	70	50
77	Y-PQ	0	0	40	20	0	0
79	Y-Z	40	20	0	0	0	0
80	Y-PQ	0	0	40	20	0	0
82	Y-PQ	40	20	0	0	0	0
83	Y-PQ	0	0	0	0	20	10
84	Y-PQ	0	0	0	0	20	10
85	Y-PQ	0	0	0	0	40	20
86	Y-PQ	0	0	20	10	0	0
87	Y-PQ	0	0	40	20	0	0
88	Y-PQ	40	20	0	0	0	0
90	Y-I	0	0	40	20	0	0
92	Y-PQ	0	0	0	0	40	20
94	Y-PQ	40	20	0	0	0	0
95	Y-PQ	0	0	20	10	0	0
96	Y-PQ	0	0	20	10	0	0
98	Y-PQ	40	20	0	0	0	0
99	Y-PQ	0	0	40	20	0	0
100	Y-Z	0	0	0	0	40	20

Table B.3 IEEE 123 Load Data

Node	Load	Ph-1	Ph-1	Ph-2	Ph-2	Ph-3	Ph-3
	Model	kW	kVAr	kW	kVAr	kW	kVAr
102	Y-PQ	0	0	0	0	20	10
103	Y-PQ	0	0	0	0	40	20
104	Y-PQ	0	0	0	0	40	20
106	Y-PQ	0	0	40	20	0	0
107	Y-PQ	0	0	40	20	0	0
109	Y-PQ	40	20	0	0	0	0
111	Y-PQ	20	10	0	0	0	0
112	Y-I	20	10	0	0	0	0
113	Y-Z	40	20	0	0	0	0
114	Y-PQ	20	10	0	0	0	0
Total		1420	775	915	515	1155	630

Table B.4 IEEE 123 Capacitor Data

Node	Ph-A	Ph-B	Ph-C
	kVAr	kVAr	kVAr
83	200	200	200
88	50		
90		50	
92			50
Total	250	250	250

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