Weighted Scalarization versus Compromise Solution in Multi-Objective Economic Dispatch for Microgrids

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Abstract

In this thesis, we evaluate a multi-objective-moving-horizon-optimization (MO-MHO) approach as an instrument for improvement of economic dispatch in microgrids. In particular, we investigate the effect of adaptation of the multi-objective optimization strategy used in a moving horizon framework on the end result of the economic dispatch. Power dispatch in microgrids is inherently a high-dimensional problem often cast as a mixed-integer stochastic program with conflicting objectives. Implied is the fact that exhaustive exploration of the whole Pareto front in a related multi-objective approach is not a computationally tractable decision tool. It is thus proposed to represent the problem as a bi-objective optimization problem. The two objective functions are formulated by carefully grouping together the least conflicting components of the microgrid dispatch problem. The optimization is performed in a moving horizon i.e. over a window "looking into the future". The solution method for the optimization problem can then be selected or adjusted in real time by employing an independent set of assessment functions evaluated along the trajectories of optimal solutions already implemented over a window in the past. The proposed strategy is applied to a case study of a remote microgrid. Its performance is evaluated based on simulation results that suggest that choosing the compromise solution method for the MO-MHO problem may be superior to the usual scalarization methods.

Résumé

Dans cette thèse, nous évaluons une approche doptimisation multi-objectifs à horizon mobile (MO-MHO) comme un instrument pour l'amélioration de la répartition économique dans les microréseaux. En particulier, nous étudions l'effet de l'adaptation de la stratégie d'optimisation multi-objectifs utilisée dans un cadre d'horizon mobile sur le résultat final de la répartition économique des puissances. La répartition de la puissance dans les microréseaux est intrinsèquement un problème de grande dimension souvent exprimé comme un programme stochastique à nombres entiers mixtes avec des objectifs contradictoires. Il est implicite que l'exploration exhaustive de l'ensemble du front de Pareto dans une approche multi-objectifs connexe ne soit pas un outil de décision informatiquement résoluble. Il est donc proposé de représenter le problème comme un problème d'optimisation bi-objectif. Les deux objectifs sont formulés en regroupant soigneusement les composantes les moins conflictuelles du problème de répartition de la puissance dans les microréseaux. L'optimisation est réalisée dans un horizon mobile, c'est-à-dire au-dessus d'une fenêtre "regardant vers l'avenir". La méthode de solution pour le problème d'optimisation peut ensuite être sélectionnée ou ajustée en temps réel en utilisant un ensemble indépendant de fonctions d'évaluation évaluées le long des trajectoires de solutions optimales déjà mises en œuvre sur une fenêtre dans le passé. La stratégie proposée est appliquée une étude de cas d'un microréseau à distance. Ses performances sont évaluées sur la base de résultats de simulation qui suggèrent que le choix de la méthode de solution de compromis pour le problème MO-MHO peut être supérieur aux méthodes de scalarisation habituelles.

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List of Acronyms

DG	Distributed Generation
DER	Distributed Energy Resource
RDER	Renewable Distributed Energy Resource
EMS	Energy Management System
CERTS	Consortium for Electric Reliability Technology Solutions
BCIT	British Columbia Institute of Technology
MAS	Multi-Agent System
GHG	Greenhouse Gas
GAMS	General Algebraic Modeling System
ESS	Energy Storage System
MPC	Model Predictive Control
PCC	Point of Common Coupling
MPPT	Maximum Power Point Tracking
RE	Renewable Energy
MOO	Multi-Objective Optimization
SOO	Single Objective Optimization
ED	Economic Dispatch
CS	Compromise Solution
NS	Nash Solution
ES	Egalitarian Solution
UP	Utopia Point
MO	Multi-Objective
SOC	State of Charge
EPS	Electric Power System
WTG	Wind Turbine Generator
BESS	Battery Energy Storage System
PV	PhotoVoltaic
IESO	Independent Electricity System Operator

List of Symbols

The following lists the most important symbols used in the thesis.

Indices

k	Index of time periods
N	Time period horizon

Functions

$C_d(\cdot)$	Cost function for power produced by the diesel generator [$]
$C_{es}(\cdot)$	Cost function for the energy storage system [$]

Parameters

K_{es}	Energy storage constant, $K_{es} > 0$
K_{deg}	Cyclic degradation of stroage unit $K_{deg} > 0$
π_D	Cost of diesel fuel [$/L]
E_{es}	Level of energy stored in storage unit [kWh]
P_{es}	Power exchanged between storage unit and microgrid [kW]
P_d^{min}	Minimum operating limit of diesel generator [kW]
P_d^{max}	Maximum operating limit of diesel generator [kW]

$\bar{P}_{cl}$	Critical load [kW]
$\bar{P}_{nl}$	Non-critical load [kW]
K_c	Power curtailment penalty, $K_c > 0$ [$]
t	Current dispatch instant [h]

Variables

P_d	Power set point for the diesel generator [kW]
P_{es}	Power set point for the energy storage system [kW]
P_c	Power curtailed [kW]
$\bar{P}_w$	Power output from the wind turbine generator [kW]
$\bar{P}_s$	Power output from the solar PV (photovoltaic) panels [kW]

The above lists of acronyms and symbols will appear repeatedly in the text of this thesis but their meaning will not be re-stated for reason of brevity and clarity.

Chapter 1

Introduction

1.1 Defining a Microgrid

Electric markets worldwide are experiencing dramatic changes in their policies and infrastructure. Electric utilities, governments and industries, the world over, are modifying their strategies and investments in an effort towards modernizing the grid. The impact of regulatory changes in the utility industry has been such that more attention is being focused to issues such as environmental factors, asset utilization and customer energy management services [2].

As environmental issues like global warming become more and more prominent, governments and industries alike are increasingly looking for ways and means to reduce carbon emissions. The trend is moving away from central steam or coal powered plants and there is an increased drive towards distributed generation — small scale decentralized power generation. Distributed generation (DG) allows for more renewable energy sources, located closer to the consumer, to be incorporated into the system [3], [4]. However, the penetration of large amounts of renewable generation comes with its own set of challenges. Some of these challenges include:

1. Due to the connection of various distributed energy resources (DERs) to the distribution voltage (low or medium) level the bi-directional power flow within the network changes it from a passive to active network. As a result, conventional control methods designed for traditional passive networks may no longer be valid [5].

2. Distribution networks are designed close to their maximum level of fault current.

Before connecting any kind of DG to the system, it is crucial that the resulting fault level be efficiently calculated. This becomes especially challenging while dealing with a high penetration of distributed generation [6].

3. Circuit protection co-ordination, power quality, reliability and stability are some of the other control issues that arise from geographically dispersed DGs [3] – [6].

The concept of microgrids was first introduced by Lasseter [7], [8] as a method of integrating distributed energy resources in a controlled and reliable manner. A microgrid is commonly defined as ‘a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid. A microgrid can connect and disconnect from the grid to enable it to operate in both grid-connected or island-mode’ [9].

Since then, microgrids have gained much popularity owing particularly to the various benefits, other than energy provision, that they provide to both stakeholders and customers. These include, but are not limited to, reduced peak loading, reduction in greenhouse gas emissions, improvement in reliability of service and power quality [10], [11].

Large electric grids are vulnerable to natural disasters and adverse weather events [9]. Building a more resilient electric grid has become a high priority in the past few years. Microgrids can contribute to this by improved service quality because of their ability to island from the grid. Islanding may be done both intentionally and unintentionally depending on grid conditions. For example, in the case of power outage in the main grid due to faults, voltage sags or frequency drops, the microgrid may be islanded and customers connected could continue to enjoy uninterrupted service. This was seen in practice at the New York University's Washington Square Campus or Princeton University that stayed alight in the wake of Superstorm Sandy, due to their self-sufficient microgrid systems.

Distribution network operators could also benefit by the implementation of microgrids. This would allow for the deference of high investment [12] and upgrade costs of aging infrastructure.

In the Canadian context, based on the country's geography, with vast stretches of land, remote communities are an inherent consequence. Estimated to cover about 40 percent of Canadian territory these communities are lightly populated. Traditionally, electricity has been supplied to these communities through diesel units. However, the high costs of fuel and transportation are becoming a major concern for the key stakeholders that supply power. In the stand alone mode, a microgrid, with a high penetration of renewable generation coupled with an energy storage system could be a possible solution to this issue however, proper validation and cost-benefit analysis would be needed before any physical system is actually set up [13–15].

Microgrids may be as versatile as the need, location or resources permit since they can accommodate various types of DGs, different types of storage and serve both critical and non-critical loads. Also, microgrids may be DC [16] or AC.

1.2 Problem Definition

While all the aforementioned microgrid benefits have been identified, it may not be possible to achieve them without the implementation of proper control strategies. Microgrid operation, the integration of renewable sources and the different modes of operation (grid connected, islanded and the transition between the two) introduce a number of control and protection challenges. A microgrid controller must be designed to address these challenges while ensuring a reliable and economic operation of the microgrid. In addition to these technical challenges, given the high intermittent nature of renewable resources and hence the complex power balancing requirements, a good business case is required before widespread implementations of microgrids becomes a reality.

The most important constraint in the power generation and distribution equation is that there cannot be more power than the load consumes. It is the role of the Energy Management System to dispatch generation so a balance between generation and load is achieved. In a microgrid the presence of uncertain renewable generation complicates the problem. If there is too much power produced by renewables, the excess power may be dumped or stored or the renewable energy source curtailed. The later however, should be avoided as it increases the cost of the kWh produced. Similarly, if there is not enough power produced within the microgrid, imports may be necessary from the main grid (grid-connected mode) or loads may be curtailed (islanded mode). Both cases would result in monetary losses for the microgrid operator.

In order to address the technical challenges and from the commercialization viewpoint, the need of the hour is a good energy dispatch and management system. The microgrid energy management system (EMS) must be designed to ensure reliable and economic operation of the microgrid while satisfying all the system constraints. Most importantly, it should be able to deal with the presence of supply and demand uncertainty while scheduling and dispatching the various distributed energy resources (DERs). Thus, it is fair to say, that as in any power system, the economic dispatch (ED) problem is of fundamental importance in microgrids. This sets the pretext for the research conducted and presented here.

1.3 Thesis Objectives

This research will aim to:

1. Propose an efficient, cost effective and reliable economic dispatch algorithm that is simple enough to permit repetitive on-line recalculation of all controls at each dispatch decision update instant t_k
2. Formulate the problem such that it ensures capability for handling uncertainity — prevalent in the microgrid case in the form of both load and renewable generation.
3. Determine the extent to which the proposed algorithm can help to render the operation of the microgrid more profitable while maintaining a high level of customer satisfaction in reliable and high quality power supply. This may be achieved by comparing the performance of the proposed method to conventional widely accepted methods.
4. Validate the performance of the proposed strategy through simulations.

In this regard, a literature review was conducted to study the state-of-the art and identify the gaps that would serve as the contributions for this research. This literature review is presented in Chapter 2.

1.4 Contributions

The contributions of this thesis include:

1. A multi-objective-moving-horizon-optimization (MO-MHO) algorithm developed as an instrument for improvement of economic dispatch in microgrids. The proposed approach is evaluated by carrying out rigorous analysis of optimality of the approach.

2. Identification of mechanisms to enable the decision maker (in this case microgrid operator) to adaptively adjust the solution method for the associated multi-objective optimization problem. This is based on an independent set of assessment functions evaluated along the trajectories of optimal multi-objective solutions already implemented over a window in the past.

3. A thorough study and analysis of the compromise solution method for multi-objective optimization. In particular, to determine how the compromise solutions relate to the Pareto front and whether the said method may be utilized as a tool to determine tuning weights for the widely accepted scalarization methods.

1.5 Thesis Outline

This thesis is structured as follows:

Chapter 1 serves as an introduction to the thesis defining a context to the research problem and stating the objectives of this work.

Chapter 2 provides a more in-depth literature review outlining the state-of-the-art in the area of microgrid energy management systems. The classical economic dispatch problem is explained. The three different control strategies for solving the microgrid economic dispatch problem as identified in the literature are reviewed. Background information and key concepts involved in the proposed methodology are presented.

Chapter 3 formally presents the proposed Multi-Objective-Moving-Horizon-Optimization (MO-MHO) economic dispatch algorithm. The weighted sum method and compromise solution method are explained. The formulation of the economic dispatch optimization problem, the cost functions and constraints are detailed. The advantages of using the Compromise Solution method within the moving horizon framework are highlighted.

Chapter 4 presents the results of testing the proposed algorithm on two different case studies. The results from each scenario are presented and analyzed. The assessment functions are explained in detail along with mathematical formulation. Comparisons with existing methods are drawn and presented. The chapter also elaborates on the finer details of the methodology.

Chapter 5 concludes the thesis by summarizing the work presented. Possible future extensions to the study conducted are suggested.

Chapter 2

Literature Review and Background

2.1 Introduction

A microgrid not only enables the integration of higher amounts of renewable generation into the grid, it also allows for the utilization of advanced sensing technologies, control methods, and integrated communications into the current electric power system. Crucial to the optimal operation of a microgrid is its energy management system which performs an economic dispatch of the generation units in the microgrid. The ultimate objective of the economic dispatch is to reduce the total power generation cost to reliably satisfy the power demand subject to system security constraints. The classical economic dispatch (ED) problem is explained in this chapter with special attention to its application in microgrids. In particular, the three different control strategies for solving the microgrid ED problem namely: real time optimization, expert systems and decentralized hierarchical control [17], [18] are reviewed in detail.

While the study conducted herein concerns the economic dispatch problem and hence only one aspect of microgrid energy management systems, yet it is worthwhile to present a brief overview on microgrid energy management systems and their significance.

2.2 Energy Management Systems (EMS)

A microgrid energy management system (EMS) is sophisticated control software [12] that operates and co-ordinates the power output from the various dispatchable and non-dispatchable distributed generation (DG) units and storage to serve the load in the most optimally possible and cost-effective way. The EMS also enables seamless transition between the various operating modes of the microgrid — grid connected and islanded and ensures that in each case the core objectives are met.

A number of microgrid implementations and test beds have been developed in different parts of the world to better understand the operations and control of microgrids. While some of these implementations are purely for research purposes, others are being used to serve isolated and remote areas. Some of these examples include ISET Germany, CESI Italy, National Technical University Athens, Labein Experimental Centre Spain, Hachinohe, Japan, CERTS [19] and BCIT in North America [3], [12].

2.2.1 EMS Architecture

There are two main approaches to EMS architecture that have been proposed in the literature and implemented in the test beds described above: Centralized and Decentralized.

2.2.2 Centralized Architecture

The centralized EMS architecture consists of one central controller that has access to all the information in the microgrid pertaining to DER outputs, load demand, mode of operation and other technical network parameters [20]. Based on this data (and information from forecasting systems, if available) the EMS determines the optimal unit commitment and dispatches the DER in the microgrid accordingly. This optimization is based on a pre-specified objective or set of objectives.

The advantages of this type of architecture is that it allows the management system a broad observability of the microgrid and permits that various different optimization techniques be applied [20]. The disadvantage however, is that one central controller receives a huge amount of data to compute and manipulate. It thus increases the computational time as compared to decentralized architectures. In addition, this type of system does not enjoy the same flexibility as that of the decentralized architecture.

A number of centralized EMS have been discussed in the literature, particularly in the context of stand-alone or isolated microgrids. For example, Olivares et al. [18] propose a centralized EMS that consists of two main blocks: a multistage economic load dispatch block and a unit commitment block. According to the authors, the advantage of separating these two blocks is to speed-up the economic load dispatch calculations and hence to achieve faster update rates for the dispatch.

2.2.3 Decentralized Architecture

The decentralized architecture solves the complex energy management problem by breaking it up into smaller parts — each solved by a separate local controller. This architecture may use either a distributed approach or hierarchical one. It is typically implemented using multi-agent systems (MAS) technologies resulting in a microgrid control that is both modular and scalable [21]. Another advantage of this type of architecture lies in its plug and play capacity which enables the microgrid to continue operating irrespective of the loss or addition of a source and without requiring any extensive re-engineering [22]. Despite having its advantages, the decentralized approach faces implementation issues when applied to microgrids that require strong cooperation between the various connected DER, as in small or isolated microgrids [18].

The decentralized and hierarchical architecture is widely popular in the literature. Foo et al. [5] focus on a MAS that integrates competitive microgrid market operations and DER implementations. In their study each intelligent agent represents either a seller or a buyer, has fixed objectives and tends to maximize (mainly economic) benefits based on the pre-defined objectives.

2.3 The Classical Economic Dispatch Problem

The economic dispatch problem is of fundamental importance in any power grid. The classical economic dispatch problem involves allocating the total demand among the various available generation units (or facilities) to reliably serve consumers, at the lowest cost, subject to system constraints. The classical dispatch is a static problem which is solved for the optimal instantaneous power generation set points to satisfy the instantaneous load. The classical problem is formulated *not to include* any storage devices. It is typically formulated as a minimization problem of generation costs subject to constraints including power balance and the operational limits of the generation units [23]. The advantage of utilizing an economic dispatch stems from the fact that different generation units have varying production costs based on the type of connected unit, size of the unit, prime source of energy to produce electricity, etc. [24].

Mathematically,

$$minimize \quad \sum_{i=1}^{n} C_i(P_{Gi}) \tag{2.1}$$

subject to

$$\sum_{i=1}^{n} P_{Gi} + P_D^{total} = 0 \tag{2.2}$$

and

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \tag{2.3}$$

where P_{Gi} is the real power generation of the i_{th} generator and $C_i(P_{Gi})$ is the generator cost. P_D^{total} represents the total system demand.

2.4 Economic Dispatch in Microgrids

Economic dispatch (ED) in microgrids is an actively researched area [25] especially because of the mix of distributed generation resources. The economic dispatch in microgrids is a dynamical problem if the microgrid includes storage devices as these devices charge and discharge over time. The literature identifies three different control strategies for microgrid ED and unit commitment namely: expert systems, hierarchical control and real time optimization [17] [18].

2.4.1 Expert Systems

Expert systems is a field of Artificial Intelligence that is being applied to problems in a wide area of applications including, but not limited to, Computer Science, Engineering, Power Systems and Medicince [26]. One of the benefits of expert system control is that it imitates human reasoning in the decision making process in addition to performing numerical computations and data retrieval [27].

The general structure of an expert system is composed of three main components: an inference engine, a knowledge base and a working memory. The inputs are provided by the user. The interference engine determines the outputs by combining the user inputs with the set of facts and associations stored in the knowledge base [28]. In a rule based expert system, knowledge is represented in the form of a set of rules [27]. The rules are represented in the form of IF-THEN statements: *If* based on the inputs to the controller the conditions defined in the facts are 'True', *Then* certain action should be taken [29].

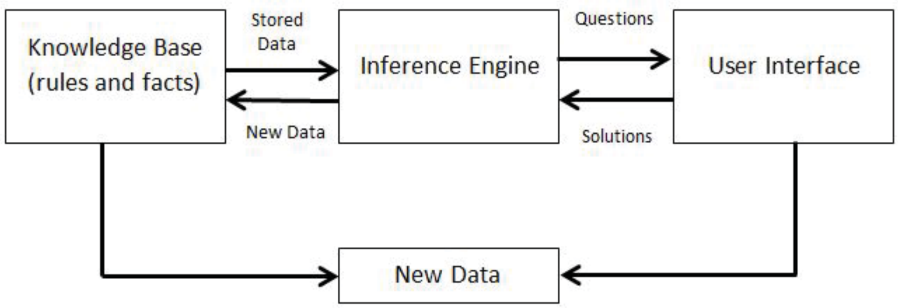

Fig. 2.1 Basic components of Rule-based Expert System

The expert system based microgrid controller approach consists of analyzing the state of the microgrid, determining which pre-defined category the current state falls into and then following a dispatch rule (generated offline) associated with that specific category. The facts and rules programmed into the knowledge base of the expert system define the conditions and premises for actions to be taken and are derived from human experts in the problem domain [29], [30]. For the microgrid dispatch problem, each constraint is implemented as a separate rule in the expert system controller. The rules are implemented using If-Then statements and are not fired in any particular order, rather, they are fired once the conditions have been met [17], [30].

2.4.2 Hierarchical Control

The hierarchical control strategy briefly touched upon in Section 2.2.3, combines aspects of both centralized and distributed EMS architectures. The energy dispatch problem is solved by providing the DER and load with the highest possible autonomy. It is typically implemented through Multi-Agent Systems (MAS) technologies. A multi-agent system consists of multiple intelligent agents, each of which is provided information related to its local jurisdiction. Agents may be able to communicate with each other and with the central controller so as to achieve both local and global objectives. The key characteristics of using MAS control technologies include high performance plug and play capabilities, modularity, scalability, dynamic and distributed approach. It is for this reason that some literature claim [21] [5] that MAS are best suited as microgrid controllers.

A MAS approach is proposed in [31] where the microgrid actors are represented by different agents such that they may participate in sending buying and selling bids to the microgrid central controller based on their specific requirements and objective functions. A similar approach is proposed in [21] with additional agents for specific tasks such as load curtailment and load shifting. Additional agents are also proposed in [32] to allow for better energy management by forecasting information in an extended operating horizon.

2.4.3 Real time Optimization

Out of the three control strategies named, real time optimization is the most computationally intensive [17]. Given the complexity of the problem and the economic benefits that could be achieved through an improved solution, a great deal of attention is being devoted to this area. The microgrid dispatch and energy management problem falls into the category of constrained optimization problems. The required microgrid attributes are formulated mathematically into an objective function to be maximized or minimized, subject to certain constraints. Many algorithms and software are available to solve optimization problems of this type and magnitude. Thus, in reviewing real time optimization strategies two broad aspects are considered: the mathematical formulation of the microgrid optimization problem and the actual algorithm employed to solve the optimization.

Formulating the Microgrid Optimization Problem

Eduardo et al. [33] present their EMS based on a heuristic optimization algorithm designed for a grid connected microgrid. The optimization objectives include the running costs of various DER and greenhouse gas emissions (GHG). Similar objectives, i.e. cost and GHG emissions are considered by [34], [35], [36], [37].

Colson et al. [38] define both major and minor objectives for the microgrid optimization problem. Some of the major objectives considered are cost, GHG emissions and revenue while the minor objectives include VAR support, use of storage and line losses.

While most of the literature on microgrid dispatch consider single objective optimization problems focusing primarily on minimizing operating costs, some authors argue that a better solution may be achieved by considering multiple objectives and utilizing Multi-Objective Optimization (MOO) techniques. The authors in [39] consider a five dimensional problem. The objective functions considered include reduction in energy cost, improvement in service reliability, reduced power fluctuations, reduced peak loading and reduced GHG emissions.

The argument is valid that in order to achieve the many microgrid benefits, they should be included in the optimization formulation and thus MOO techniques could result in improved solutions. The formulation of the optimization problem in this thesis is based on the same principles.

Optimization Strategies and Algorithms

Two optimization methods: Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) are discussed by [38]. The authors argue that there are advantages of Intelligent Methods over Traditional Computational Techniques for Optimization. Their point is that the since microgrid optimization problem is a complex one using traditional methods which involve computing the inverse of large matrices is both computationally expensive and requires significant amount of time. On the other hand, intelligent methods do not derive large matrix inverses since they remain within the search domain only. This results in a faster convergence to a near-optimal solution even when the microgrid problem complexity increases. In addition to this, gradient based methods rely heavily on the initialization. Both PSO and ACO are independent of any initial values.

A number of innovative computational techniques have also been proposed in the literature to solve the microgrid energy management problem. For example, in [40] the authors employ the fire fly optimization technique to solve the economic dispatch problem while minimizing carbon emissions. In [41] Xiang et al present a robust energy management strategy which compensates for uncertainty in both renewable generation and load. Using Taguchis Orthogonal Array a number of worst case scenarios are generated and used for the operational planning process. Jeyakumar et al. describe in their paper [42], a multi-objective evolutionary programming algorithm; the objectives considered being fuel cost and emissions. The authors in [43] present results of their optimal scheduling problem solved using two methods: General Algebraic Modeling System (GAMS) and Genetic Algorithm (GA). The objective considered is to minimize generation costs however the authors state that this in turn would result in lower carbon emissions. Chen and Gooi [44] propose a smart energy management system that is capable of minimizing the total cost and the total line losses of the power system. The mixed integer nonlinear multi-objective optimization problem is solved by means of the "jump and shift" method whereby each objective is solved until convergence is achieved. Only the stand alone mode of the microgrid is considered in this paper.

Jiang et al. [45] propose energy management strategies for a microgrid that is grid connected or in the stand alone mode, based on a double layer co-ordinated control approach. The two layers proposed are the Schedule layer and the Dispatch layer. The Schedule layer is mainly for an economic operation based on forecasting data — which in turn allows for forecasting error in the power generated from non-dispatchable DG units. It utilizes a look ahead multi-step optimization. The Dispatch layer optimizes the power flow using real-time data. Thus by adjusting the power of the controllable units, the dispatch layer ensures the safe and stable operation of the system. The optimization software package used was CPLEX. Having two layers allows that both the economic and technical aspects of energy management are covered.

Model Predictive Control (MPC) is recently gaining both attention and popularity in the power system community. In the microgrid context, MPC is attractive since it has unparalleled capability for handling uncertainty (modeled and unmodeled). Many authors have addressed the uncertainty in load and generation profiles by using the MPC approach [20].

Parisio et al. [25] formulate the optimization problem as a mixed integer linear program (MILP) and embed it within an MPC framework so as to implement a feedback control law. The authors add uncertainties in the renewable generation through stochastic forecasting and then use stochastic model predictive control [46] to solve the problem.

Garcia and Bardons [47] present the microgrid dispatch problem formulated as a mixed integer quadratic program. The optimization is done using MPC to maximize the economic benefits of the microgrid while minimizing the defined cost of storage. The DERs in the microgrid considered include wind, photovoltaic, fuel cells and energy storage systems. The forecasting for renewable generation output, energy prices and demand is done on a 24 hour basis through an autoregressive moving average model. The authors argue that degradation of batteries (energy storage) over time, especially due to elevated temperature and high currents is a significant cost. To compensate for this, they include in their economic dispatch formulation a penalty for high power charging and discharging of the battery storage. Similarly, the cost functions of the hydrogen storage and fuel cells are also based on the degradation costs owing mainly due to fluctuating power profiles and start-up costs of the system.

Patino et al [48] discuss an economic model predictive control. The aim is to develop a microgrid controller purely driven to obtain economic objectives. Although the renewable DERs and battery storage have been modeled the main focus seems to be on ensuring that the economic objective function does not lead to unstable behaviour. For this, the original cost function is modified to enforce convergence. This, however, is a trade-off since the new cost function is no longer a pure economic one rather it involves a tracking term and thus from the economic perspective there is a decrease in the performance. The modification of the cost function is aimed at achieving strong duality or strict dissipativity of the problem.

Chapter 3

The MO-MHO based Economic Dispatch

3.1 Introduction

The formulation of the microgrid optimization problem requires that foremost attention be paid to identify the desired attributes of the microgrid. It has already been shown through the extensive literature review presented in Chapter 2 that the components of the optimization cost functions can represent both major and minor objectives. These include but are not limited to: minimizing fuel and operation costs, minimizing the environmental impact from microgrids such as harmful emissions, maximizing utility revenues, minimizing transient periods following an event and including issues such as VAR support and line losses, etc.

There are thus many disparate objectives involved in determining an optimal dispatch in microgrids, some of them even conflicting. It is probably for this reason that studies have suggested a better and efficient dispatch of microgrid power set points may be achieved by using multi-objective optimization approaches as opposed to single objective optimization techniques [39].

This chapter presents the proposed multi-objective-moving-horizon-optimization approach for economic dispatch in microgrids. The proposed algorithm, formulation of the optimization problem, constraints and methodology are discussed in detail.

We initiate the discussion by reviewing key concepts in multi-objective optimization.

3.2 Multi-Objective Optimization

Multi-objective optimization (MOO) is a class of optimization problems involving two or more conflicting objective functions that are to be optimized simultaneously. Mathematically,

$$\begin{aligned} &minimize\ \{\Phi_1(x), \Phi_2(x), ..., \Phi_n(x)\} \\ &subject\ \ to\ \ x \in \mathcal{F} \end{aligned} \tag{3.1}$$

$$\mathcal{F} = \{x \in R^m : h(x) = 0, g(x) \geq 0\} \tag{3.2}$$

where $n \geq 2$ and $\mathcal{F}$ is the set of constraints. The decision variable in the form of a vector,

$$x = (x_1, x_2, ..., x_m)^T \tag{3.3}$$

belongs to the feasible set $\mathcal{F}$.

Equation 3.1 entails all objective functions Φ_n are to be minimized simultaneously. Under the condition that the objective functions do not conflict, a solution may be found such that every objective function attains its optimum [49]. However, most often these functions are conflicting, rendering the multi-objective problem non-trivial. This is because contradiction amongst the different functions simply suggests that it is not possible to find a single solution that would be optimal for all n objectives simultaneously.

3.2.1 Pareto Optimality

The scalar concept of 'optimality' does not apply in the multi-objective setting i.e. there is no single solution that would be optimal for every objective function. Instead, the notion of Pareto optimality is introduced. The Pareto optimal is defined as a feasible vector $x^* \in \mathcal{F}$ such that all the other feasible vectors $x \in \mathcal{F}$ have a higher value for at least one of the objective functions Φ_i where $i = 1, ...n$. The set of Pareto optimal solutions (also referred to as non-dominated or efficient solutions) when plotted together in the criterion space yield the Pareto front [50].

According to the definition of Pareto optimality, moving from one efficient solution to

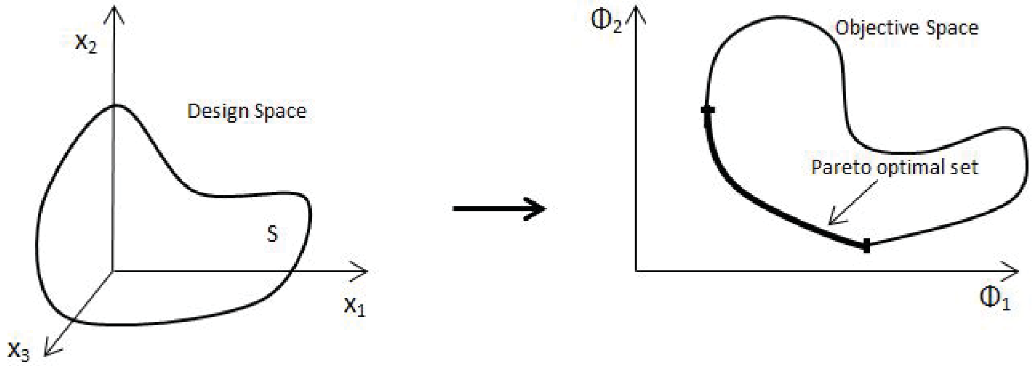

Fig. 3.1 Paretian Optimality: Mapping from design to objective space

the other, on the Pareto front, requires trading off. The price to pay for the multi-objective approach is that the Pareto front usually implicates the existence of a continuum of Pareto optimal (efficient) multi-objective solutions while only a single one can be implemented. Making this decision is a crucial aspect of solving MOO problems. This process may be undertaken by imposing additional criteria or by considering a single point that represents a fair compromise between the various trade-offs [50]. In either case, it is necessary that the *decision maker* have better understanding and insight into the problem at hand [49].

3.2.2 MOO in the Microgrid Context — the Scalarization Methods

In the microgrid context, in order to determine components of the objective functions, attention must be paid to identifying the desired attributes and benefits of the microgrid. This would suggest that designing a dispatch algorithm is not only specific to the microgrid topology but also to the needs and requirements of the microgrid operator. The choice and formulation of the objective functions would dictate the geometry of the Pareto front.

A consistent goal to pursue in the multi-objective based economic dispatch requires an unambiguous decision making strategy in which to choose a single point on the Pareto front at each time step. The most widely used approach for solving multi-objective optimization (MOO) dispatch problems involves scalarization, in particular, the weighted sum method. This method consists of assigning non-negative weights w_i to each objective function Φ_i and summing the weighted objectives hence transforming the multi-objective problem to a single objective problem.

While this transformation is advantageous as traditional optimization methods can be employed to solve the resulting single objective optimization problem, yet it comes with a set of drawbacks. If all the functions Φ_i are convex and the feasible set in this optimization $\mathcal{F}$ is also convex then any point on the Pareto front is reachable by some selection of constant weights w_i. However, if the convexity assumption does not hold, then there may exist points on the Pareto front that cannot be reached by any selection of weights. It seems to be an open question as to what happens when any of the cost functions is quasi-convex, rather than convex. Since a sum of quasi-convex functions, and even a sum of a strictly convex and quasi convex functions, *are seldom quasi-convex* , our guess is that for quasi-convex costs a similar result would be false. This would imply, in particular, that in the quasi-convex case, a Nash equilibrium could not be reached by simple scalarization.

Even for the convex case, the weight scalarization idea is encumbered by some issues; different choices of weights yield different points on the Pareto front. But the Pareto optimal points may be very "sensitive" to the variation of weights — a problem manifesting itself by steepness of Pareto fronts (relaxing one objective by a small amount could lead to a disproportional increase in the other) [50]. The rationale behind a choice of weights is often unclear and missing within the literature of economic dispatch in microgrids.

A better choice of a consistent goal seems to focus on the pursuit of some well defined point on the Pareto point with some clear interpretation, such as the Compromise Solution (CS), Nash Solution(NS), Kalai-Smorodinsky Solution (KS) or Egalitarian Solution (ES) [1].

(CS) *Compromise Solution* — the feasible point $x \in \mathcal{F}$ which yields a point in the Pareto front that is closest to the Utopia Point [51]

(NS) *Nash Solution* — the feasible point $x \in \mathcal{F}$ which yields a point in the Pareto front that creates the largest rectangle which is constructed using a pair of axes with the baseline as their origin and then drawing horizontal and vertical straight lines off these axes to meet the Pareto front [52]

(KS) *Kalai-Smorodinsky Solution* — the feasible point $x \in \mathcal{F}$ which yields a point in the Pareto front at the intersection with the straight line that connects the Threat Point and the Utopia Point [50]

(ES) *Egalitarian Solution* — the feasible point $x \in \mathcal{F}$ which yields a point in the Pareto front at the intersection with the straight line of 45^o passing through the Threat

Point [53].

Among these methods defined above, the Compromise Solution (CS) seems particularly attractive as it is easy to compute [1].

This motivates the present research.

3.3 The Weighted Sum Solution

The most widely used scalarization method, and approach in general for solving multi-objective optimization (MOO) dispatch problems, is the weighted sum method. It is a linear scalarization method. This method consists of assigning non-negative, user defined weights w_i to each objective function Φ_i. The weighted objective functions are then summed such that the multi-objective problem is transformed into a single objective optimization (SOO) problem,

$$min\{\sum_{i=1}^{n} w_i \Phi_i(x) \mid x \in \mathcal{F}\} \tag{3.4}$$

where n is the number of objective functions in the original multi-objective problem, Φ_i is the objective function i and w_i is the weight assigned to the objective function i.

It is important to point out here that all the weights w_i must be positive since negative weights would destroy the convexity of the scalarized problem. Also, in order to ensure the weights form a linear convex combination they must satisfy,

$$\sum_{i=1}^{n} w_i = 1 \tag{3.5}$$

It is most practical and advantageous to normalize the objectives first using function transformation methods, since the objectives may have different range values [54]. Thus, the objective functions Φ_i are normalized prior to scalarization in the weighted sum method:

$$\Phi_i^N(x) = \Phi_i(x)/\Phi_i^U(x) \tag{3.6}$$

3.4 The Compromise Solution

First introduced by Yu [55] in 1973, the concept of the compromise solution is based on the idea of finding a feasible point as close as possible to the ideal solution or utopia point (UP). The utopia point defines the optimal value for each objective function when treated separately. It is unattainable in the multi-objective framework since it lies outside the feasible space [1]. A schematic representation of these concepts is given in Fig. 3.2.

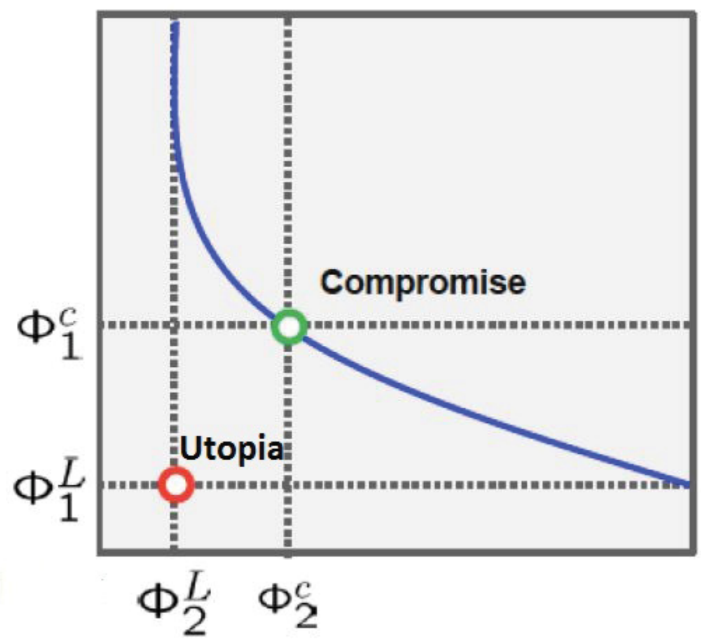

Fig. 3.2 Schematic representation of Utopia point, Compromise Solution and Pareto front [1].

To calculate the compromise solution (CS) one proceeds first with the minimization of each of the objective costs separately, obtaining the Utopia Point. In a bi-objective setting, this pertains to:

$$UP \stackrel{def}{=} [\Phi_1^L, \Phi_2^L] \in \mathcal{R}^2 \tag{3.7}$$

$$\Phi_1^L = \min \{ \Phi_1(x) \mid x \in \mathcal{F}\} \tag{3.8}$$

$$\Phi_2^L = \min \{ \Phi_2(x) \mid x \in \mathcal{F}\} \tag{3.9}$$

$$\hat{x}_1 \triangleq argmin \{ \Phi_1(x) \mid x \in \mathcal{F}\} \tag{3.10}$$

$$\hat{x}_2 \triangleq argmin \{ \Phi_2(x) \mid x \in \mathcal{F}\} \tag{3.11}$$

Since the cost value functions can have drastically different values it is then advisable to apply cost normalization [54]:

$$\bar{\Phi}_i(x) \overset{def}{=} \frac{\Phi_i(x) - \Phi_i^L}{\Phi_i^U(x) - \Phi_i^L}, \quad \bar{\Phi}_i(x) \in [0, 1], \quad i = 1, 2 \tag{3.12}$$

where Φ_i^U is the upper bound or maximum value for the objective i defined for the two cost functions as [54]:

$$\Phi_1^U = \Phi_1(\hat{x}_2) \tag{3.13}$$

$$\Phi_2^U = \Phi_2(\hat{x}_1) \tag{3.14}$$

where $\hat{x}_1$ and $\hat{x}_2$ are the points that minimize the objective cost functions Φ_2 and Φ_1 respectively.

The Compromise Solution is then calculated by means of a minimum-distance problem

$$\min \{ ||\bar{\Phi}(x)||_2 \mid x \in \mathcal{F}\} \tag{3.15}$$

$$\bar{\Phi}(x) \overset{def}{=} [\bar{\Phi}_1(x), \bar{\Phi}_2(x)] \tag{3.16}$$

where $|| \cdot ||_2$ denotes the Euclidean norm.

3.5 The Multi-Objective-Moving-Horizon-Optimization Problem

In this section, we will start formulating the proposed multi-objective-moving-horizon optimization (MO-MHO) problem as it pertains to the two case studies presented in the later chapter. Whatever the scalarization method employed the proposed MO-MHO is in fact a two-level approach to economic dispatch. It starts by representing the microgrid dispatch problem as a bi-objective optimization problem with the two costs grouping together the least conflicting components. The first level of the moving horizon approach employs a "look-ahead" (prediction horizon) window for the purpose of forecasting the fluctuating demand and uncertain weather data or associated stochastic process realizations that affect the outcome of dispatch optimization. The MOO problem is solved over this window producing future dispatch trajectories that would be optimal if the forecasts turn out to be correct. The MOO can be cast as a single-cost scalarized problem or else can seek specific Pareto points such as a *Compromise Point*. This is decided in the second level by an auxiliary comparison of the values of a number of independent assessment functions over a suitably selected testing horizon from "the past".

The MO-MHO Economic Dispatch Strategy

The algorithm for the proposed multi-objective-moving-horizon optimization (MO-MHO) approach is stated in discrete time as follows:

1. Select the lengths of the prediction horizon window and control window, N and $M < N$, respectively. Set the initial conditions of the system (e.g. the initial State of Charge (SOC) of the battery unit). Set iteration counter $i = 0$ and initial time $t_0 = 0$.

2. Obtain predictions (or stochastic realizations of the relevant processes) for the demand and weather forecasts over the current prediction window in discrete time $[t_i, t_{i+N}]$.

3. Solve the multi-objective optimization problem using the scalarization (linear or non-linear) solution method to obtain the optimal economic dispatch set points for the entire prediction horizon; i.e. for all $t_j \in [t_i, t_{i+N}]$.

4. Implement *only* the dispatch set points at time instants within the control window $[t_i, t_{i+M}] \subset [t_i, t_{i+N}]$.

5. Shift the prediction window by setting $i := i + M$. Update the initial state of the system at i using results of the optimization from the previous horizon. Repeat from 2).

The advantage of the moving horizon approach is now clear as it allows for any changes in the load or weather forecasts to be taken into account and compensated for by repeated solution of the multi-objective problem. The use of the scalarized (linear or non-linear) method ensures that the implemented dispatch set points are Pareto optimal [56].

3.6 Economic Dispatch Problem Formulation: The Basic Multi-Objective Problem

3.6.1 The Microgrid Model

The basic multi-objective (MO) problem discussed below is formulated for an inherently islanded microgrid. While such small scale remote power systems may not fit the true definition of microgrids, due to their inability to function in grid-connected mode, nonetheless from a research point of view they provide a functional and effective demonstration of microgrid technologies [57]. The distributed energy resources (DERs) for the remote microgrid considered include diesel generators, wind turbines, solar panels and battery energy storage systems (BESS). A brief discussion on the system modeling follows.

Diesel Generation

When modeling the diesel generation, two important aspects were considered: fuel consumption of the diesel generator and its operating constraints.

The generator cost can be represented by four curves namely fuel cost, heat rate, input/output and incremental cost curves [58]. In this analysis, the quadratic fuel cost curve was employed. The cost associated with the diesel generator is then determined by multiplying the corresponding fuel consumption with the market price of diesel fuel. This is common practice especially when dealing with fuel based generation systems. A typical fuel curve is shown in Figure 3.3. For the remainder of this work the diesel generator output is represented by P_d.

The power output of any diesel generator must be within its operating bounds for stable operation and prolonged engine life. The upper boundary P_d^{max} is directly related to generator rating while the lower boundary P_d^{min} represents the minimum loading requirement. For most diesel generator sets this is 30 percent of rated output. Operating a diesel generator at load levels less than its minimum loading requirement for long periods of time leads to power losses, poor performance and accelerated wear of the generator components [59].

Energy Storage

Two parameters were considered while modeling the energy storage system: the level of energy stored in the storage unit at time t_i denoted by E_{es}, and the power exchanged

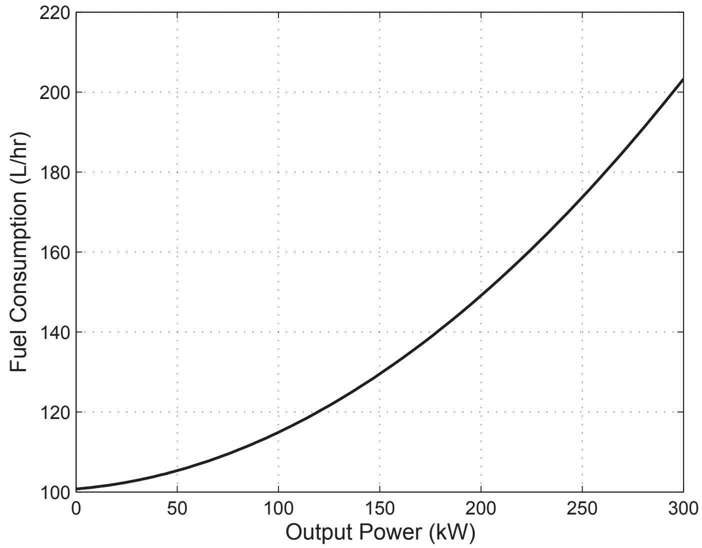

Fig. 3.3 Diesel generator fuel curve

between the storage unit and the microgrid denoted by P_{es}. The convention used is $P_{es} < 0$ in the charging mode and $P_{es} > 0$ when discharging. Also,

$$\eta = \begin{cases} \eta_{ch}, \text{ if } P_{es}(t_i) < 0 \text{ (charging mode)} \\ 1/\eta_{dis}, \text{ if } P_{es}(t_i) > 0 \text{ (discharging mode)} \end{cases} \tag{3.17}$$

where η is the (charging and discharging) efficiency and accounts for the losses.

The discrete time model of the storage unit is given by:

$$E_{es}(t_i) = E_{es}(t_{i-1}) - \eta P_{es}(t_i)\Delta t \tag{3.18}$$

$$\Delta t = t_i - t_{i-1} \tag{3.19}$$

Renewable Generation

Unlike the diesel generator and storage system, renewable DERs (wind turbine generator and solar pv panels) are dependant on intermittent sources and thus their power output is not completely controllable. These are referred to as non-dispatchable resources. Despite their intermittency, the penetration of renewable energy sources into our grids is becoming more prevalent owing to their benefits such as reduction in operating costs and greenhouse gases [60].

In terms of the microgrid controller, the renewable energy outputs (wind turbine generator output ($\bar{P}_w$) and solar PV panel output ($\bar{P}_s$)) are treated as negative load. It is assumed that these sources are operated at Maximum Power Point Tracking (MPPT) at all times.

A typical hourly profile for wind turbine and solar panel outputs is shown in Figure 3.4.

Load Model

A microgrid energy management system that allows a microgrid to control its demand in addition to supply is a valuable and attractive option since demand control would lead to a more efficient and better microgrid performance [57], [17].

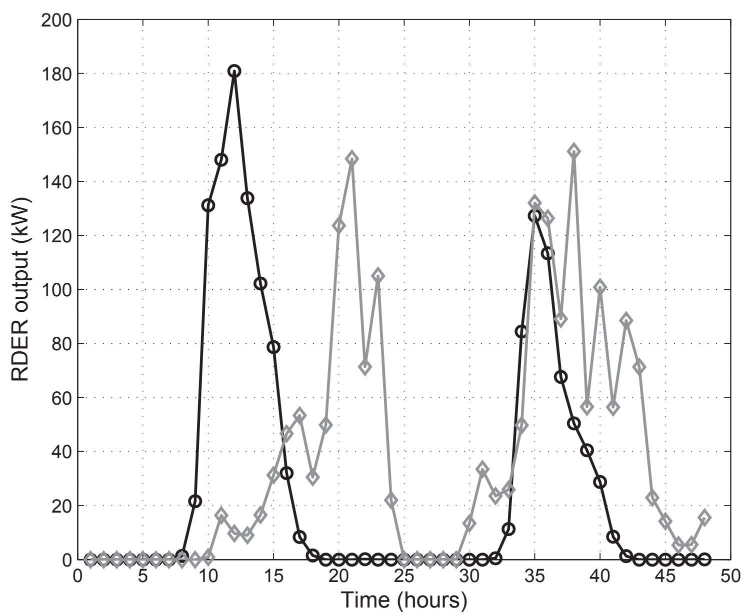

Fig. 3.4 Typical hourly profile for wind turbine ('◇') and solar panel output ('O').

Thus, our system model allows that demand control is incorporated into the system by considering two types of loads:

Critical Loads:

Critical loads, denoted by $\bar{P}_{cl}$, include demand which must be met at all times. For example, servers and loads related to essential processes.

Controllable Loads:

Controllable loads, denoted by $\bar{P}_{nl}$, include demand which may be reduced or shed when necessary such as when there are power quality problems, supply constraints or even emergency situations. Examples of controllable loads include dimmable lighting, standby devices and thermostatically controlled loads like electric water heaters, building cooling systems, space heaters, etc. While these loads have a preferred level, they are flexible and their demand level may be reduced when required. For example, water or space heaters operate at a certain demand level to output the required temperature set point. If this demand level were to be reduced for a certain time, it would result in lower water or space temperatures. This may result in end-user discomfort and hence a certain cost (penalty for the microgrid) is associated with the load curtailment. However, during supply constraints or emergency situations, the cost of this curtailment may be outweighed by the incremental cost of electricity purchased.

The microgrid load was modeled using profiles obtained from IESO Power data. The data includes variations in the load based on the time of the day and day of the week. Seasonal variations may be considered by taking longer forecast horizons.

3.6.2 Assumptions

This study is based on the following initial assumptions:

1. The wind turbine generators and PV panels are operated at Maximum Power Point Tracking (MPPT) at all times i.e. the maximum power possible at a given wind speed and solar irradiance is extracted under all conditions. The renewable generation (wind and solar) is treated as a negative load and are utilized entirely. $P_L(t_i)$ *is the effective load that is to be satisfied by the power output from the diesel generator and storage battery or otherwise curtailed* at every time instant t_i.

$$P_L(t_i) = P_{totalload}(t_i) - \bar{P}_w(t_i) - \bar{P}_s(t_i) \tag{3.20}$$

2. The total load of the microgrid is composed of both critical and non-critical (controllable) loads so that

$$P_{totalload}(t_i) = \bar{P}_{cl}(t_i) + \bar{P}_{nl}(t_i) \tag{3.21}$$

3. Only active power management is considered. For the purpose of this study, reactive power and voltage set points have been neglected.

4. System maintenance costs, startup and shutdown costs have not been included in the formulation of the problem.

5. Lastly, we assume the system is lossless.

3.6.3 Cost Functions in the MO-MHO Problem

The cost functions and constraints in the microgrid economic dispatch problem generally exhibit non-linear, non-homogeneous and time varying characteristics. While these functions may be linearized, it is often not the most desirable option [38].

This thesis proposes to represent the microgrid economic dispatch problem as a bi-objective optimization problem with the two costs grouping the least conflicting components. The advantage of this approach is two fold: firstly, it allows to differentiate between conflicting objectives, thus enabling the proper application of multi-objective solution methods. Secondly, such aggregation/polarization of objectives will facilitate the initial evaluation of the MO-MHO approach as the criterion space will be two dimensional and the Pareto front will be easy to visualize in the plane. The non-negotiable satisfaction of the critical load and other hard constraints will define a common feasible set for both objectives.

Thus, the microgrid economic dispatch is formulated as a non-linear constrained bi-objective optimization problem of the type:

$$\min \left\{ [\Phi_1(x), \Phi_2(x)] \mid x \in \mathcal{F} \subset \mathcal{R}^{3\times(N+1)} \right\} \tag{3.22}$$

where $\mathcal{F}$ is the feasible set and $\Phi_i, i = 1, 2$ are the two conflicting objective functions.

In the broadest sense, the desired attributes of a microgrid can be classified into two broad groups: utility profits and customer satisfaction. In fact, for our basic problem formulation it is these two objectives that will dominate the global play. This is detailed below.

Utility Profits

The cost of producing power from diesel fueled equipment and total storage costs are used to define the overall utility profits.

Total power cost for a single generator over the horizon $[t_k, t_{k+N}]$ is calculated as

$$J_1(P_d) \stackrel{def}{=} \Sigma_{i=k}^{k+N}[C_d(t_i, P_d(t_i))] \tag{3.23}$$

Assuming that only costs associated with fuel consumption are taken into consideration, the cost versus active power curve may be used to obtain the quadratic equation:

$$C_d(t_i, P_d(t_i)) = \pi_D.(a(P_d(t_i))^2 + bP_d(t_i) + c) \tag{3.24}$$

where a, b and c are the generator quadratic parameters and π_D is the cost of diesel fuel.

Storage cost over the horizon $[t_k, t_{k+N}]$ is calculated as :

$$\begin{aligned} J_2(P_{es}) &\stackrel{def}{=} \Sigma_{i=k}^{k+N} C_{es}(P_{es}(t_i)) \\ C_{es}(P_{es}(t_i)) &= K_{es}P_{es}(t_i) + K_{deg} \end{aligned} \tag{3.25}$$

where K_{es} represents the operation cost and K_{deg} accounts for the cyclic degradation of the storage unit.

The power costs associated with the wind turbine generators and solar panels are absent here since the renewable generation (wind and solar) is treated as negative load. In addition, the cost of maintenance and amortization of the wind turbines and solar panels is neglected.

Customer satisfaction

The penalties for curtailing non-critical loads are thought to capture the customer satisfaction.

Power curtailment penalty, is the penalty payable by the microgrid operator for the curtailment of power and is defined over the horizon $[t_k, t_{k+N}]$ as

$$J_3(P_c) = \Sigma_{i=k}^{k+N} K_c P_c(t_i) \tag{3.26}$$

The *multivariate* optimization variable x in Equation (3.22) is defined as

$$x \overset{def}{=} [P_d, P_{es}, P_c] \in \mathcal{R}^{3\times(N+1)}$$

with (3.27)

$$P_d \overset{def}{=} [P_d(t_k), ..., P_d(t_{k+N})], \tag{3.28}$$

$$P_{es} \overset{def}{=} [P_{es}(t_k), ..., P_{es}(t_{k+N})] \text{ and} \tag{3.29}$$

$$P_c \overset{def}{=} [P_c(t_k), ..., P_c(t_{k+N})] \tag{3.30}$$

The cost functions of equation (3.22) can now be specified as

$$\Phi_1(P_d, P_{es}, P_c) \overset{def}{=} J_1(P_d) + J_2(P_{es}) \tag{3.31}$$

$$\Phi_2(P_d, P_{es}, P_c) \overset{def}{=} J_3(P_c) \tag{3.32}$$

Where the costs Φ_1 and Φ_2 are thought to be related to grid-utility profits and customer satisfaction with the services respectively. The objective function Φ_1 accounts for the total costs of power production and storage and hence represents the operating costs to be minimized as per the interests of the utility. The objective function Φ_2 on the other hand captures the customer satisfaction as it penalizes curtailment of the load demand.

It should be noted that the optimization is a discretized version of a dynamical optimization problem over a horizon $t_k, ..., t_{k+N}$. It is dynamical in character because of the presence of the storage battery whose "state" depends on the storage history as described in Equation 3.18 i.e.

$$E_{es}(t_i) = E_{es}(t_{i-1}) - \eta P_{es}(t_i)\Delta t \tag{3.33}$$

$$\Delta t = t_i - t_{i-1} \quad i = k, ...k + N \tag{3.34}$$

3.6.4 Constraints

The optimization is subject to the following constraints:

1. Power balance must be met at all times i.e. the total generation must satisfy the total load.

2. Each DER must operate within its operating limits

3. The critical loads must be met at all times

The constraints are stated as:

$$\mathcal{F} \overset{def}{=} \{(P_d, P_{es}, P_c) \in \mathcal{R}^{3\times(N+1)} \mid \text{subject to}$$

$$P_L(t_i) = P_d(t_i) + P_{es}(t_i) + P_c(t_i) \tag{3.35}$$

$$P_d^{min} \leq P_d(t_i) \leq P_d^{max} \tag{3.36}$$

$$(1/\eta\Delta t)(E_{es}^{min} - E_{es}(t_{i-1})) \geq P_{es}(t_i) \geq (1/\eta\Delta t)(E_{es}^{max} - E_{es}(t_{i-1})) \tag{3.37}$$

$$P_c(t_i) \leq P_{nl}(t_i)\} \tag{3.38}$$

The effective load P_L and non-critical load P_{nl} are the only realizations of stochastic processes that enter the optimization. It is worth discussing the constraint on the storage variable since it is the storage unit that introduces the dynamics in this problem as given in Equation 3.33. Equation 3.37 defines the limits on the power exchanged between the storage unit and the microgrid — this includes both the charging and discharging modes of the storage device. The storage device is modeled considering two parameters: the level of energy E_{es} stored in the unit at time t_i and the power exchanged P_{es} between the storage unit and the microgrid, where power is in fact the energy consumed per unit time as defined by $P_{es}(t_i) = E_{es}(t_i)/\Delta t$. The capacity of the storage unit is defined in terms of the energy it can contain:

$$E_{es}^{min} \leq E_{es}(t_i) \leq E_{es}^{max} \tag{3.39}$$

Also, the energy contained in the storage unit at any given time is equal to,

$$E_{es}(t_i) = E_{es}(t_{i-1}) - \eta P_{es}(t_i)\Delta t \tag{3.40}$$

Thus,

$$E_{es}^{min} \leq E_{es}(t_{i-1}) - \eta P_{es}(t_i)\Delta t \leq E_{es}^{max} \tag{3.41}$$

$$E_{es}^{min} - E_{es}(t_{i-1}) \leq -\eta P_{es}(t_i)\Delta t \leq E_{es}^{max} - E_{es}(t_{i-1}) \tag{3.42}$$

$$(1/\eta\Delta t)(E_{es}^{min} - E_{es}(t_{i-1})) \geq P_{es}(t_i) \geq (1/\eta\Delta t)(E_{es}^{max} - E_{es}(t_{i-1})) \tag{3.43}$$

3.6.5 Linear Scalarization of the Multi-Objective Problem on a Single Prediction Window

The weighted sum solution is a linear scalarization method that we apply here. The micro-grid optimization problem defined by Equation 3.22 applied to the weighted sum method takes the form:

$$min\{w_1\Phi_1(x) + w_2\Phi_2(x) \mid x \in \mathcal{F}\} \tag{3.44}$$

where $\Phi_1(x)$ and $\Phi_2(x)$ are as defined in Equations 3.31 and 3.32 respectively and $\mathcal{F}$ is as defined in Equations 3.35 - 3.38.

It is most practical and advantageous to normalize the objectives first using function transformation methods, since the objectives may have different range values [54]. Thus, the objective functions Φ_i $i = 1, 2$ are normalized prior to scalarization in the weighted sum method:

$$\Phi_i^N(x) = \Phi_i(x)/\Phi_i^U(x) \quad i = 1, 2 \tag{3.45}$$

To summarize, the optimization problem on the prediction window $[t_k, t_{k+N}]$ employing the weighted sum solution as stated in Equation 3.44 is subject to the dynamical constraints on the energy storage given in Equation 3.33. At this point it has to be noticed that the dynamical constraint involves the energy storage at time t_{k-1} which is outside the prediction window $[t_k, t_{k+N}]$. This value is taken from the previous prediction window and serves as the initial condition for the dynamical storage unit in the current prediction window.

3.6.6 Non-linear Scalarization of the Multi-Objective Problem on a Single Prediction Window

The compromise solution is a type of non-linear scalarization that we employ to solve the economic dispatch problem. To summarize, the optimization problem on the prediction window $[t_k, t_{k+N}]$ employing the compromise solution as stated in Equation 3.15 is subject to the dynamical constraints on the energy storage given in Equation 3.33. At this point it has to be noticed that the dynamical constraint involves the energy storage at time t_{k-1} which is outside the prediction window $[t_k, t_{k+N}]$. This value is taken from the previous prediction window and which serves as the initial condition for the dynamical storage unit in the current prediction window.

Chapter 4

Results and Discussion

4.1 Introduction

The proposed Multi-Objective-Moving-Horizon-Optimization (MO-MHO) approach was applied to two case studies — both microgrids but with different DER and load settings. In Case 1, the basic formulation developed in Chapter 3 was applied to the case of a remote microgrid with one dispatchable diesel generator. Case 2 extends the formulation with additional constraints to include unit commitment for two diesel generators. The objective of this analysis was to evaluate the proposed MO-MHO approach as an instrument for improvement of economic dispatch in microgrids.

This chapter presents the results of those validations along with an analysis and discussion. The results of the MO-MHO approach are compared against results of an economic dispatch using the usual scalarization methods. An independent set of Assessment functions are explained in detail along with mathematical formulation.

4.2 Case Study 1

The test microgrid system consists of a diesel generator, wind turbine generator, solar PV panels and a Lithium-ion battery energy storage system.

The wind turbine generator and solar PV panels are operated at Maximum Power Point Tracking (MPPT) at all times. Both renewable DER (wind and solar) are treated as negative loads and the costs of maintenance and amortization are assumed negligible. Weather forecast data — wind speed and solar irradiance were obtained from the University of Waterloo (UW) Weather Station [61]. Technical specifications of the solar panels were obtained from [62]. The model parameters used for the wind turbine generator are given in Table 4.1. Figure 4.1 shows how the power output of the wind turbine generator varies with the wind speed.

Table 4.1 Wind Power Model

Parameter	Value
Air density (ρ)	1.225 kg/m^3
Rated output power	335 kW
Rated output speed	13 m/s
Cut in speed	3 m/s
Cut out speed	25 m/s

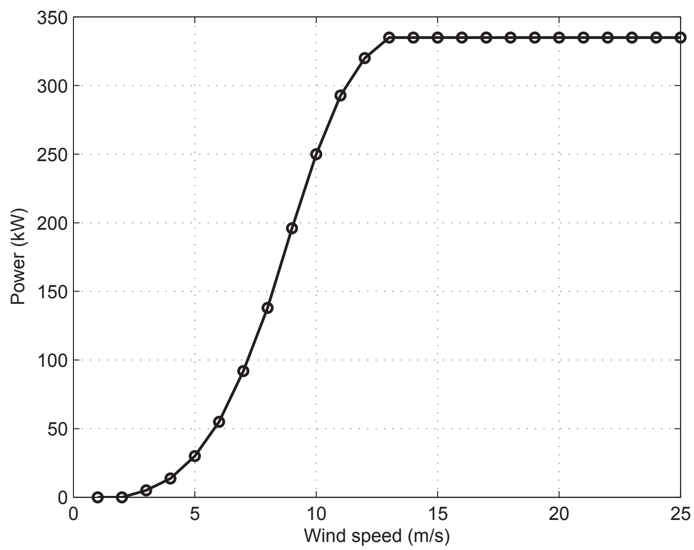

Fig. 4.1 Wind turbine generator power curve

Using the model parameters defined above and the weather data obtained from [61] an hourly profile for the solar panel and wind turbine generator outputs for a horizon of one week was obtained and is shown in Figures 4.2 and 4.3.

The load model used contains both critical and non-critical (controllable) loads. The load profile used for modeling the microgrid load forecasts was that of the region of Ottawa, Canada. This profile was obtained from the data archives of the Independent Electricity

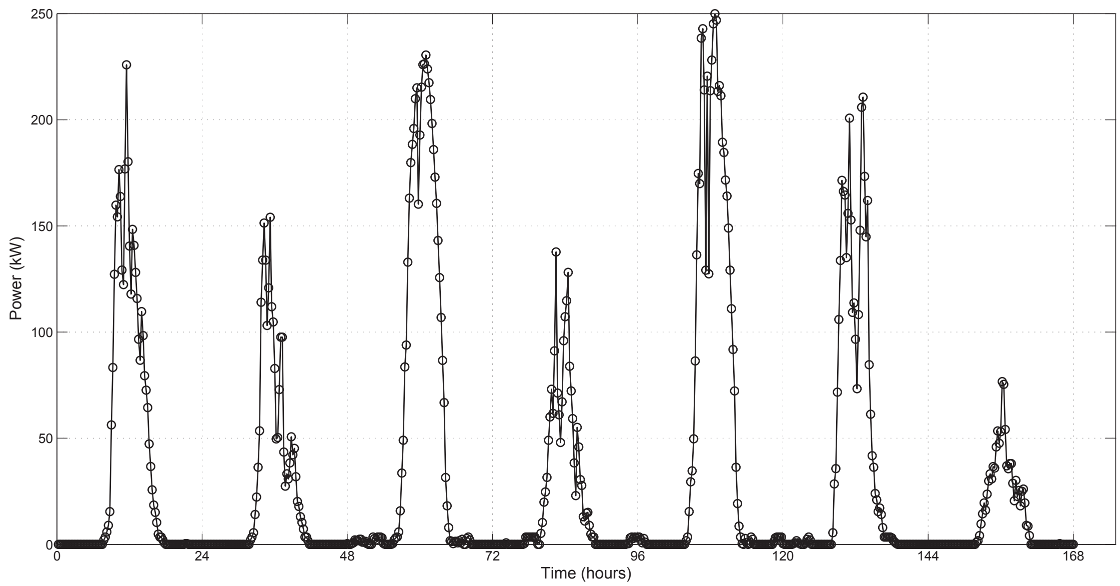

Fig. 4.2 Renewable generation: Solar panel output ('O') over the horizon of a week.

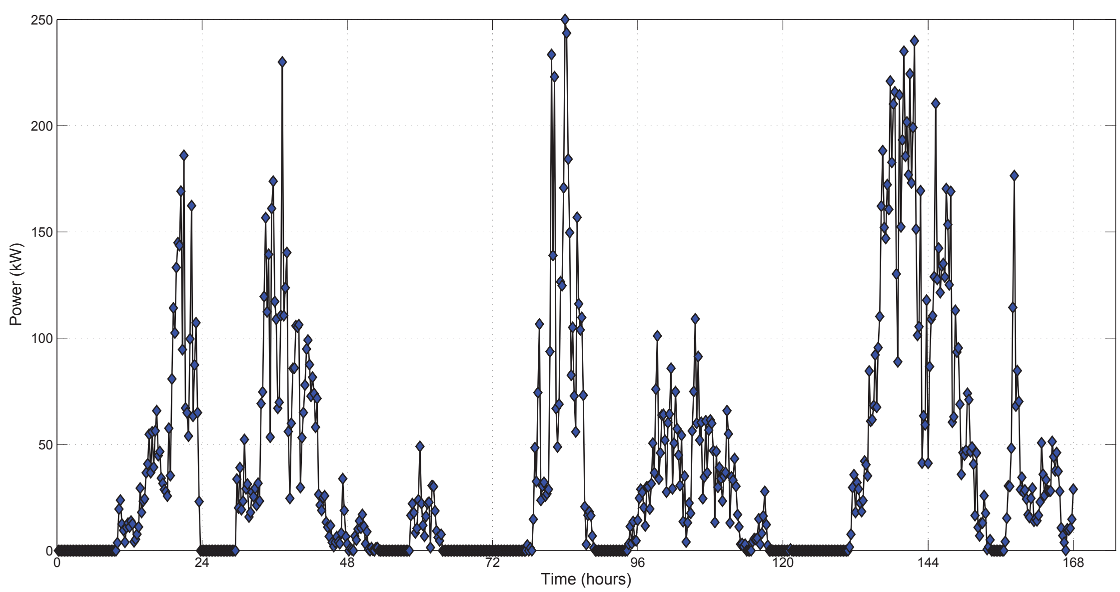

Fig. 4.3 Renewable generation: wind turbine generator ('◇') output over the horizon of a week.

System Operator (IESO) [63] — the corporation responsible for operating the electricity market in the province of Ontario, Canada. The hourly load data obtained from IESO was normalized to the microgrid's base load. The range values are given in Table 4.2.

Table 4.2 Remote Microgrid Load Profile

Range	Total	Critical	Controllable
Maximum (kW)	500	150	350
Minimum (kW)	291.7	87.5	204.2

The diesel generator is modeled with a maximum power output greater than the critical load. While the actual set points for the generator is determined as a result of the optimization, such an assumption basically allows for the critical load to be met at all times. The model parameters and operating bounds for the diesel generator are given in Table 4.3.

Table 4.3 Diesel Generator Parameters

Parameter	Value
Generator quadratic parameters	$a = 0.0001$, $b = 0.2177$, $c = 10.7625$
Lower operating limits	$P_{min} = 96$ kW
Upper operating limits	$P_{max} = 320$ kW

The model of the battery energy storage system (BESS) used in this research is based on a physical Lithium-ion battery system from [64]. The BESS energy rating, maximal charge and discharge rates and efficiencies are given in Table 4.4.

Table 4.4 Energy Storage System Parameters

Parameter	Value
Energy capacity bounds	$E_{es}^{min} = 12.5$ kWh , $E_{es}^{max} = 125$ kWh
Charge rate	-100 kW
Discharge rates	100 kW
Charge and discharge efficiencies	$\eta_{ch} = \eta_{dis} = 0.9$

4.2.1 Multi-Objective (MO) Solution Methods

A key aspect of the proposed Multi-Objective-Moving-Horizon-Optimization (MO-MHO) approach presented is that it allows for the solution method for the associated MOO problem to be adaptively adjusted and selected based on an independent set of assessment functions evaluated along the trajectories of optimal multi-objective solutions already implemented over a window in the past. Such an approach is likely to lead to economic gains. To explain the motivation behind an *adaptive* MO-MHO strategy and before we delve further into the assessment functions, it would be useful to have some insight on the performance of the different MO solution methods in the microgrid economic dispatch problem.

The following MO solution methods were compared for the microgrid optimization problem:

(i) Linear Scalarization method: Weighted sum multi-objective optimization applied in a moving horizon framework.

(ii) Compromise solution method: The proposed Compromise Solution based multi-objective-moving-horizon optimization approach.

The objective functions remained the same in each case, as described in Chapter 3. Simulation studies were carried out using a control window of $M = 1$ hour while, the look-ahead prediction horizon used was $N = 48$ hours. As discussed in Section 3.5, the control window M represents the part of the prediction horizon N that is implemented at each time instant. The prediction horizon is then shifted and the optimization re-computed for the entire prediction horizon, but again, only the dispatch points for the control window are implemented. Simulations were carried out for a week.

The Effect of Varying the Weights in the Linear Scalarization Method

In the quest for the best solution method for the MO-MHO approach, it is worth examining how the weights affect the solution of the weighted sum method. For this analysis nine (9) different set of weights were employed. The microgrid optimization problem was solved for each of these nine different set of weights and the resulting dispatch set points for the diesel generation, energy storage and curtailment were examined. The nine (9) set of weights used for this analysis are given in Table 4.5.

Table 4.5 Set of Weights Employed in the Weighted Sum MO-MHO approach

Weights	Set 1	Set 2	Set 3	Set 4	Set 5	Set 6	Set 7	Set 8	Set 9
w_1	0.9	0.1	0.8	0.2	0.7	0.3	0.6	0.4	0.5
w_2	0.1	0.9	0.2	0.8	0.3	0.7	0.4	0.6	0.5

For each set of weights given in Table 4.5, the weighted sum method was applied in a moving horizon framework using a control window of $M = 1$ hour and a prediction horizon of $N = 48$ hours. The simulations were carried out for a horizon of 1 week (7 x 24 = 168 hours). To allow a fair comparison, the same load and weather profiles were used for each set of weights. It is important to note that the dispatch set points shown in the results are the actual implemented set points (diesel generator, storage and curtailment) for the horizon of 1 week. In other words, the plots given below show the dispatch set points (for the diesel generator, energy storage and curtailment) at time instants within the control window as the prediction horizon shifts forward in the moving horizon. It may be recalled from Section 3.5 that in the multi-objective-moving-horizon approach, at each time instant, the optimization problem is solved for the entire prediction horizon (48 hours) but only the dispatch set points for the control window (1^{st} hour) are implemented. The prediction horizon then shifts forward and the optimization (for the *new* prediction horizon) is computed. Again, only the dispatch results for the control window are implemented. This process is repeated till the end of the horizon — in our example, the horizon of 1 week (168 hours).

The plots in Figures 4.4 – 4.9 compare the dispatch results for the diesel generator, energy storage and power curtailment obtained from the weighted sum method using different weights as given in Table 4.5. The figures indicate that for a particular horizon, and hence the same load and weather conditions, *the weighted sum method may come up with any number of solutions based on the value of the weights*. To examine this further, eight different control windows were randomly selected out of the 1 week horizon. The dispatch results for each of these control windows, using different sets of weights in the weighted sum method, were compared. The dispatch results for these selected control windows are highlighted in blue in Figures 4.4 – 4.9 and the actual values in kilowatts (kW) are given in Table 4.6 (diesel generator), Table 4.7 (energy storage) and Table 4.8 (curtailment).

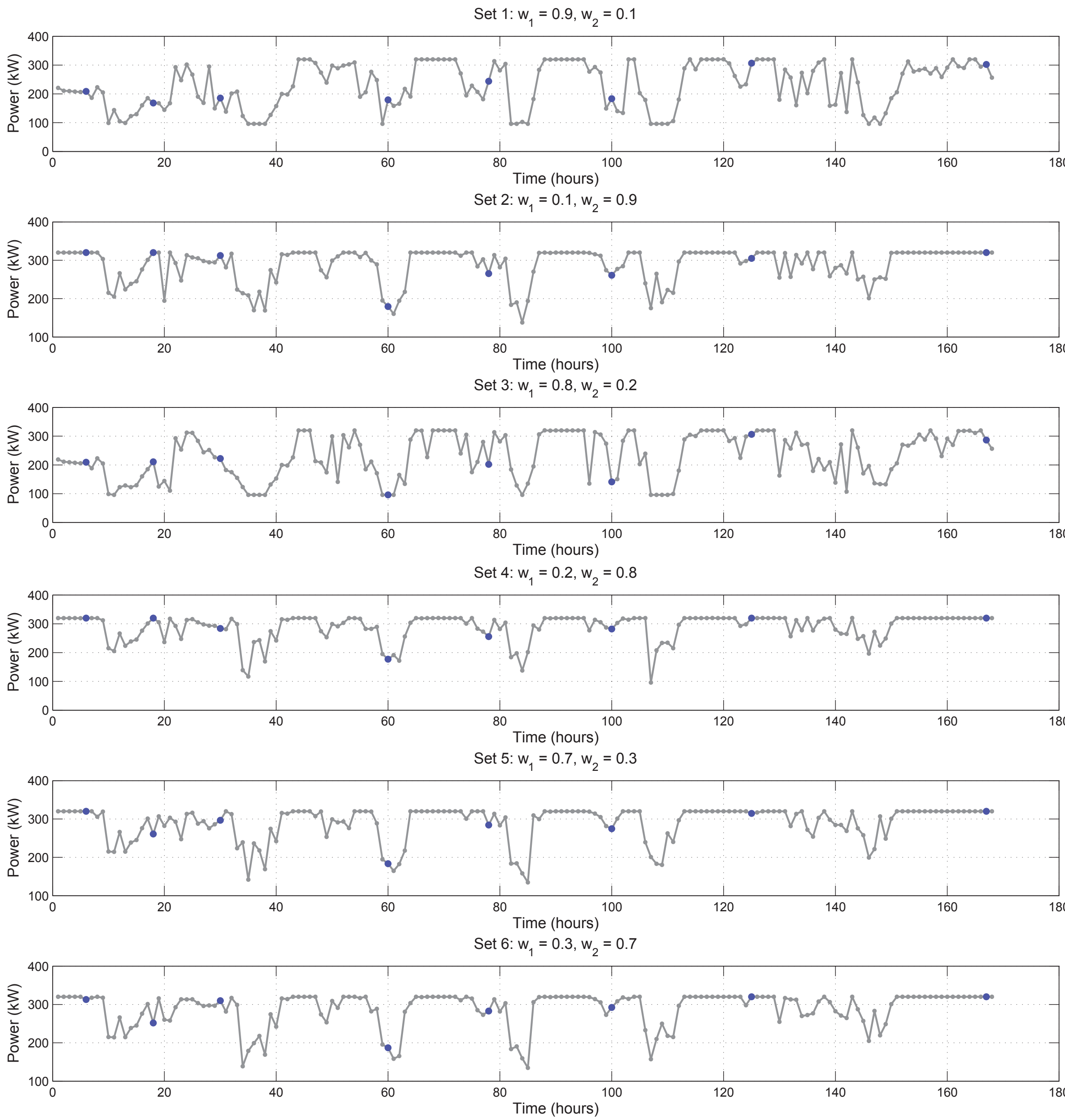

Fig. 4.4 Comparison of dispatch results for the diesel generator from the weighted sum method (using different set of weights) implemented in the moving horizon framework for 1 week.

Figures 4.4 and 4.9 show the effect of using different weights in the weighted sum method on the end result of the optimization. The plots show that the effect of varying the weights is very pronounced in the case of the dispatch results for the diesel generation and curtailment. While there are differences in the storage set points, the general trend of charging and discharging the storage unit remains the same even with a change of weights.

Figure 4.4 shows that using the weights in Set 1 ($w_1 = 0.9$, $w_2 = 0.1$) and Set 3 ($w_1 = 0.8$, $w_2 = 0.2$) results in lower diesel consumption compared to any of the other set of weights. This result can also be seen in Table 4.6. The diesel generator dispatch results obtained by using the weights in Set 1 and Set 3 are the lowest for all the eight control windows examined. For example, when the load is 351.69 kW, using the weights in Set 1 for the optimization results in a dispatch of 168.31 kW and using Set 3 results in a dispatch of 210.69 kW. In comparison, for the same load of 351.69 kW the other weights produce dispatch set points ranging from 251.69 kW (Set 6) to 320 kW (Set 2, Set 4, Set 8 and Set 9). It is also observed from Figure 4.5 and Table 4.6 that the dispatch results for the diesel generator using the weights in Set 7 ($w_1 = 0.6$, $w_2 = 0.4$), Set 8 ($w_1 = 0.4$, $w_2 = 0.6$) and Set 9 ($w_1 = 0.5$, $w_2 = 0.5$) are very similar. This may be due to the fact that the difference between the two weights w_1 and w_2 in each of these three sets (Set 7, 8 and 9) is very small.

The plots in Figures 4.6 and 4.7 show the effect of varying the weights on the dispatch results for the storage unit. The storage unit is modeled using the convention that $P_{es} < 0$ in the charging mode and $P_{es} > 0$ when discharging. It is interesting to note that the general trend of charging and discharging the storage unit remains similar with a change of weights. However the actual power (kW) exchanged with the microgrid varies with a change of weights, as seen in Table 4.7.

Figures 4.8 and 4.9 compare the dispatch results for curtailment from the weighted sum method (using different set of weights as specified in Table 4.5) implemented in the moving horizon framework. Similar to the diesel generator dispatch results, the weights in Set 1 ($w_1 = 0.9$, $w_2 = 0.1$) and Set 3 ($w_1 = 0.8$, $w_2 = 0.2$) produce the most disparate (higher) curtailment dispatch compared to the other sets of weights. This observation can be seen clearly in Table 4.8. When the load is 328.37 kW, the curtailment set point determined by using the weights in Set 1 and Set 3 is 116kW while that determined by all the other weights is 0kW. Like in the case of the diesel generation, the curtailment set points determined using the weights in Set 7, Set 8 and Set 9 are almost identical.

Based on the results presented above, we select the four sets of weights that produce the

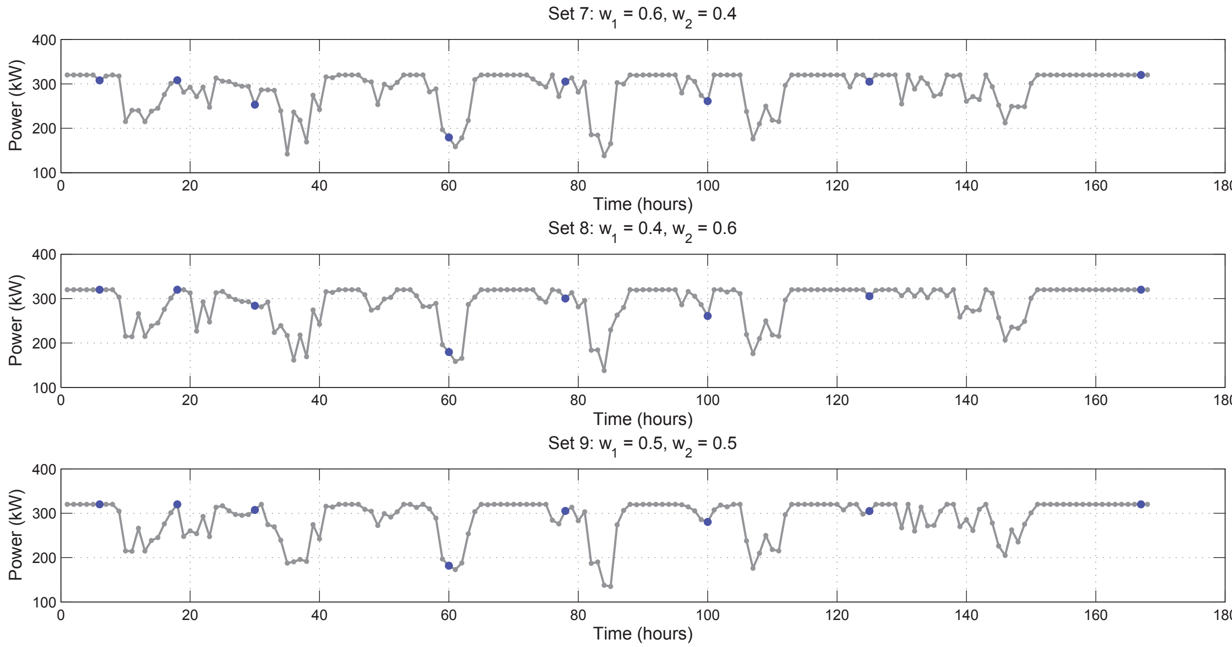

Fig. 4.5 Comparison of dispatch results for the diesel generator from the weighted sum method (using different set of weights) implemented in the moving horizon framework for 1 week.

Table 4.6 Comparison of Dispatch Results for the Diesel Generator from the Weighted Sum MHO method using Different Weights as highlighted (in blue) in Figures 4.4 and 4.5

Load (kW)	Diesel generator set points — Sets of weights as per Table 4.5[a]								
	Set 1	Set 2	Set 3	Set 4	Set 5	Set 6	Set 7	Set 8	Set 9
328.37	208.45	320.00	209.23	320.00	320.00	312.80	308.00	320.00	320.00
351.69	168.31	320.00	210.69	320.00	260.82	251.69	308.20	320.00	320.00
284.01	185.60	312.22	222.21	284.01	296.68	309.82	253.24	284.01	307.27
178.53	179.21	179.40	96.00	176.99	183.51	187.07	179.40	179.81	181.83
327.29	243.85	265.35	202.11	255.70	284.30	282.98	305.17	300.23	305.05
258.98	183.43	261.01	141.28	282.12	274.58	292.29	261.07	260.95	280.30
354.59	306.46	304.93	306.31	320.00	314.51	320.00	304.91	305.53	304.94
418.39	302.37	320.00	286.46	320.00	320.00	320.00	320.00	320.00	320.00

[a]All values rounded to two decimal places

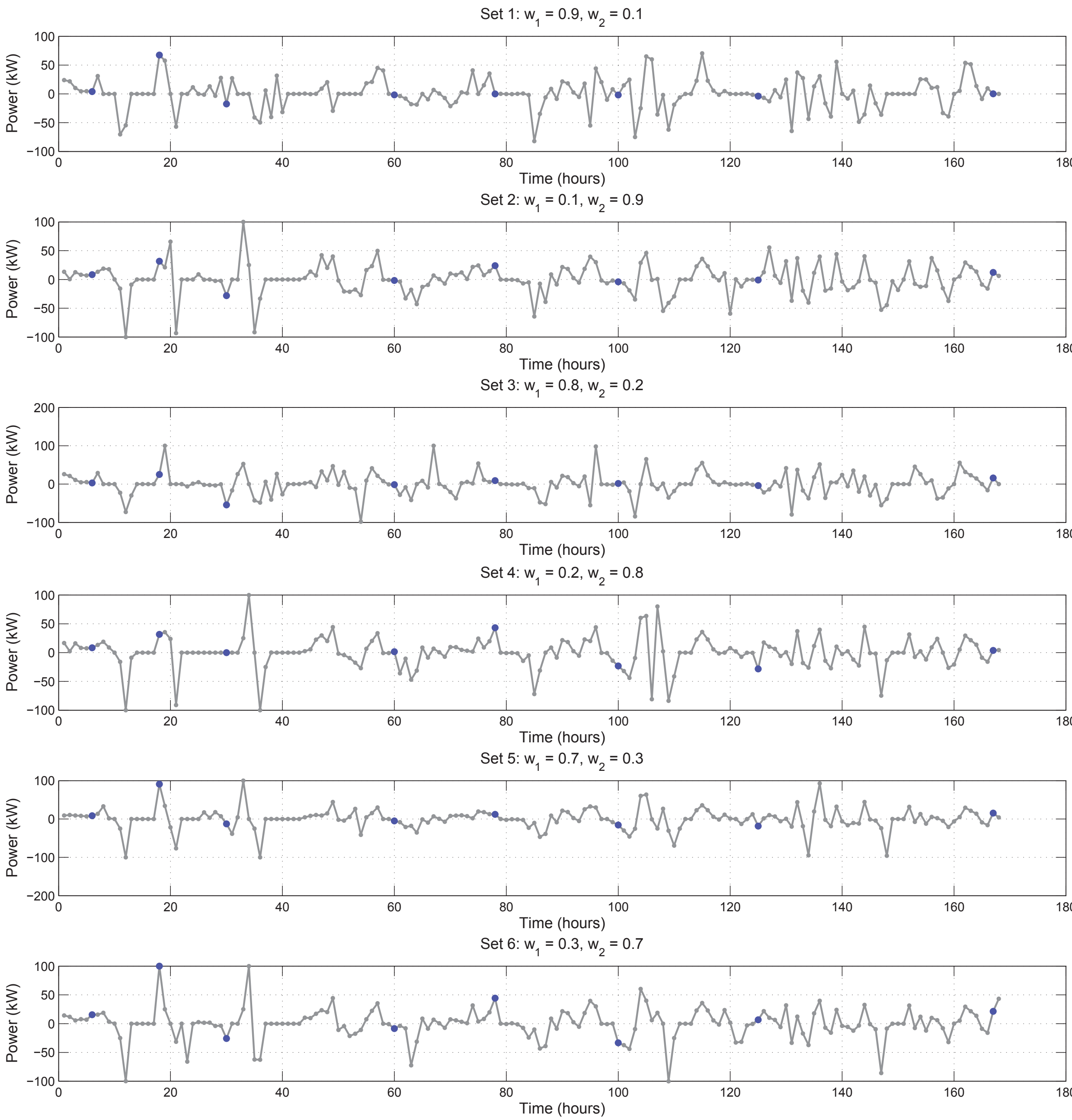

Fig. 4.6 Comparison of dispatch results for the energy storage from the weighted sum method (using different set of weights) implemented in the moving horizon framework for 1 week.

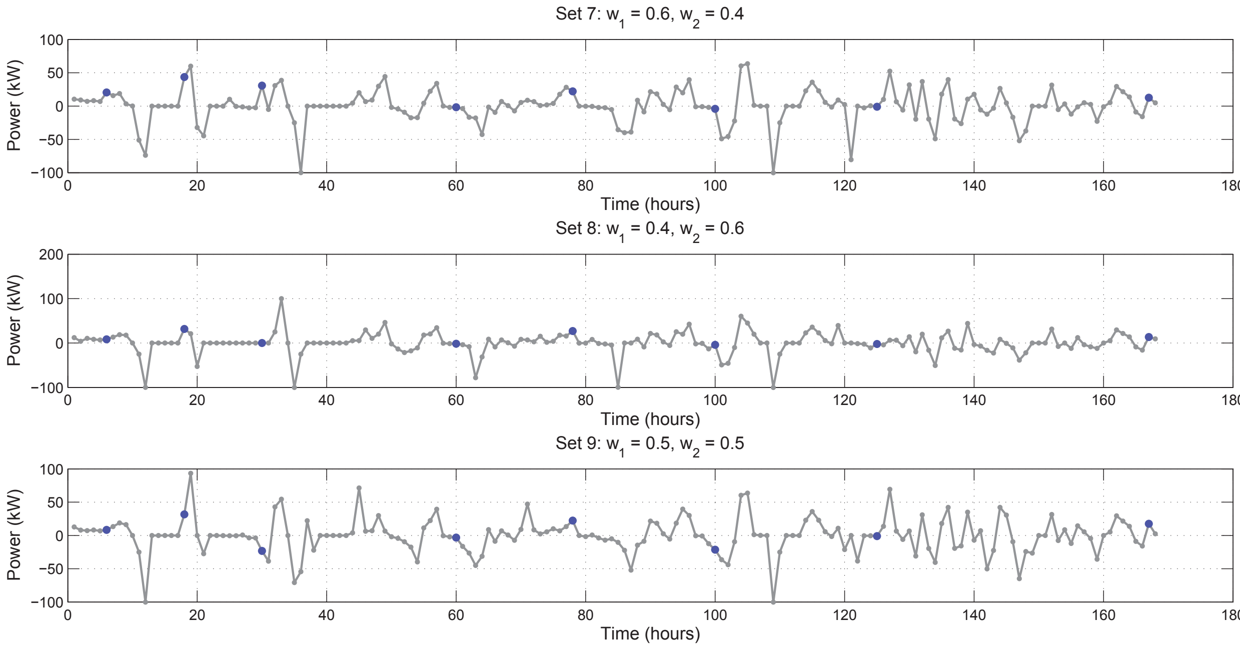

Fig. 4.7 Comparison of dispatch results for the energy storage from the weighted sum method (using different set of weights) implemented in the moving horizon framework for 1 week.

Table 4.7 Comparison of Dispatch Results for the Energy Storage from the Weighted Sum MHO method using Different Weights as highlighted (in blue) in Figures 4.6 and 4.7

Load (kW)	Energy Storage set points (kW) — Sets of weights as per Table 4.5[a]								
	Set 1	Set 2	Set 3	Set 4	Set 5	Set 6	Set 7	Set 8	Set 9
328.37	3.92	8.37	3.14	8.37	8.37	15.57	20.37	8.37	8.37
351.69	67.38	31.69	25.00	31.69	90.87	100.00	43.49	31.69	31.69
284.01	-17.58	-28.21	-54.20	0.00	-12.67	-25.80	30.77	0.00	-23.26
178.53	-1.74	-1.74	-1.33	1.54	-4.98	-8.54	-1.74	-1.74	-3.30
327.29	0.00	23.89	9.18	43.17	12.09	44.31	22.12	27.07	22.24
258.98	-1.86	-4.06	1.70	-23.14	-15.61	-33.31	-4.18	-3.95	-21.32
354.59	-4.02	-0.95	-3.72	-28.36	-18.36	6.62	-0.92	-2.16	-0.98
418.39	0.00	12.28	15.91	3.81	15.42	21.30	12.49	13.55	17.47

[a] All values rounded to two decimal places

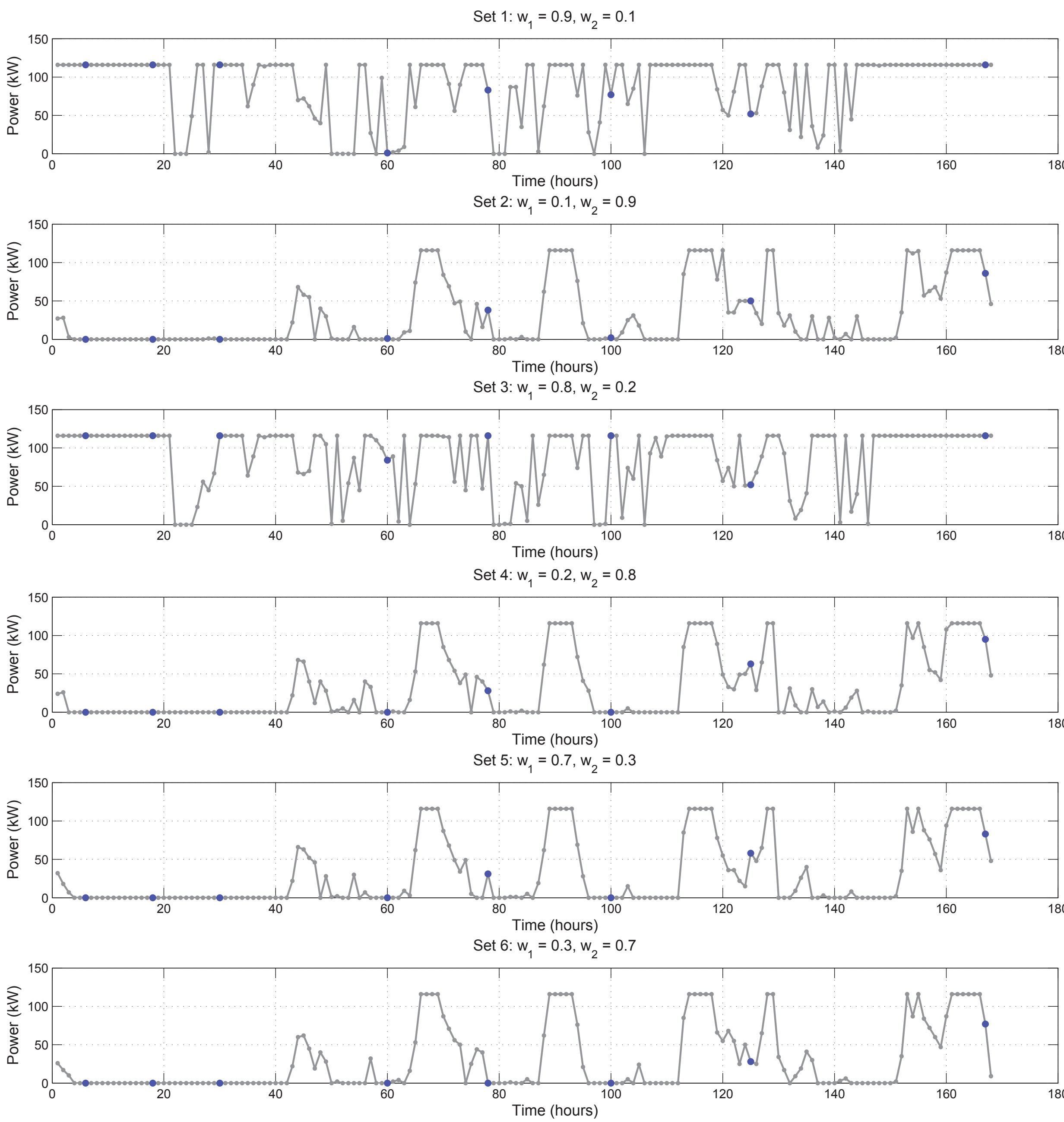

Fig. 4.8 Comparison of dispatch results for curtailment from the weighted sum method (using different set of weights) implemented in the moving horizon framework for 1 week.

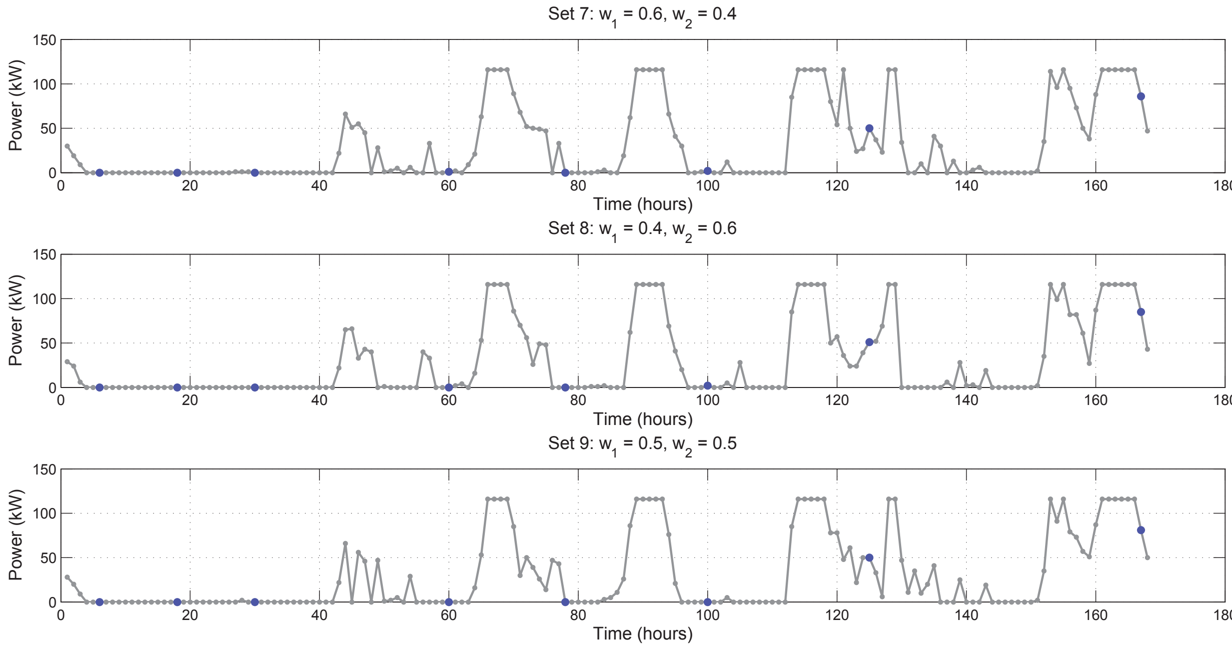

Fig. 4.9 Comparison of dispatch results for curtailment from the weighted sum method (using different set of weights) implemented in the moving horizon framework for 1 week.

Table 4.8 Comparison of Dispatch Results for Curtailment from the Weighted Sum MHO method using Different Weights as highlighted (in blue) in Figures 4.8 and 4.9

Load (kW)	Curtailment set points (kW) — Sets of weights as per Table 4.5[a]								
	Set 1	Set 2	Set 3	Set 4	Set 5	Set 6	Set 7	Set 8	Set 9
328.37	116	0	116	0	0	0	0	0	0
351.69	116	0	116	0	0	0	0	0	0
284.01	116	0	116	0	0	0	0	0	0
178.53	1	1	84	0	0	0	1	0	0
327.29	83	38	116	28	31	0	0	0	0
258.98	77	2	116	0	0	0	2	2	0
354.59	52	50	52	63	58	28	50	51	50
418.39	116	86	116	95	83	77	86	85	81

[a]All values rounded to two decimal places

most disparate dispatch results for the diesel generator, curtailment and energy storage. To allow a clearer visual image of how these weights affect the solution of the weighted sum optimization, they are plotted together and for a smaller horizon of 72 hours. These results are given in Figures 4.10, 4.11 and 4.12. The legend for these Figures is given in Table 4.9.

Table 4.9 Weights used in the Weighted Sum MO-MHO approach for Figures 4.10, 4.11 and 4.12

Weights	Plot Color and Marker			
	Grey ('o')	Black ('o')	Blue ('*')	Cyan ('Δ')
w_1	0.9	0.8	0.5	0.6
w_2	0.1	0.2	0.5	0.4

Figure 4.10 compares the dispatch results for the diesel generator obtained by varying the weights. The four sets of weights given in Table 4.9 were used in the weighted sum method. The optimization problem is formulated such that the cost function of the diesel generator is directly related to the fuel consumption and price of diesel fuel. If the diesel generator was assumed the most expensive resource in the microgrid, the choice of weights would directly impact the economics of the system. Generator ramp rates were not considered in this analysis.

The effect of varying the weights is now very clear in the case of power curtailment. Figure 4.12 highlights two such extreme cases where the power curtailment for the first 24 hours varies between zero (blue ($w_1 = 0.5$, $w_2 = 0.5$) and cyan ($w_1 = 0.6$, $w_2 = 0.4$) plots) and the maximum curtailment (gray ($w_1 = 0.9$, $w_2 = 0.1$) and black ($w_1 = 0.8$, $w_2 = 0.2$) plots) permissible (116 kW), keeping in mind the constraint of meeting critical loads at all times.

It is interesting to note that the general trend of when to charge ($P_{es} < 0$) and discharge ($P_{es} > 0$) the storage unit remains similar with a change of weights, as seen in Figure 4.11. However, the actual kilowatt value of the power exchanged between the storage unit and microgrid varies with a change of weights.

To summarize the results and conclude the discussion presented above, the analysis shows how varying the weights affect the solution of the weighted sum MO-MHO method and highlights one of the key challenges of this method. *The difficulty lies in selecting*

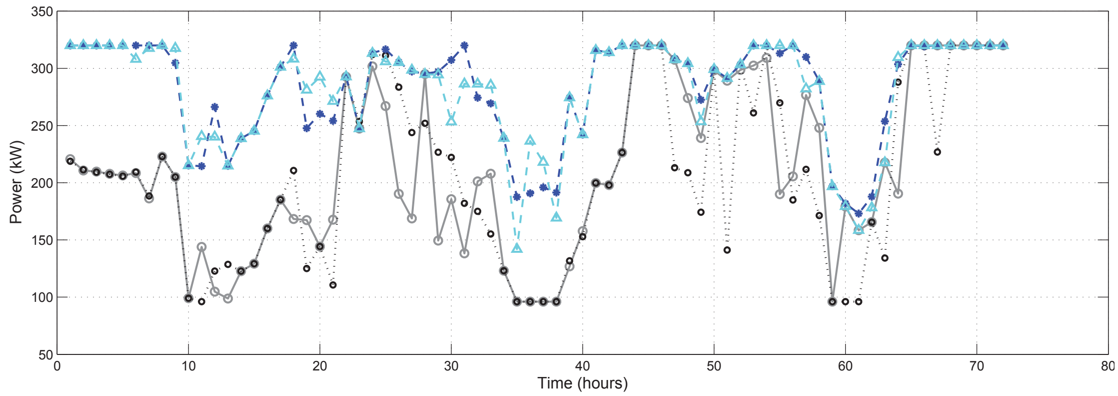

Fig. 4.10 Set points for diesel generator using four different sets of weights in the Weighted Sum method as per Table 4.9.

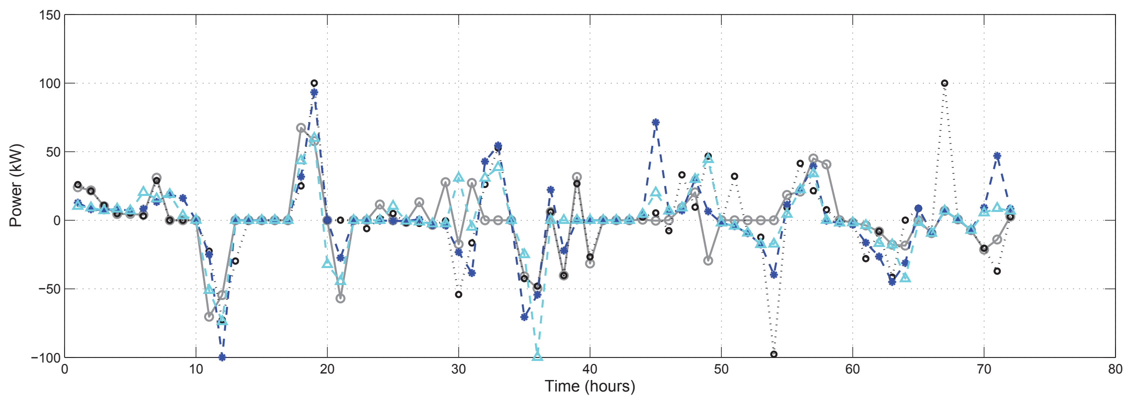

Fig. 4.11 Set points for energy storage using four different sets of weights in the Weighted Sum method as per Table 4.9.

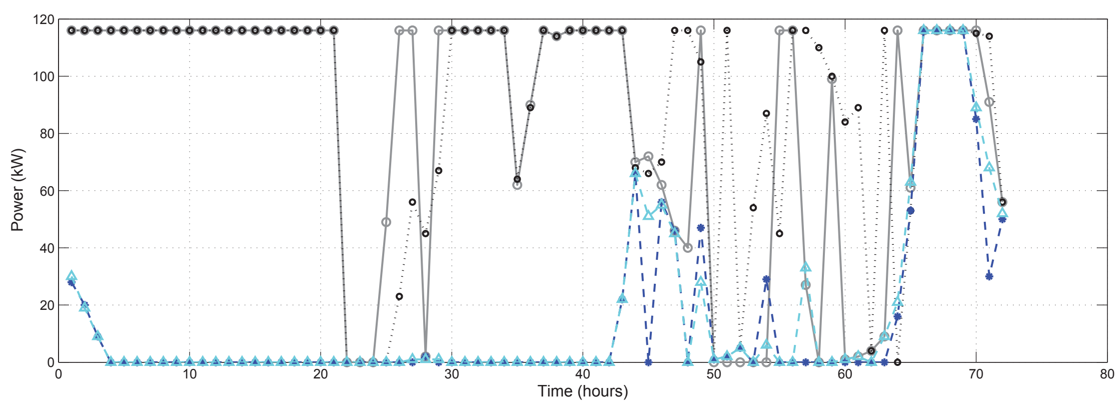

Fig. 4.12 Set points for power curtailment using four different sets of weights in the Weighted Sum method as per Table 4.9.

a set of weights that can accurately mimic the microgrid operator's preference. In fact, a satisfactory, a priori selection of weights does not necessarily guarantee that the final solution will be acceptable.

The analysis was repeated using nine different sets of weights. Figures 4.4 – 4.9 and Tables 4.6 – 4.8 show these results. The results accentuate the impact of a different choice of weights on the dispatch solution. Indeed, the dispatch problem is "sensitive" to the variation of weights — relaxing one objective by even a small amount leads to a disproportional increase in the other. Using the weighted sum method, one must quantify opinions before actually viewing points in the criterion space [54]. This problem is further complicated if the objectives do not have the same units. For example, quantifying the relative importance of economics versus system performance in order to optimize operations could prove a challenge using the weighted sum method.

4.2.2 Comparison of MO Solution Methods

Unlike the weighted sum method, the compromise solution does not require a priori articulation of preferences. The compromise solution is essentially the Euclidean distance to the utopia point or ideal solution. Thus, given a particular load and weather condition, the optimal solution (dispatch points) computed through the compromise solution would always be the same unlike the weighted sum method which could result in different (dispatch) solutions based on the choice of weights.

To this effect, the weighted sum and compromise solution multi-objective methods were compared, side by side, both implemented within the moving horizon framework. Both solution methods were implemented using a control window of $M = 1$ hour and a look ahead prediction horizon of $N = 48$ hours. The dispatch results obtained from both methods satisfy the system constraints.

The weighted sum MHO method was implemented using each of the set of weights defined in Table 4.5. The compromise solution MHO method was compared to each of the nine different weighted sum solutions. These results are presented in Figures 4.13 – 4.18. All simulation studies were conducted using MATLAB®and the TOMLAB Optimization Suite. The solvers used for the optimization include fmincon, SNOPT and MINLP. TOMLAB /MINLP is integrated with the TOMLAB optimization environment.

Figures 4.13 and 4.14 compare the dispatch results for the diesel generator obtained by

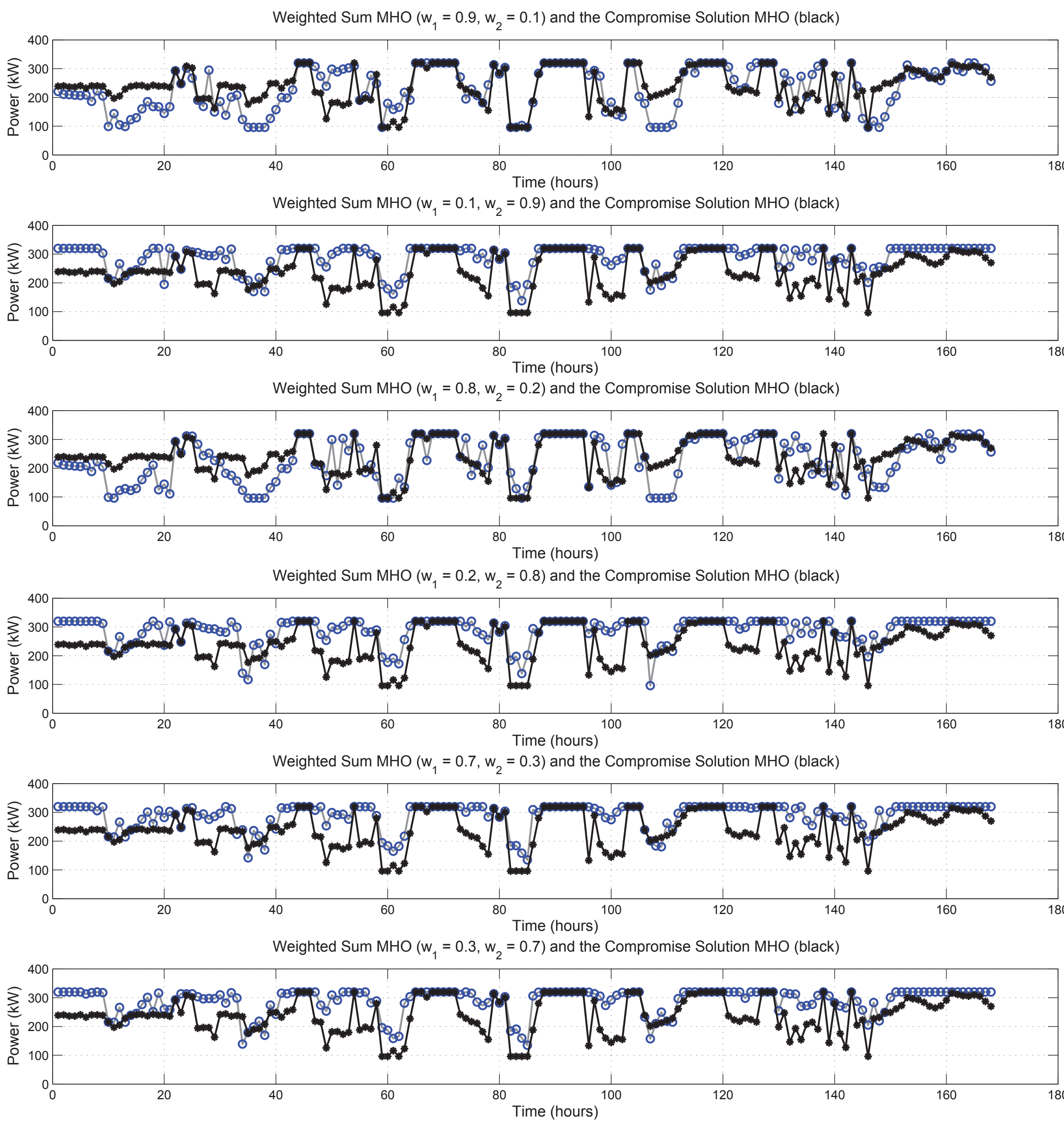

Fig. 4.13 Comparison of dispatch results for the diesel generator from the weighted sum method ('o'),using different set of weights, and the compromise solution method ('*') implemented in a moving horizon framework for 1 week.

application of the compromise solution and weighted sum MO-MHO methods.

The trajectories given in Figures 4.15 and 4.16 show the dispatch results for the storage unit as obtained by application of the weighted sum MO-MHO and compromise solution MO-MHO methods. The positive power values represent that the storage device is in discharging mode (energy is being supplied by the storage device to the microgrid) while the negative values represent that the storage device is charging (energy is drawn from the microgrid).

Figures 4.17 and 4.18 compare the dispatch results for curtailment obtained by application of the compromise solution and weighted sum MO-MHO methods.

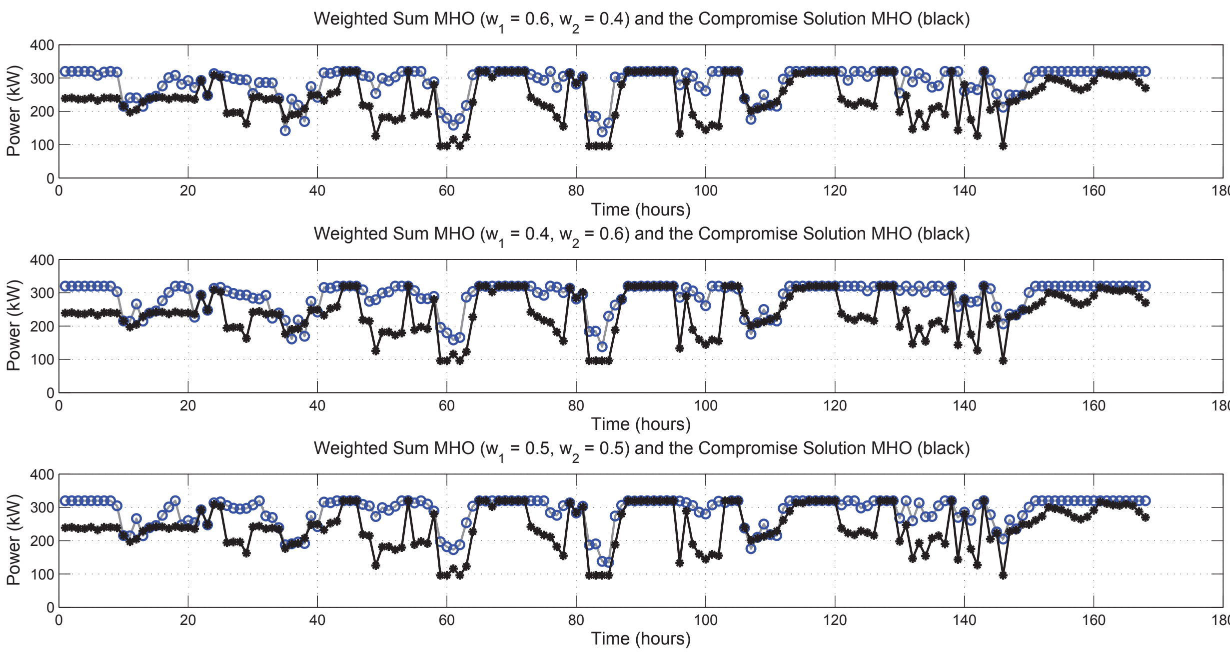

Fig. 4.14 Comparison of dispatch results for the diesel generator from the weighted sum method ('o'),using different set of weights, and the compromise solution method ('*') implemented in a moving horizon framework for 1 week.

To allow a clearer visual image of the comparison of dispatch results for the weighted sum and compromise solution methods, we zoom into the plots for 1 prediction horizon. In both Figures 4.19 and 4.20, the compromise solution is represented by the black plot while the weighted sum solution is given by the gray plot with blue markers. In Figure 4.19, the weighted sum method was applied using weights $w_1 = 0.9$ and $w_2 = 0.1$. The weights used for the plot in Figure 4.20 are $w_1 = 0.1$ and $w_2 = 0.9$.

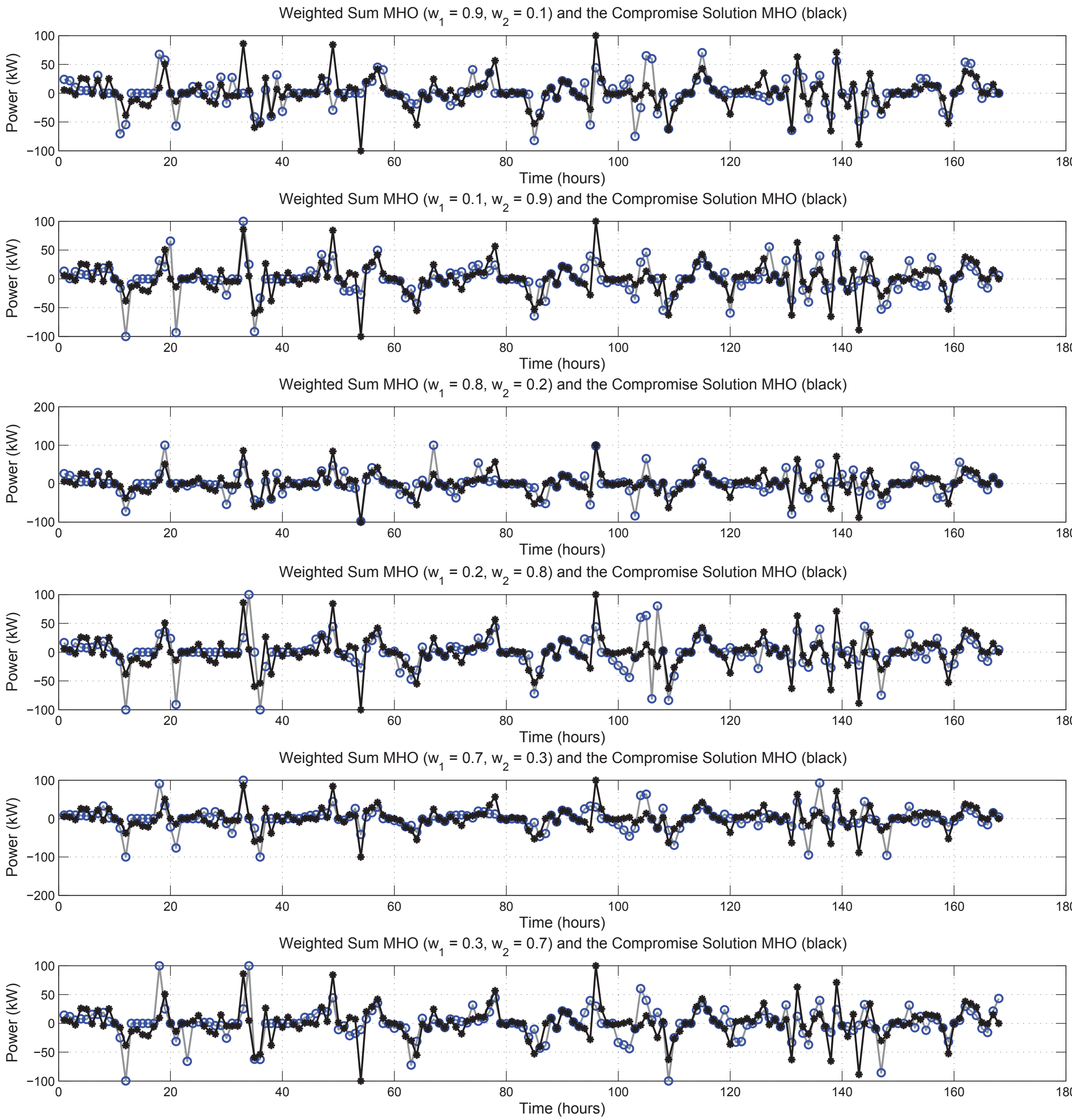

Fig. 4.15 Comparison of dispatch results for the energy storage from the weighted sum method ('o'),using different set of weights, and the compromise solution method ('*') implemented in a moving horizon framework for 1 week.

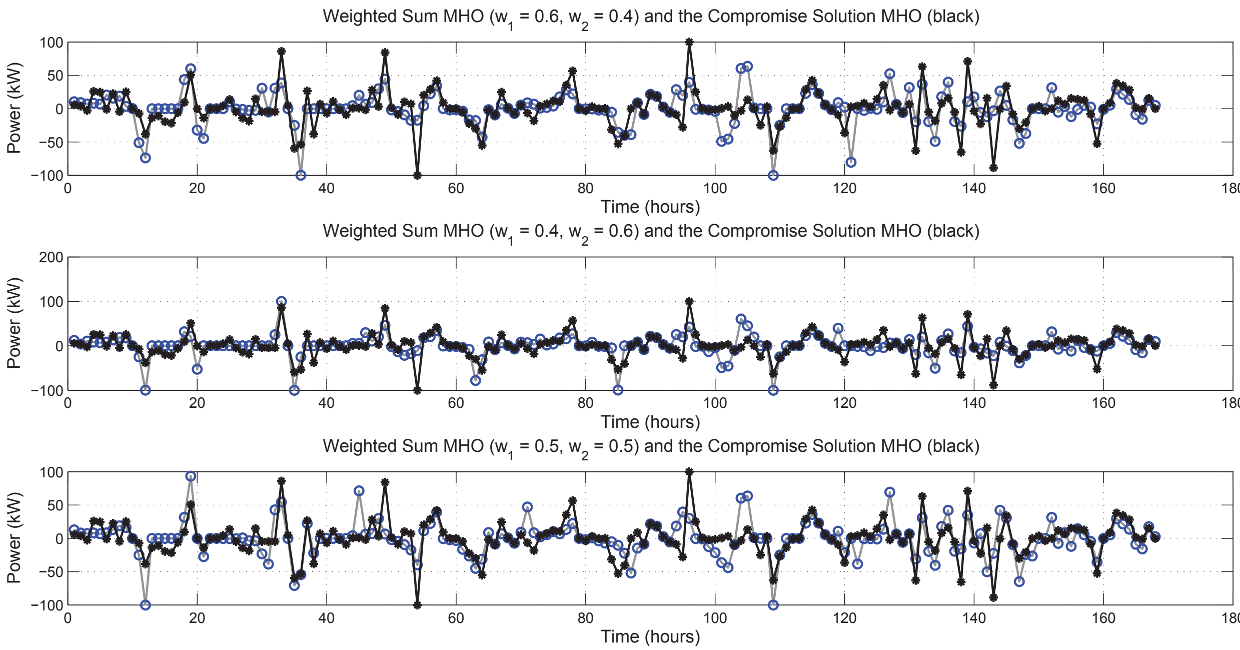

Fig. 4.16 Comparison of dispatch results for the energy storage from the weighted sum method ('o'),using different set of weights, and the compromise solution method ('*') implemented in a moving horizon framework for 1 week.

With regards to the two objective functions considered, the diesel generator output relates directly to the utility profits while minimizing the curtailment represents the consumer satisfaction. In addition to power balance, the bound constraints play an important role in the optimization. At this point, we examine how the two solution methods — weighted sum and compromise, perform in terms of satisfying system bound constrains. Figures 4.21 and 4.22 respectively, show an example of the diesel generation and curtailment dispatch points obtained by applying the weighted sum and compromise solution methods for 1 prediction horizon (48 hours). The weighted sum method was applied using weights $w_1 = 0.9$ and $w_2 = 0.1$. The horizontal red lines in these figures represent the bound constraints. It can be seen that the set points determined by each of the two methods satisfy the constraints at all time instants within the prediction horizon. While the bound constraints are satisfied in both cases, the set points determined for the diesel generator by the weighted sum method are very close to the minimum loading requirement of the generator. It is shown that the compromise solution method leads to a more efficient utilization of the diesel generator and allows for smaller power curtailment.

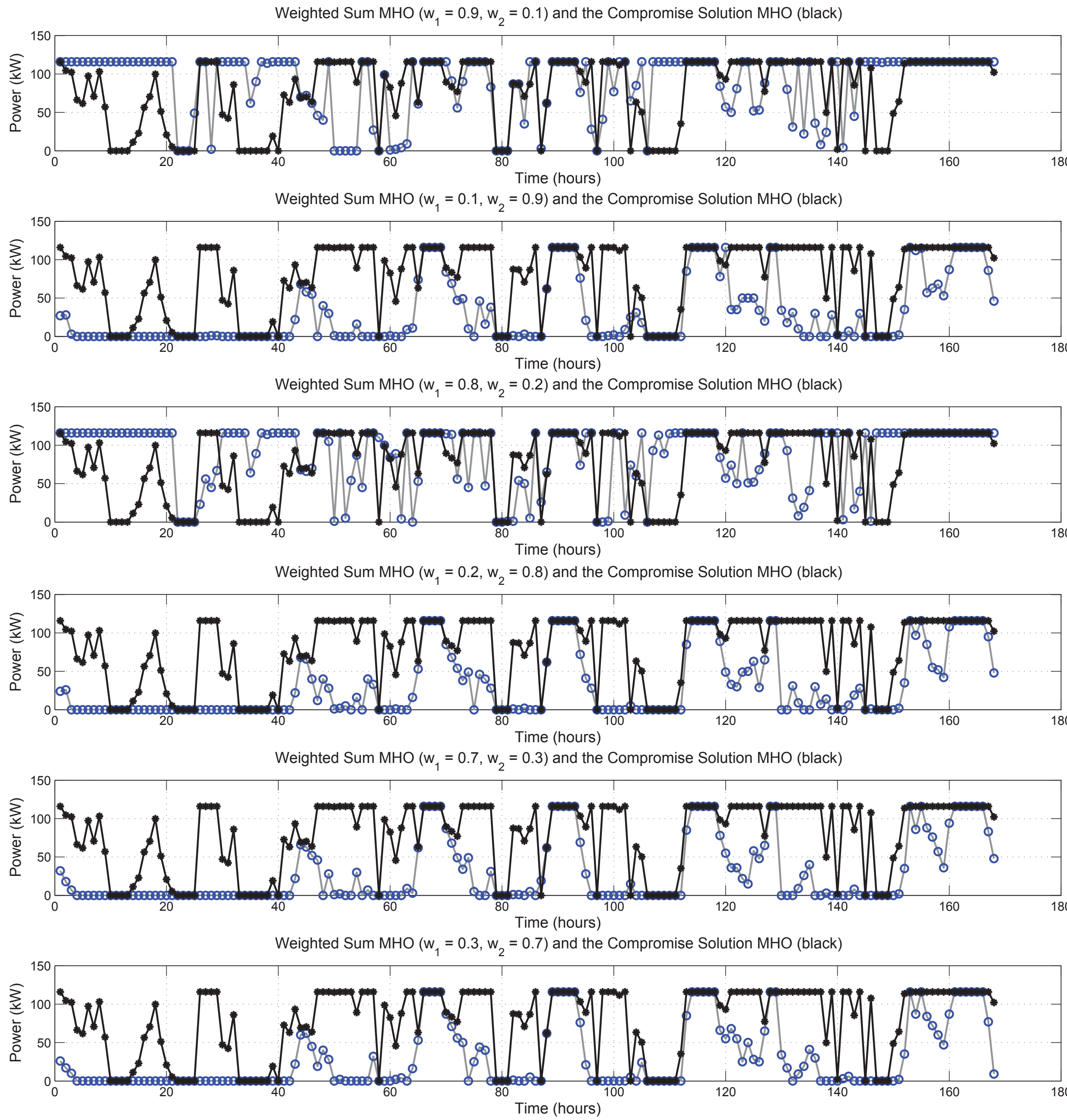

Fig. 4.17 Comparison of dispatch results for curtailment from the weighted sum method ('o'),using different set of weights, and the compromise solution method ('*') implemented in a moving horizon framework for 1 week.

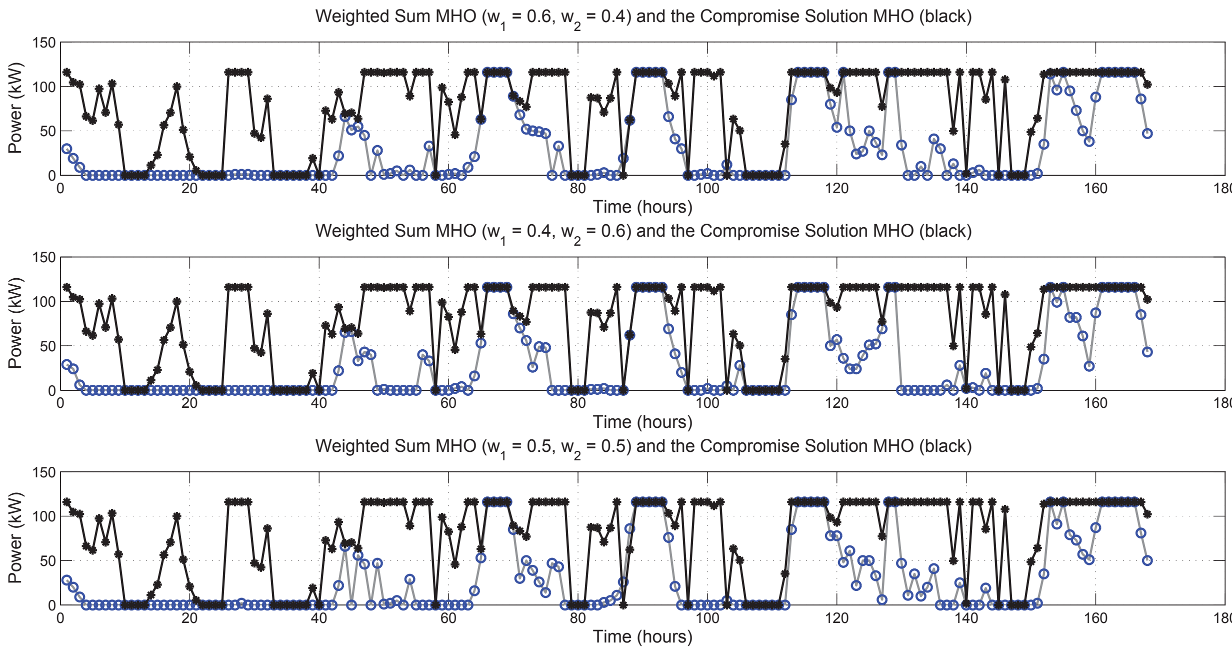

Fig. 4.18 Comparison of dispatch results for curtailment from the weighted sum method ('o'),using different set of weights, and the compromise solution method ('*') implemented in a moving horizon framework for 1 week.

4.2.3 Measures of Assessment and Comparison Serving the Choice of the MO Solution Method

The results and discussions presented so far add value to our proposed methodology in which the specific approach to the solution of the MO problem (in the form of weighted sum or else compromise solution) is decided upon based on a different set of assessment functions. The values of these assessment functions are calculated using only dispatch points that were implemented over some past window. Such strategy permits to select the MO solution mode on-line which ultimately leads to superior economic decisions over long periods of time. The details of these assessment functions are explained below.

The following independent assessment functions could be used for comparison between the weighted sum and the compromise solutions in the MO-MHO framework over a chosen horizon in the past $[t_i, t_{i-K}]$, relative to a specific time instant t_i. Hence, comparison would actually be performed employing the computed dispatch set points using different MO solution methods.

To this end, we define three indices of *long term* utility profits (for large values of K).

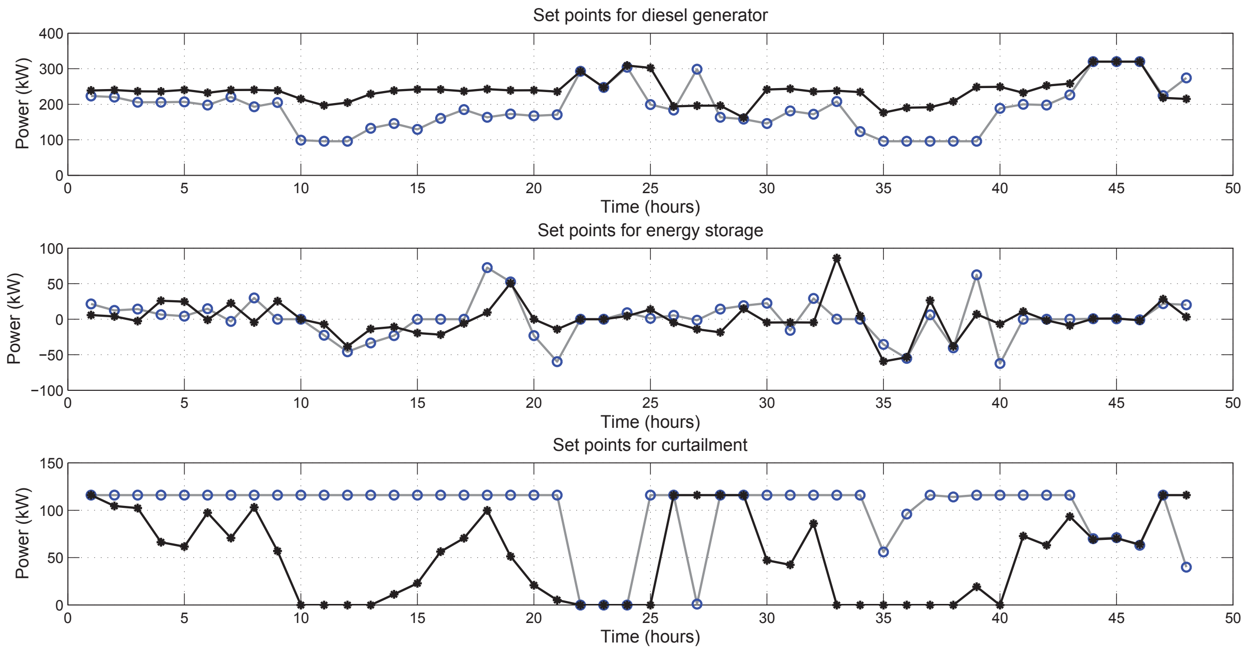

Fig. 4.19 Comparison of dispatch results for the weighted sum ('O') ($w_1 = 0.9$, $w_2 = 0.1$) and compromise solution ('*') methods for 1 prediction window.

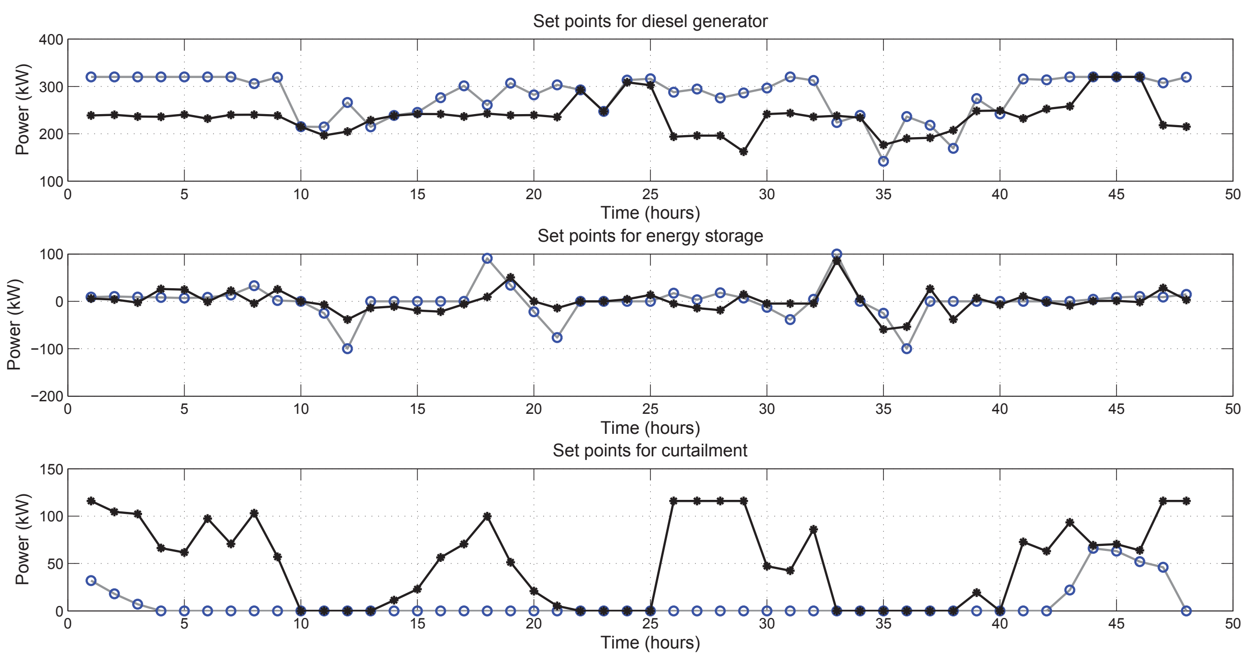

Fig. 4.20 Dispatch results for weighted sum ('O') ($w_1 = 0.1$, $w_2 = 0.9$) and compromise solution ('*') methods, for 1 prediction window.

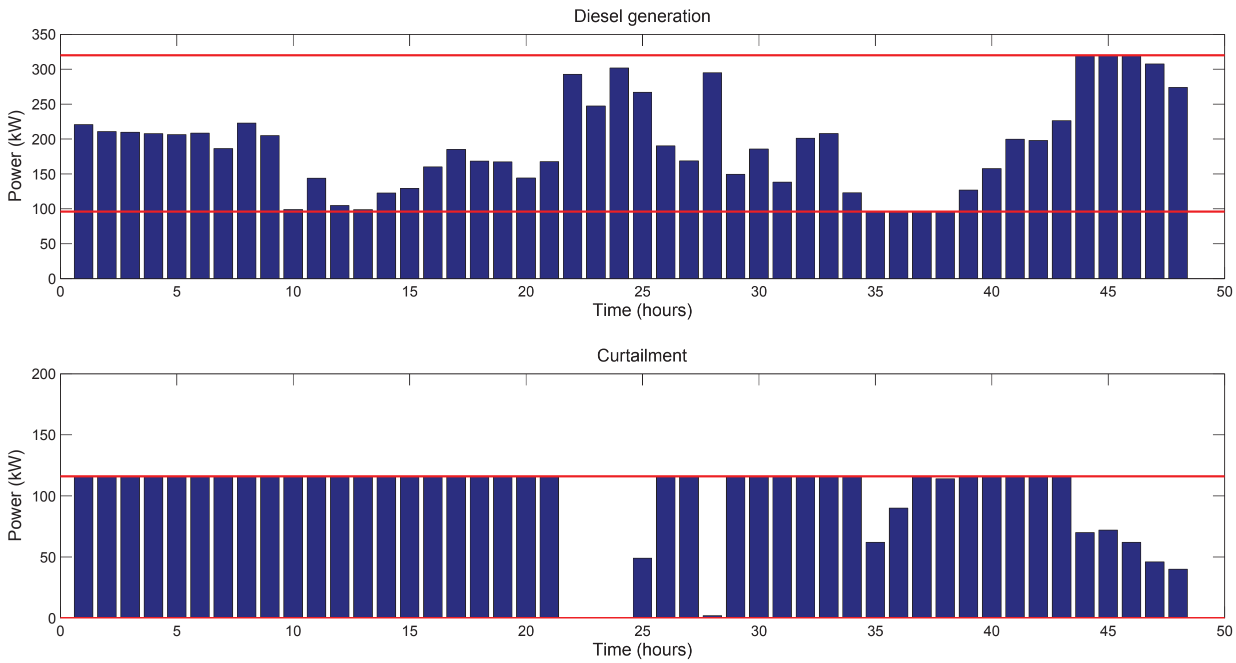

Fig. 4.21 Diesel generation and curtailment as a result of the Weighted Sum method ($w_1 = 0.9$, $w_2 = 0.1$) over 48 hour horizon.

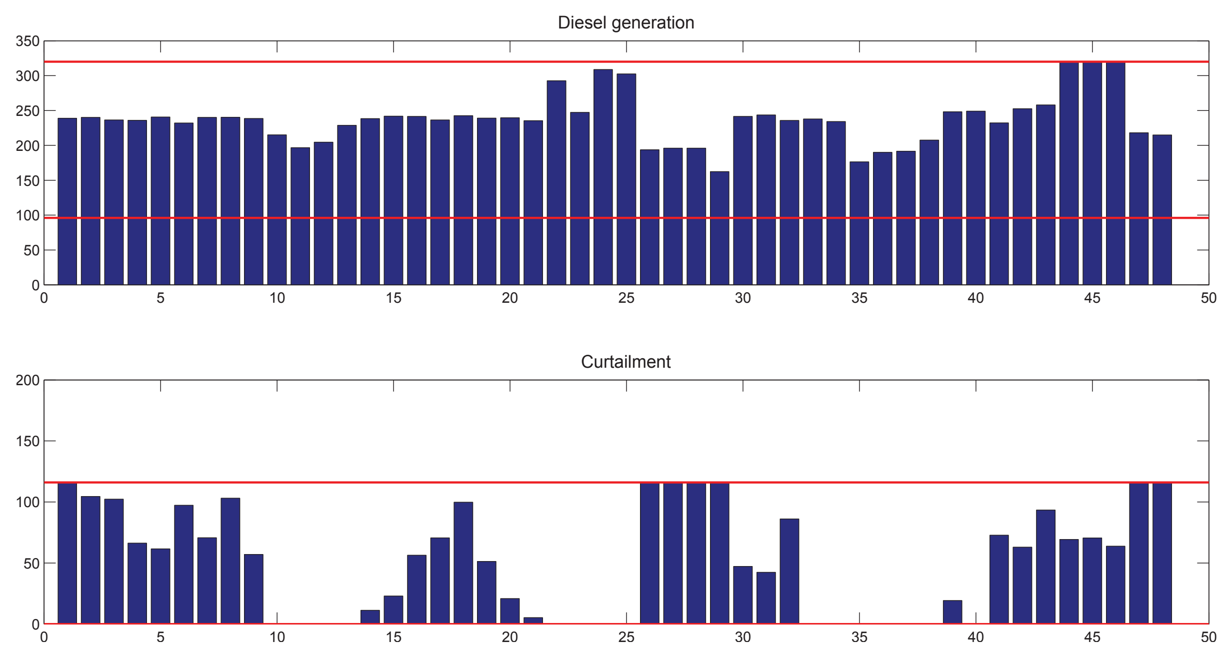

Fig. 4.22 Diesel generation and curtailment as a result of the Compromise Solution method over 48 hour horizon.

The Index of Utility Profits

This long-horizon utility profit is defined by:

$$
\begin{aligned}
I_{UP} \overset{def}{=} \Sigma_{k=i}^{i-K}\{ \ & C_M(t_k)[\bar{P}_{cl}(t_k) + \bar{P}_{nl}(t_k) - P_c^*(t_k)] \\
& - C_d(t_k, P_d^*(t_k)) - C_{es}(P_{es}^*(t_k)) \ \}
\end{aligned} \tag{4.1}
$$

where i indicates the left boundary of the prediction horizon, $[t_i, t_{i+N}]$ at the beginning of which the comparison is performed and K is the length of the Past Window over which this comparison is sought, i.e. $[t_i, t_{i-K}]$. The times $t_k \in [t_i, t_{i-K}]$ are the times at which the ED are compared, but the values $P_d^*(t_k)$, $P_{es}^*(t_k)$, $P_c^*(t_k)$ are the actual Pareto optimal set-points calculated as the MO-MHO proceeds forward (these are the values that would normally be implemented in real time as the horizon rolls forward). If $C_M(t_k)$ is understood to be the price of electricity at t_k, then the expression under the summation sign reflects the net profits of the grid utility over the comparison horizon $[t_i, t_{i-K}]$ as it was actually applied by the microgrid dispatcher in the past. It provides the dispatcher with information that can assist his decision making process whether to change the weights or adopt a compromise approach over future times.

Two more long-horizon indices can be proposed as follows:

The Index of Consumer Dis-Satisfaction

$$
I_{CD} \overset{def}{=} \Sigma_{k=i}^{i-K}\{ \ K_c P_c^*(t_k)\} \tag{4.2}
$$

The Index of Efficient Storage

$$
I_{ES} \overset{def}{=} \Sigma_{k=i}^{i-K}\{ \ K_{deg} + K_{es} P_{es}^*(t_k) \ \} \tag{4.3}
$$

The results presented below pertain to the comparison of different MOO solution methods over a horizon of length $K = 7 * 24$ hours (rolling horizon simulation stretching over a full week). Table 4.10 shows the values of the three assessment functions obtained for the weighted sum (using different weights) and compromise solution methods.

Table 4.10 Comparison of Optimization Methods

Optimization	Index of Comparison[a] (\$)		
	Utility Profit	Consumer Dissatisfaction	Efficient Storage
Weighted Sum[b]	1458.60	35,183.0	87.9514
Weighted Sum[c]	1449.02	35,462.5	87.9507
Weighted Sum[d]	1430.53	36,047.5	87.9507
Compromise Soln.	1502.018	33,885.59	87.7806

[a]All values computed for a horizon of 1 week
[b]Using equal weights: $w_1 = w_2 = 0.5$
[c]Varying weights: $w_1 = 0.25, w_2 = 0.75$
[d]Varying weights: $w_1 = 0.75, w_2 = 0.25$

Clearly, the compromise solution is superior to the scalarization approach in this example as it yields better values of the assessment functions and does not require choosing any weights. This implies that the compromise solution based MO-MHO is likely to result in overall better performance of the microgrid utility.

4.2.4 Compromise Solution and Pareto Optimality: Discussion

The discussion and analysis that follows stems from the following two statements:

1. For a huge class of norms, every compromise solution is Pareto optimal [56].
2. For the weighted sum approach, if the weights are positive and add to unity, then this provides for the satisfaction of the sufficient condition for Pareto optimality [65], [66].

For our multi-objective optimization problem,

$$\min\{\Phi(x) = [\Phi_1(x), \Phi_2(x)] \text{ subject to constraints } x \in \mathcal{F} \subset \mathcal{R}^{3(N+1)}\} \tag{4.4}$$

the criterion set $\vartheta \in \mathcal{R}^2$ in the criterion space $\mathcal{R}^2$ is the image of the feasible set $\mathcal{F}$ under the mapping Φ, i.e. $\vartheta = \Phi(\mathcal{F})$. The points in ϑ are called feasible as they can be generated as values $\Phi(x)$ for some feasible $x \in \mathcal{F}$. The Pareto front constitutes a subset of the boundary of the feasible set; the points of $\mathcal{F}$ corresponding to the points on the Pareto front are called "efficient solutions". In other words, the Pareto front is thus the image of the set of all Pareto optimal points under the mapping Φ [50].

The Utopia Point is a point in the criterion space, but not in the feasible criterion set. For the dispatch problem, calculated by minimizing Φ_1 and Φ_2 separately, the utopia point coordinates are

$$\Phi_1^L = \min\{\Phi_1(x) \text{ subject to constraints } x \in \mathcal{F} \subset \mathcal{R}^{3(N+1)}\} \tag{4.5}$$
$$\Phi_2^L = \min\{\Phi_2(x) \text{ subject to constraints } x \in \mathcal{F} \subset \mathcal{R}^{3(N+1)}\} \tag{4.6}$$

The utopia point is not feasible.

The proposed method entails that the dispatch be performed in a moving horizon framework. The advantage of the moving horizon approach is that it allows for variations in the load demand or weather forecasts to be taken into account (as they actually arrive) and to be compensated for by the repetitive re-calculation of all the controls as called for by the MO-MHO at each dispatch decision update instant. This implies that as the horizon moves forward, we would expect the compromise solution to evolve accordingly.

An analysis was carried out in this respect, to determine how the compromise solution moves on the Pareto front. Furthermore, it is an effort to understand the relation between the compromise solution and the weighted sum solution; both solutions as already stated, being Pareto optimal. *The advantage of representing the problem as a bi-objective optimization problem, by grouping together the least conflicting components, is now clear as it allows for better visualization of the problem in the objective space.*

Figures 4.23 - 4.28 give some insight into the behavior of the compromise solution in the moving horizon framework. Six different control windows (48 hour horizon) were randomly selected out of the 168 hours (horizon of 1 week). The utopia point, compromise solution and pareto optimal points determined as a solution of the weighted sum scalarization method, were plotted in the objective space. In each of these plots, the utopia point is represented by the blue square '□' and the compromise solution by the red star '*'. The 'O' represent the pareto optimal points determined by using the different sets of weights, given in Table 4.5, in the weighted sum method. Also, it should be noted that the 'O' points shown in the figures are not single points but rather an *aggregation* of points that are superimposed over each other.

It is interesting to observe how the compromise solution moves on the Pareto front and in the process, how its proximity to different pareto points changes. The compromise solution touches different weighted sum solutions in the process. This might imply that changing the weights adaptively may result in better dispatch. Also, the compromise solution might even serve as a tool to determine the optimal weights for a given situation. Further analysis into this would be required to separate speculation from fact. However, this is beyond the scope of this thesis.

It should be clear that an exhaustive exploration of the entire Pareto front was not conducted. However, the selection of equally distributed weights as those given in Table 4.5 and the utilization of these weights to determine the pareto optimal points confirms yet another difficulty with the weighted sum method i.e. *varying the weights consistently and continuously may not necessarily result in an even distribution of Pareto optimal points.* In turn, this also implies that equally distributed weights would not necessarily yield an accurate nor complete representation of the Pareto optimal set. The pareto points found using the equally distributed weights, as given in Table 4.5, are those represented by 'O' in the plots given in Figures 4.23 - 4.28.

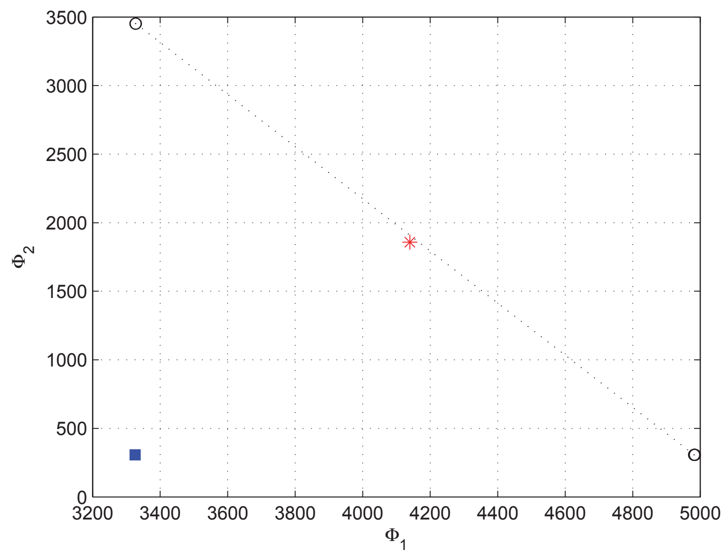

Fig. 4.23 Utopia point '□', compromise solution '*' and pareto optimal points 'O' determined by the weighted sum method.

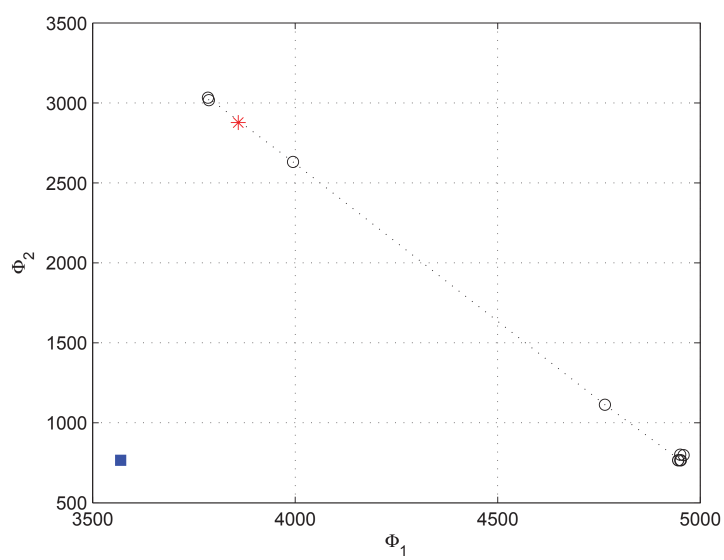

Fig. 4.24 Utopia point '□', compromise solution '*' and pareto optimal points 'O' determined by the weighted sum method.

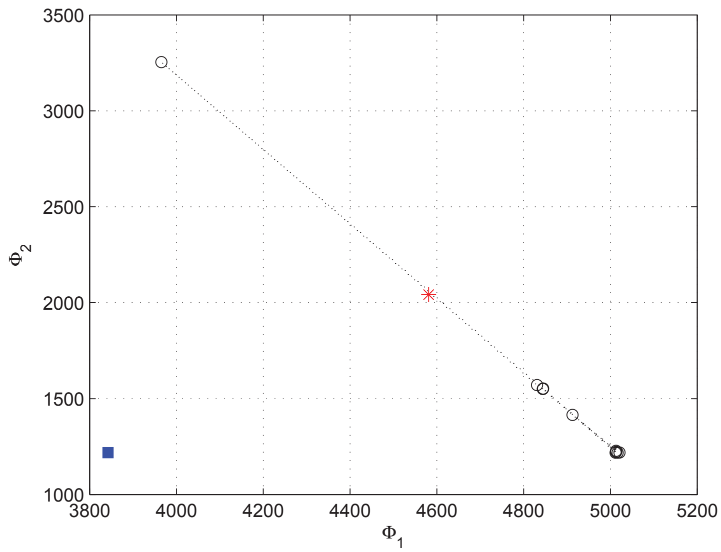

Fig. 4.25 Utopia point '□', compromise solution '*' and pareto optimal points 'O' determined by the weighted sum method.

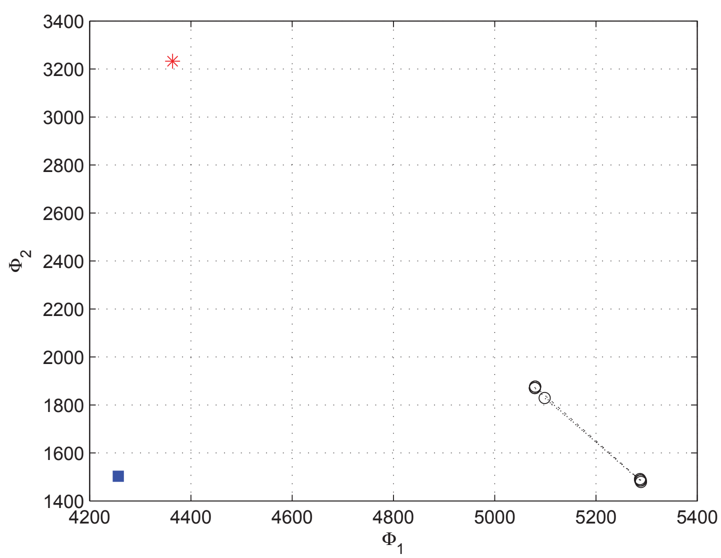

Fig. 4.26 Utopia point '□', compromise solution '*' and pareto optimal points 'O' determined by the weighted sum method.

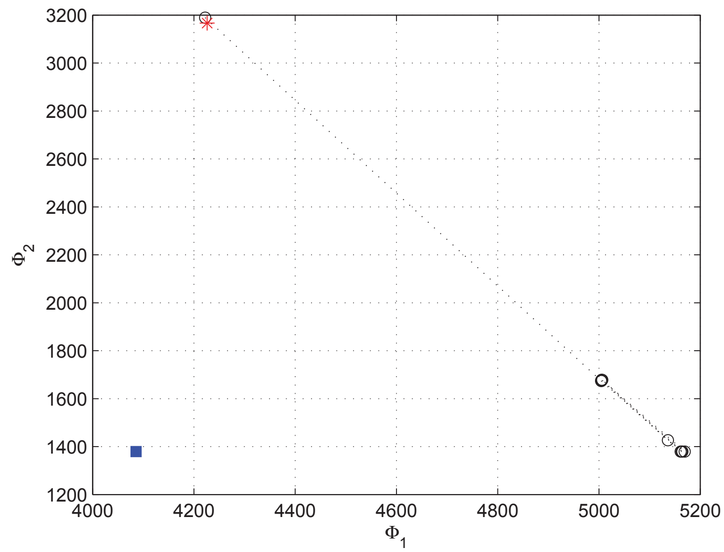

Fig. 4.27 Utopia point '□', compromise solution '*' and pareto optimal points 'O' determined by the weighted sum method.

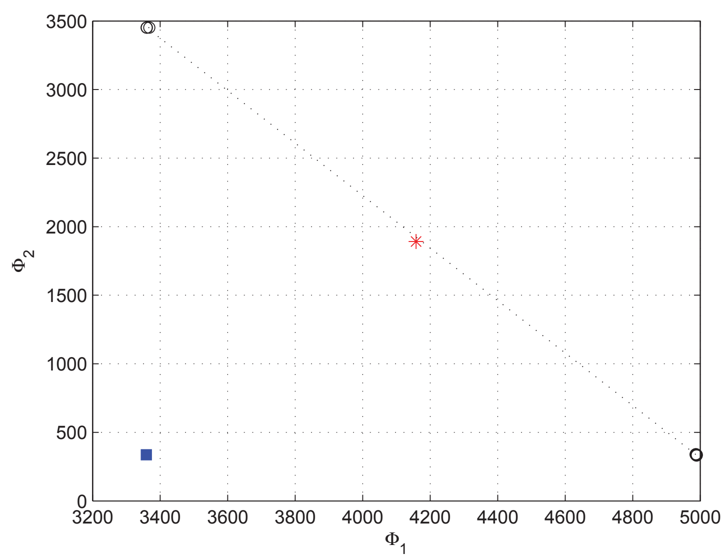

Fig. 4.28 Utopia point '□', compromise solution '*' and pareto optimal points 'O' determined by the weighted sum method.

4.3 Case Study 2

Case study 1 was extended to the case of a standard mixed-integer unit commitment problem. Unit commitment allows for generation units to be started up and shut down over time unlike the economic dispatch problem where the units are always online.

To this effect, another dispatchable diesel generator was added to the microgrid model presented in Chapter 3. The cost function for power production for a generator defined in Equation 3.23 takes the form:

$$J_1(P_d) \stackrel{def}{=} \Sigma_{j=1}^{n} \Sigma_{i=k}^{k+N} [C_{d_j}(u_j(t_i), P_{dj}(t_i))] \tag{4.7}$$

where $n = 2$ and the index j pertains to the number of the diesel unit.

Additional constraints were added to account for the extra generator and to allow for units to be shut down when needed:

1. The operating limits of the diesel generators were modified to include the unit commitment variable,

$$u_j(t_i).P_{dj}^{min}(t_i) \leq P_{dj}(t_i) \leq u_j(t_i).P_{dj}^{max}(t_i) \tag{4.8}$$

2. The unit commitment variable is binary, such that

$$u_j(t_i) \in \{0, 1\} \quad \text{and} \tag{4.9}$$

$$u_j(t_i) = \begin{cases} 1, & P_{dj}(t_i) > 0 \\ 0, & P_{dj}(t_i) = 0 \end{cases} \tag{4.10}$$

The formulation was kept basic — start-up costs and ramping limits were neglected. The focus remaining an evaluation of the preferred MO-MHO mode.

The quadratic parameters of the second diesel generator were modified so that its fuel consumption is five times that of the generator represented in Table 4.3. This in turn renders generator 2 the more expensive resource. The maximum microgrid load was adjusted accordingly to allow for situations when both diesel generators are required. The storage unit and its parameters remained the same.

The MO-MHO economic dispatch approach was implemented using both the weighted sum and compromise solution methods. The dispatch results obtained from both methods satisfy the system constraints. The analysis was repeated with different choice of weights. One such comparison, using equal weights $w_1 = w_2 = 0.5$, is presented in Figures 4.29-4.32. In the Figures 4.29- 4.32, the blue bar graphs represent the implemented dispatch set points for the diesel generator, energy storage and curtailment over the 48 hour horizon. The horizontal red lines represent the bound constraints.

The dispatch results from the two methods (weighted sum and compromise solution) are quite similar with slight differences observed in the case of set points for the second diesel generator. Minor variations are also observed in the case of power curtailment.

The assessment functions defined in Equations 4.1, 4.2 and 4.3 were calculated using only the dispatch points that were implemented over the horizon of 1 week. Table 4.11 shows the values of the three assessment functions obtained for the weighted sum and compromise solution methods.

Table 4.11 Comparison of Optimization Methods

Optimization	Index of Comparison[a] ($)		
	Utility Profit	Consumer Dissatisfaction	Efficient Storage
Weighted Sum[b]	-43195[c]	1764.483	101.72
Compromise Soln.	-40432	2031.425	101.72

[a]All values computed employing MO-MHO over a horizon of 1 week
[b]Using equal weights: $w_1 = w_2 = 0.5$
[c]negative (-) sign represents loss to the utility

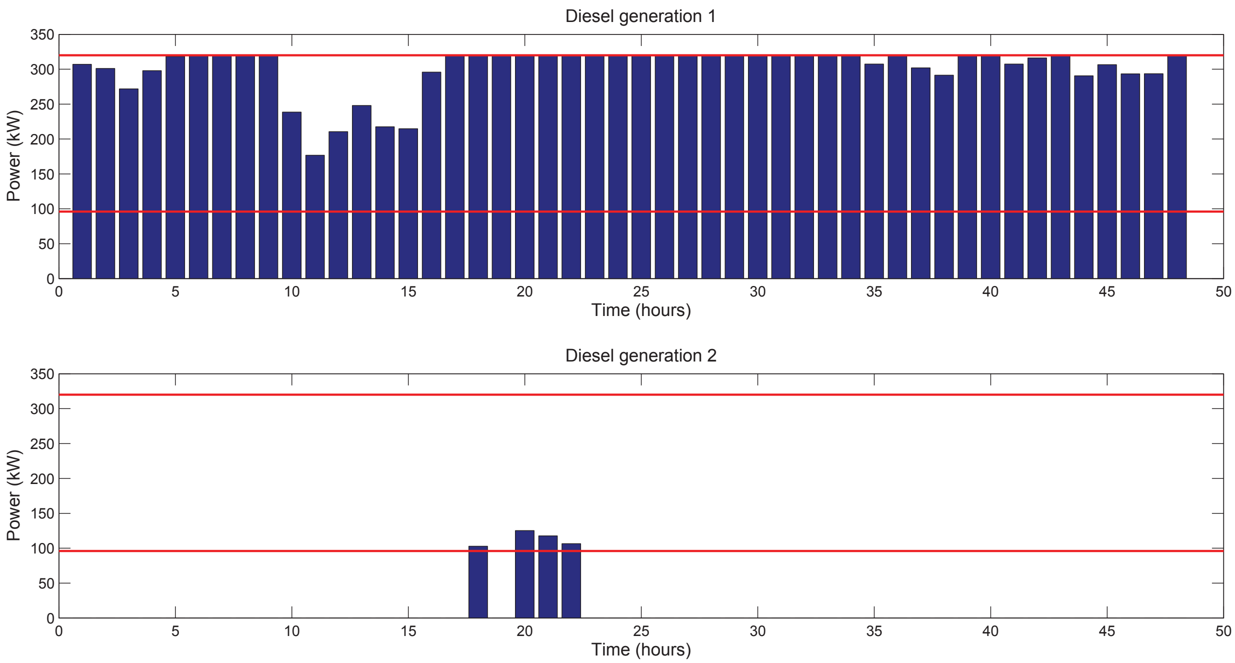

Fig. 4.29 Diesel generation as a result of the Weighted Sum method (using equal weights $w_1 = w_2 = 0.5$) over 48 hour horizon.

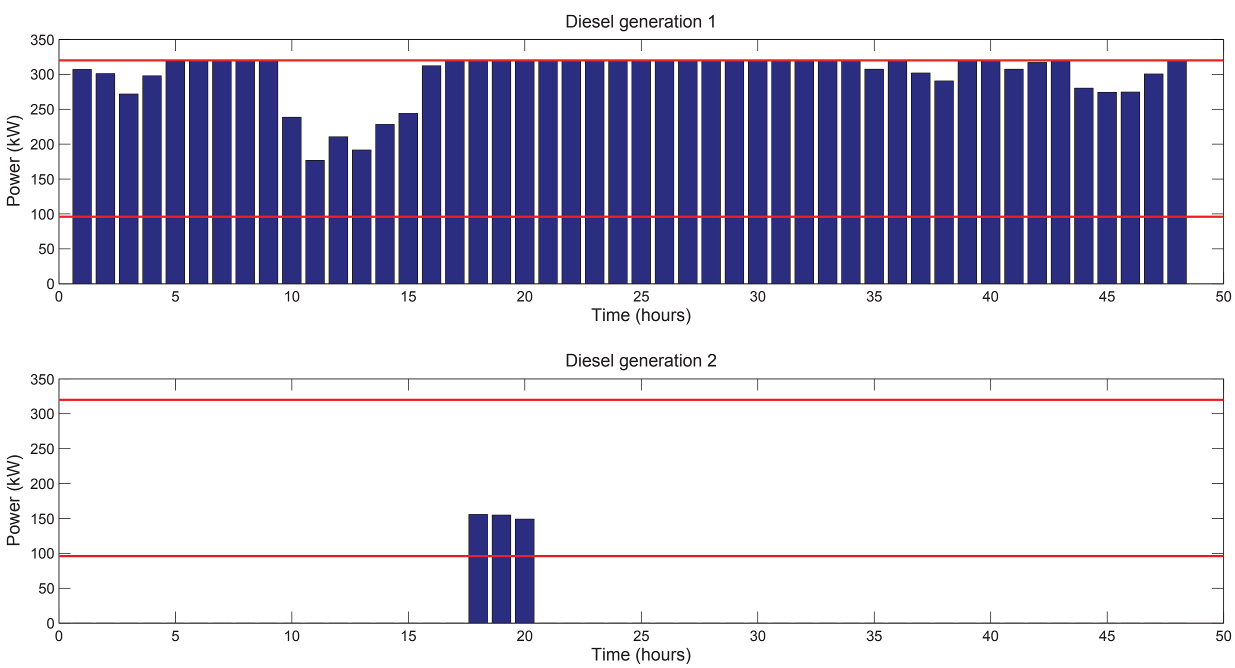

Fig. 4.30 Diesel generation as a result of the Compromise Solution method over a 48 hour horizon.

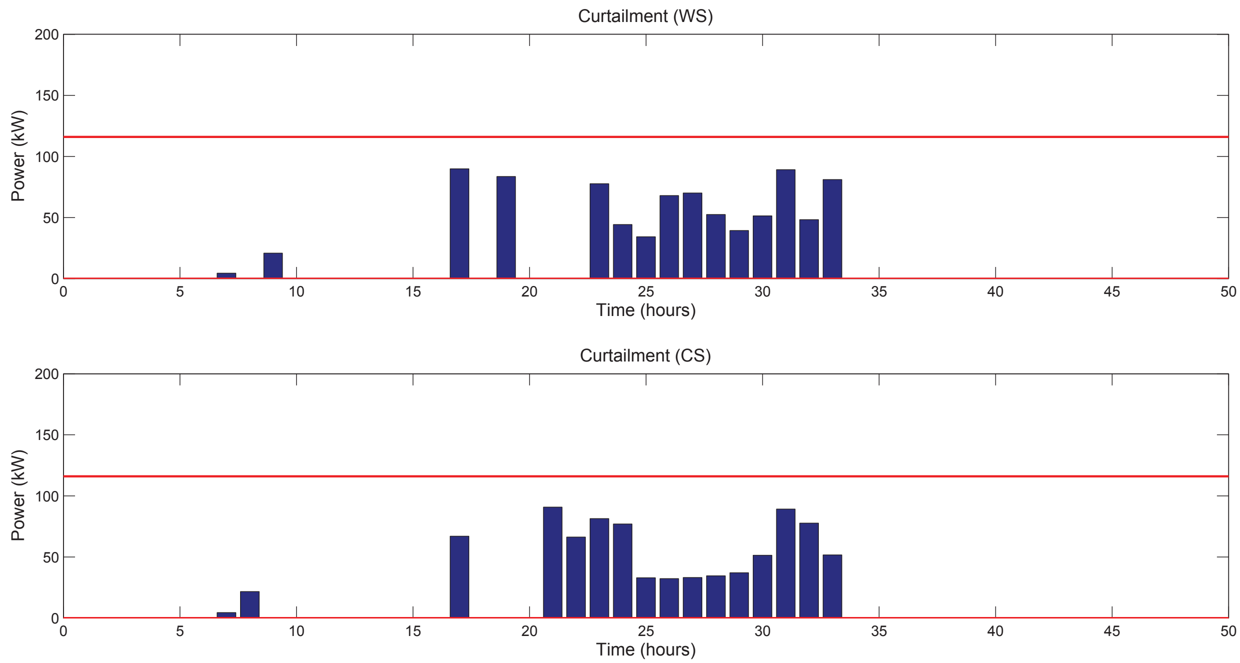

Fig. 4.31 Curtailment determined by weighted sum (equal weights $w_1 = w_2 = 0.5$) and compromise solution methods over a 48 hour horizon.

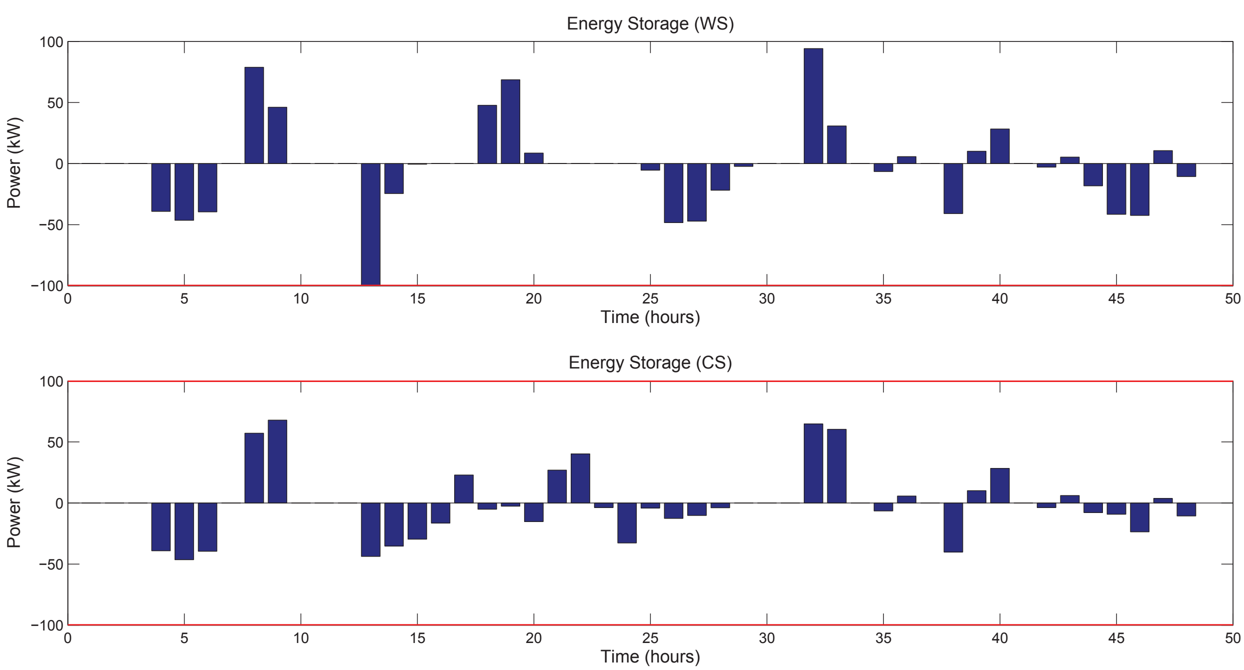

Fig. 4.32 Energy storage determined by weighted sum (equal weights $w_1 = w_2 = 0.5$) and compromise solution methods over a 48 hour horizon.

Chapter 5

Conclusions

5.1 Thesis Summary

In this thesis, we examine one of the fundamental problems in power system management — the economic dispatch problem specifically applied for the case of microgrids.

A multi-objective-moving-horizon-optimization (MO-MHO) approach for an optimal economic dispatch is proposed and implemented for the specific case of an isolated microgrid. The desired attributes of the remote microgrid are classified into two broad groups: utility profits and consumer satisfaction. The cost of producing power from diesel fueled equipment and total storage costs are used to define the overall utility profits while the consumer satisfaction is measured by minimizing the load curtailment. The optimization is carried out in a moving horizon framework using multi-objective solution methods. Two solution methods were used in this analysis — the widely used weighted sum method and the compromise solution method. The solution method for the optimization problem over a window "looking into the future" can then be adjusted in real time by employing an independent set of assessment functions to evaluate the performance of the optimization over a horizon in the past.

Results for two case studies were presented: (Case I) continuous diesel power production and (Case II) unit commitment problem permitting switching off the diesel engines. Based on these two case studies initiated in this work, the compromise solution based MO-MHO is likely to be superior in such a process yielding the best, weight independent, long-term economic performance of the microgrid.

5.2 Conclusions

The results and conclusions of this thesis are summarized and presented below.

Chapter 2

This chapter provides an introduction and background to the research conducted by means of a thorough literature review of the most recent and state-of-the-art in the area of microgrid energy management. The classical economic dispatch problem is stated and explained. The three main control strategies applied to the microgrid economic dispatch problem are examined.

Chapter 3

This chapter formally presents the proposed multi-objective-moving-horizon-optimization (MO-MHO) approach for economic dispatch in microgrids. The MO-MHO approach is a two level approach to solve the economic dispatch problem in microgrids: the first level pertains to applying MO solution methods in the moving horizon framework to account for fluctuating demand and uncertain weather data that may affect the outcome of the dispatch optimization. The second level involves evaluating the trajectories of optimal dispatch (obtained from the MO solution methods) by means of independent assessment functions that are specific to the microgrid and requirements at hand. In order to best apply this method, it is suggested that the desired optimization problem should first be represented as a bi-objective problem by grouping together the least conflicting components. This allows for proper visualization of the problem and enables an easy computation of the Euclidean compromise solution — the feasible point as close as possible to the utopia point. Detailed mathematical formulations for the computation of the compromise solution are given in this chapter. A basic multi-objective problem is formulated for an inherently islanded microgrid to demonstrate the application of the MO-MHO approach on test cases. The test cases and results of this evaluation are presented in Chapter 4.

Chapter 4

In this chapter, the multi-objective-moving-horizon-optimization (MO-MHO) approach is applied to a remote microgrid. Two case studies are considered. The first case involves the basic formulation presented in Chapter 3. The DER units are considered online and ready to produce at all times. The second study is an extension to the case of a standard mixed-integer unit commitment problem. The optimization algorithm then determines not only the optimal dispatch set points but also the status of the generating units — units may be online or off-line. In both cases the performance of the proposed strategy is evaluated using the weighted sum and compromise solutions of the multi-objective optimization problem in the moving horizon framework. The results suggest that choosing the compromise solution method for the MO-MHO problem may be better than the usual scalarization methods. Simulation studies were conducted using MATLAB®and the TOMLAB Optimization Suite. The solvers used are based on the branch and bound technique — the main advantage being that if the optimization succeeds, the solution reached is globally optimal. In addition to this, a separate analysis was carried out to gain some understanding of the behaviour of the compromise solution as it moves forward in the moving horizon framework. Specifically, the relation of the compromise solution to different weighting solutions and the utopia point was studied.

5.3 Recommendations for Future Work

The MO-MHO approach presented in this thesis is a tool for performing an optimal economic dispatch in microgrids. Further validation of this approach could be performed by considering other MO solution methods such as the Nash solution, Kalai-Smorodinsky solution or Egalitarian solution. It may also be interesting to study the impact of including some of the system constraints that were relaxed or neglected in the basic formulation presented here such as the diesel ramping rates, start-up and shut-down costs, minimum down time constraints and system losses. Most importantly, the proposed approach lends itself to straightforward extensions:

- Reformulation as a full-blown stochastic mixed-integer MO-MHO problem
- Reformulation as a MO-MHO which partially employs robust optimization
  In the case of robust optimization some "belief envelopes" of future load and renewable power capacity may be available.
- Reformulation as a decentralized or distributed MO-MHO

The basic optimization problem was formulated for a specific case of an isolated microgrid, the methodology could be refined to include grid connected microgrids. This would involve additional cost functions and constraints pertaining to the import and export of energy from and to the main Electric Power System (EPS).

On a larger scale, a possible extension of this work would be to embed the methodology of the MO-MHO approach into a complete microgrid energy management system. A number of options are possible in this regard based on the type of architecture chosen for the final EMS. In the centralized approach, the MO-MHO based central controller could be used to perform economic dispatch and unit commitment as well as manage the intra-dispatch and islanding operations. In the decentralized hierarchical architecture, this methodology could be employed by individual DER agents to manage their respective cost functions and local objectives. In particular, the moving horizon approach could add value to the equipment maintenance scheduling problem. Using this approach, the maintenance shutdowns could be scheduled to minimize power losses by matching the down-times with forecasted periods of least productivity over the moving horizon. Finally, a very exciting research avenue would be to consider dynamic pricing in economic dispatch of grid connected microgrids in a fully deregulated energy market.

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