Optimal Planning of Advanced Microgrids with an Energy Management System

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Abstract

With an increased focus on reliability and a desire to reduce environmental impacts, power system planners are exploring the advantages of distributed energy resources (DERs) to compliment the central grid. Emerging technologies are making it possible to deploy advanced microgrids capable of integrating multiple DERs into the power system, and can operate either in isolation or parallel to the grid. Microgrids can also aid in the reduction of greenhouse gas emissions, the improvement of local system reliability and efficiency, as well as the management and control of power generation. Nevertheless, successful implementation and deployment of microgrids will require advance planning strategies that seek to best balance its operational and financial benefits.

This thesis proposes a bi–level formulation for a realistic sequential planning and operation problem of an advanced microgrid. The proposed model recast as a mathematical programming with equilibrium constraints (MPEC), jointly determines the optimal configuration of a microgrid while optimizing the outputs of its installed energy resources through the implementation of an energy management system. The coupled formulation characterizes an hierarchical decision making process where a microgrid planner or designer and a proxy operator solving an economic dispatch problem independently control a set of variables at each level of the model. The work further analyzes available investment options for microgrid implementation and uses capital budgeting techniques to determine the return on investment to potential microgrid stakeholders. Within the same context of bi–level modeling, the proposed model is modified and extended to characterize the interaction between a microgrid planner and a distribution systems operator (DSO). The modified model is developed within the context of a new DSO paradigm. Given that microgrid implementation and operation are mainly justified by the benefits accrued to microgrid stakeholders, the unified modeling language is utilized in the thesis to allocate discovered benefits and identify corresponding stakeholders to whom they may apply.

The aim of the thesis work is to transform the proposed model into a techno-economic tool that can be used for planning and evaluation of microgrid implementation, and capable of estimating benefits of deploying advanced microgrids. Application of the proposed work to develop business cases for practical microgrids (remote, commercial and industrial) are also discussed. Results obtained through these applications are verified using DER-CAM (a commercially accepted microgrid planning software package).

Abrégé

Avec un accent accru sur la fiabilité et un désir de réduire les impacts environnementaux, les planificateurs du système énergétique explorent les avantages des ressources énergétiques distribuées pour compléter le réseau central. Les technologies émergentes permettent de déployer des microgrilles évoluées capables d'intégrer de multiples ressources énergétiques distribuées (DER) dans le système d'alimentation et peuvent fonctionner soit isolément, soit parallélement au réseau. Les microgrilles peuvent également contribuer à la réduction des émissions de gaz à effet de serre, à l'amélioration de la fiabilité et de l'efficacité du système local, ainsi qu'à la gestion et au contrôle de la production d'électricité. Cependant, la réussite de la mise en uvre et du déploiement des microgrilles exigera des stratégies de planification anticipée visant à mieux équilibrer ses avantages opérationnels et financiers.

Cette thèse propose une formulation par bi-niveaux pour un problème de planification et d'exploitation séquentielle réaliste d'une microgrille avancée. Le modèle proposé transformé comme un problème de Programmation Mathématique avec des Contraintes d'Equilibre (MPEC), détermine conjointement la configuration optimale d'une microgrille tout en optimisant les sorties de ses ressources énergétiques installées par la mise en uvre d'un système de gestion de l'énergie. La formulation couplée caractérise les actions d'un planificateur ou d'un concepteur de microgrille et d'un opérateur système mandataire (proxy) résolvant un problèm de distribution économique. Les travaux analysent davantage les options d'investissement disponibles pour la mise en uvre des microgrilles et utilisent des techniques de budgétisation du capital pour déterminer le retour sur investissement des parties prenantes potentielles de microgrille. Étant donné que la mise en uvre et l'exploitation de la microgrille sont principalement justifiées par les avantages acquis par les parties prenantes de la microgrille, la thèse utilise le langage unifié de modélisation pour attribuer les avantages découverts et identifier les parties prenantes correspondantes auxquelles ils peuvent s'appliquer. Dans le méme contexte, le travail de thèse tente également d'établir la relation entre le planificateur de microgrille et l'opérateur des systèmes de distribution.

Le but du travail de thèse est de transformer le modèle proposé en un outil technoéconomique qui peut être utilisé pour la planification et l'évaluation de la mise en uvre de microgrille et est capable d'estimer les avantages du déploiement de microgrilles avancées. Il est également discuté de l'application des travaux proposés en vue de développer des cas business pour des microgrilles pratiques (isolés, commerciales et industrielles). Les

résultats obtenus grâce à ces applications ont été vérifiés à l'aide de DER-CAM (un logiciel de planification de microgrille commercialement accepté).

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Contents

List of Figures

List of Tables

List of Abbreviations

AS	Ancillary services
BIEX	Bi–level "Excel"
CCA	Capital cost allowance
CHP	Combined heat and power
CO_2	Carbon dioxide
DER-CAM	Distributed energy resources customer adoption model
DERs	Distributed energy resources
DG	Distributed generation
DR	Demand response
DSO	Distribution system operator
EMS	Energy management system
ESS	Energy storage system
GHGs	Green house gas emissions
HV	High voltage
IPP	Independent power producer
IRR	Internal rate of return

KKT	Karush–Kuhn–Turker
LCOE	Levelised cost of energy
MILP	Mixed integer linear programming
MOO	Multi–objective optimization
MPEC	Mathematical programming with equilibrium constraints
MV	Medium voltage
NDE	Non–delivered energy
O& M	Operations and maintenance
PV	Photovoltaic
PVR	Present value ratio
RERs	Renewable energy resources
SDT	Strong duality theorem
SOC	State of Charge
TSO	Transmission system operator
USDOE	United States Department of Energy

Nomenclature

The main symbols used in the dissertation are listed here for the convenience of the reader.

Indices

e	Superscript for electrical resources
h	Superscript for heat/thermal resources
i	Index for all energy resources
m	Discretization of τ such that τ=$m\mathcal{T}$
q	Economic dispatch step/period
r	Index of demand response (DR)
t	Index for hour
y	Index for years of project lifetime
τ	Intra-hourly receding-horizon time

Sets

I_A	Set of existing resources i in the network
I_B	Set of indices for new DERs
$I_{\bar{B}}$	Set of indices of new DERs except storage
I_D	Set of indices of diesel generating units

I_E	Set of indices of electrical resources i
I_G	Set of dispatchable generating units
I_H	Set of non-CHP gas fired thermal units
I_N	Set of combined heat and power (CHP) units
I_S	Set of electrical energy storage (ESS) devices
T	Set of indices of time t within a year
I_U	Set of remote community power resources or utility
I_W	Set of indices of wind power generating units
Y	Set of indices of years in the project lifetime J

Parameters

ℓ	litres of fuel consumed
v_i	Wind speed for wind energy resource $i \in I_W$
w_r^e	Percentage of electrical load available for DR
w_r^h	Percentage of thermal load available for DR
C_i^b	Budget constraint for resource i
C_i^c	Capital expenditure of resource i
C_y^d	Demand charge by the remote community energy provider or utility
C_i^e	Cost of purchased energy from remote community provider or utility $i \in I_U$
C_i^f	Fuel cost for resource i
C_i^o	Maintenance(O & M) cost for resource i
$C_y^{CO_2}$	Cost of carbon permit per kg CO_2 in year y

C'_i	Unit cost of reserve capacity provided by resource i
$L^e(y,t)$	Electrical load at time t
$L^h(y,t)$	Thermal load at time t
$L^{e,\max}$	Peak electrical load
$L^{h,\max}$	Peak thermal load
$P_i^{\max}$	Maximum power output of existing resource i
$P_i^{\min}$	Minimum power output of existing resource i
$X_i^{\max}$	Maximum power capacity of for a new resource i
$\mathcal{A}_i$	Power capacity of existing asset i
$\mathcal{L}_i$	netload forecast
$\mathcal{R}_i$	Ramp rate of resource i
$\mathcal{T}$	Sampling period of receding horizon
$\mathcal{V}_y$	value of non-delivered energy in year y
$\mathcal{W}^{\uparrow}$	Upward segment of flexible energy requirement envelope
$\mathcal{W}^{\downarrow}$	Downward segment of flexible energy requirement envelope
η_i^e	Electrical efficiency of energy resource i
κ_r^e	Electrical DR energy to power ratio
κ_r^h	Thermal DR energy to power ratio
ν_i	Energy to capacity ratio of storage resource i
ς_i	Electric to heat ratio of CHP unit i

Operation Variables

$g_i^{\uparrow}$	Feasible upward deviation of dispatchable generating resource $i \in I_G$
$g_i^{\downarrow}$	Feasible downward deviation of dispatchable generating resource $i \in I_G$
$a_i^{\uparrow}$	Feasible upward deviation of storage resource i
$a_i^{\downarrow}$	Feasible downward deviation of storage resource i
$z_r^{\uparrow}$	Feasible upward deviation of DR resource
$z_r^{\downarrow}$	Feasible downward deviation of DR resource
μ_i	Commitment status (binary) of storage resource i
μ_r	Commitment status (binary) of flexible DR resource
$E_i^e(y,t)$	Electrical energy level of resource i at time t
E_r^e	Records of electrical DR energy already interrupted
E_r^h	Records of thermal DR energy already interrupted
$P_i^e(y,t)$	Hourly electrical output of resource i
$P_i^h(y,t)$	Hourly thermal output of resource i
$P_r^e(y,t)$	Hourly electric power from demand response
$P_r^h(y,t)$	Hourly thermal output from demand response

Design Variables

x_i	Capacity of DER assets to be installed
$\mathcal{U}_y^p$	Peak power drawn from neighbouring community resources in year y
$\Upsilon_y]$	Carbon permits bought in year y

DSO level Variables

$P_i'(y,k,t)$	Electrical output of flexible DER assets i for reserve provision
x_i'	Reserve capacity of DER assets i

Chapter 1

Introduction

Over the last few years, the traditional power system of developed countries has undergone tremendous changes. Government policies, technological advancement, economic and environmental incentives, are changing the features of power systems while the presence of distributed energy resources (DERs) is increased. Power outages during hurricane *Katrina* and *Sandy* have exposed the vulnerability of a centralized power system and highlighted the benefits of DERs. Many key industrial players have developed energy saving strategies and are investing in renewable energy infrastructure. Federal and provincial authorities in Canada have introduced programs and plans to reduce green house gas emissions and encourage investment in renewable energy. Particularly, the provincial government of Quebec introduced a carbon levy or tax as part of its climate action plan for 2006 to 2012. Quebec later joined the Western Climate Initiative and introduced a carbon cap and trade system as the center piece of the province's climate action plan for 2013 to 2020 to further reduce its green house gas emissions [1].

In the same vein, microgrids can also be seen as vehicles for a greater integration of renewable energy resources (RES), the reduction in emissions of greenhouse gases, improvement in local system reliability and efficiency as well as the management and control of power generation. It is 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" [2]. A remote microgrid is a variation of a microgrid that operates in islanded conditions. Microgrids can be configured for a number of applications including the following: (a) remote, isolated and off-grid electric systems, namely remote communities, remote mining sites and other remote installations, such as military compounds; (b) grid-connected configurations, namely critical infrastructures, university communities and campuses, commercial and industrial installations. In general, microgrids can be owned by a utility, a customer, or an independent power producer (IPP). A typical microgrid consists of generating and non-generating based resources. Generating resources may include but not limited to: renewable resources – wind, solar and biomass technologies; fossil fuel resources – combined heat and power (CHP) and diesel generators, while non generating resources include energy storage systems and demand response (DR) technologies, and an energy management system (EMS) for controlling power exchanges, generation and load. An example of a microgrid layout adopted from [3] is shown in Fig.1.1.

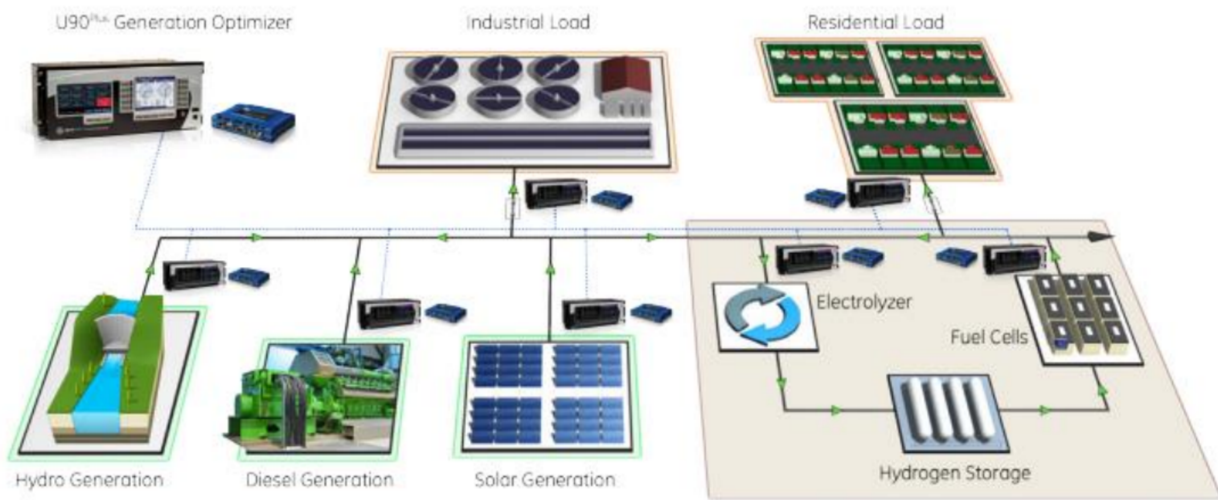

Figure 1.1. An example of a Microgrid Layout

1.1 Background

1.1.1 Microgrid Concept and Evolution

Microgrid concept and functionality has evolved over the years to fully realize its benefits in terms of aiding renewable energy integration, energy cost savings, improvement in reliability and resiliency to the grid. Its definition has expanded to include an EMS [4] that controls and dispatches resources within the microgrid [5]. Likewise, microgrid application has expanded from individual entities to large industrial and commercial customers with critical need for reliable energy source. Researchers in the early days of microgrids viewed it as the epitome of the move towards a distributed power system, where DERs will coordinate to serve the needs of local distribution networks and provide services to the main grid [6–8]. The term has since assumed different interpretations within the power systems community, with some researchers considering it as a subset of the smart grid and referred to it as a pillar of the smart grid [9]. However, the functionality of microgrids can be clearly distinguished from that of the smart grid concept which refers to the integrated array of technologies, devices and systems that provide and utilize digital information, communications and controls to optimize the efficient, reliable, safe and secure delivery of electricity [10]. Microgrid is considered in [11, 12], as necessarily containing dispatchable generation and resources (i.e. storage devices and controllable loads) that have the ability to intentionally disconnect from the main power grid and to operate in a disconnected state (islanding mode). Future concepts of microgrid are likely to include the aggregation of multiple microgrids in the architecture of the main grid to provide ancillary services and aid in the control of the megagrid [4]. Currently the US Department of Energy (USDOE) defines microgrid as provided in [2] and emphasized in the previous paragraph.

The evolved concept of micogrids and its changing functionality characterizes the advanced microgrid referred to in this thesis work.

1.1.2 Recent Microgrid Application

The advanced microgrid is envisioned playing a larger role in power grids of developed countries and emerging economies as well as rural communities. Municipalities across the globe are increasingly interested in these microgrids as one of the means to address their sustainability challenges. Such localized operation within an electric utility has the potential to revolutionize urban electricity grids, permitting local use of generation from DERs and thus increasing efficiency and environmental sustainability. Energy intensive industrial consumers tasked with the challenge of seeking alternative energy sources in the face of fluctuating fuel prices and tightened commodity prices are also looking to advanced microgrids as potential solutions. The El Toqui zinc underground mine located in a remote area in southern Chile has installed a wind/diesel/hydro based microgrid to solve stability issues and reduce energy cost [13]. Most remote communities in Canada rely on diesel generation for the production of electricity [14]. Several of these communities are considering implementation of microgrids with renewable energy resources to reduce dependency on diesel and also reduce energy cost. The Diavik diamond mine in remote Canada has also installed a wind-diesel microgrid that consist of four 2.3 MW turbines (9.2MW total), projected to provide 17 GWh of renewable energy per year to reduce diesel consumption and carbon footprint of the mine [15]. The department of defence is also installing microgrids on military bases and facilities to improve reliability and resilience of its power system. Detailed description of military microgrid applications at the Naval Support Facility (NSF) Dahlgren, *Fort Detrick*, and Marine Corps Air Ground Combat Center (MCAGCC), *Twentynine Palms* is provided by authors in [16]. University campuses such as Princeton university, Illinois Institute of Technology (IIT) and British Columbia Institute of Technology have installed campus applications of microgrids to improve energy delivery on their campuses.

To justify the setting up of microgrids, and for widespread deployment and successful implementation of microgrids, convincing business cases have to be established.

1.2 Problem Identification

1.2.1 Microgrid Benefits Quantification and Buisness Models

Microgrid business cases will require a more complete picture of benefits and services that microgrids can provide in order to be justified. These benefits include an increased resiliency to exceptional atmospheric events and contingencies, a reduction in the cost of supplying electric energy from central generation plants through a transmission network, mitigation of greenhouse gas emissions where thermal power plants are used, and diversification of energy supply. Also, there are some benefits (social benefit, health benefit, etc.) of microgrids to local communities that can not be readily expressed financially. One of the guiding principles in evaluating investments designed to improve power systems operations is the economic efficiency of these investments. Authors of [13, 17–24] identify benefits of microgrids and attempt to estimate/quantify these benefits. They further provide cost benefit analysis to support their approach and business cases. Among them, various microgrid ownership models and their corresponding business models are detailed in [25] and [26], while the evolution of micogrids (including distribution automation strategies) and their relation to the microgrid business cases are discussed in [21, 22, 27]. Further analysis of the effects of market price variations and different pricing policies on the total economic benefit of microgrid is provided in [22]. Similarly, authors in [17] outline a use case inspired framework in identifying key impacts, benefits, and stakeholders and for establishing the relationship between these entities. They also examine the dependency of microgrid benefits on microgrid types and objectives to minimize the cost of energy. Within the same framework, authors in [19] suggested a quantification methodology for more significant and measurable benefits of implementing microgrids. The adoption of the use case paradigm in [17] and [25] provides a clear illustration of the relationships between microgrid impacts, benefits and stakeholders. It maps available benefits and identifies corresponding stakeholders to whom they may apply [17]. The authors define stakeholders as parties who either have a direct financial interest in the microgrid, or who will be impacted by it in some way. Each stakeholder has different types of benefits that may accrue to it. In each case, benefits may be valued differently; the DNO may place more value on technical benefits such as reduced peak loading, whereas the customer would likely value energy cost reduction [13,23]. Microgrid benefits from the perspective of the regulator and policy maker are also outlined by authors in [5, 24, 28]. Specifically, discussions on the potential value of microgrid, as well as pathways and barriers to deploying microgrids in New York State are provided in [5]. Depending on how favourable markets and regulations are in a particular jurisdiction, microgrids may be able to provide energy to its internal loads strictly without exporting power to the utility system, or may export power at wholesale prices, or at retail prices.

Provision of Ancillary Services

Microgrids may sell or provide a variety of services to the main grid [29]: they can serve as resources for ancillary services and demand-side management. Provision of ancillary services such as frequency support, voltage support, reserve capacity and black start support can be a viable source of benefits for multiple stakeholders, given the history of compensation for these services in some jurisdictions [29]. A depreciation-based valuation method of these benefits has been proposed and further developed for long-term planning consideration and system security improvements in [30]. However, microgrid resources can only contribute significantly to ancillary services market and flexibility of the main grid through aggregation and better integration of the power system management and control. Another important issue is that, the transmission system operator (TSO) has no visibility and control of microgrid resources, while traditionally, the distribution system operator (DSO) has very limited control over these assets. Thus, it will be challenging for the main grid to take full advantage of services and benefits provided by microgrids in power grids with deep penetration of DERs.

The New DSO Construct
To this end, new roles have been proposed for a DSO in the future grid that allows it to take full advantage of benefits that microgrids can provide as well as clarification of the extent to which microgrids can actively contribute to the macro system's operation [31–33]. Particularly, authors in [32] propose new business models (extended central dispatch, local dispatch by the DSO and scheduled program at HV/MV interface models) that can be implemented to evolve the structure and organization of power systems in order to exploit full benefits of microgrid resources. The business models also provide opportunities for both TSOs and DSOs to make efficient use of services that microgrid technologies may offer. Local dispatch by the DSOs, where the DSO could procure services to satisfy its own needs and also manage resources on behalf of the TSO, is of great interest to the thesis work. Here, the TSO will not act on any individual DER connected to the distribution grid; however, orders from the TSO can be executed by the DSO. Within a similar context, the authors of [31], propose a shift in paradigm towards a DSO construct where the DSO is intended to take on the responsibility for balancing supply and demand variations at the distribution level. It will also link wholesale and retail market agents while maintaining the traditional role of the operator as a custodian for distribution system reliability. The paradigm shift is supported by actions of the New York Public Service Commission, which in late April 2014 opened proceedings ("Reforming the Energy Vision or REV") [34] to rethink the central–station utility paradigm, and to consider redefining the local distribution utility more as platform that serves as an interface between various products, services, and market players, including prosumers (consumers who may produce their own energy or sell to other end users).

Other larger projects such as EPRI's "*Methodological Approach for Estimating the Benefits and Costs of Smart Grid Demonstration Projects*", provides additional evaluationand quantification methodologies that take into account a number of smart grid benefits applicable to microgrids [10]. Authors in [35] also suggest that with proper incentives in place, profit maximization for the IPP could automatically optimize the benefits for other stakeholders .

1.2.2 Microgrid Planning and Operational Optimization

Given that microgrid implementation and operation are mainly justified by the benefits accrued to microgrid stakeholders; microgrid type, design and the operation optimization strategies play key roles in developing its business case. Various optimization strategies have been proposed that maximizes specific or multiple benefits of microgrids.

Microgrid Operation/ Energy Management System

Among these strategies are those that pertain to operational planning; here, authors in [36–47] assume a known microgrid design capacity/configuration, and propose different optimization algorithms to minimize the systems operational cost considering environmental and reliability implications. Their applications span remote networks all the way to industrial applications. Also, a set of guidelines is provided in [48] to design an EMS with both electrical and thermal loads that can take advantage of the microgrid's energy diversity. DERs must be managed appropriately when connected to the main system and perhaps differently when operating in isolation from the grid to maximize their benefit. Sound operation of microgrids with DER units, requires robust power/energy management strategies, especially for microgrids in autonomous mode [49]. Bose in [16] also outlined microgrid energy management controllers for improved energy efficiency and renewable integration at US Department of Defense installations. The advanced control and optimization functions include optimal dispatch of DERs (including renewable resources and energy storage), initial capability of load management during grid connected or islanded operation, and energy efficiency optimization by simultaneously controlling DERs and managing major electrical loads [16]. Recent publications within the context of microgrid operational planning have focused on energy management strategies that deal with supply/demand uncertainties and highlight the value of flexible resources within the network [39–42]. Likewise alternate scheduling methods capable of estimating uncertainties within microgrids and harnessing major benefits of microgrid's flexibility have also been discussed in [50–52].

Other operational planning strategies and EMS based on a rolling horizon that maximizes the utilization of flexible resources and minimizes deviations of forecasted resources from real time data are also proposed in [53–56].

Planning / Design Optimization

From the planning perspective, most literature reviewed considered direct economic evaluation and optimization of microgrids. Their contributions proposed planning problem formulations seeking to configure and size the assets of microgrids. The design problem formulations here are generally presented either as single or as multi–objective optimization problems [8, 42, 45–47, 57–59]. Each of them has a generic energy cost minimization, emissions reduction or reliability improvement objective with some variations around constraints, objective functions and available technologies. Specifically, the proposed approach in [8] utilizes a mixed-integer linear programming (MILP) formulation and solution algorithm to determine the configuration of a potential microgrid that minimizes its energy procurement cost and CO_2 emissions, the proposed formulation is further expanded to develop the DER-CAM software package developed and maintained by the Lawrence Berkeley National Laboratory (LBNL), California. In [58], a particle swarm algorithm is implored to solve a planning problem that attempt to determine the optimal location and configuration of DERs within a microgrid. Here, a benefit to cost ratio is used to determine the best/cost effective planning option. Complex, cumbersome and costly fuel logistics unique to several remote networks are also highlighted in [21], [22], where heuristic methods are used to establish the microgrid design.

Bi-level Optimization

Clearly, if one is attempting to choose and size the components of a microgrid, there is a need to have a representation of the expected operations into the design problem. At the same time, it is clear that past microgrid design decisions can have a direct effect on the operating costs and space; therefore, there is a need to find a way to unify these two with the objective of finding the *best microgrid design* which would provide the *best operating costs* over the microgrid's assets lifetime.

These objective can be coupled and cast as a bi–level optimization problem [60]. Detailed background on bilevel optimization can be found in [60]– [61]. Among examples of bi–level optimization in power systems, we find [62] where its authors have developed a two-step mixed-integer linear programming (MILP) model that optimizes the configuration of a hybrid microgrid and seeks to determine an operating policy based on the design. The first step solves an MILP to select and size the microgrid assets, while this solution is then passed to a second step where a data mining analysis is used to establish the logic of a microgrid controller. A bi–level optimization design approach based on Benders' decomposition with uncertain physical and financial information is also proposed in [63]. This work, however, has limitations with respect to the breath of technological options and does not cater for multi-energy demands (heat, power) and their inherent planning and operational tradeoffs. The authors of [64] also attempt to nest the microgrid planning and operational problem in the form of a generalized double shell framework based on an evolutionary algorithm. The outer shell objective minimizes the microgrid's capital cost which is aligned with the inner shell's objective of minimizing the operational cost. The aligned objectives of these formulations may defeat the necessity of the bi–level approach since other alternative multi–objective planning models could solve similar problems. Also, the economic analysis of the design options in [64] is not established systematically.

1.2.3 Objectives of thesis work

From the above review, one can conclude that there are several challenges to be addressed when considering joint microgrid asset and operations planning, which this thesis work sets to address. These include:

The need to include the widest range of asset classes for system designers.

The need to design multi-energy microgrids systematically.

The need to formulate joint optimal design-operation problems in ways to take advantage of available powerful mixed-integer solvers.

The need to revise the operational and planning arrangements within power systems to support a new paradigm capable of enabling the provision of services by microgrids for the overall benefit of the power system

The need to have a microgrid planning approach that characterizes interactions between a microgrid planner and other distribution level market agents particularly the DSO.

1.3 Thesis Statement

Thus, this thesis seeks to develop an optimal planning approach for microgrids acknowledging the wide array of technologies available to microgrid designers: generation, energy storage, combined heat and power, and demand response, which can represent their operations with good fidelity over a microgrid's lifetime. The high-fidelity operational representation is enabled by the formulation of the problem as a bi–level optimization problem, which can be solved systematically by commercially available MILP solvers. The bi–level model involves a two way hierarchical interaction between the designer and an EMS which acts as a proxy system operator. The idea here could be seen as a repeated game where the microgrid designer "plays" a microgrid configuration with the objective of maximizing its own payoff (the net present value of the microgrid) to the microgrid operator. Given the move of the designer, the operator would also "play" a dispatch strategy to maximize its payoff of minimizing microgrid running costs. The designer, observing the operator's actions, could then play a new design which the operator would then play on. This process could go on until the designer and operator find an equilibrium (fixed point) of the game where neither of them has an incentive to change their play, *i.e.*, the microgrid design and the operating strategy.

Within the same context of bi–level formulation for microgrid planning, the thesis also attempts to incorporate projected actions of a DSO into an alternate microgrid power and reserve planning model that fits the narative of the new DSO paradigm. Here, the upper level problem of the bi–level model represent a microgrid planner whose interest is to minimize its planning and operational cost while the lower level problem represents a DSO whose duty is to ensure reliable power supply. The microgrid planner, pursues its own interest by co–optimizing the design configuration and power output of individual DERs, while the DSO maximizes the capacity of flexible resources available for reserve provision. Again this struggle continues until an equilibrium is reached where neither players has an incentive to improve its interest.

The thesis work further proposes a systematic approach and a methodology for formulating and quantifying a microgrid business case. The framework adapts the use case approach to the microgrid context. It defines stakeholders, benefits and beneficiaries and determines the dependency of the business case on microgrid technologies. The work seeks to explore how microgrid models and key elements can be put together to develop a strong microgrid business case. The thesis argues that, regardless of the complexity and target audience of the microgrid business case, the key for developing a strong business case is a fundamental understanding of how each of its elements, models and concepts fit together.

1.4 Thesis Contribution

The following main results of this dissertation can be considered as distinct contributions of the thesis work to the best knowledge of the author:

1. The thesis work proposes an optimal design approach for microgrids acknowledging the wide array of technologies available to microgrid designers– generation, energy storage, combined heat and power, and demand response–, and which can represent their operations with good fidelity over a microgrids lifetime [65].

2. A bi-level optimization model for a coupled microgrid planning and operations problem, involving a two way hierarchical interaction between the microgrid designer and an EMS which acts as a proxy system operator is also developed. The problem is further transformed into an equivalent MILP problem that can be solved systematically by commercially available MILP solvers [66].

3. A bi-level formulation for a coupled microgrid power and reserve capacity planning problem. The model is cast within the context of a distribution system operator(DSO) whose duty is to ensure reliable power supply and may request reserve capacity from a microgrid planner whose interest is to minimize its planning and operational cost [67].

1.5 Dissertation Outline

Microgrid Simulation Models and Tools

Chapter two of the thesis provides a detailed outline of DER models and tools and set out the framework for the thesis work. The chapter introduces technical and economic models for specified DER technologies as well as other component of the distribution system. Models of intermittent meteorological conditions such as wind speed, solar irradiance and ambient temperature that influence the output of wind and solar energy resources are discussed and used in their technical models. The chapter adapts the unified modeling language to the microgrid context and defines potential microgrid stakeholders and ownership models. The models and context are put together to outline the framework for advanced microgrid planning.

Microgrid Bi–level Planning Models

Chapter three primarily, discusses bi–level formulation for coupled microgrid planning models which are the main proposition of this thesis work. The chapter starts with an introduction to a bi-level formulation for a coupled microgrid planning and operation problem. It explains the uniqueness of the coupled problem and justifies the need for the proposed bi–level formulation. Methods available to transform the primal problem into a mathematical programming with equilibrium constraints (MPEC) are also discussed in the chapter. Here, the chapter will seek to establish that transformation of the primal problem via the strong duality theorem provides a better alternative to the Karush–Kuhn–Turker (KKT) conditions. The preferred transformation is applied to the planning of the energy infrastructure of a mine. Results obtained from the application are analysed and discussed. Later part of the chapter briefly introduces the emerging concept of the DSO paradigm and outlines a coupled microgrid power and reserve capacity planning problem. The proposed bi–level model is cast within the context of a DSO. A case study implementation of the proposed formulation to a Canadian utility network is discussed and the results are compared to a traditional multi-objective optimization approach.

Business Cases for Isolated and Grid Connected Microgrids

A systematic approach and a methodology for formulating and quantifying microgrid business case is proposed in chapter four. The chapter outlines how DER models, optimization strategies and other elements of the planning framework discussed in previous chapters are put together to develop business cases for representative microgrids. A method to quantify and allocate microgrid benefits, particularly reliability improvement, is discussed. Here, the proposed method estimates/quantifies energy not delivered in a way that reflects the stochastic/uncertain occurrence of DER failures. Applications to practical microgrids are discussed, including remote communities, remote mining sites and grid connected critical distribution grids. Sensitivity analysis on identified parameters of the microgrid planning problem is also considered.

Harnessing Flexibility of Microgrid Resources for its Operational Planning

Chapter five discusses an operational planning formulation of a microgrid that can also serve as an alternate formulation of the lower level problem of the bi–level model in the first part of chapter three of the thesis. The proposed formulation is referred to in the thesis work as an energy centric energy management system. The energy centric operational planning strategy seeks to harness identified benefits of flexibility provided by microgrid resources, to match the dynamics of uncertainty within the microgrid. The chapter explains power and energy centric concept of microgrid planning and seeks to highlight the flexible value of microgrid resources under uncertainty. Application of the proposed strategy to an energy infrastructure of a mine and its comparison to a traditional operational planning dispatch are discussed.

Conclusion

Chapter 6 summarizes key achievements of this thesis and outlines recommendations for future research.

Appendices

Appendix A.1 provides an overview of information available on a manufacturer's data sheet that can serve as input to the developed planning tool.

Detailed description of the *Excel-VBA* tool termed *BIEX* is provided in appendix A.2. The appendix also describes the front-end user interface of the tool where input data and other DER modeling information are entered by a user.

Appendix B seeks to provide further clarity to the bi–level formulation proposed in chapter three of the thesis via geometric illustration of the modeled Problem.

Appendix C outlines KKT transformation of the coupled bi–level problem and also detailed transformation or linearization of the strong duality reformulation into an MILP.

Chapter 2

Microgrid Simulation Models and Tools

2.1 Introduction

As previously mentioned in the introductory chapter, an inherent benefit of the thesis work is the development of a planning tool, for evaluation of microgrid implementation projects and also has the capability to estimate benefits of deploying advanced microgrids. Thus, this chapter outlines the context of the framework within which the microgrid planning tool is developed. The chapter first describes simulation models of individual microgrid resources used in the thesis work. Here, simplified mathematical models of DER technologies and basic principles of their operation are outlined. Input resources such as fuel and meteorological data (wind speed, solar , e.t.c.) are transformed by developed models into energy or power outputs. The chapter also describes various microgrid ownership models and how they impact allocation of microgrid benefits. The unified modeling language is used to help visualize the relationship between stakeholders/actors and microgrid benefits. A brief overview of the techno-economic tool is also provided. The models are generally assembled to manage the complicated interactions among heat and electrical power generation, power demand, energy storage, and power distribution and delivery.

2.2 Distributed Energy Resource Technology Models

Distributed energy resources commonly refer to DG types, energy conversion equipment and ESS. They can be further divided into dispatchable and non-dispatchable units. Dispatchable generation units are generating units whose operating points or system loading can be adjusted to meet changing energy demand. They include conventional units such as diesel generators, natural gas, biomass systems, e.t.c.. ESS and DR technologies are also dispatchable but non-generating units. Non-dispatchable units unlike dispatchable units can not have their outputs and set-points readily adjusted or controlled to meet changing demand. They include intermittent energy resources such as solar and wind. Dispatchable units such as diesel generators, CHPs, ESS and DR and non-dispatchable solar and wind energy resources are considered for purposes of this thesis work.

The approach used in modeling these resources is in two parts: the first part outlines primary characteristics and principle of operation of these DERs based on which mathematical models are developed in the second part.

2.2.1 Diesel Generator

Characteristics / Principle of Operation

Diesel generators typically operate at constant engine speed and provide power to a constant electric load during a period of time t. They primarily consist of a diesel engine with an electric generator. The engine is usually the well known four-stoke piston-driven internal combustion engine as found in auto-mobiles and trucks. It is connected to a constant-speed alternating current generator to produce electric power. One of the methods of maintaining desired engine operating point is to use a governor, that regulates fuel flow rate in order to maintain a constant engine speed.

Mathematical Model

Fundamental to the economic operation of a diesel generating unit is the set of input and output characteristics of the generator. The technical model of an electric generator is based on the system's efficiency curve that describes the relationship between the electrical efficiency and the electrical load on the generator. Data on the efficiency of the system or the system's efficiency curve is usually provided by the manufacturer in the system's data sheet. The efficiency curve is usually based on four operating points and their corresponding efficiency. To get the efficiency for other loading or operating points of the generator, a polynomial curve fitting method is used to estimate the corresponding efficiency η_i^e according to (2.1):

$$\eta_i^e = \mathbb{k}_{1i}\mathbf{P}_i^4(y,t) + \mathbb{k}_{2i}\mathbf{P}_i^3(y,t) + \mathbb{k}_{3i}\mathbf{P}_i^2(y,t) + \mathbb{k}_{4i}\mathbf{P}_i(y,t) + \mathbb{k}_{5i} \tag{2.1}$$

where $\mathbb{k}_{1i}, \mathbb{k}_{2i}, \mathbb{k}_{3i}, \mathbb{k}_{4i}, \mathbb{k}_{5i}$ are all constants for diesel generator $i \in I_D$. Here $\mathbf{P}(y,t)$ is the operating point or loading on the electric generator $i \in I_D$ during time $t \in T$ of year $y \in Y$ and expressed as a percentage (%). The actual load on the electric generator is converted to its equivalent percentage value by dividing the actual load with the rating of the electric generator.

The loading on the diesel engine (the input to the electric generator) is obtained from the system load (the output of the electric generator) and the electrical efficiency of the generator according to the expression in (2.2) for all generators $i \in I_D$, during time $t \in T$ of year $y \in Y$:

$$P_{eng}(y,t) = \frac{P_{gen}(y,t)}{\eta_i^e} \tag{2.2}$$

where $P_{eng}(y,t)$ is the load on the engine, $P_{gen}(y,t)$ is the load on the generator, and η_i^e is the electrical efficiency of the generator. The fuel curve for a diesel engine describes the amount of fuel consumed depending on the system or engine load. A typical fuel curve and engine efficiency are provided in Fig. 2.1 for a 2000 kW diesel generator. The electrical generator performance curve and diesel engine performance curve are combined to obtain the overall fuel consumption for the given system load or load profile. Thus the fuel consumed in litres can be expressed as a function of the engine loading $((P_{gen}(y,t)))$, or generator loading $(P_{gen}(y,t))$ (refer to as the operating point of diesel generator $P_i(y,t)$ in the thesis):

$$\ell_i^f(y,t) = \mathbf{F}(P_i(y,t)) \tag{2.3}$$

where ℓ_i^f refers to litres of fuel consumed by generator $i \in I_D$ during time $t \in T$ of year $y \in Y$ and $\mathbf{F}$ can be expressed based on a polynomial fitting curve equivalent to (2.1) for all $i \in I_D$ during time t of year y.

The production cost model then becomes a function of the cost of diesel per litres

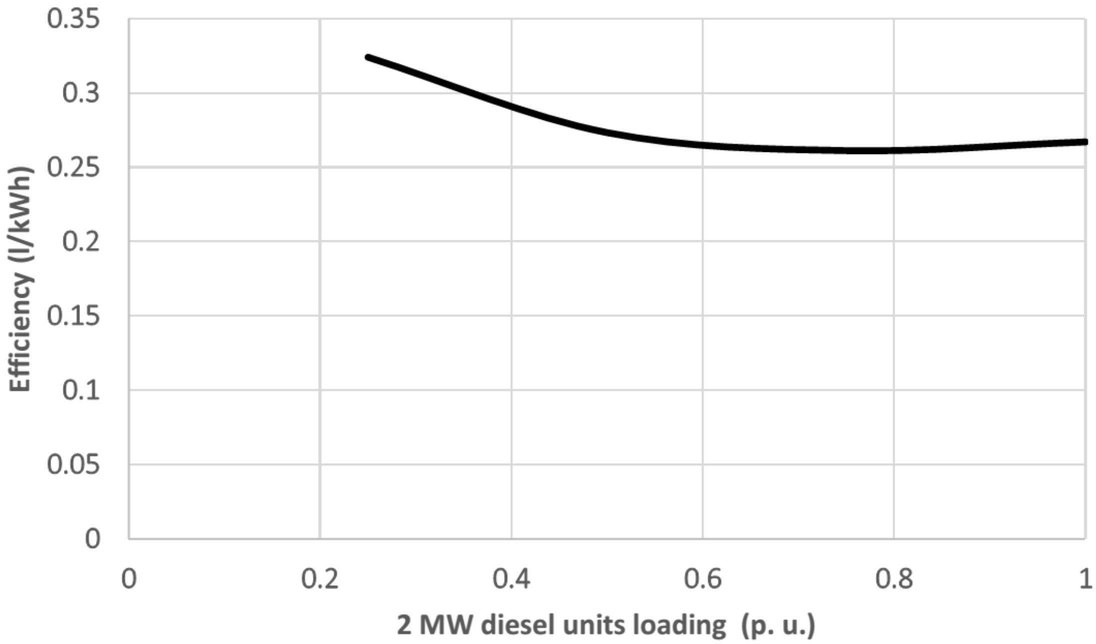

Figure 2.1. Generation efficiency of 2MW diesel generator

of fuel consumed, maintenance cost and other cost components which will be detailed in subsequent chapters of the thesis. It is important to note that the generator loading varies from $0 - 100$ % of its maximum capacity. Generators may have a minimum operating point higher than 0%.

2.2.2 Combined Heat and Power (CHP)

Characteristics / Principle of Operation

Combined heat and power is an efficient method of providing power and useful thermal energy (heating or cooling) at the point of use with a single fuel source. A CHP system consist of a prime mover, the unit in which fuel is consumed (e.g. turbine, boiler, engine), an electric generator, and a heat recovery unit that transforms otherwise waste heat to useable thermal energy. A schematic diagram of a CHP system is shown in Fig. 2.2. A variety of fuel sources such as biomass, natural gas, ethanol, propane, etc., can be used to power CHP systems; however, for the purposes of this thesis work, discussions on CHPs are limited to the widely used natural gas fired CHPs in the power industry. These systems burn natural gas to generate electricity while a heat recovery unit captures heat from the exhaust and cooling system. The recovered heat is converted into useful thermal energy, usually in the form of steam or hot water. CHP systems efficiency depends on the technology used to generate electricity and thermal energy, the system design, and the amount of thermal energy used by the system [68, 69]. The high part-load efficiency of reciprocating engines ensures economic operation of electric load following applications. The technology of the

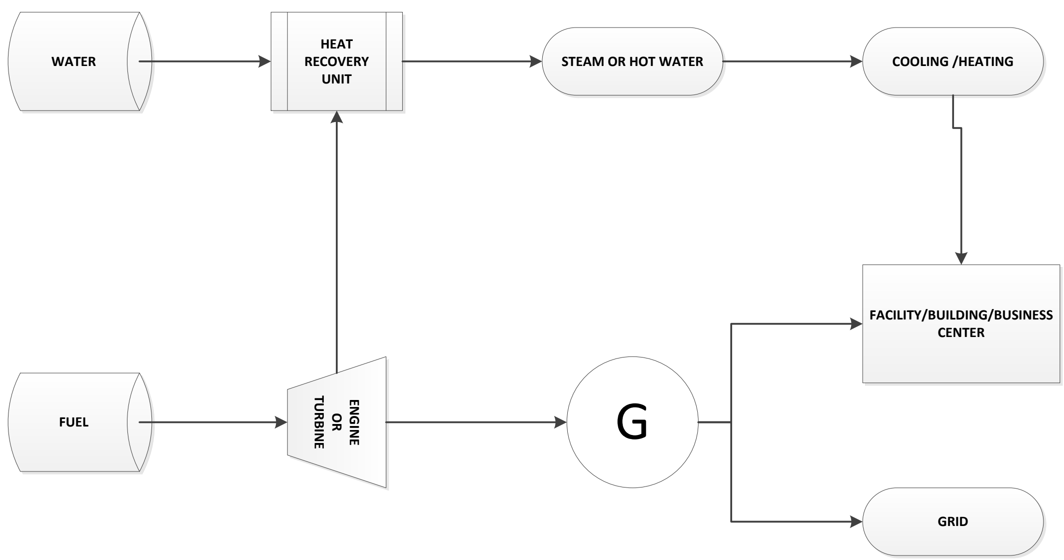

Figure 2.2. Schematic diagram of CHP Systems operation

prime mover typically identifies the CHP system. The prime mover can be:

1. Reciprocating internal combustion engines
2. Combustion turbines
3. Steam turbines
4. Microturbines
5. Fuel cells

Reciprocating engines– Reciprocating engines are well established and matured technology as found in diesel generators . They are well suited for a variety of distributed generation applications, and are used throughout industrial, commercial, and institutional facilities for power generation and CHP. Reciprocating engines start quickly, follow load well and have good partial loading efficiency. In many cases, having multiple reciprocating engine units further increases overall plant capacity and availability. Reciprocating engines have higher electrical efficiency than gas turbines of comparable size [68]. The technology is used in automobiles, trucks, trains, emergency power systems, portable power systems, farm and garden equipment. They can range in size from 30 kW to 30 MW with many larger plants comprised of multiple units. The exhaust heat characteristics of reciprocating engines make them ideal for producing hot water.

Combustion turbines– Gas turbines have been a popular choice for new power generation plants in North America. They are widely used by the electric utility industry. Combined cycle turbine plants contribute to base load power needs, and simple cycle turbines are used for meeting peak-load. However, with changes in the power industry and advancements in the technology, gas turbines are now being increasingly used for base load power. They are available in sizes ranging from 500 kW to more than 300 MW. The most efficient commercial technology for utility-scale power plants is the gas turbine-steam turbine combined-cycle plant that has efficiency of more than 60 percent (measured at lower heating value [LHV]) [68]. Simple-cycle ones are available with efficiency of over 40 percent (LHV). Gas turbines produce exhaust heat at high temperatures that can be recovered in a CHP configuration to produce steam for process use. Such CHP configurations can reach overall system efficiency (electricity and useful thermal energy) of 70 to 80 percent

Steam turbines–Steam turbines are one of the oldest prime mover technologies still being used to drive generators or mechanical machinery. They offer a wide array of designs and complexity to match the desired application and/or performance specifications ranging from single stage back pressure or condensing turbines for low power ranges to complex multi-stage turbines for higher power ranges. Steam turbines for utility service may have several pressure casings and elaborate design features, all designed to maximize the efficiency of the system. Their sizes can range from 50 kW to several hundred MW for large utility power plants. For industrial applications, steam turbines are generally of simpler single casing design and less complicated for reliability and cost reasons. CHP can be adapted to both utility and industrial steam turbine designs. Here, steam at lower pressure is extracted from the steam turbine and used directly in a process or for district heating, or it can be converted to other forms of thermal energy including hot or chilled water [68].

Microturbines–Microturbines are small combustion turbines that burn gaseous or liquid fuels (natural gas in our case) to drive an electrical generator. They operate on the same thermodynamic cycle as larger gas turbines and share many of the same basic components. They have lower compression ratios and operate at lower combustion temperatures compared to gas turbines. In order to increase efficiency, microturbines recover a portion of the exhaust heat in a heat exchanger called a recuperator, to increase the energy of the gases entering the expansion turbine thereby boosting efficiency [68]. Their sizes range from $30 - 250$ kW for single turbine systems with multiple turbine packages available up to 1000 kW. Microturbines are well suited to be used in CHP applications because the exhaust heat can either be recovered in a heat recovery boiler, or the hot exhaust gases can be used directly. Temperatures available from the exhaust of microturbines allows effective use of the turbines when combined with absorption cooling equipment driven either by low pressure steam or by the exhaust heat directly. Cooling can be added to CHP in a variety of commercial/institutional applications to provide both cooling and heating.

Fuel cells– Fuel cells use an electro-chemical process to convert chemical energy of hydrogen into water and electricity. They use hydrogen, which can be obtained from natural gas, coal gas, methanol, and other hydrocarbon fuels. Fuel cells are characterized by the type of electro-chemical process utilized: phosphoric acid (PAFC), proton exchange membrane (PEMFC), molten carbonate (MCFC), solid oxide (SOFC), and alkaline (AFC) [68]. PAFC systems are commercially available in two sizes, 200 kW and 400 kW, and two MCFC systems are commercially available, 300 kW and 1200 kW. Fuel cells are relatively clean, quiet, and efficient power generation technology. Fuel is not combusted, but instead reacts electro-chemically, and there is also minimal air pollution associated with its use. The most prevalent and economical DG application of fuel cell is CHP due to its high capital cost.

Mathematical Model of CHP System

Many of the benefits of CHP systems come from the relatively high efficiency of CHP systems compared to other DERs. The mathematical model of a CHP system is similar to that of the diesel generator and thus its performance largely depends on its efficiency. The system's efficiency is measured and expressed in a number of different ways due to the simultaneous production of electricity and useful thermal energy. Total system efficiency and effective electric efficiency are the two most commonly used methodologies to determine the efficiency of a CHP system. The total system efficiency (η_i of a CHP $i \in I_N$) is calculated as the sum of the net useful power output (P_i^e for all $i \in I_N$) and net useful thermal outputs (P_i^h for all $i \in I_N$) divided by the total fuel input (ℓ_i^f), and given by equation (2.4). Corresponding values of η_i are often provided on the manufacturers data sheet.

$$\eta_i = \frac{P_i^e + P_i^h}{\ell_i^f} \tag{2.4}$$

On the other hand, the effective electric efficiency allows for a direct comparison of CHP to conventional power generation system. The effective electric efficiency (η_i^e) can be calculated as:

$$\eta_i^e = \frac{P_i^e}{\ell_i^f - \dfrac{P_i^h}{\imath_i}} \tag{2.5}$$

where $\imath_i$ denotes the efficiency of the conventional technology of producing thermal energy if CHP is not used.

Since CHP systems produce both electrical and thermal output at the same time, a relationship between the net heat and power output (Power to heat ratio) can be defined by:

$$\varsigma_i = \frac{P_i^e}{P_i^h} \tag{2.6}$$

Based on this expressions, the electrical energy output P_i^e and the electrical efficiency can be expressed as a function of the system efficiency as follows:

$$P_i^e = \frac{\eta_i \ell_i^f}{1 - \dfrac{1}{\varsigma_i}} \tag{2.7}$$

$$\eta_i^e = \frac{\dfrac{\eta_i}{1 + \dfrac{1}{\varsigma_i}}}{1 - \dfrac{\dfrac{\eta_i \varsigma_i}{1 + \dfrac{1}{\varsigma_i}}}{\imath_i}} \tag{2.8}$$

$\imath_i$ and ς_i are constant for a given CHP system $i \in I_N$. With the partial load system efficiency provided, the effective electrical efficiency could be computed for every loading point. A polynomial interpolation could be employed for this purpose just as described in the previous section on diesel generators. With the efficiency known, the fuel consumed for corresponding loading can be determined. An example of a polynomial interpolation to compute the effective electrical efficiency of a 1.1 MW gas turbine is provided in appendix A.1.

2.2.3 Wind Turbine

Characteristics / Principle of Operation

Wind turbines are electro mechanical energy conversion devices that turn kinetic energy from wind into electricity. They are seen as the fastest growing renewable source of electricity in remote areas around the world. A wind turbine, rotates and power an electric generator that supplies an electric current. The blades spin a shaft, which connects to a generator and generates electricity. Modern wind turbines are classified into two basic groups; *horizontal-axis* and *the vertical-axis*.

One of the major challenges of using wind as a source of power is its intermittent nature and does not always blow when electricity is needed. Wind cannot be stored (although wind-generated electricity can be stored, if batteries are used), and not all winds can be harnessed to meet the timing of electricity demands. Furthermore, good wind sites are often located in remote locations far from areas of electric power demand (such as cities). Even though the cost of wind power has decreased dramatically in the past 10 years, the technology requires a higher initial investment than fossil-fueled generators.

Mathematical Model

Many works can be found in literature [70, 71] that have previously modeled power output of wind turbines. Wind speed is required as input for most of these models. The uncertain nature of wind require careful analysis to build models that reflect these characteristics. In this thesis, Weibull distribution function is used to model the wind speed. Weibull distribution function has been advocated as one of the best models for wind speed [72] considering the speed's uncertain nature. Historical data of wind speed over a six year period is obtained from Canadian weather energy and engineering datasets (CWEEDS) for the wind energy model. The time series wind speed data is utilized to estimate an hourly frequency distribution of the wind speed for each season of the year, with each season represented by a $24hr$ daily distribution. The mean $\bar{v}$ and standard deviation σ_v of the data are given by (2.9) and (2.10) respectively.

$$\bar{v} = \frac{1}{n}\sum_{j=1}^{n} v_j \tag{2.9}$$

$$\sigma_v = \left[\frac{1}{n-1}\sum_{j=1}^{n}(v_j - \bar{v})^{\flat}\right]^{0.5} \tag{2.10}$$

where n is the data size and the value of $\flat$ taken to be 2 for purposes of the thesis work. The weibull probability distribution function (pdfs) needed to model the hourly wind speed is then computed as a function of the mean speed ($\bar{v}$) and standard deviation (σ_v) as shown in (2.11) below:

$$f(v) = \frac{\flat}{\aleph}\left(\frac{v_i}{\aleph}\right)^{\flat-1} e^{\frac{-v^{\flat}}{2\sigma_v^{\flat}}} \tag{2.11}$$

The shape parameter ($\flat$) and scale parameter ($\aleph$) can also be obtained by (2.12) and (2.13) respectively.

$$\flat = \left(\frac{\sigma_v}{\bar{v}}\right)^{-1.086} \tag{2.12}$$

$$\aleph = \frac{\bar{v}}{\Gamma\left(1 + \frac{1}{\flat}\right)} \tag{2.13}$$

Finally the output power (P_i^e, $\forall i \in I_W$) of the wind turbine is computed as a function of the modeled hourly speed and given by (2.14). The rated power (P_i^{rated}), cut in speed (v^{in}), rated speed (v^{rated}) and cut out speed (v^{out}), are provided on the manufacturer's specification sheet. Fig. 2.3 shows the variable output of the wind generator.

$$P_i^e = \begin{cases} 0, & 0 < v \leq v^{in} \\ P_i^{rated}\dfrac{v - v^{in}}{v^{rated} - v^{in}}, & v^{in} < v \leq v^{rated} \\ P_i^{rated}, & v^{rated} < v < v^{out} \\ 0, & v^{out} < v \end{cases} \tag{2.14}$$

It is assumed that, the cost of generating power from wind is free hence we consider only

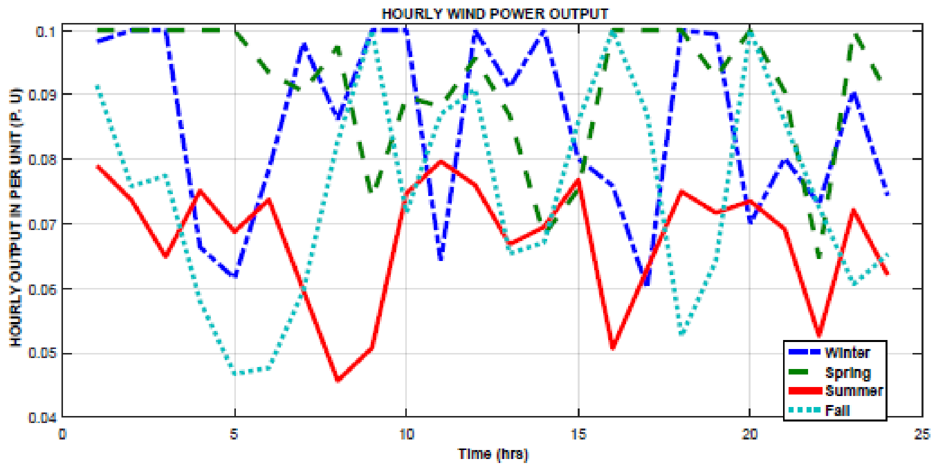

Figure 2.3. Hourly Wind Power Output

the O & M cost in our generation cost model.

2.2.4 Photovoltaic Systems

Characteristics / Principle of Operation

Solar electric or photovoltaic (PV) systems use technologies that converts sunlight into electricity. The basic device of a PV system is the PV cell, which may be grouped to form panels or arrays. First generation products use the same silicon wafers as in microelectronics. Second and third generation systems have high performing thin-films, with potential to greatly improve the economics of the material costs [73]. The silicon (Si) PV cells are composed of a thin Si film connected to the electric terminals. One of the sides of the Si layer is doped to form the p–n junction [74]. A thin metallic grid is placed on the sun-facing part of the semiconductor. This exposure to the radiation of the sun generates an electric current by transporting free carriers at the p-n junction that can be used as electric power when the circuit is closed. Alternate technologies that use gallium arsenide, amorphous silicon, copper indium di-selenide, and gallium indium phosphide in the production of high-efficiency multi-junction devices may eventually result in drastic improvement of PV system efficiencies. Further reading on the generation concept of PV systems can be found in [48, 74, 75].

The capital cost for PV systems is relatively high compared to fossil fuel power plants and some other renewable energy sources. The high capital cost is often tied to the high cost of semiconductors (silicon) used in the production of the PV array [76].

Mathematical Model

Technical models of the power output of PV systems also require uncertain input variables (solar irradiance and temperature) similar to that of wind. However, unlike wind speed, the variability of solar irradiance is not totally random. Its value is certain to be zero at nights and at dawn, thus the use of Weibull pdfs may not be appropriate in its modelling [77]. Consequently, a bimodal beta pdf model is used to model solar irradiance based on data obtained from historical records. To develop the model, the mean $\bar{\mathcal{S}}$ and standard deviation $\sigma_{\mathcal{S}}$ of the historical data solar irradiance are determined. The mean and standard deviation of the data is then used to compute parameters of the beta distribution α_i and β_i for all $i \in I_V$ where I_V is the set of solar energy resources:

$$\alpha_i = \bar{\mathcal{S}} \left(\frac{(1-\bar{\mathcal{S}})\bar{\mathcal{S}}}{\sigma_{\mathcal{S}}} - 1 \right) \tag{2.15}$$

$$\beta_i = (1-\bar{\mathcal{S}}) \left(\frac{(1-\bar{\mathcal{S}})\bar{\mathcal{S}}}{\sigma_{\mathcal{S}}} - 1 \right) \tag{2.16}$$

consequently the probability distribution function is calculated as a gamma function:

$$\mathbf{F}(\mathcal{S}) = \left(\frac{\Gamma(\alpha_i + \beta_i)(1-\mathcal{S})^{\beta_i - 1}\mathcal{S}^{\alpha_i - 1}}{\Gamma(\alpha_i)\,\Gamma(\beta_i)} \right) \tag{2.17}$$

The output power $(P_i^e(\mathcal{S}, \mathcal{T}))$ is then calculated as a function of the solar irradiance $(\mathcal{S})$ and ambient temperature $(\mathcal{T})$ as given by 2.18 below:

$$P_i^e(\mathcal{S}, \mathcal{T}) = \left(\frac{\mathcal{S}}{\mathcal{S}^{ref}} \right) P_i^{max} \left[1 + \lambda \left(\mathcal{T} - \mathcal{T}^{ref} \right) \right] \tag{2.18}$$

Where the maximum power output (P^{max}), reference temperature$(\mathcal{T}^{ref})$ and reference irradiance $(\mathcal{S}^{ref})$ is predetermined or provided on the manufacturers specification. Fig.2.4 also illustrates the output of a typical solar panel. Similar to the wind energy, no cost of generation is assumed for the PV system.

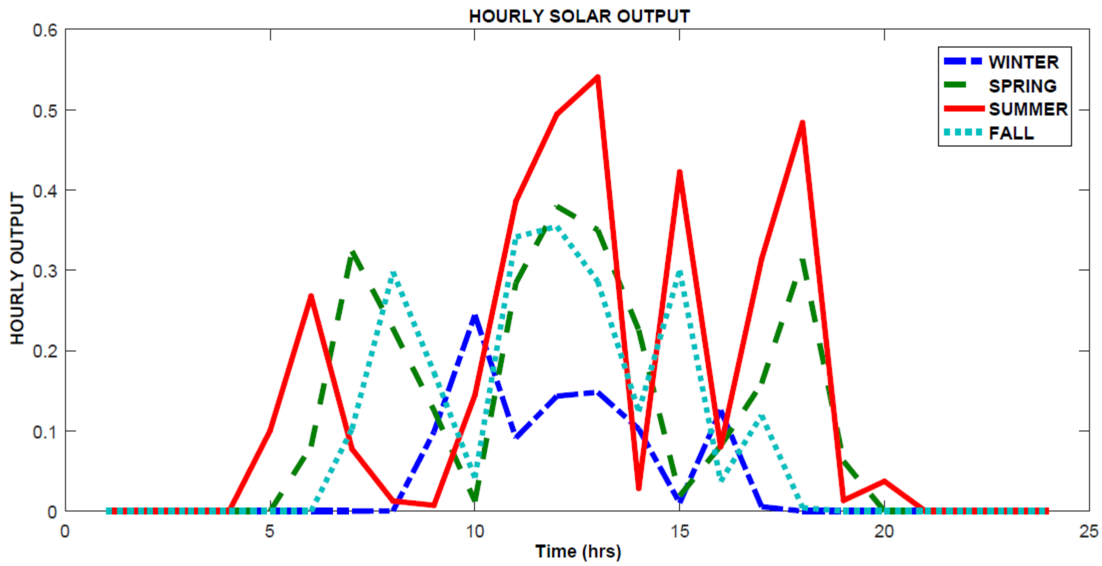

Figure 2.4. Hourly Solar Power Output

2.2.5 Energy Storage Systems (ESS)

Characteristics / Principles of Operation

An energy storage system is a device used to store energy. They usually store energy when the power system has surplus energy and may deliver energy during peak load periods or inadequacy in the power system's energy supply. ESS also coordinate with renewable resources and stores excess energy from these resources. When a storage technology is available, renewable generation can be used to its maximum potential to provide some cost savings. A brief overview of ESS types will help appreciate opportunities available for different energy storage technologies in the power system. ESS technologies can be classified as follows [78]:

Group 1 – The first group considered are ESS, capable of withdrawing electrical energy (electricity) from the grid, store the energy for a period of time and then re-inject this energy back into the grid. These type of ESS include flywheels, batteries, compressed air and pumped hydroelectric.

Group 2 – The second group of ESS are capable of withdrawing electrical energy (electricity) from the grid and store the energy for a period of time. However, instead of injecting it back into the grid, the stored energy is used to displace electricity consumption (demand) of their host facility at a later time. These type of ESS include, but not limited to, heat storage or ice production for space heating or cooling.

Group 3 –The final group looked at are ESS that only withdraw electricity from the grid like other loads but convert it into a storable form of energy or fuel that is subsequently used in an industrial, commercial or residential process or to displace a secondary form of energy. They are generally integrated with a host process that uses the secondary form of energy directly or are connected to a transmission or distribution network for their secondary form of energy (e.g., natural gas, steam or coolant). These type of ESS include fuel production (hydrogen or methane), steam production and electric vehicles.

Recent advancement in storage technology has led to the emergence of smart batteries on the market. Smart batteries are energy storage appliances that combine lithium battery modules with sophisticated power electronics to couple directly with solar energy systems. Electric vehicle manufacturers introduced the smart battery concept in 2015 and others following suit.

Various works have been reported in literature that model different storage technologies and the type of storage technology implemented usually informs the model used.

Mathematical Model

The thesis depart from a detailed dynamic model of a specific storage technology and adapt a simplified steady state model, that is applicable to all groups of storage technologies. The model can be extended and modified into detailed models for particular technology specification. General equations describing the steady state operation of an energy storage system with no transient characteristics are provided in (2.19)–(2.21) for all storage technologies $i \in I_S$:

$$E_i^e(y,t) = E_i^e(y,t-1) + \eta_i^e P_i^e(y,t)\Delta t \tag{2.19}$$

$$0 \le E_i^e(y,t) \le x_i \tag{2.20}$$

$$-\nu_i x_i \le P_i(y,t) \le \nu_i x_i \tag{2.21}$$

The variation of the state of charge ($E_i^e(y,t)$) depends on the charging/discharging power, the charging and discharging efficiency (η_i^e), and the storage capacity of the system (x_i).

The ESS technology considered dictates the value of v_i in (2.21). A larger v_i suggests a faster charging and discharging storage device and vice versa. Similar to wind and solar, the only costs associated with the ESS implementation are the fixed costs and variable costs of the ESS operations and maintenance (O&M) throughout the projected lifetime.

2.3 Microgrid Stakeholders and Ownership Models

Prior to analysing microgrid planning justification and business cases, one has to be clear about entities/parties in relation to whom these justification or benefits may accrue. These entities are referred to as *stakeholders or actors* in this thesis work. They can be people, groups, organizations, corporations, or systems who either have a direct financial interest in microgrids, or who will be affected in some way by its impacts. Stakeholders with direct financial interest may include but not limited to: the microgrid owner or an independent power producer (IPP), who owns and operates the microgrid and its DGs; the end-use microgrid customers (MGCs); the distribution network operator (DNO); and utilities or bulk energy suppliers (BESs), that may be impacted by activities of microgrids. Customers outside the microgrid, herein referred to as "Grid Customers" (GCs), are somewhere in between direct and indirect beneficiaries. They may directly be affected by the existence of microgrids, e.g. they may experience improved reliability or power quality as a result of microgrid islanding or providing ancillary services (AS); however, they do not often have financial stake [79] in microgrid projects. Here, society represents every entity not already listed that can be affected by externalities such as environmental and economic impacts of microgrids, whether directly or not.

The framework further adapts the use case paradigm approach to the microgrid context and implore the unified modeling language that allows the visualization of the complex relationship between stakeholders, microgrid parameters and functions, and microgrid benefits. Further details on microgrid parameters and its functions can be found in [17] and [18]. A simplified overview of the framework context in the thesis work is shown in Fig. 2.5 and chapter four of the thesis.

Microgrid Ownership Models

Three microgrid ownership models are identified and used in this thesis work. They include microgrid ownership by DNO, ownership by a customer or consortium of customers, and

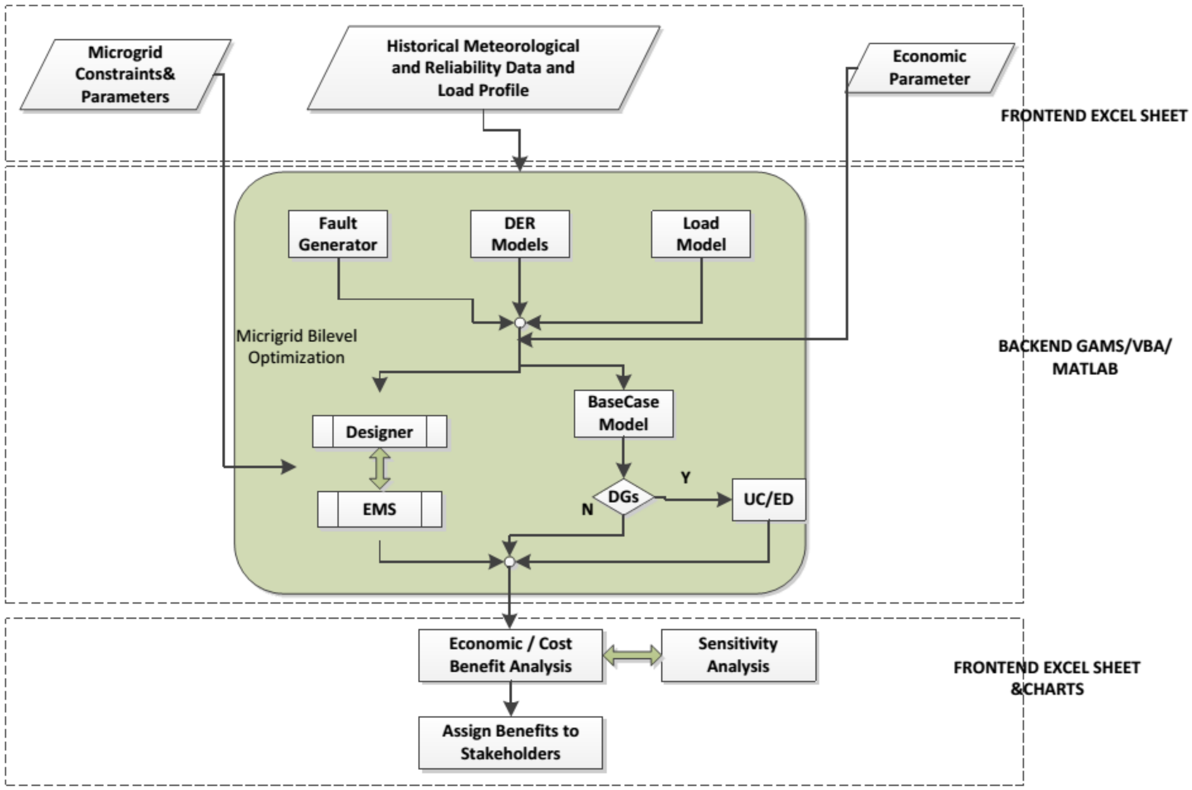

Figure 2.5. Simpliefied Overview of Framework and Tool

independent ownership [80]. In each case, the microgrid may tend to operate so as to maximize the benefit of the owning stakeholder. For example in a DNO or utility-owned cases, the microgrid would likely operate in a way that maximizes the distribution system's technical benefits and resilience interest, while the microgrid in a customer-owned model, on the other hand, would likely operate in a way that maximizes customers economic benefit.

Customer or Community Owned Microgrids

Customer owned microgrids are relatively small in size with the primary goal of supplying enough power to meet customers' demand. The major investing entity in this type of microgrid ownership structure is the customer or consortium, hence, majority of the benefits accrued in these microgrid implementation are allocated to customers. Applicable microgrid types may include campus microgrids, grid connected military and mining microgrids, microgrids for prison facilities and some few remote microgrids.

Independent Power Producers Microgrids

In an IPP-owned model, a variety of demands and interest must be balanced. Here, it has been suggested that with the right financial incentives in place, profit maximization in an independent or free-market model can optimize benefits for all stakeholders. That is, impacts and resultant benefits can generally be increased by taking into account their value in an economic dispatch of microgrid assets. This valuation can be done by means of market price signals, which for example, might cause the microgrid to import less power in times of high demand, or by some other means of controlling a microgrid's dispatch.

Applicable microgrid types may include urban micorgrids with independent power supplier or bulk energy suppliers.

Utility Owned Microgrids

Utility owned microgrids are relatively big in size and cover a larger service area. Obviously, the major investing entity is the utility or DNO, hence majority of the benefits accrued from these implementations are allocated to the Utility. Applicable microgrid types may include urban microgrids, some remote microgrids and commercial microgrids.

2.4 Conclusion

Different models of DERs incorporated into the microgrid planning framework of the thesis work have been discussed in this chapter. Concepts, assumptions and limitation of the models used in the work have been outlined. Here, the polynomial curve fitting method is employed to estimated the efficiency of generators at any loading point, while the Weibull distribution model is used to estimate the stochastic nature of wind energy. ESS are classified into groups to project opportunities available for different energy storage technologies in the power system. The use of a simplified steady state model of ESS is determined to be a better option for purposes of the thesis work. The chapter further explained the adoption of the unified modeling language to the microgrid context; here, microgrid ownership models and stakeholders relative to whom economic justification of microgrid investments are made are defined. Stakeholders identified in the chapter include the utility operator or DNO, customers, society and independent power producers. The chapter concludes that not all stakeholders are necessarily investing entities of the micorgrid. Consequently, they are impacted differently by microgrid projects.

Chapter 3

Bi–level Planning Models of Microgrids

3.1 Introduction

This chapter introduces bi–level formulation for coupled microgrid planning models. The chapter begins with an outline of a bi-level formulation for a coupled microgrid planning and operation problem. It details mathematical equations that characterize the primal formulation of the problem and assess its convexity. The Karush-Kuhn-Tucker (KKT) conditions and the strong duality theorem are considered in transforming the primal formulation into an MPEC. The chapter provides an overview of the transformed MPEC and its further linearization into an equivalent MILP. Application of the proposed formulation to the planning of the energy infrastructure of an off-grid mine is discussed. Later part of the chapter introduces an emerging concept of a new DSO construct and outlines another bi–level formulation that fits the narrative of the emerging concept. It extends the bi–level formulation approach to solve a coupled microgrid power and reserve planning problem, within the context of a DSO. The chapter provides a case study implementation of the proposed formulation to a Canadian utility network and compares results obtained to that of a traditional multi–objective optimization approach.

3.2 Bi–level Formulation for a Microgrid Planning and Operation Problem

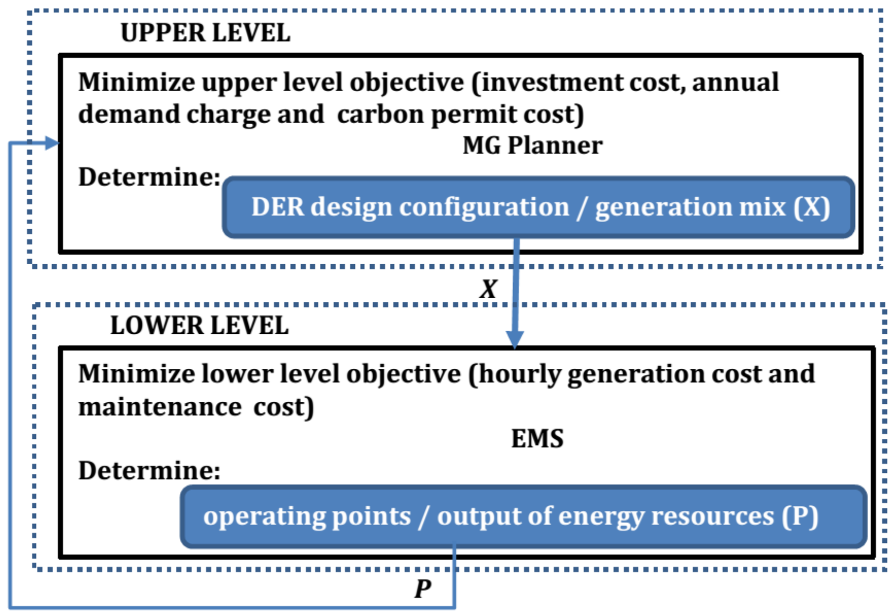

Figure 3.1. Schematic diagram of the bilevel design-operating model.

3.2.1 Bi–level Model Outline

A key component of the planning framework of this thesis work is the optimization engine. The optimization engine characterizes an hierarchical decision making model for a coupled microgrid planning and operational problem. The model is formulated as a bi–level optimization problem, where each level independently controls its decision variable as illustrated in Fig. 3.1. Here, the microgrid designer, acting as the leader, is represented by the upper level problem while the lower level problem represents the EMS (a proxy operator) which acts as the follower. The designer receives input information about the planning horizon, peak load, available DER options with their possible ratings and economic parameters *i.e.*, capital costs of DERs, interest rate, budget constraints and other capital expenses. It then selects a design configuration (capacity of DERs, $x_i, \forall i \in I_B$, where I_B is the set of all DER options) seeking to maximize its payoff, and passes it to the EMS. The design capacities from the upper level, serve as parameters in the lower level problem defining the inducible region of the lower level problem. The EMS thus determines the operating points of the DERs minimizing hourly running costs based on the parameters received. The hourly running costs and DER set points (P_i) are passed back to the upper level to evaluate the total cost over the entire planning horizon. The designer, observing the EMS' selection, optimizes its objective and passes a new configuration to the lower level problem. This process is repeated until an equilibrium is found where neither level has an incentive to change their selection.

Design – Upper Level Problem

The upper level objective function in (3.1) minimizes the annualized investment cost of the new DERs (first and second terms) and the annual demand charge by the remote community energy provider or utility if grid connected (third term) and the cost of carbon permit or allowance purchases (fourth term). The variable x_i denoting the design capacities of each DER option to be installed is the solution to the upper level's problem. The total planning cost is converted into its present value by a factor γ, with ϱ_y being the capital recovery factor.[1] The objective function is constrained by a budget allocation for investment (3.2) and the maximum allowable carbon permits purchased (3.3). The parameter ζ_i denotes CO_2 emitted by resource i per kWh.

$$\min_{x,\mathcal{U},\Upsilon\geq 0} \gamma \sum_{y\in Y} \left\{ \varrho_y \left(\sum_{i\in I_{\bar{B}}} C_i^c x_i + \sum_{i\in I_S} C_i^c x_i \right) + C_y^d(\mathcal{U}_y^p) + C_y^{CO_2}(\Upsilon_y) \right\} \tag{3.1}$$

subject to

$$\sum_{i\in I_{\bar{B}}} C_i^c x_i + \sum_{i\in I_S} C_i^c x_i \leq C^b \tag{3.2}$$

$$\sum_{i\in I_G} \sum_{t\in T} \zeta_i P_i^e(y,t) + \sum_{i\in I_H} \sum_{t\in T} \zeta_i P_i^h(y,t) \leq (\Upsilon_y) \tag{3.3}$$

where $\mathcal{U}_y^p$ is the maximum demand from the remote community energy provider or

[1] By definition, the capital recovery factor in year y is $\varrho_y = [\mathcal{Z}(\mathcal{Z}+1)^y]/[(\mathcal{Z}+1)^y - 1]$, where $\mathcal{Z}$ is the annual interest rate. Moreover, $\gamma = [1-(\mathcal{Z}+1)^{-J}]/\mathcal{Z}$ is used to bring all annual values to the present, where J is the length of the planning horizon in years. Here the investment cost is thought of as a loan that converts the capital cost into a series of equal annual payments that eventually pay off the loan with interest.

utility (U) and given by 3.4 for all $i \in I_U$

$$\mathcal{U}_y^p \geq P_i \tag{3.4}$$

EMS – Lower Level Problem

The formulation of the lower level problem, equivalent to an EMS solving an economic dispatch problem in a given time period t, is given by (3.5)–(3.19). The objective function defined by (3.5) minimizes the hourly operational cost in period t, given fuel cost (first term), the costs of providing heat from a non-CHP resource (second term), the cost of electric energy from the neighbouring remote community provider or utility (third term), the maintenance cost of the new DERs as well as the existing units (fourth and fifth terms, respectively).

$$\begin{aligned} P_i^e(y,t), P_i^h(y,t) \in \underset{P}{\operatorname{argmin}} & \sum_{i \in I_G} C_i^f P_i^e(y,t) + \sum_{i \in I_H} C_i^f P_i^h(y,t) \\ & + \sum_{i \in (I_U \subset I_E)} C_i^e P_i^e(y,t) + \sum_{i \in B} C_i^o x_i + \sum_{i \in I_A} C_i^o \mathcal{A}_i \end{aligned} \tag{3.5}$$

The lower level objective is constrained by hourly electrical and thermal generation and load balances, (3.6) and (3.7). The electrical power balance for all hours $t \in T$ and years $y \in Y$ is

$$\sum_{i \in I_E} P_i^e(y,t) = L^e(y,t); \qquad \lambda(y,t) \tag{3.6}$$

while the thermal power balance requires that, for each hour t of all years y

$$\sum_{i \in I_H} P_i^h(y,t) = L^h(y,t); \qquad \phi(y,t) \tag{3.7}$$

where $\lambda(y,t)$ and $\phi(y,t)$ are the Lagrange multipliers associated with those constraints.[2]

The hourly dispatch problem is further constrained by maximum and minimum limits of the dispatchable generating resources, (3.9). Other DERs considered here are CHP units, wind turbines and ESS. Modeling of the operational output of the combined heat and power

[2]All Greek letters appearing to the right of semicolons represent Lagrange multipliers of the various constraints presented along the length of the paper.

unit is similar to that of a diesel generating unit as explained in the previous chapter. The relationship between the thermal and electric load in this formulation is provided in (3.8). Wind generation is non-dispatchable and the uncertainty associated with its speed is modeled based on the Weibull distribution function as outlined in [12], [81] and also provided in the previous chapter. Energy from storage technologies available within the microgrid are also used to mitigate the deviation of wind from its forecasted values. The design capacities of potential DERs x_i, passed by the upper level, serve as maximum limits of the operational output of these resources as found in (3.10). The heat output from the CHP system is given by

$$P_i^h(y,t) = \frac{P_i^e(y,t)}{\varsigma_i}; \qquad \omega_i(y,t) \tag{3.8}$$

for all $i \in I_N$, $t \in T$ and $y \in Y$. The generation limits are

$$P_i^{\min} \leq P_i^e(y,t) \leq P_i^{\max}; \qquad \alpha_i^{\min}(y,t), \alpha_i^{\max}(y,t) \tag{3.9}$$

for all $i \in I_D$, $t \in T$ and $y \in Y$, in addition

$$0 \leq P_i^e(y,t) \leq x_i; \qquad \delta_i^{\min}(y,t), \delta_i^{\max}(y,t) \tag{3.10}$$

for all $i \in I_{\bar{B}}$, $t \in T$ and $y \in Y$.

General equations describing the operation of ESS and its constraints are provided in (3.11)–(3.13). The variation of the state of charge (SOC) E_i^e in (3.11) as mentioned in the previous chapter depends on the charging/discharging power, the charging and discharging efficiency, and the storage capacity of the system. The maximum available energy (3.12) is constrained by the design capacity passed by the upper level problem. The charging and discharging power limits of the storage device are outlined in (3.13). The constant ν_i in (3.12) is dependent on the type of storage technology installed. A larger ν_i suggests a faster charging and discharging storage device and vice versa. Here, for each ESS resource $i \in I_S$, hours $t \in T$ and years $y \in Y$.

$$E_i^e(y,t) = E_i^e(y,t-1) + \eta_i^e P_i^e(y,t)\Delta t \quad ;\rho_i(y,t) \tag{3.11}$$

$$0 \le E_i^e(y,t) \le x_i \qquad ;\pi_i^{\min}(y,t), \pi_i^{\max}(y,t) \tag{3.12}$$

$$-\nu_i x_i \le P_i(y,t) \le \nu_i x_i \quad ;\xi_i^{\min}(y,t), \xi_i^{\max}(y,t) \tag{3.13}$$

Similarly, the dispatch problem is also subject to limits on energy available for both electrical (3.14), (3.15) and thermal DR resources (3.17), (3.18). Equations (3.16) and (3.19) outline constraints on the hourly electric and thermal power available for DR respectively. Note that parameters κ_r^e and κ_r^h are dependent on the DR technology/strategy used. The electric-side demand response has to satisfy

$$E_r^e(y,t) = E_r^e(y,t-1) + P_r^e(y,t)\Delta t; \qquad \chi(y,t) \tag{3.14}$$

$$0 \le E_r^e(y,t) \le w_r^e L^{e,\max}; \qquad \vartheta^{\min}(y,t), \vartheta^{\max}(y,t) \tag{3.15}$$

$$-\kappa_r^e w_r^e L^{e,\max} \le P_r^e(y,t) \le \kappa_r^e w_r^e L^{e,\max}; \qquad \varphi^{\min}(y,t), \varphi^{\min}(y,t) \tag{3.16}$$

and the thermal load is flexible according to, for all $t \in T$ and $y \in Y$,

$$E_r^h(y,t) = E_r^h(y,t-1) + P_r^h(y,t)\Delta t; \qquad \beta(y,t) \tag{3.17}$$

$$0 \le E_r^h(y,t) \le w_r^h L^{h,\max}; \qquad \theta^{\min}(y,t), \theta^{\max}(y,t) \tag{3.18}$$

$$-\kappa_r^h w_r^h L^{h,\max} \le P_r^h(y,t) \le \kappa_r^h w_r^h L^{h,\max}; \qquad \psi^{\min}(y,t), \psi^{\max}(y,t) \tag{3.19}$$

It should be noted that uncertainty in operations – *e.g.*, coming from uncertain wind and solar generation could be considered by having several operating scenarios at the lower level. Concretely, this would turn the problem into a single-leader, multiple-follower bilevel problem, where each low-level follower would optimize its operations based on its given operating scenario for the common microgrid configuration provided by the leader. The upper-level leader's task would be to configure the microgrid based on probability-weighted operating costs coming from the low-level operating scenarios. The designer would find a compromise between the need to minimize the costs of the average operating scenario, while also appraising the value of being able to operate adequately for low-probability scenarios. Nonetheless, it is worth noting that the main downside of this would be the multiplication of lower level variables and constraints by the number of scenarios considered.

3.2.2 Co-Linearity and Justifying a Bi–level Planning Approach

Bi–level programming problems are closely related to multi–objective (and multistage) optimization problems. This relation has been illustrated in [82] and can be observed considering[3] the bi–level problem $\mathcal{B}$, which consists of (3.20)–(3.23), and the multi-objective problem $\mathcal{M}$, (3.24)–(3.26):

$$(\mathcal{B}) \qquad \min_{x,y} cx \tag{3.20}$$

subject to

$$y = \underset{y}{\operatorname{argmin}}(dx + fy) \tag{3.21}$$

$$Ax + By \leq a \tag{3.22}$$

$$Cy \leq b \tag{3.23}$$

and

$$(\mathcal{M}) \qquad \min_{x,y} cx + dx + fy \tag{3.24}$$

subject to

$$Ax + By \leq a \tag{3.25}$$

$$Cy \leq b \tag{3.26}$$

Here, it is easy to observe that a solution of the bi–level programming problem $\mathcal{B}$ is Pareto optimal for the corresponding multi-objective optimization problem $\mathcal{M}$ if $c = \xi d$, where $\xi > 0$, and $c, d \in \mathbb{R}^n$. Thus, in such cases, where vectors c and d are *co–linear* the bi–level problem $\mathcal{B}$ reduces to the multiobjective (single-level) problem $\mathcal{M}$. Otherwise, when vectors c and d are not co-linear, problems $\mathcal{B}$ and $\mathcal{M}$ will have different solutions [83], with $\mathcal{B}$ not realizing more optimistic results than $\mathcal{M}$.

Bi–level problem formulations ($\mathcal{B}$) are meant to tradeoff conflicting objectives, just like multi–objective problems ($\mathcal{M}$). Bi–level problems find the best cx satisfying the constraints

[3]The variables used here are for illustrative purposes and do not relate to the problem at stake in this thesis.

(3.22) and (3.23), while constraining y on the basis of the prior choice of x. Improvements in cx are possible until no feasible y are found, which means that here we find *one* solution.

On the other hand, with multi–objective problems, the objectives cx and $dx + fy$ are considered on the same footing. At the optimum, although changing x would affect y (through the need to maintain feasibility), an improvement in cx would lead to a corresponding degradation in the second objective $dx + fy$. The Pareto front, where the sum of the sub-objectives is minimized, represents a *set* of solutions of equal quality. The selection of one solution over the others would generally involve some degree of subjectivity.

The effective lack ambiguity of bi–level problem formulations is what makes them attractive in the context of this work. It is however, worthy to note that multi-objective problems may have an advantage of being relatively small and thus more efficient. While addressing the planning of a microgrid, the focus of its optimization and decisions should be at the strategic level: the choice of assets and their ratings, emission permits' management and the reliance or lack thereof on external power sources. For sure these choices are bound to have repercussions on day-to-day operations, as the lower level problem captures.

As will be seen in the following section, the solution of bi–level optimization problems is nontrivial in comparison to their multi–objective counterparts. Therefore, it is essential to ascertain that indeed the upper and lower level problems' objectives are not co-linear. It can be observed from (3.1) and (3.5) that this is indeed the case because the upper-level variable $\mathcal{U}_y^p$, which is there to capture the annual capacity charge for drawing peak power from the neighbouring community system or utility is not present at the operational level. Therefore, the problem we are tackling here is a true bi–level problem.

3.2.3 Convexity

Bi–level problems are usually difficult to solve; even the linear bi–level problem is an NP-hard problem [84]. A problem is said to be NP-hard (non deterministic polynomial time) if an algorithm for solving it can be translated into one for solving any other NP–problem and an NP–problem is a problem solvable in polynomial time by a non–deterministic Turing machine. Thus in order to decide on the algorithm to be used in solving the proposed bi–level problem, one has to ensure that the problem is well posed and determine its convexity.

In an effort to simplify the understanding of this section, we begin by providing some basic notation and theoretical characteristics of the bi–level problem:

(a) Constraint region ($\mathcal{F}$) of the bi–level Problem:

$$\mathcal{F} \triangleq \{(x_i, P_i) : x_i \in X, P_i \in \mathcal{P},\ \text{Constraints}(3.2)-(3.3),\ \text{Constraints}(3.6)-(3.19)\} \quad (3.27)$$

where P_i is the lower level variables and X and $\mathcal{P}$, are the set of upper level and lower level variables.
(b) Feasible set $\mathcal{H}$ for the follower for each fixed $x_i \in X$:

$$\mathcal{H} \triangleq \{P_i \in \mathcal{P} :\ \text{Constraints}(3.6) - (3.19))\} \quad (3.28)$$

(c) Projection of $\mathcal{H}$ onto the leader's decision space:

$$\mathcal{H}(X) \triangleq \{(x_i, P_i) : x_i \in \mathcal{X}, P_i \in \mathcal{P},\ \text{Constraints}(3.2) - (3.3),\ \text{Constraints}(3.6) - (3.19)\} \quad (3.29)$$

To ensure that the bi–level problem is well posed, one could assume that $\mathcal{F}$ is nonempty and compact, and that for all decisions taken by the designer, the EMS has some room to respond. The rational reaction set $\mathbf{J}(x_i)$ defines the response of the EMS while the inducible region **IR** represents the set over which the designer may optimize.
(d)Follower's rational reaction set $\mathcal{F}$ for $x_i \in X$:

$$\mathbf{J}(x_i) \triangleq \{P_i \in \mathcal{P} : P_i \in \arg\min[f(x_i, \hat{P}_i) : \hat{P}_i \in S(x_i)]\} \quad (3.30)$$

(e)Inducible Region(**IR**):

$$\mathbf{IR} \triangleq \{(x_i, P_i) : (x_i, P_i) \in \mathcal{H} : P_i \in \mathbf{J}(x_i)\} \quad (3.31)$$

With the linearization of the generation cost function and an assumed constant charging and discharging efficiency of the storage device, for each value of the upper level variable x_i, the lower level problem is proven to be linear (thus convex) as parametric in x_i, $\forall i \in I_B$. Nonetheless the two problems (upper and lower level problems) becomes non-linear and therefore needs to be transformed and linearized. Appendix B.1 details geometric illustration of how the two problems when combined together becomes non–linear.

3.2.4 MPEC Transformation and Linearization

The aforementioned bi–level formulation for the combined microgrid planning and EMS problems can be transformed into a single level problem and solved jointly, since the lower level's rational reactional set is assumed to be non empty and its inducible region proven to be singleton [84]. Hence, there are two practical options in solving this problem:

1. KKT formulation: to replace each lower-level problem by its corresponding Karush-Kuhn-Tucker (KKT) conditions.

2. Primal-dual formulation: to replace each lower-level problem by its primal constraints, its dual constraints, and by enforcing the strong duality theorem (SDT) equality.

KKT Condition

Thus, we first discuss the KKT transformation of the problem. Here, the lower level problem (3.5)–(3.19) of the bi–level model is replaced by the KKT conditions of the formulation, thus transforming the model into a single level problem as outlined in (3.32)–(3.61). The transformed problem for all $t \in T$ and $y \in Y$ becomes a minimization of the upper level's objective function:

$$\min_{x \geq 0} (3.1) \tag{3.32}$$

subject to its primal constraints and the lower level's primal:

$$\text{Constraints } (3.2) - (3.3) \tag{3.33}$$

$$\text{Constraints} (3.6) - (3.19) \tag{3.34}$$

as well as feasible dual constraints of the lower level's problem

$$C_i^f - \lambda(y,t) - \alpha_i^{\min}(y,t) + \alpha_i^{\max}(y,t) = 0 \ \forall i \in I_D \tag{3.35}$$

$$C_i^f - \lambda(y,t) - \delta_i^{\min}(y,t) + \delta_i^{\max}(y,t) - \frac{\omega_i(y,t)}{\varsigma_i} = 0 \ \forall i \in I_N \tag{3.36}$$

$$-\lambda(y,t) - \delta_i^{\min}(y,t) + \delta_i^{\max}(y,t) = 0 \ \forall i \in I_W \tag{3.37}$$

$$-\lambda(y,t) - \xi_i^{\min}(y,t) + \xi_i^{\max}(y,t) - \rho_i(y,t) = 0 \ \forall i \in I_S \tag{3.38}$$

$$-\rho_i(y,t) - \pi_{y,i}^{\min}(t) + \pi_{y,i}^{\max}(t) = 0 \ \forall i \in I_S \tag{3.39}$$

$$-\lambda(y,t) - \varphi^{\min}(y,t) + \varphi^{\max}(y,t) - \chi(y,t) = 0 \tag{3.40}$$

$$-\vartheta^{\min}(y,t) + \vartheta^{\max}(y,t) - \chi(y,t) = 0 \tag{3.41}$$

$$-\phi(y,t) - \psi^{\min}(y,t) + \psi^{\max}(y,t) - \beta(y,t) = 0 \tag{3.42}$$

$$-\theta^{\min}(y,t) + \theta^{\max}(y,t) - \beta(y,t) = 0 \tag{3.43}$$

$$-\phi^{\min}(y,t) + \omega_i(y,t) = 0 \tag{3.44}$$

$$C_i^f - \phi(y,t) = 0 \ \forall i \in I_H \tag{3.45}$$

and their complementary slackness:

$$\alpha_i^{\min}(y,t)(P_i^e(y,t) - P_i^{\min}) = 0 \quad \forall i \in I_D \tag{3.46}$$
$$\alpha_i^{\max}(y,t)(P_i^{\max} - P_i^e(y,t)) = 0 \quad \forall i \in I_D \tag{3.47}$$
$$\delta_i^{\min}(y,t)(P_i^e(y,t)) = 0 \quad \forall i \in I_{\bar{B}} \tag{3.48}$$
$$\delta_i^{\max}(y,t)(x_i - P_i^e(y,t)) = 0 \quad \forall i \in I_{\bar{B}} \tag{3.49}$$
$$\pi_i^{\min}(y,t)(E_i(y,t)) = 0 \quad \forall i \in I_S \tag{3.50}$$
$$\pi_i^{\max}(y,t)(x_i - E_i(y,t)) = 0 \quad \forall i \in I_S \tag{3.51}$$
$$\xi_i^{\min}(y,t)(P_i^e(y,t) + v_i x_i) = 0 \quad \forall i \in I_S \tag{3.52}$$
$$\xi_i^{\max}(y,t)(v_i x_i - P_i^e(y,t)) = 0 \quad \forall i \in I_S \tag{3.53}$$
$$\vartheta^{\min}(y,t)(E_r^e(y,t)) = 0 \tag{3.54}$$
$$\vartheta^{\max}(y,t)(w_r^e L_r^{e,max} - E_r^e(y,t)) = 0 \tag{3.55}$$
$$\varphi^{\min}(y,t)(P_r^e(y,t) + k_r^e w_r^e L^{e,max}) = 0 \tag{3.56}$$
$$\varphi^{\max}(y,t)(k_r^e w_r^e L^{e,max} - P_r^e(y,t)) = 0 \tag{3.57}$$
$$\theta^{\min}(y,t)(E_r^h(y,t)) = 0 \tag{3.58}$$
$$\theta^{\max}(y,t)(w_r^h L_r^{h,max} - E_r^h(y,t)) = 0 \tag{3.59}$$
$$\psi^{\min}(y,t)(P_r^h(y,t) + k_r^h w_r^h L^{h,max}) = 0 \tag{3.60}$$
$$\psi^{\max}(y,t)(k_r^h w_r^e L^{h,max} - P_r^h(y,t)) = 0 \tag{3.61}$$

The complementary slackness can be linearized by disjunctive constraints proposed in [85] and detailed in appendix C.1.

Strong Duality Approach

Transforming the bi-level problem based on the strong duality approach is similar to the KKT conditions approach except for the complementary slackness. This transformation comprises replacing the lower level problem of the original model with its primal constraints (3.6)–(3.19) and its feasible dual constraints (3.65)–(3.75). This is combined with the equality associated with the strong duality approach (3.76) and the upper level problem (3.1)–(3.3) to make up the transformed MPEC.

$$\min_{x \geq 0}(3.1) \tag{3.62}$$

subject to

$$\text{Constraints } (3.2) - (3.3) \tag{3.63}$$

$$\text{Constraints}(3.6) - (3.19) \tag{3.64}$$

dual constraints

$$C_i^f - \lambda(y,t) - \alpha_i^{\min}(y,t) + \alpha_i^{\max}(y,t) = 0 \ \forall i \in I_D \tag{3.65}$$

$$C_i^f - \lambda(y,t) - \delta_i^{\min}(y,t) + \delta_i^{\max}(y,t) - \frac{\omega_i(y,t)}{\varsigma_i} = 0 \ \forall i \in I_N \tag{3.66}$$

$$-\lambda(y,t) - \delta_i^{\min}(y,t) + \delta_i^{\max}(y,t) = 0 \ \forall i \in I_W \tag{3.67}$$

$$-\lambda(y,t) - \xi_i^{\min}(y,t) + \xi_i^{\max}(y,t) - \rho_i(y,t) = 0 \ \forall i \in I_S \tag{3.68}$$

$$-\rho_i(y,t) - \pi_{y,i}^{\min}(t) + \pi_{y,i}^{\max}(t) = 0 \ \forall i \in I_S \tag{3.69}$$

$$-\lambda(y,t) - \varphi^{\min}(y,t) + \varphi^{\max}(y,t) - \chi(y,t) = 0 \tag{3.70}$$

$$-\vartheta^{\min}(y,t) + \vartheta^{\max}(y,t) - \chi(y,t) = 0 \tag{3.71}$$

$$-\phi(y,t) - \psi^{\min}(y,t) + \psi^{\max}(y,t) - \beta(y,t) = 0 \tag{3.72}$$

$$-\theta^{\min}(y,t) + \theta^{\max}(y,t) - \beta(y,t) = 0 \tag{3.73}$$

$$-\phi^{\min}(y,t) + \omega_i(y,t) = 0 \tag{3.74}$$

$$C_i^f - \phi(y,t) = 0 \ \forall i \in I_H \tag{3.75}$$

and the strong duality equality

$$\begin{aligned}
&\sum_{i\in I_G} C_i^f P_i^e(y,t) + \sum_{i\in I_H} C_i^f P_i^h(y,t) \\
&= \lambda L^e(y,t) + \sum_{i\in I_D} (\alpha_i^{\min}(y,t)P_i^{\min} - \alpha_i^{\max}(y,t)P_i^{\max}) \\
&- \sum_{i\in I_{\bar{B}}} \delta_i^{\max}(y,t)x_i - \sum_{i\in I_S}(v_i\xi_i^{\min}(y,t)x_i + v_i\xi_i^{\max}(y,t)x_i) \\
&- \sum_{i\in I_S} \left(\pi_{y,i}^{\max}(y,t)x_i - \rho_i(y,t)E_i(y,t-1)\right) \\
&+ \chi(y,t)E_r^e(y,t-1) - w_r^e\vartheta^{\max}(y,t)L^{e,\max} \\
&- (\varphi^{\min}(y,t)k_r^e w_r^e L^{e,\max} + \varphi^{\max}(y,t)k_r^e w_r^e L^{e,\max}) \\
&+ \phi(y,t)L^h(y,t) + \beta(y,t)E_r^h(y,t-1) - \theta^{\max}(y,t)w_r^h L^{h,\max} \\
&- (k_r^h w_r^h \psi^{\min}(y,t)L^{h,\max} + k_r^h w_r^h \psi^{\max}(y,t)L^{h,\max})
\end{aligned} \tag{3.76}$$

The primal–dual approach has been demonstrated in [86] and [87] to be more efficient than the KKT option. The complementary slackness present in the KKT approach is eliminated in the second formulation via the strong duality theorem in which the primal and the dual objective functions are equated. Given that, we take the primal-dual approach in this work.

The non-linearities associated with the products of variables $\delta_i^{\max}(y,t)x_i$, $v_i\xi_i^{\max}(y,t)x_i$, $v_i\xi_i^{\min}(y,t)x_i$ and $\pi_i^{\max}(y,t)x_i$ in (3.76) of the MPEC can be linearized at the expense of more constraints and auxiliary variables, transforming the problem into an equivalent MILP problem [60, 88, 89]. An overview of the linearization of (3.76) is outlined in the Appendix C.2. Note that all the Lagrange multipliers are positive variables here.

3.2.5 Case Study

The proposed bi–level design approach is applied to a microgrid implementation of a remote mine in northern Quebec, Canada. The energy infrastructure of remote mines is characterized by unique features that differentiate them from most remote community microgrids. A remote mine is an intensive energy user with rated load in the range of 5 MW to 650 MW of peak load depending on the type of product mined and the process employed [90]. Its load profile is often very steady with a little fluctuation over the course of a day. High reliability is required of these sites for worker safety and for economic reasons (auxiliary back-up is indispensable). Load growth in most mines often occurs during the first few years of production as new sections of operation are opened. Once a steady production is attained, load growth in subsequent years is unlikely. In addition, for most mines surface and sub-surface ventilation represent a base electrical load [62]. The adoption of ventilation on demand technology, however, allows these loads to be regulated, making it possible to implement demand response strategies.

The peak electric load of the mine considered here is 10 MW with an average load of 9.5 MW. This load is currently supplied by a 5 MW diesel generator and two smaller 1.5 MW units. Space heating at the mine site is provided by a gas-fired heat exchanger. The diurnal and annual daily heating and cooling profiles from [62, 91] are adapted for this work. Seven day type loads are considered in modeling the entire monthly load. These day types represent 5 weekdays and 2 weekend days in a week. They are aggregated by a factor based on the numbers of day type in a particular month. The weekly profile is then modeled for each and every month to reflect the seasonality in the year. Ten percent of the mine's electrical and heating load is assumed to be available for DR. The mine has been in operation for some years now so load growth is negligible. It is also known to have some level of control and communication devices already installed to regulate its load during emergencies; hence, additional costs to implement DR are negligible. The cost of diesel fuel delivered at the mine location is relatively high due to limited transportation options for diesel. Fuel escalation rate based on historical pattern is also considered. Here, fuel escalation rate refers to the rate at which the cost or price of fuel will change within a defined economic period (in our case annual). ESS technology considered is a new generation compressed air energy storage system with a ratio of energy storage capacity to power capacity of four hours. The hypothetical layout of the mine with some modification is provided in Fig. 3.2.

Three planning scenarios are considered for expanding the energy infrastructure of the existing remote microgrid: i) the base case plus wind power generation, ii) the base case plus wind power generation and ESS, and iii) the base case plus wind power generation, ESS and demand response. Economic parameters of the mine and other required data are provided in Table 3.1. Moreover, a capital cost allowance of 50% is considered for corporate tax purposes.

The cost associated with CO_2 emission ($C_i^{\wp}$) is taken to be 14.32 $/t$CO_2$, the clearing price of carbon permits in an auction window on the carbon market.

Table 3.1
Summary of Input Parameters

Diesel Generators		**Wind Turbine**	
Diesel cost [92]	5 \$/ℓ	Capital cost [93]	2213 \$/kW
Fixed O &M [92]	15 \$/kW/yr	Fixed O&M [93]	10 \$/kW/yr
Variable O&M [92]	3 \$/MWh	**Biomass**	
Emission rate [94]	2.64 kgCO_2/ℓ	Capital cost [93]	4114 \$/kW
ESS		**Remote Energy Provider**	
Capital cost [95]	600 \$/kW	Cost of energy supplied	0.8 \$/kWh
CHP		**Financial Parameters**	
Capital cost [29]	1200 \$/kW	Interest rate	3.5 %
Natural gas cost [29]	3.1 \$/GJ	Planning horizon	20 yrs
O&M Cost [29]	0.006 \$/kWh	Carbon permits	14.3 \$/ton CO_2
		Fuel escalation rate	3 %

3.2.6 Results and Discussion

Investment Decisions

The above case study is evaluated using a custom-made Excel tool interfacing with the CPLEX solver of GAMS, termed BIEX (Bi–level Excel). To validate the proposed approach, the results are compared with those of DER-CAM (a commercially accepted software based on the traditional MILP) [8] and the output is presented in Table 3.2. Both tools were provided with the same input data and parameters to make the comparison reliable. From Table 3.2, it could be observed that the total cost (capital plus operating) of BIEX is lower than that of DER-CAM and the Multi–objective optimization(MOO) alternative [44], although their optimal configuration is comparably similar. This could be attributed to better representation of the order of the decision making process by BIEX. Here, the operator has a better perspective of the designer's decision, hence its solution lead to a lower operation cost in BIEX compared to DER-CAM, where both problems are solved concurrently. Also, the BIEX solution is compared to that of the MOO where the

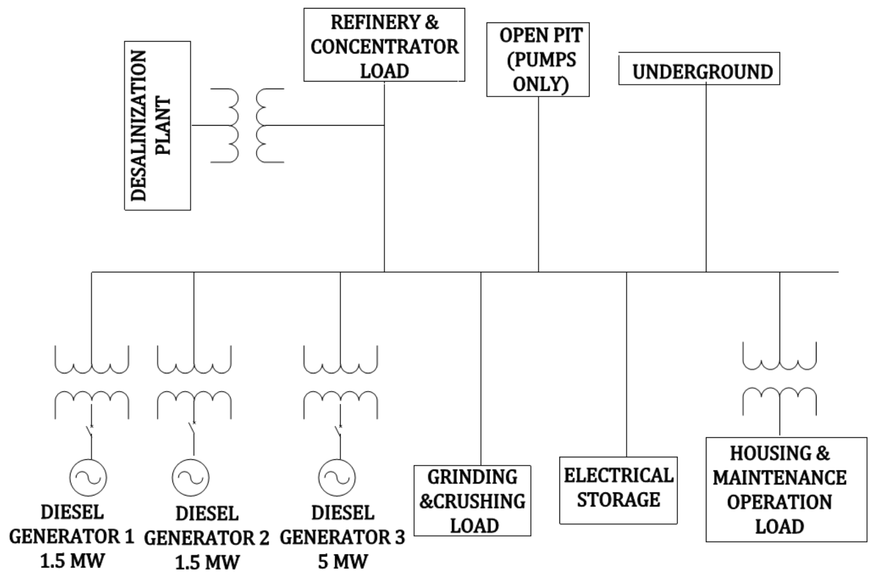

Figure 3.2. Schematic Diagram of the Remote Mine's Power System.

cost of planning is co–optimized with operational cost to illustrate the difference in the two approach. From Table 3.2, it can be observed that, the bi–level model provided a less expensive configuration compared to the MOO. This is due to its selection of a lesser capacity of the expensive biomass although the biomass has a higher capacity factor. Also, the hierarchical nature of the formulation makes it possible for the upper level problem to increase its interest (shift from the pareto optimal) without necessary being detrimental (to the disadvantage) to the lower level; however, the MOO formulation may have to find a compromise (pareto optimal) among the two objectives. Hence, its solution selects a reasonable capacity of the expensive bomass as well as other DER as shown in Table 3.2. The cost presented in Table 3.2 (last column) is the sum of the annualized investment costs of the design solution and annual the operational costs.

EMS Output

The performance of the EMS is presented in Fig. 3.5 and Fig. 3.7, while Fig. 3.4 shows the hourly generation profile of the generating units in the base case. Figs. 3.5 and 3.7 also show the electrical and thermal output of DERs set by the EMS on a typical day. It could be observed from Fig. 3.4 that the mine often utilizes all its three generators in the base

Table 3.2
Optimal Microgrid Expansion

	Wind (kW)	CHP (kW)	ESS (kWh)	Biomass (kW)	Cost (k$)
BIEX	7458	690	3965	547	38792
MOO	7350	579	4075	644	38823
DERCAM	7300	600	4000	700	39015

case while keeping the third diesel unit (Diesel III) constant at higher operating point and buying last resort power from the remote community energy provider.

However, with the implementation of the EMS in Case III, the two smaller generators (*i.e.*, Diesel I and Diesel II) and power from the remote community energy provider are not utilized. Considering the difference in efficiency when the generators operate at lower loads(below 50%) and the capacity of the generators, microgrid implementation results in significant savings. Fig. 3.3 outlines the operating efficiency of the two smaller generators. The output of the largest generator (Diesel III) is also seen to experience some level of fluctuation unlike in the base case. With high output from the wind turbine, less power needs to be provided by Diesel III as well as power purchased from the remote community and vice versa when the wind output is low. The ability of the EMS to take full advantage of the no-cost energy from the wind also contributes to further reduction in the total energy costs. The output of the heat exchanger is primarily dictated by the thermal need of the mine in the base case. Nonetheless, heat from the CHP also offsets parts of the energy extracted from the heat exchanger in the base case. Also, the performance of the EMS in the case where the MOO approach is considered is shown in Fig.3.12.

Financial Performance Metrics and Results

Key financial metrics such as the Present Value Ratio (PVR) and the Internal Rate of Return (IRR) are used next in determining the profitability of the investment options. The PVR is the ratio of the present value (PV) of the microgrid benefit/revenue to the PV of the investment cost. A PVR greater than one indicates profitability of an investment, which is unprofitable when its PVR less than one. IRR is the discount rate that makes the net present value of the energy investment equal to zero. Further elaboration on the IRR is provided in a subsequent subsection.

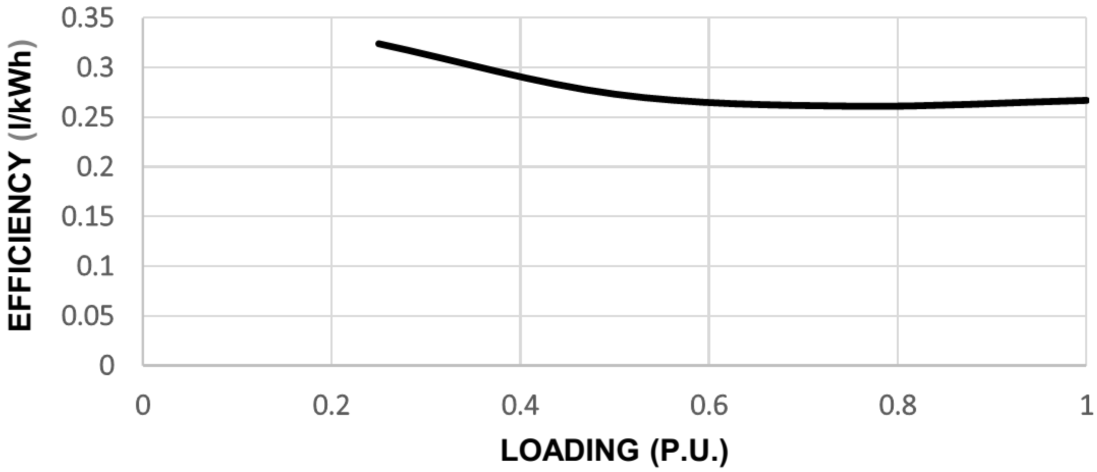

Figure 3.3. Generation efficiency of 1.5 MW units diesel I and diesel II

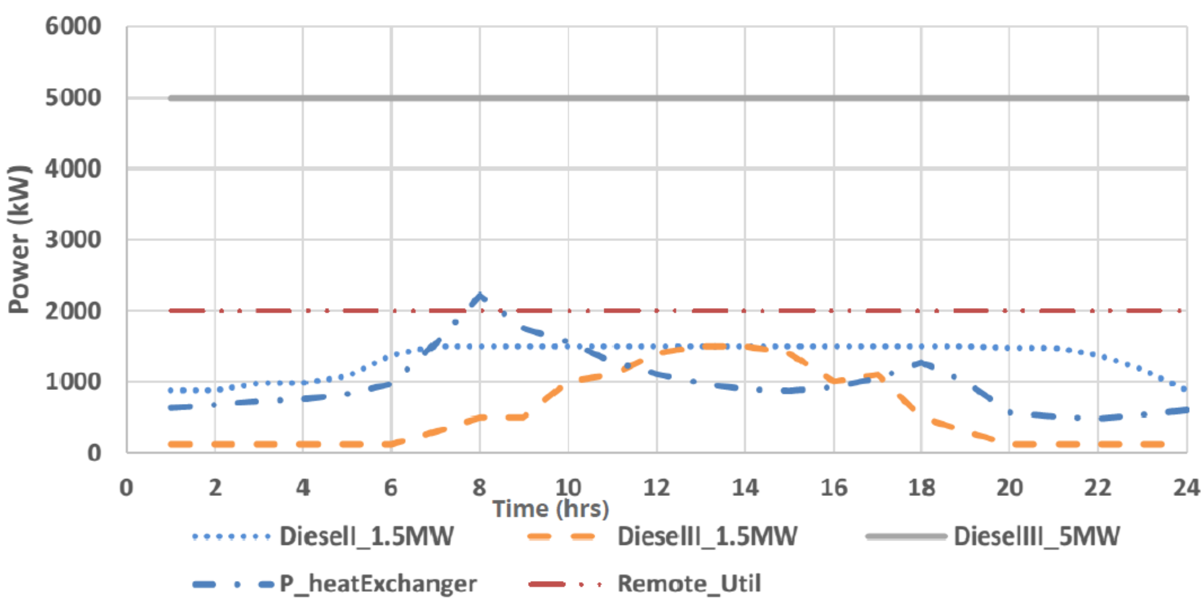

Figure 3.4. Generating units operating points in a typical day in the base case scenario

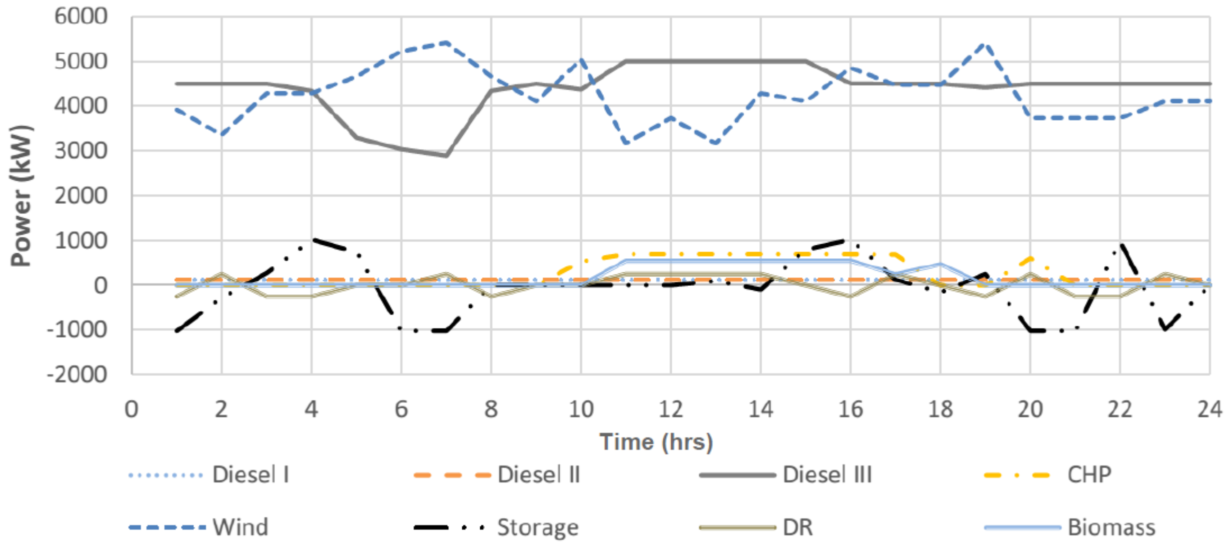

Figure 3.5. Electrical output of DERs in a typical day for BIEX.

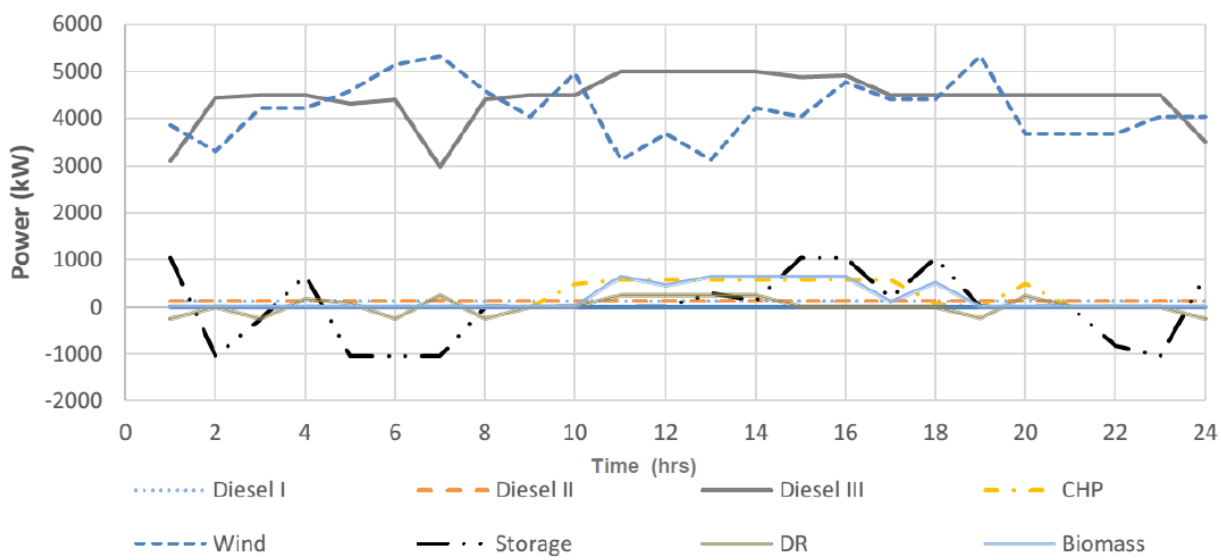

Figure 3.6. Electrical output of DERs in a typical day for MOO.

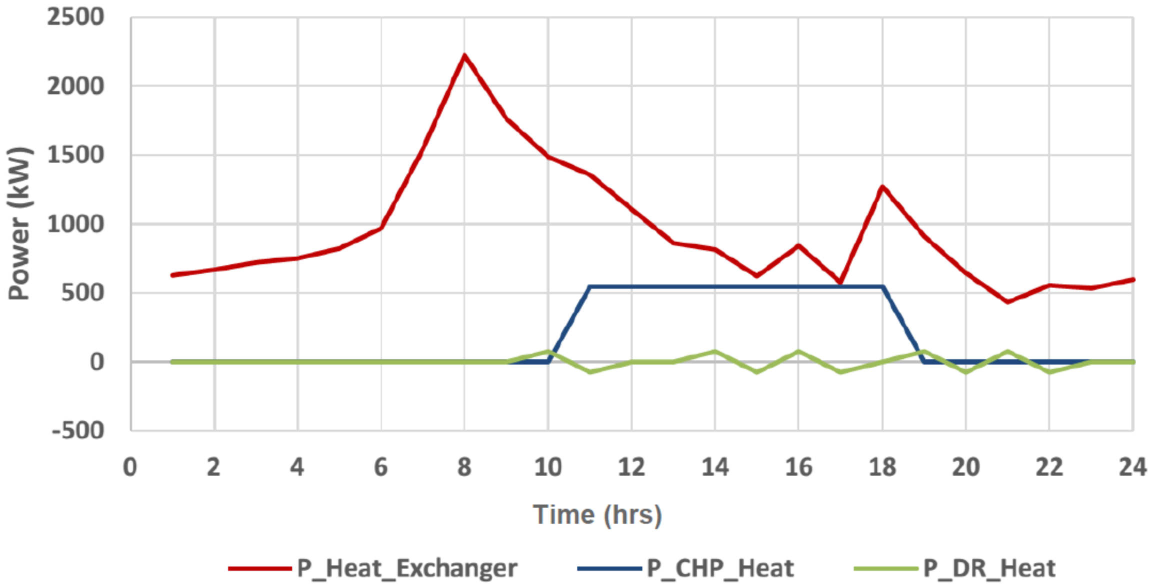

Figure 3.7. Thermal output of DERs in a typical day.

The output of the bi-level planning strategy is subjected to cost benefit analysis. Results obtained show significant savings in energy costs for all three planning scenarios or cases. Nevertheless, case III happens to yield the most benefit to all participating stakeholders. Table 3.3 outlines the outcome of the economic analysis for all three scenarios. It illustrates the benefit to cost ratio or PVR for the corresponding stakeholders (the mine's management in this case). The base unit corresponds to the base case total cost. A high percentage of savings to the mines can be observed from Table 3.3. The reduced fuel costs due to a lower consumption of diesel coupled with the strategic optimization by the EMS contribute to the increase in the mine's savings. The low PVR in the third scenario is due to the high penetration level of DERs which further translates into a higher capital investment cost.

Table 3.3
Per Unit Costs and Benefits

Costs	Basecase	CaseI	CaseII	CaseIII
Emission	0.175	0.080	0.088	0.080
Fuel	0.611	0.360	0.590	0.360
Power	0.214	0.000	0.000	0.000
Investment	0.000	0.038	0.045	0.269
Total	1.000	0.784	0.723	0.708
Savings		**21.61%**	**27.7%**	**29.22%**
PVR				**1.08**

Project Internal Rate of Return (IRR)

The discount rate is varied to determine the interest rate at which an investment in expanding this mining microgrid would break even as shown in Fig. 3.8. A high IRR of 21.5% is obtained, which suggests the attractiveness of implementing a DER rollout in a remote mining context. This would be especially the case for potential investors in areas with competitive borrowing rates.

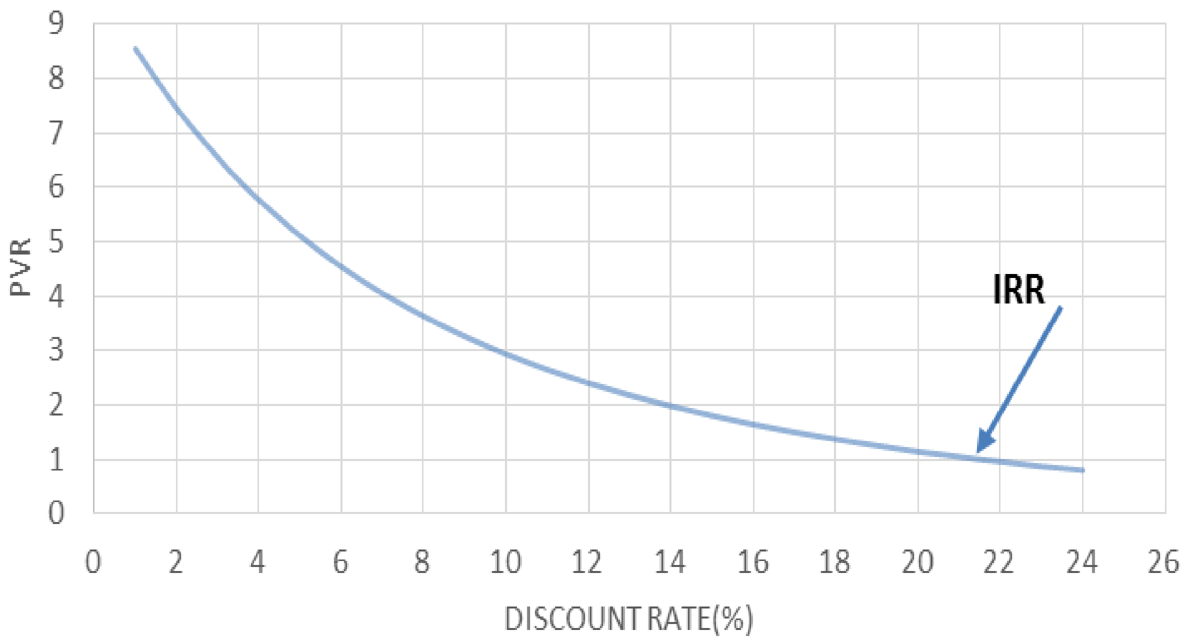

Figure 3.8. Change of PVR with respect to interest rate

3.3 DSO–Microgrid Planner Bi-level Model Formulation

3.3.1 Microgrid Planner's Challenge within the DSO context

Microgrid operational strategies, controls and communications, when better integrated in the planning stages of microgrids, can contribute not only to the optimization of generation and load in the microgrid as outlined in the previous section, but can also provide services to the benefit of the distribution grid as well [24]. The new DSO paradigm outlined in chapter one of the thesis has been suggested as one approach [31] that can take advantage of the benefits of microgrid and capable of enabling the provision of services by microgrids for the overall benefit of the power system. Given the background of the new DSO paradigm in chapter one, the DSO paradigm is structured in a way to accommodate activities of microgrids and other prosumers. It will also be responsible for local ancillary service (AS) markets, acting as an interface between the TSO and demand-side or distribution–level market players. Here, operational and planning information or orders are exchanged and coordinated between the DSO and the TSO to ensure the success of the local AS markets. Subsequently, the DSO may request reserve provision from local retail market agents including microgrids.

However, a microgrid planner working within this new DSO paradigm is likely to face a dilemma between satisfying the DSO's reserve capacity requirement, and pursuing its own interest of minimizing the design and operational cost of its microgrid. To assist microgrid planners make such difficult choices and for an effective operation of microgrids within the new DSO paradigm, this section of the chapter outlines a non co–linear bi–level power and reserve planning formulation for a DSO–microgrid planning problem. Here, a DSO whose duty is to ensure reliable power supply may request reserve capacity from a microgrid planner whose interest is to minimize its planning and operational cost. The proposed formulation can be seen as a classical example of a Stakelberg game where the upper level or leader's problem characterizes the actions of the microgrid planner, and the lower level or follower's problem represent that of the DSO. The microgrid planner acting as the leader selects DER capacities and operating points that minimizes its planning and operation cost in anticipation of the DSO's decision. The DSO, upon observing the planner's decision will move to maximize reserve capacity it can obtain from the microgrid. This struggle continues until an equilibrium is reached where neither players has an incentive to improve its interest. The proposed model also seeks to establish a better representation of the relationship between the microgrid planner and a DSO.

3.3.2 DSO–Microgrid Planner Bi-level Outline

As mentioned in the previous subsection, the structure of the bi–level formulation illustrated in Fig. 3.9 fits the narrative of the new DSO construct. Here, the actions of the microgrid planner are represented by the upper level problem while the DSO's decisions are represented by the lower level problem. The decision-making process is sequential with the microgrid planner having the first choice of selecting a design configuration (capacity of DERs, x_i; $\forall i \in I_B$) and dispatch set points (P_i; $\forall i \in I_G$) that minimizes its total planning and operational cost. In view of the planner's decision, the DSO, determines reserve capacities of DERs that the microgrid will provide. The available operating space of the lower level's problem is constrained by the decision of the upper level. The microgrid planner upon observing the reaction of the DSO may alter his selection. This process is repeated until an equilibrium is found where neither level has an incentive to change its selection.

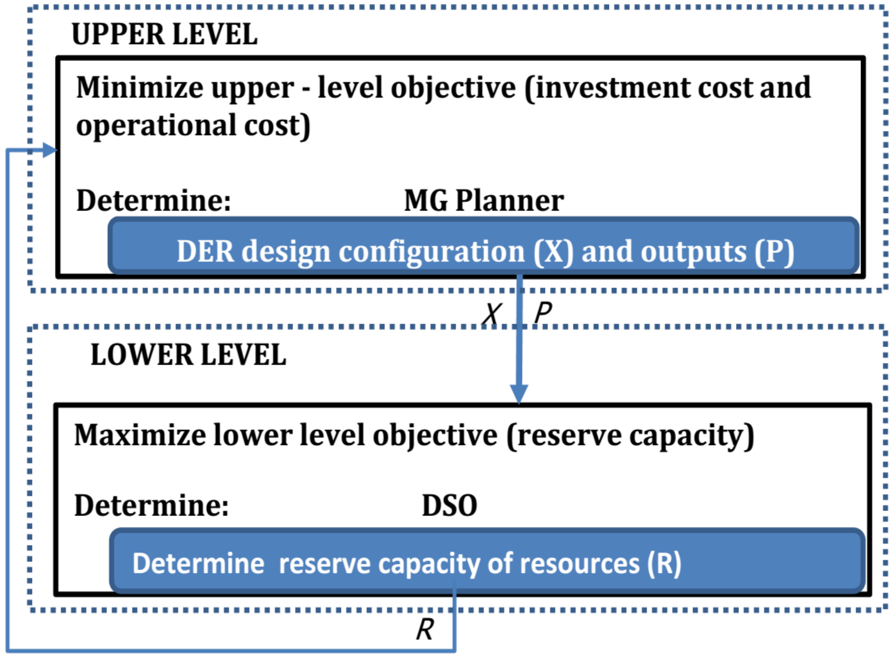

Figure 3.9. Schematic diagram of the bilevel planning and reserve capacity model

Microgrid Planner – Upper Level Problem

The upper level objective function (3.77), co–optimizes the annualized investment cost of new DERs (first term), annual operational cost of the microgrid (second term) over the planning horizon and the cost of carbon permit purchases (third term). The variable x_i and P_i denote the capacities of DER options to be installed and the operation set points of the dispatchable resources respectively; these constitute the solution to the upper level problem. The total planning and operational cost is converted into its present value by the factor γ, as indicated in the previous section.

$$\min_{x,P\geq 0} \gamma \sum_{y\in Y} \left\{ \varrho_y \sum_{i\in I_B} C_i^c x_i + C_y(P) + C_y^{CO_2}(\Upsilon_y) \right\} \tag{3.77}$$

where all variables have the same meaning as defined in the previous section and the operational cost ($C_y(P)$) is defined by:

$$C_y(P) = \rho(0)\sum_{t\in T}\left\{\sum_{i\in I_G} C_i^f P_i^e(y,t) + \sum_{i\in I_U} C_i^e P_i^e(y,t) + \sum_{i\in I_H} C_i^f P_i^e(y,t)\right\} +$$
$$\sum_{k\in K}\sum_{t\in T}\rho(k)\left\{\sum_{i\in I_G} C_i^f P_i^e(y,k,t) + \sum_{i\in I_U} C_i^e P_i^e(y,k,t) + \sum_{i\in I_H} C_i^f P_i^e(y,k,t)\right\} \quad (3.78)$$

The first component of the operational cost $C_y(P)$ is divided into two parts: the first part covers the generation cost during normal operation of the power system (and is multiplied by the probability of non-occurrence of any pre-selected contingency event $\rho(0)$) while the second part covers the cost during contingency $k \in K$ in the microgrid and multiplied by the probability of its occurrence $\rho(k)$. The quantity $\rho(k)$ is calculated from expected mean time to failure data (taken to be constant over the scheduling horizon [96]) as detailed in [96].

Similar to the model in the previous section, the upper level objective is constrained by a budget allocation for investment (3.79) and allowable carbon permits purchased (3.80).

$$\sum_{i\in I_{\bar{B}}} C_i^c x_i + \sum_{i\in I_S} C_i^c x_i \le C^b \quad (3.79)$$

$$\sum_{i\in I_G}\sum_{t\in T}\zeta_i P_i^e(y,t) + \sum_{i\in I_H}\sum_{t\in T}\zeta_i P_i^h(y,t) \le \Upsilon_y \quad (3.80)$$

The upper level problem is further constrained by hourly generation and load balance, (3.81) and (3.82), while both thermal and electrical loads are considered. The electrical power balance is given by

$$\sum_{i\in I_E} P_i^e(y,t) = L^e(y,t) \quad (3.81)$$

for all hours $t \in T$ of all years $y \in Y$, while the thermal power balance requires that

$$\sum_{i\in I_N} P_i^h(y,t) + \sum_{i\in I_H} P_i^h(y,t) = L^h(y,t). \quad (3.82)$$

Furthermore, the hourly dispatch problem is constrained by maximum and minimum limits of the dispatchable generating resources including CHP [4], (3.83) and (3.84) given below:

$$P_i^{\min} \leq P_i^e(y,t) \leq P_i^{\max} - x_i' \tag{3.83}$$

for all $i \in I_G, t \in T$ and $y \in Y$, and

$$0 \leq P_i^e(y,t) \leq x_i - x_i' \tag{3.84}$$

for all $i \in I_B, t \in T$ and $y \in Y$. The thermal output from the CHP is given by (3.85)

$$P_i^h(y,t) = \frac{P_i^e(y,t)}{\varsigma_i} \tag{3.85}$$

for all $i \in I_N, t \in T$ and $y \in Y$.

The operation of the ESS in the microgrid is also constrained by (3.86) – (3.88) for each ESS resource $i \in I_S$, for all hours $t \in T$ and years $y \in Y$:

$$E_i^e(y,t) = E_i^e(y,t-1) + \eta_i P_i^e(y,t)\Delta t \tag{3.86}$$

$$0 \leq E_i^e(y,t) \leq x_i \tag{3.87}$$

$$-\nu_i x_i \leq P_i^e(y,t) \leq \nu_i x_i \tag{3.88}$$

Likewise, the electrical DR has to satisfy

$$E_r^e(y,t) = E_r^e(y,t-1) + P_r^e(y,t)\Delta t \tag{3.89}$$

$$0 \leq E_r^e(y,t) \leq w_r^e L^{e,\max} \tag{3.90}$$

$$-\kappa_r^e w_r^e L^{e,\max} \leq P_r^e(y,t) \leq \kappa_r^e w_r^e L^{e,\max} \tag{3.91}$$

for all hours $t \in T$ of years $y \in Y$.

DSO – Lower Level Problem

The lower level problem represents the DSO's objective of maximizing reserve capacity provided by the microgrid to support the power system's operation. The objective function as outlined in (3.92) minimizes outage cost by minimizing non–delivered energy for a given

[4] where $P_i^{\max}$ for the CHP unit will the same as x_i its design variable

period t during a contingency k (first term), as well as minimize the cost of reserve capacity (last term). It is worth noting that C_i' is determined based on a long term contract and assumed to be given in $\$/kW$–per year for purposes of this work.

$$x_i' \in \underset{x',P'}{\operatorname{argmin}} \sum_{y\in Y} \left\{ \sum_{k\in K} \sum_{t\in T} \mathcal{V}_y \left(L^e(y,k,t) - \sum_{i\in I_E} P_i'(y,k,t) \right) + \sum_{i\in I_G} C_i' x_i' \right\} \tag{3.92}$$

The lower level objective is constrained by DER capacities x_i, $\forall i \in I_G$ and a limit on the available reserve energy according to (3.93) and (3.94) respectively:

$$0 \le x_i' \le x_i \qquad ; \ \epsilon_i^{\min},\ \epsilon_i^{\max} \tag{3.93}$$

$$0 \le P_i'(y,k,t) \le x_i' \quad ; \ \varpi_i^{\min}(y,k,t),\ \varpi_i^{\max}(y,k,t) \tag{3.94}$$

here, x_i for existing assets are known and equal to P_i^{max}, $\forall i \in I_D$ while x_i for new assets $i \in I_G \subset I_B$ are part of the decision variables passed by the upper level problem.

The lower level problem, must also satisfy post contingency power balance (3.95):

$$\sum_{i\in I_E} P_i^e(y,k,t) + \sum_{i\in I_G} P_i'(y,k,t) = L^e(y,k,t) \quad ; \ \lambda'(y,k,t) \tag{3.95}$$

where $\lambda'(y,k,t)$, $\epsilon_i^{\min}$, $\epsilon_i^{\max}$ and $\varpi_i^{\min}(y,k,t)$, $\varpi_i^{\max}(y,k,t)$ are Lagrange multipliers associated with their respective constraints.

3.3.3 Transformation to MPEC and MILP

Obviously, for each value of the upper level variable x_i, the lower level problem is proven to be linear (thus convex) as parameterized in $x_i, \forall i \in I_B$. Hence, this bi–level model can also be transformed by the primal–dual approach outlined in the previous section and given by (3.96)–(3.101). The transformation, as outlined below, comprises replacing the lower level problem with its primal constraints (3.93)–(3.95) and its dual constraints (3.99)–(3.100). This is combined with the equality associated with the SDT (3.101) and the upper level problem (3.79)–(3.91) to make up the transformed MPEC.

$$\min_{x,x_i',P_i',P\ge 0} (3.77) \tag{3.96}$$

subject to

$$\text{Constraints}(3.79) - (3.91) \tag{3.97}$$

$$\text{Constraints}(3.93) - (3.95) \tag{3.98}$$

dual constraints

$$C_i' - \epsilon_i^{\min} + \epsilon_i^{\max} = 0 \ \forall i \in I_G \tag{3.99}$$

$$\mathcal{V}_y - \lambda'(y,k,t) - \varpi_i^{\min}(y,k,t) + \varpi_i^{\max}(y,k,t) = 0 \ \forall i \in I_G \tag{3.100}$$

and the strong duality equality

$$\left(\mathcal{V}_y \left(L^e(y,k,t) - \sum_{i \in I_E} P_i'(y,k,t)\right) + \sum_{i \in I_G} C_i' x_i'\right) = \lambda'(y,k,t) L^e(y,k,t) + \sum_{i \in I_G} \epsilon_i^{\max} x_i + \sum_{i \in I_G} \varpi_i^{\max} x_i' \tag{3.101}$$

The non-linearity associated with the products of the upper variable and lagrange variables in (3.101) of the MPEC can be linearized at the expense of more constraints and auxiliary variables, transforming the problem into an equivalent MILP problem as explained in the previous sections and appendix C.2.

3.3.4 Case Study

The proposed bi–level microgrid planning approach is applied to a microgrid implementation within a distribution network in the western part of Canada. The local electric utility, supplies energy to potential customers of the microgrid at a rate of CAD 12.23 ¢ per kWh. There is also a customer charge of CAD 23 ¢/day and an average demand charge of CAD 10.42 $/kW per month. The average yearly demand of customers is 1 MW with a peak demand of 1.2 MW and an annual load growth of 2%. Available reliability records indicate that the grid has three failures per anum on the average. The cost of non–delivered energy (NDE) is taken as 25 per kWh [17] while heat is provided by the local gas utility. The charges for reserve capacity is taken as 68 ¢/kW. Prior to microgrid investment, there was a 420 kW diesel generator installed to support critical/sensitive load. The existing local distribution system infrastructure with no microgrid functionality is considered to be the base case. Here, the existing assets support or meet some portion of their local load during normal operation and maintain supply to sensitive loads during an emergency. DER considered for the microgrid implementation include wind turbines, combined heat and power (CHP), ESS, DR and an energy management system. ESS technology considered is a new generation compressed air energy storage system with a ratio of energy storage capacity to power capacity v_i of four hours. It is also assumed that 10% of the load is available for DR operation. A hypothetical layout of the microgrid connected to the grid is provided in Fig. 4.3. Economic parameters of the exisiting and new DERs as well as other required data are provided in Table 3.1 and Table 3.4. The probability $\rho(k)$ of an event k due to a failure of a resource i in time $t \in T$ of year $y \in Y$ is given in Table 3.5 based on parameters obtained from [97, 98]. Four 24 hour daily load scenarios are used in modeling the load for the system with each daily profile representing a season. They are aggregated by a factor based on the number of days in a season. Consequently the optimization model runs for a 24 hour schedule window for all the seasons in the year. Here, we consider only single failures and assumed that, when an event k occurs, it may last for rest of the day. Assets depreciation based on capital cost allowance (CCA) is applied to the energy infrastructure in this work. The cost associated with CO_2 emission ($C_i^{\wp}$) is taken to be 14.32 \$/tCO_2, the clearing price of carbon permits in an auction window on the carbon market.

Table 3.4
Summary of Input Parameters Of Existing Assets

Diesel Generator	
Fuel cost [99]	0.76 (\$/L)
Fixed O&M [99]	15 (\$/kW–yr)
Variable O&M [99]	3 (\$/MWh)
Emission rate [100]	2.64 (kg/L)

Table 3.5
Reliability Data for Microgrid DERs

DERs (i)	$\rho(k)$
Wind turbine	0.0000280
CHP	0.00002
ESS	0.00001857
Diesel generator	0.003598

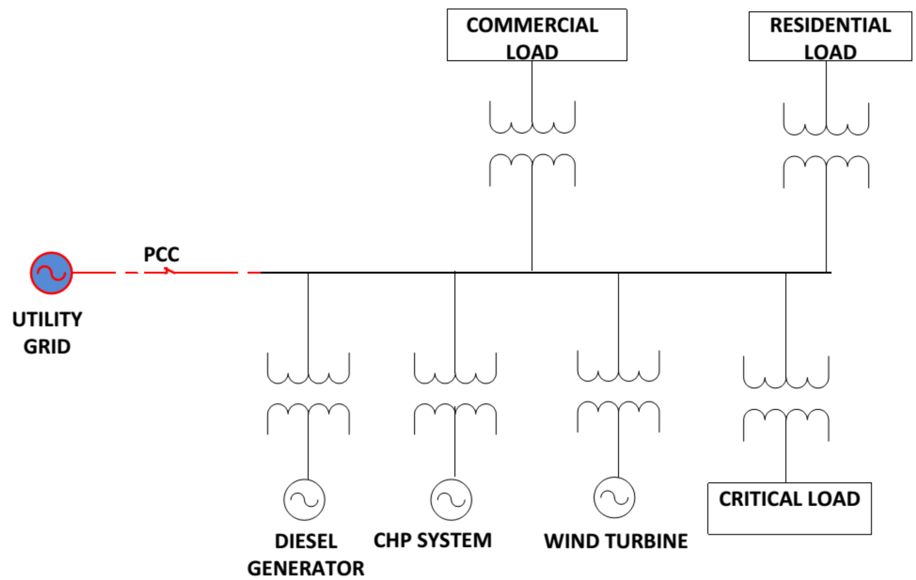

Figure 3.10. Single line diagram of a generalized grid connected microgrid.

3.3.5 Results and Discussion

Planning Decisions

The proposed planning model is also evaluated using the custom-made *Excel–VBA* tool BIEX. Here annual optimization of the proposed model is run for the entire planning horizon. Results obtained based on the proposed approach are compared with those of a more traditional multi–objective optimization (MOO) [101] where the DSO and the microgrid are considered concurrently. The results of the planning exercise are shown in Table 3.6. Both algorithms are provided with the same input data and parameters to make the comparison valid. Both cases are also compared with the base case (Base Case) which has no microgrid energy infrastructure and the results shown in Table 3.6. From Table 3.6, it could be observed that, the implementation of the proposed bi–level model and the MOO model yielded lower annualized costs of energy when compared to the base case. Nonetheless, the optimal configuration of the proposed model resulted in a lower cost of operation when compared to that of the MOO algorithm. This can be attributed to the fact that, in the bi–level model, either of the levels (microgrid planner or the DSO) could increase its interest without necessarily compromising the interest of the other, where as in the multi–objective case, an increase in the objective of one of the players may require a compromise from the other objectives, i.e. an increase in the interest of the microgrid planner to minimize cost may require some compromise on reliability from the DSO.

Table 3.6
Optimal Microgrid Configuration

	Diesel (kW)	Wind (kW)	CHP (kW)	ESS (kWh)	Cost (k$/year)
Base Case	420	0	0	0	1003
BIEX	420	3000	1546	750	495
MOO	420	3000	875	750	598

Furthermore, it can be seen from Fig. 3.11 and Fig. 3.12 that, in both the proposed bi–level model and the MOO model, the capacity of resources allocated for reserve services are different. In the case of the proposed bi–level model, about 46.6% of its CHP design capacity and 93.5% of the design capacity of ESS are allocated for reserve provision. However, with the multi–objective model implementation, only 37.1% of the design capacity of ESS is available for reserve provision while the other resources are used for normal operation of the microgrid.

3.3.6 Allocation of Benefits to Stakeholders

Benefits realized from the implementation of the proposed microgrid configuration approach are assigned to corresponding stakeholders and shown in Table 3.7. Here, it is assumed that the microgrid is customer owned, hence, the main stakeholders considered are the microgrid owner/customer and the DSO. Consequently, three main benefits were realized: reduced energy cost, improvement in reliability and investment deferral. Prior to the implementation of the proposed microgrid, the non-transformed microgrid system was a net importer of energy from the distribution system it is connected to. However, with the modification of the network into a microgrid, enough capacity of DERs are available to support the microgrid load while surplus energy is supplied to the distribution system. Excess energy supplied to the distribution system translates into additional revenue to the microgrid owner and thus reduces cost of energy for the microgrid owner/customer. Also, incorporation of reserve planning at the design stage of the proposed model ensures that there is adequate capacity of resources to maintain reliable power supply for all microgrid customer loads, unlike the base case, where only critical loads were supported in the event

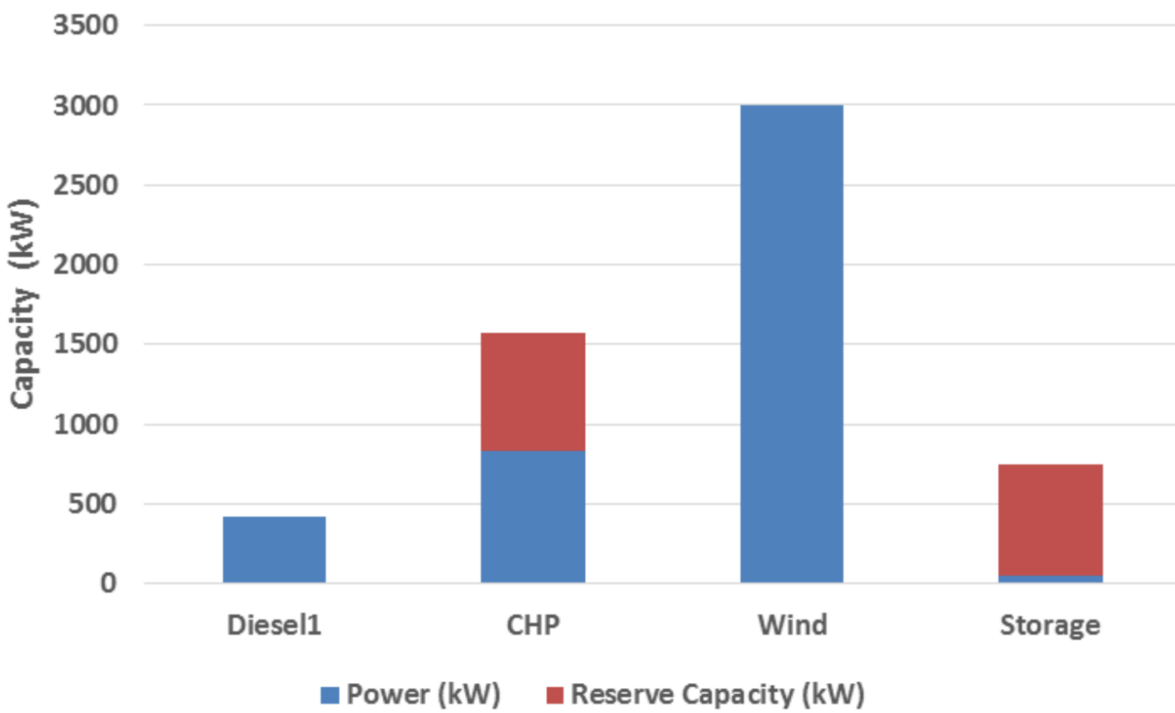

Figure 3.11. Capacity of resources available for reserve and normal operation in the microgrid (Bilevel case)

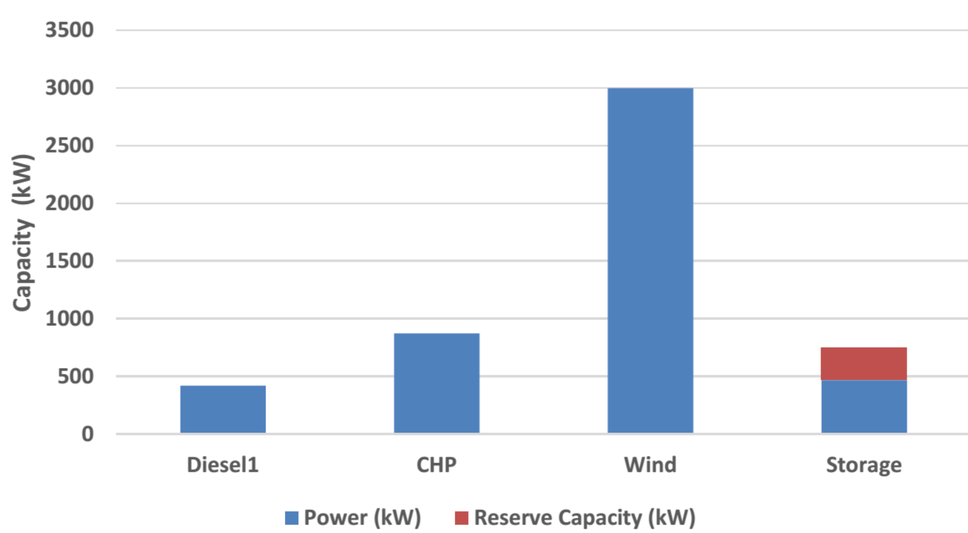

Figure 3.12. Capacity of resources available for reserve and normal operation in the microgrid (MOO Case)

of a contingency. Additional investment needed to enforce the local distribution system to support growth in peak load (annual growth of 2%) is differed because of additional capacity provided by the installed DERs in the microgrid. It could also be observed from Table 3.7 that, reduced energy cost is assigned to the microgrid owner and customers while investment deferral is assigned to the DSO. Also, reliability improvement or reduced NDE seems to benefit both the microgrid owner and DSO. It is also important to note that emission reduction is not considered in this analysis. This is due to the fact that, power supply to customers of the existing network (base case) prior to its transformation into a microgrid was from a hydro source. Thus the argument for emission reduction cannot be sustained.

Table 3.7
Per Unit Costs and Benefit Allocation

Stakeholders	**Costs**	**Base case**	**Microgrid case**
Microgrid Owner	Energy	0.89	0.393
	NDE	0.11	0
	Total	1.000	0.393
Savings			**0.607**
DSO	NDE	0.11	0.000
	Network Reinforcement (Investment deferral)	0.06	0.000
	Total	0.16	0.000
Savings			**0.160**

ESS versus Demand Response

Attempts were made in this work to analyze the impact of the net benefit of each non–generating flexible resources namely DR or ESS on the planning configuration of the proposed model. Here we consider the case where a microgrid planner has to make a choice between an ESS and a DR technology and the resulting configuration is presented in Table 3.8. It could be observed from the table that, the optimal configuration of both cases differs from the previous cases where both technologies were available for selection. In the ESS *only* case, the configuration and resources available for reserve provision as shown in

Fig. 3.13 is similar to the optimal configuration in the case with all technologies available, however, the same cannot be said about the DR *only* case shown in Fig. 3.14. Also the annualized cost of the ESS only case is lower than that of the DR *only* case where no ESS is considered. Thus, one may opt for the ESS only technology mix in the microgrid design and experience comparatively similar benefit as installing both ESS and DR technology. Nonetheless, it is worth noting that, the capacity of energy available for DR operation is far less than the capacity of ESS installed.

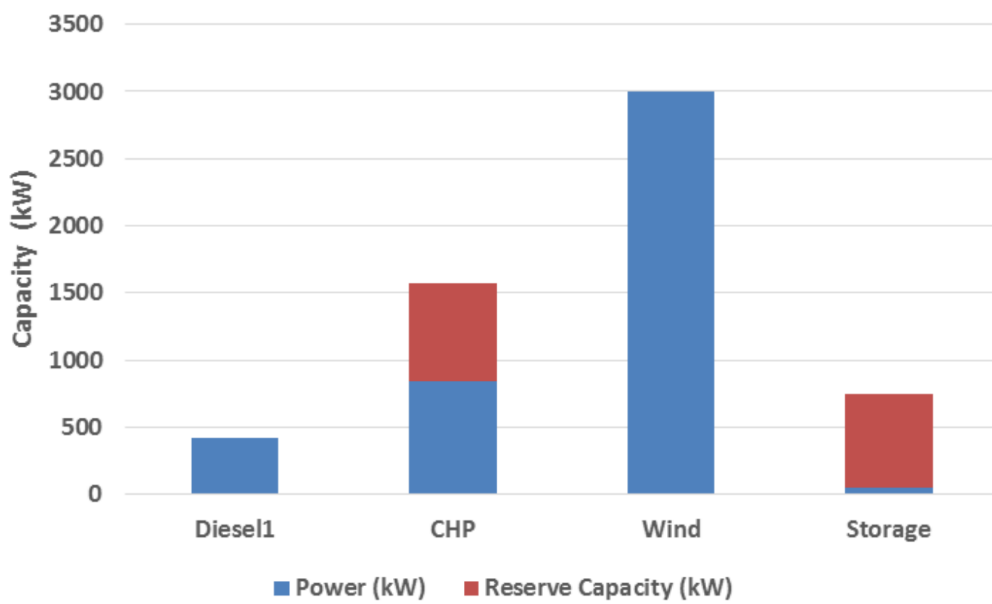

Figure 3.13. Capacity of resources available for reserve and normal operation in the microgrid (Bilevel Demand response only case)

Table 3.8
Comparison of optimal microgrid configuration for the ESS case and the DR case

	Diesel	Wind (kW)	CHP (kW)	ESS (kWh)	Cost (k$/year)
ESS	420	3000	1578	750	536
DR	420	3000	2510	0	703

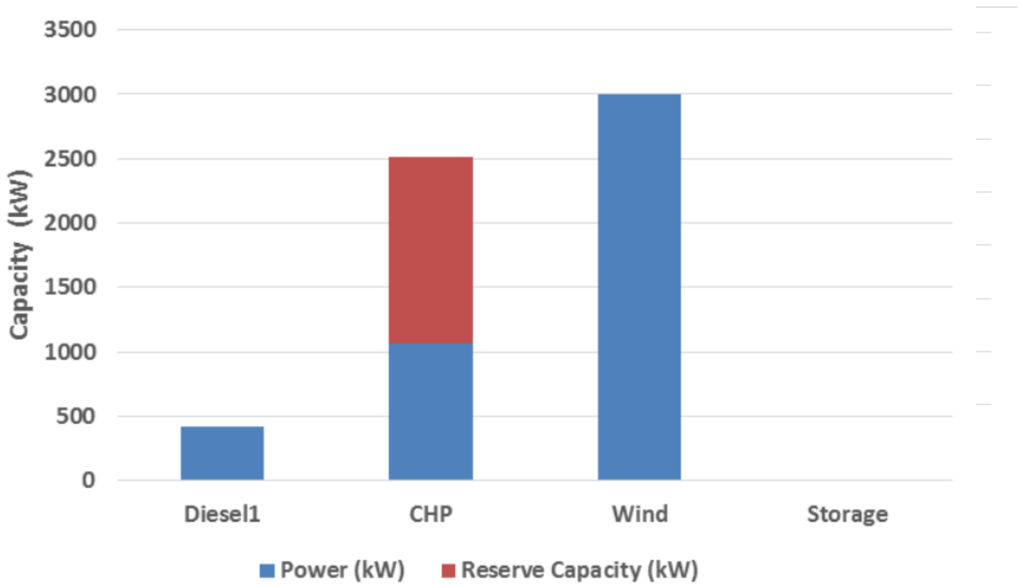

Figure 3.14. Capacity of resources available for reserve and normal operation in the microgrid (Bilevel ESS only with no DR case)

3.4 Conclusion

In this chapter bi–level formulation of a coupled microgrid planning and operational problem has been outlined. Methods to recast the problem into an MPEC were discussed. The convexity of the lower level problem of the primal formulation has been explained in the chapter. The strong duality theorem approach is seen as a more efficient method of transforming the proposed problem into an MPEC compared to the KKT conditions. The transformed MPEC is linearized into an equivalent MILP at the expense of more constraints. The bi-level formulation is applied to the energy infrastructure of an off-grid mine. Results obtained through its application show significant savings in the cost of energy and improved benefits to stakeholders. An alternate model of the bi–level formulation that fits the narrative of a DSO paradigm has also been developed and explained in the later part of the chapter. The proposed model solves a coupled microgrid power and reserve planning problem within the context of a DSO. Also, a case study implementation of the formulation to a Canadian utility network is discussed and the results compared to a traditional MOO approach.

Chapter 4

Business Cases for Isolated and Grid Connected Microgrids: Methodology and Applications

4.1 Introduction

This chapter discusses a systematic approach and methodology for formulating and quantifying microgrid business cases. Here a general overview of business cases is presented, what is required to create one and how the microgrid case presents a unique opportunity are outlined. Consequently, within the larger framework outlined in chapter two, and in reference to the use case paradigm, this chapter investigates the dependency of microgrid business cases on microgrid generation technology mix, reliability of these technologies and the microgrid operational strategy. Given the importance of the optimization strategy in the development of microgrid business cases, the chapter adapts the first bi–level formulation in the previous chapter to a larger context of representative microgrids and identifies practical microgrid stakeholders, benefits and beneficiaries. Here, the bi–level formulation is modified to include the quantification of NDE in a way that reflects the stochastic/uncertain occurrence of failures of the DERs. Applications of the approach to practical microgrids including remote communities, remote mining sites and grid connected critical distribution grids are further discussed in this chapter.

4.2 General Overview of business case models

Business cases capture the reasoning for initiating a specific project, activity or task. They can range from a highly comprehensive and well structured document to an informal briefing and may aim to seek funding or approval, or may sought to influence a policy making process. The business case document should provide the strategic context for an investment decision, a detailed description of the viable option and its analysis and recommended decision [102].

The traditional approach to most engineering investment analysis or business cases is to estimate the total revenue or benefit realized through the investment and compare it with the total cost incurred to determine the profitability of the investment. However, for microgrid investments, not all cost and benefits may be captured by the investing entity. These benefits may affect various stakeholders within the power system such as the utility, microgrid customers, independent power producers (IPP), policy makers and society, which may not necessary be the investing actors. These stakeholders are significant components of the business case whose interests have to be adequately accounted for. Their interest may vary from technical benefits such as power quality, power losses, and reliability improvement to monetary benefits such as reduced energy cost and return on investment. Fig. 4.1 lays out the work plan for building a microgrid business case where specific interests of individual stakeholders are illustrated. By answering questions posed in Fig. 4.1, one is guided to provide relevant information needed to develop a microgrid business case.

4.3 Economic Metrics and Business Case Input Data

With the drivers of microgrid and its business needs outlined in the introductory chapter of the thesis and question 1 of Fig. 4.1 addressed, the next prescribed step towards building a microgrid business case is to gather or outline the required data, models and metrics incorporated, as required by question 2a of Fig. 4.1. These may include a detailed description of the existing system, DER models, economic, financial and optimization models as provided in chapters two and three of this thesis.

The bi–level formulation in the previous chapter is modified within the context of a business case to account for the monetization and quantification methodology proposed here (particularly for reliability improvement or minimizing NDE). Here, the lower level

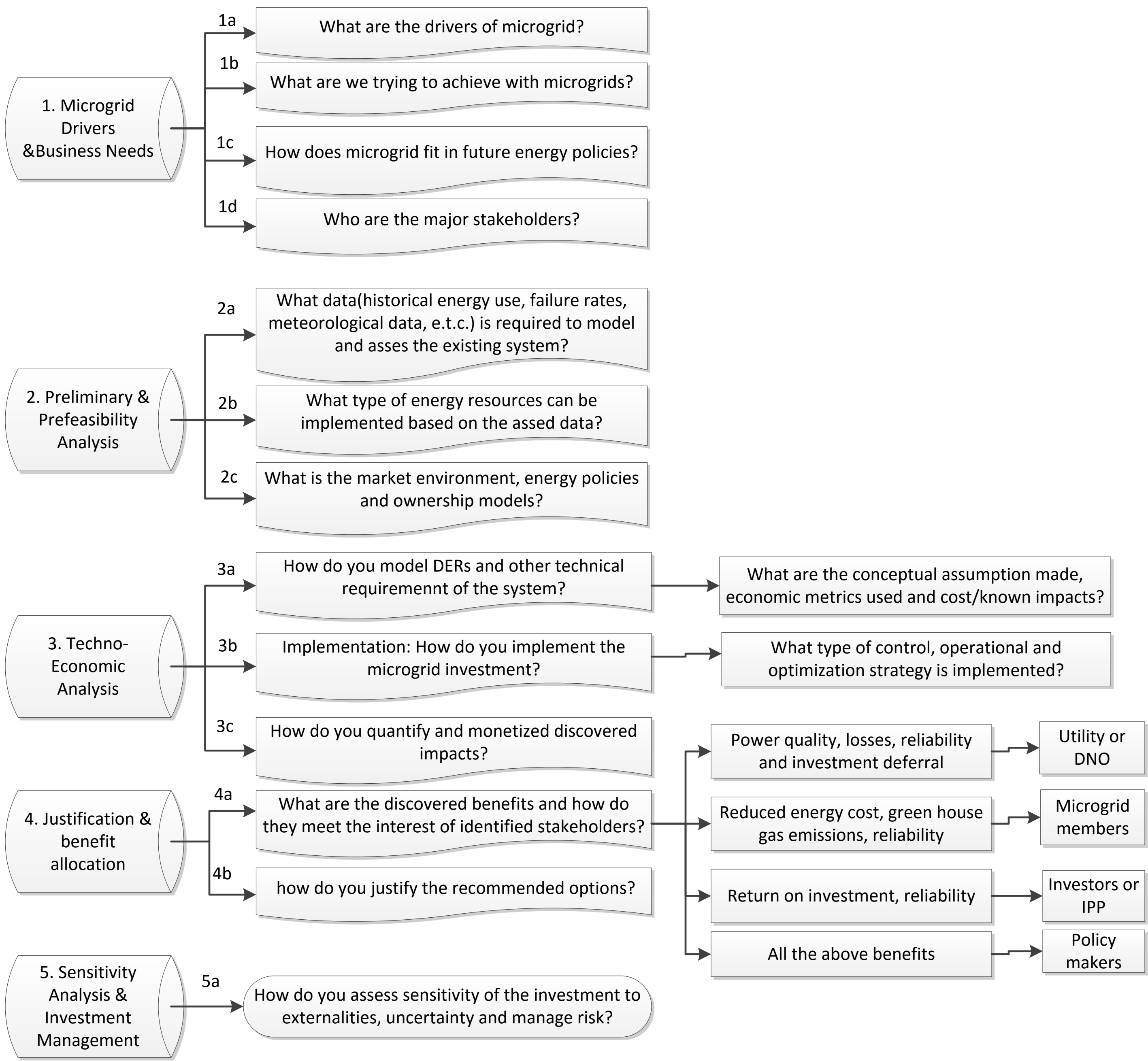

Figure 4.1. General overview of microgrid business case

EMS considers the probability of occurrence of predefined pairings of contingency event in its estimate of NDE. This is indirectly passed to the upper level problem which influence its choice of DER's and subsequently impact the business case. This is an important component of the proposed strategy, particularly for remote power systems where repair works may take longer period to complete. This section highlights and outlines only modified aspects of the optimization model to avoid repetition of the formulation outlined in previous chapters. All other constraints and limitation in the bi–level planning and operational model of the previous chapter are applicable here unless otherwise stated. The upper level objective remains the same as in chapter three and defined by (4.1):

$$\min_{x,\mathcal{U},\Upsilon \geq 0} \gamma \sum_{y \in Y} \left\{ \varrho_y \left(\sum_{i \in I_{\bar{B}}} C_i^c x_i + \sum_{i \in I_S} C_i^c x_i \right) + C_y^d(\mathcal{U}_y^p) + C_y^{CO_2}(\Upsilon_y) \right\} \tag{4.1}$$

The modified lower level problem is equivalent to an EMS solving an hourly pre- and post-contingency economic dispatch problem. Its objective function defined by (4.2), minimizes the hourly operational cost given fuel costs (first term), the costs of providing heat from a non-CHP resource (second term), the cost of energy from the grid (third term), the maintenance cost of all units and the value of non-served energy (last two terms).

$$\begin{aligned}
\min_{P,\hat{l}} \rho(0) \sum_{t \in T} & \left(\sum_{i \in I_G} C_i^f P_i^e(y,t) + \sum_{i \in I_H} C_i^f P_i^h(y,t) \right. \\
& \left. + \sum_{i \in (I_U \subset I_E)} C_i^e P_i^e(y,t) + \sum_{i \in (I_U \subset I_H)} C_i^h P_i^h(y,t) \right) \\
+ \sum_{k \in K} \sum_{t \in T} \rho(k) & \left(\sum_{i \in I_G} C_i^f P_i^e(y,k,t) + \sum_{i \in I_H} C_i^f P_i^h(y,k,t) \right. \\
& \left. + \sum_{i \in (I_U \subset I_H)} C_i^e P_i^e(y,k,\tau) + \sum_{i \in (I_U \subset I_H)} C_i^h P_i^h(y,k,t) + \mathcal{V}_y \hat{l}(y,k,t) \right) \\
& + \sum_{i \in I_B} C_i^m x_i + \sum_{i \in I_A} C_i^m \mathcal{A}_i
\end{aligned} \tag{4.2}$$

The first component of the operational cost is further divided into two parts as explained in the later part of the previous chapter: the first part covers the generation cost during normal operation of the power system (and is multiplied by the probability of non-occurrence of any pre-selected contingency event $\rho(0)$) while the second part covers the cost during contingency $k \in K$ and multiplied by the probability of its occurrence $\rho(k)$. The quantity $\rho(k)$ is calculated from expected mean time to failure data (taken to be constant over the scheduling horizon [96]) as detailed in [96].

The term $\mathcal{V}_y$ in (4.2) represent the unit value of interrupted load and $\hat{l}(y,k,t)$ denotes the non-served load due to contingency $k \in K$ during time $t \in T$. The amount of load shed or interrupted cannot be negative and must satisfy the following constraint:

$$\hat{l}(y,k,t) = L^e(y,k,t) - \sum_{i \in I_E} P_i^e(y,k,t) \tag{4.3}$$

The lower level objective is constrained by hourly load balance (both thermal and electrical load) and generating limit of the generating resources. It is important to note that both pre- and post-contingency load balance must be satisfied.

When a storage technology is considered in the business case or added to the microgrid design option, the lower level problem is further constrained by the operation of the storage device. The variation of the state of charge or energy level of the storage system depends on the charging/discharging power, efficiency, and the storage capacity of the system, as well as the type of storage technology selected for the microgrid.

Similarly, the dispatch problem is also subjected to limits on energy available for both electrical and thermal DR resources, if DR technology is considered. The above optimization strategy is a general model that could be used in the development of business cases for most microgrid types; however, some components and constraints may be omitted based the microgrid project and technology specifics.

4.3.1 Impact Monetization/Quantification Metrics

While attempting to address question $3a$ of the business development chart, known and discovered impacts need to be outlined. Impacts are the expected changes when a microgrid is implemented. These could be changes in any part of the systems of which the microgrid is a part: the electrical system, the economic system, or the environmental system. All impacts can be classified into two categories: *known impacts* (those which must be known a priori), and *discovered impacts* (those which must be found through simulation or calculation) [17–19]. Impact monetization metrics used in quantifying the main benefits of microgrids are informed by previous work reported in [17], [19] and [103]: metrics for economic benefits (reduced energy cost), reliability improvements, emission reductions and investment deferrals among others. These benefits could be further categorized into general benefits (i.e., benefits realized in all microgrid types) and the non-general benefit (those benefits unique to specifics of microgrid). The benefits and corresponding metrics are given in Table 4.1. Interesting among them is reliability improvement, whose computation, as outlined in the previous section, is characterized by the uncertain occurrence of failure of generators. Here, $\hat{L}_{base}$ denote the sum of non-served load in the base case and $\hat{L}_{\mu G}$ the sum in a microgrid case.

Table 4.1
Impact Monetization Metrics

Benefits	**Metrics**
Reduced Energy Cost (C_{EC})	$C_{EC} = C_{base} - C_{\mu G}$
Reliability Improvement (C_{RI})	$C_{RI} = v_y \left(\hat{L}_{base} - \hat{L}_{\mu G} \right)$
Network Reinforcement Deferral (NRD)	$NRD = NPV_{base} - NPV_{\mu G}$

4.4 Methodology

As previously mentioned, it is important to understand how key elements of a microgrid business case fit together to create a compelling case. Given that, the background information and the larger context of the methodology and business case development chart has been outlined in previous sections, this section details the sequence of steps taken to assemble key elements of a microgrid business case to create a stronger one. The sequence of steps details the implementation of microgrid investment and determines the economic merits of planning scenarios for representative microgrid case studies as required by questions $4a$ and $4b$ of the business case overview in Fig. 4.1. The methodology generally combines DER models, economic metrics, and the optimization models developed and implement them in annual simulations over a planning horizon. Fundamental to the methodology is the coupled planning and operational optimization engines that account for uncertain load interruptions and maximizes the operational benefits of the microgrid. Details of the simulation are presented below and illustrated in Fig.4.2.

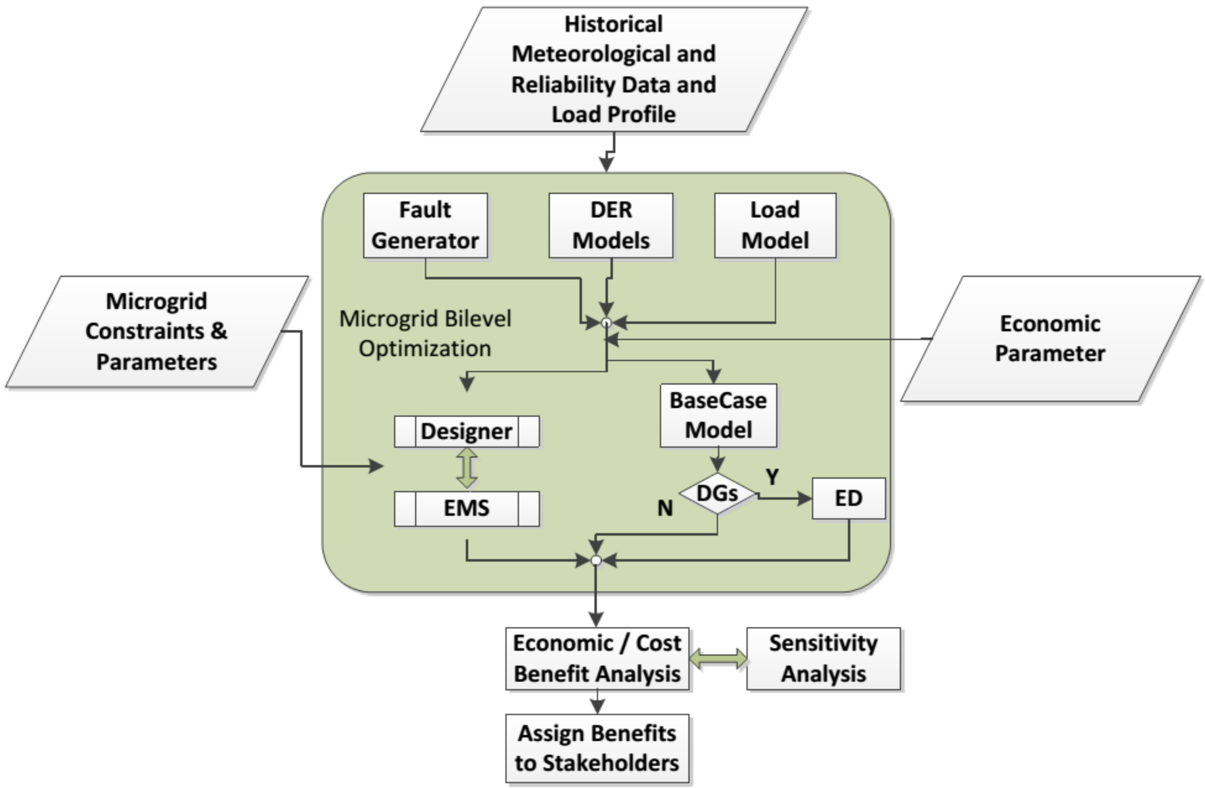

Figure 4.2. Methodology Flow.

Input data such as meteorological data, load mix and load profile required for the business cases is gathered. Historical reliability information are used together with Markov chains to model system failures [104] which may result in load interruption or islanding (for grid connected microgrids).

The existing power infrastructure and technical models of DERs are developed. This may also include the determination of feasible resources that can be installed.

Technical analyses such as load flow analysis are undertaken to establish the integrity of the modeled power system.

Clear identification of existing and proposed modification to the base system (additional microgrid infrastructure/technology to be included). Here, the type of modification to be made or technology to be considered will inform the objectives of the optimization model of the business case.

Economic parameters applicable to the microgrid and existing power system are determined and passed on to the optimization engine together with the input data and technical models. The optimization engine is activated: discovered impacts are maximized through the optimization process.

All impacts discovered are monetized through a cost-benefit analysis. This implies transforming the impacts into monetary values and comparing the proposed microgrid feasible alternatives against each other and to the base case. Though all alternative are likely to yield some benefit, the most economical option will have the strongest business case.

The derived benefits are then assigned to their corresponding stakeholders.

Sensitivity analysis is undertaken to ascertain important parameters and factors influencing the microgrid business case. It is also important to understand how the microgrid business case could manage future risk in economic and other parameters.

4.5 Case Study

The proposed approach is applied in developing business cases for a remote mining site, a remote community and a grid connected critical distribution network. In all cases, four planning scenarios are considered: the base case (existing power system with no microgrid infrastructure), DG only scenario (Scenario A), where available DGs are added to existing infrastructure in the base case, DG plus energy storage scenario (Scenario B) and the final one, DG, electric energy storage and DR (Scenario C). The planning scenarios are similar to those in the previous chapter and applicable to all networks considered here.

Case Study I Isolated Community

The first case study considered is a microgrid implementation for an isolated remote community energy infrastructure. The community's electricity is supplied by three generators: two 420 kW diesel units and a 210 kW unit. The average efficiency of the two 420 kW unit is 0.27 ℓ/kWh [95] while the smaller unit has a steep efficiency curve averaging around 0.60 ℓ/kWh. The 210 kW unit runs during very low and high demand states. A higher efficiency can be gained by adjusting the generator dispatch set points to avoid the operation of the 210 kW generator. The community has a peak load of 700 kW and an annual load growth of 2 % is assumed. Network improvement and transformer upgrade costs are taken to be $\$56,000$ per MW peak [95]. The unit cost of NDE is assumed to be \$1 per kWh. A generalized single line diagram of the remote power system is shown in Fig. 4.3. Renewable resources considered for the microgrid are wind turbines, since local meteorological data do not support solar generation. Economic parameters outlined in Table 3.1 and Table 3.5of the previous chapter are applicable here.

Case Study II Remote Mine

The second case study considered is a microgrid implementation for a remote mine. The energy infrastructure of the mining site is characterized by unique features that differentiate them from the regular community power system.

The characteristics and parameters of the remote mine are the same as those in the previous chapter's case study.

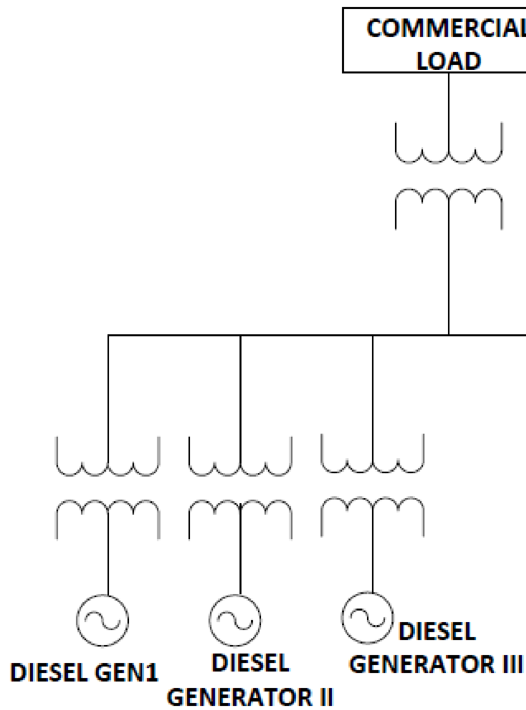

Figure 4.3. Single line diagram of a generalized remote power network.

Case Study III Grid Connected Microgrid

The third case study is a grid-connected network with a reliability index of two upstream failures per year. The energy need of the network is provided by a local electricity and gas company. A 13 month average electricity rate of 7.52¢/kWh and a gas price of 3.1$/GJ is assumed. The network consists of mainly commercial and housing loads, which are further grouped into thermal and electric loads. The peak load of the network is 7.35 MW with an annual load growth of 2 %. Ten percent of the thermal and electric load (including cooling load) is assumed to be controllable and available for DR implementation. The average costs of non-delivered energy is taken to be $2.50 per kWh, $10 per kWh, and $25 per kWh for residential, commercial, and industrial customers respectively [17]. DGs considered in this case are CHP and wind turbines. Electric storage is considered in alternative planning scenarios as in other case studies. A generalized single line diagram of the network is shown in 4.4

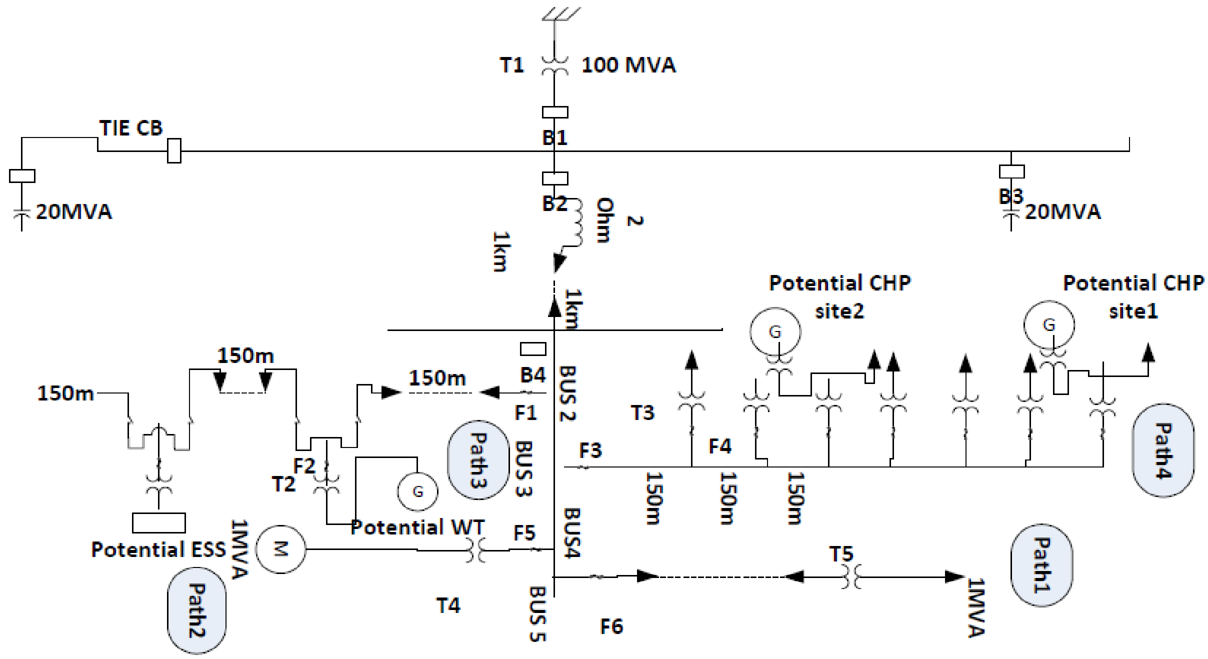

Figure 4.4. Single line diagram of the grid connected system.

4.6 Results and Discussion

The above case studies are also implemented within the customized VBA-EXCEL framework (BIEX) developed in this thesis work. The input to BIEX as given in Table 3.1 are entered in the frontend excel–sheet. These are passsed on to the optimization engine through the backend VBA and the results returned to the frontend excel–sheet. For the sake of clarity, the results are discussed case study by case study and the present value ratio (PVR) is used to determine the profitability of the microgrid investment options as found in the previous chapter.

Case Study I

Here, the community owns and runs their own utilities including the electrical system. Significant incentives and financial support are available from the government for such projects; however, for the sake of brevity and ease in comparison, the community is the only stakeholder considered. The sum of various cost components in the base case is compared to that of the microgrid alternatives. Microgrid Scenario C appears to be the optimal planning option as observed in Table 4.2. Justification of the recommended option as required by question 4*b* of the business case overview in Fig. 4.1 is evident from Table 4.2. The optimal configuration is found to be 597 kW of wind and 497 kWh (124 kW) of storage with DR implementation.

Table 4.2
Costs and Benefit Allocation - Case Study I

Stakeholder(s)	**Costs**	**Basecase**	**Scenario A**	**Scenario B**	**Scenario C**
Community	Fuel	0.783	0.667	0.609	0.542
	Emission	0.198	0.104	0.100	0.089
	NDE	0.017	0.000	0.000	0.000
	Investment	0.002	0.028	0.045	0.018
	Total	1.000	0.798	0.754	0.649
Savings			**20.22%**	**24.60%**	**35.10%**
PVR			**7.22%**	**5.46%**	**19.5%**

In an attempt to monitor the effect of the penetration level of each DER technology on the business case, the size of ESS and wind turbines are varied while the total energy cost is observed. Here, DER technology with and without DR implementation (base case plus wind, base case, wind plus storage; base case plus wind plus DR, base case, wind plus storage plus DR) are considered. It can be observed from Fig. 4.5 that energy cost decreases with an increase in penetration of wind until it reaches 82% penetration level, where the energy cost begins to increase with an increase in penetration. The fraction of storage as a percentage of peak load follows a similar trend till 17%, when its energy cost increases with increasing penetration level.

Also the impact of reliability of available DER technology on the total cost of the system's operation and planning configuration was observed. Here, Fig. 4.6 shows a decrease in the total cost of NDE with increasing penetration of DER till 40% where further investment in DERs do not result in any change in the cost of NDE. Furthermore, the unit value of energy not served is varied while we observed the cost of energy. From Fig. 4.7, it could be observed that an increase in the value of NDE results in an increase in the per unit cost of energy until a value of $2 per kWh. As the value of NDE increases above $2, the quantity of NDE decreases which results in a decrease in the cost of energy. However, the optimal configuration changes in order to balance the uninterrupted energy. Also, increasing the

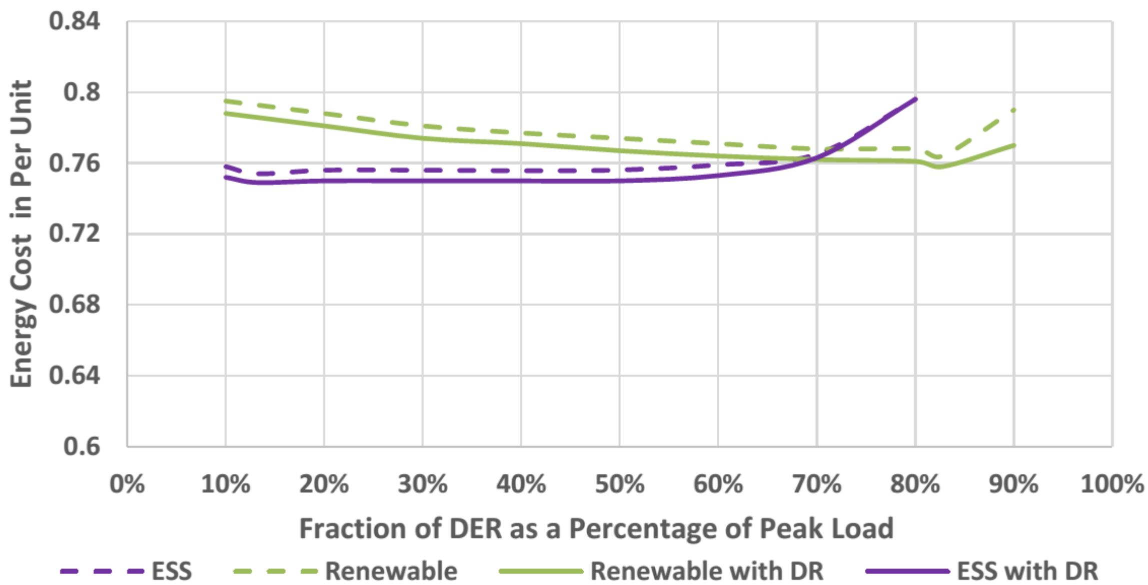

Figure 4.5. Impact of penetration level on the annual energy cost of remote community microgrid without considering NDE

value of NDE above $6 per kWh does not impact the business case since no load is interrupted beyond this point. Furthermore, contrary to expectation that increasing the value NDE will yield an optimal configuration that favours resources with firm output (e.g. diesel and CHP), the optimal configuration continues to favour relatively reliable wind turbines and electric storage systems.

In addition to the above observation, it can also be seen from Fig. 4.5 and Fig. 4.6 that at low penetration levels of renewables, the cost of energy is relatively low in the case where no NDE was considered. However, as the penetration level increases, the energy cost appears to be relatively the same. A similar observation is made as the penetration level of ESS is varied (i.e. relatively equal cost of energy in both cases even at low penetration). Though similar observation are made in both cases, the optimal penetration level or configuration for the scenario where NDE is considered, appears to support a higher penetration level (17%) of the more reliable ESS compared to an 11% penetration in the no NDE case.

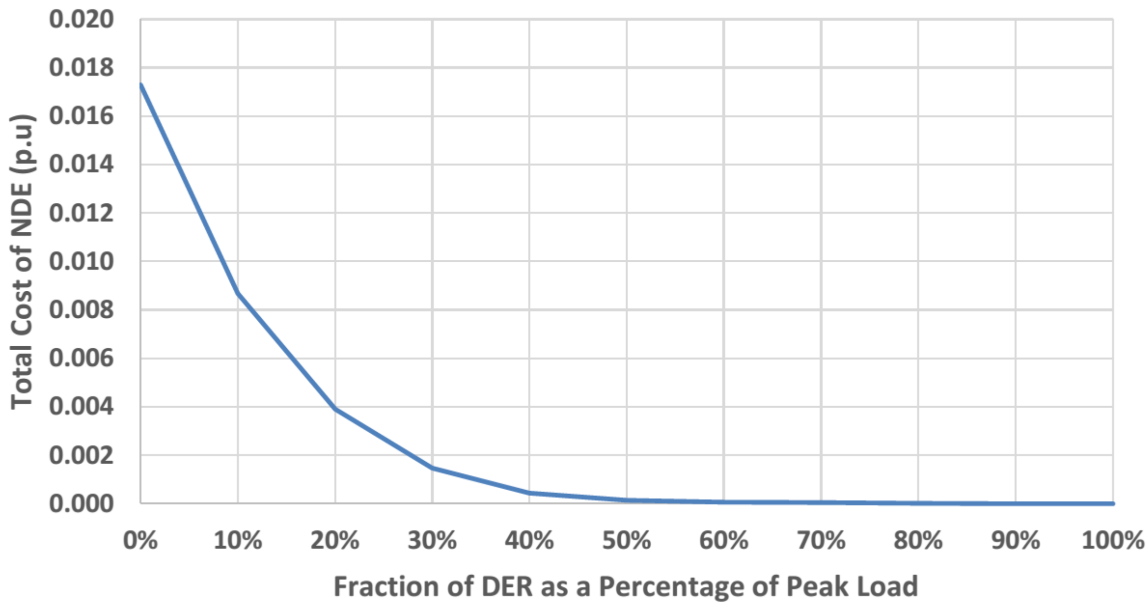

Figure 4.6. Impact of penetration level of DERs on the total cost of NDE

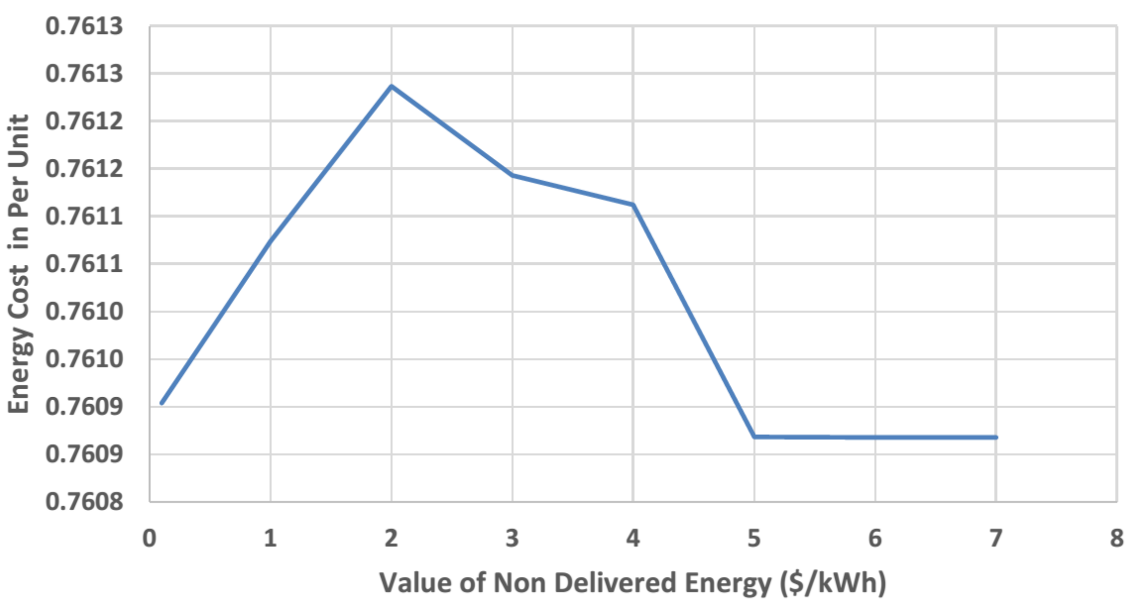

Figure 4.7. Impact of NDE on the annual energy cost of remote community microgrid

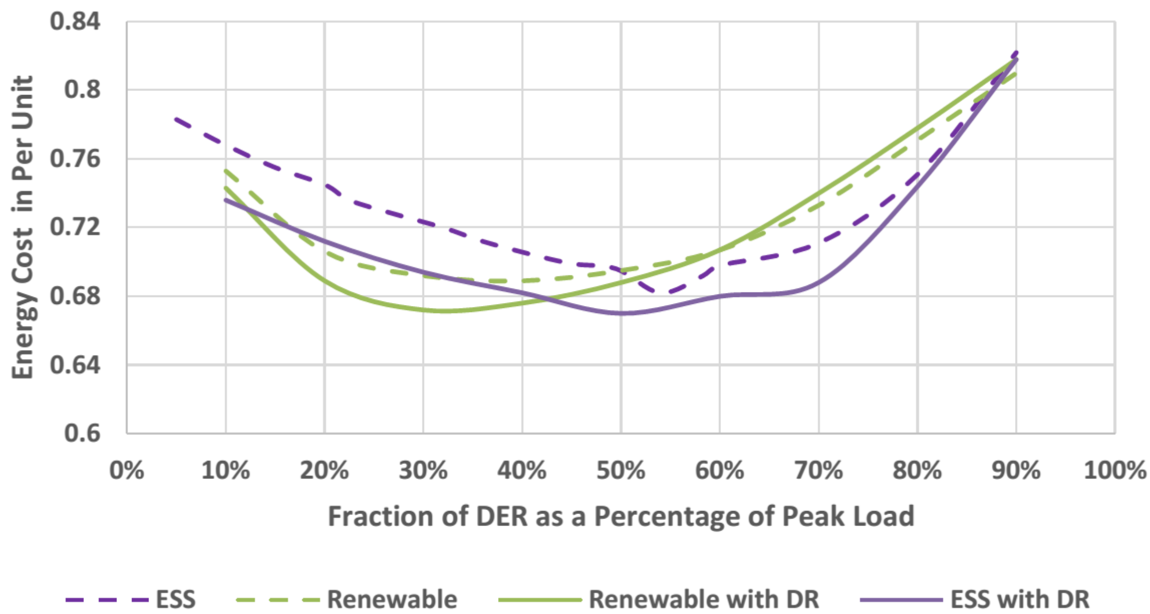

Figure 4.8. Impact of penetration level on the annual energy cost of a remote mine microgrid

Case Study II

The second case study is also within the remote network, here two stakeholders are identified in all the four planning scenarios defined in the introductory paragraph of the section on case studies: the society who is affected by the mine's/microgrid activity and the mine's management that own and operate the microgrid. Table 4.3 shows the various actors and their corresponding benefits where the total cost in the base case is taken to be the base unit. All values are in net present value and in per units. Savings in greenhouse gas emissions benefiting the society is determined by comparing the emissions cost discovered through simulation in the base case with that of the microgrid planning scenarios and the difference expressed as a percentage. Likewise the sum of the various cost components accrued by the mine's management are compared with the microgrid alternatives and the difference expressed as a percentage. The difference is also mapped onto corresponding stakeholders as shown in Fig. 4.9 which provides a graphical illustration of benefits accruing to stakeholders. Though all the three microgrid scenarios in this case study showed significant savings to both stakeholders, planning Scenario C (Base case plus DGs, plus ESS, plus DR) yields the most savings, and is thus the optimal way forward. The optimal configuration is determined to be 3445 kW of wind energy and 4762 kWh (1190 kW) of ESS with DR technology implemented. The optimal allocation of resources by the EMS/proxy operator present in the bi–level optimization formulation in the microgrid also contributed to a further decrease in the total cost of energy compared to the base case.

Table 4.3
Costs and Benefit Allocation - Case Study II

Stakeholder(s)	Costs	Basecase	Scenario A	Scenario B	Scenario C
Mines Management	Fuel	0.875	0.553	0.550	0.538
	Emission	0.125	0.74	0.072	0.070
	Investment		0.062	0.062	0.063
	Total	1.00	0.689	0.682	0.670
Savings			**31.11%**	**31.80%**	**33.00%**
PVR			**5.318**	**5.656**	**6.416**

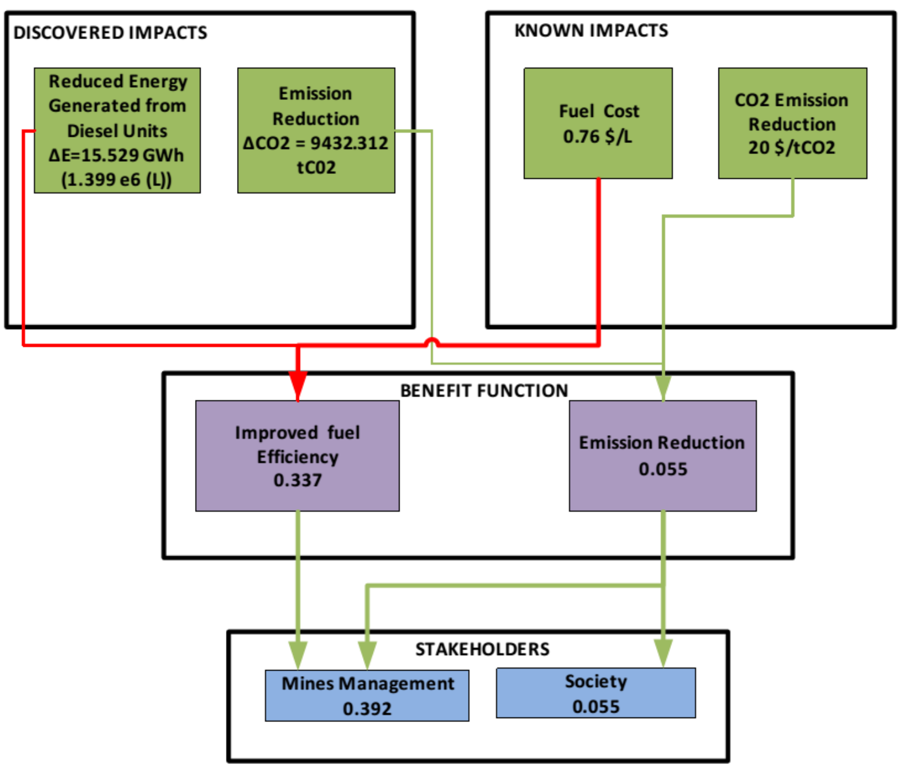

Figure 4.9. Benefits Mappings for Stakeholders in the Remote Mine

As observed in Fig. 4.8, the total cost of energy decreases with increasing penetration of wind till 30% penetration and then starts to increase. Likewise when storage is added to the technology mix, the energy cost also decreases with increasing storage penetration level till 50%, when the cost of energy increases with increasing storage penetration. It could also be noted that the implementation of DR results in lower energy cost in both cases but does not significantly impact the penetration level.

Case Study III

Table 4.4
Costs and Benefit Allocation - Case Study III

Stakeholders	**Costs**	**Basecase**	**Scenario A**	**Scenario B**	**Scenario C**
Customer	Energy	0.881	0.456	0.461	0.434
	Emission	0.125	0.74	0.072	0.070
	NDE	0.032	0.004	0.005	0.005
	Total	1.000	0.544	0.507	0.478
Savings			**45.60%**	**49.30%**	**52.20%**
IPP	Emission		0.083	0.041	0.039
	Energy Sold		(0.456)	(0.461)	(0.434)
	NDE		0.005	0.006	0.005
	Investment		0.021	0.015	0.015
Profit			**0.347**	**0.399**	**0.375**
PVR			**16.5**	**26.6**	**15.0**
DNO	NDE	0.033	0.005	0.006	0.005
	Network Reinforcement	0.003	0.000	0.000	0.000
	Total	0.036	0.005	0.006	0.005
Savings			**86.10%**	**83.60%**	**86.10%**

The impact of the penetration level of DERs on the business case of grid connected systems is considered in this case study. A similar trend is observed in here as observed in the previous cases with the optimal penetration of wind being 67% and storage 26.6% as illustrated in Fig. 4.10.

The third case study, unlike the previous ones has three stakeholders: the urban dwellers acting as both customers and society, independent power producer (IPP) and the utility or Distributed Network Operator (DNO). Similar to the previous case studies, the various cost components are compared to that of the base case. Nevertheless, the IPP is absent in the base case, hence its benefit/profit is determined by subtracting its corresponding cost components from the revenue received from the sales of energy (values in between brackets in Table 4.4 represent revenue or negative cost). The optimal configuration is determined to be 2780 kW of wind turbine and 1920 kW of ESS with 10% of peak load available for DR (Scenario C).

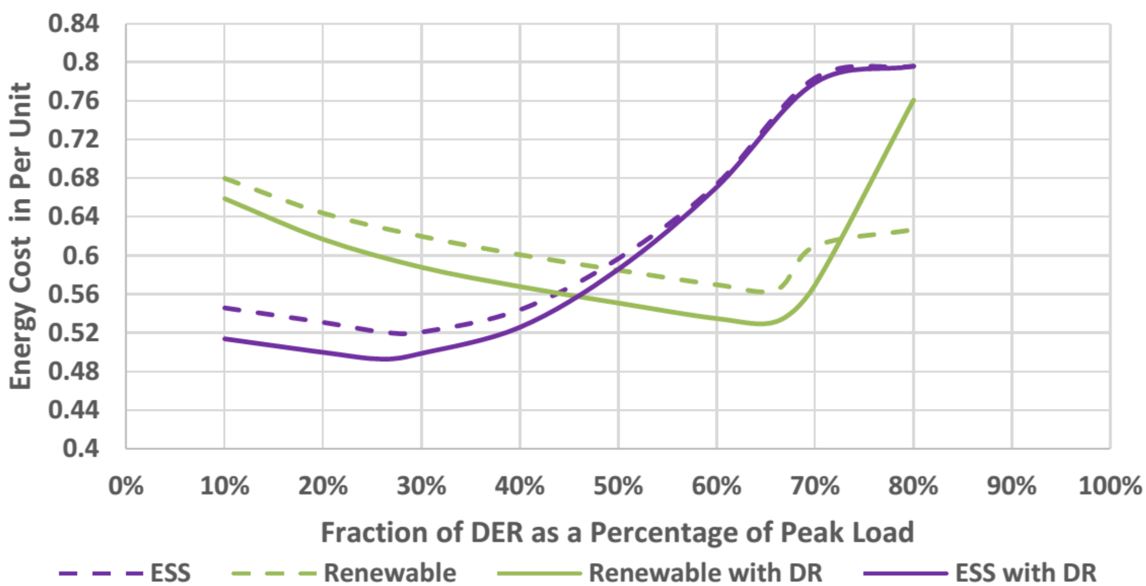

Figure 4.10. Impact of DER penetration level on the annual energy cost of Grid Connected power system..

4.7 Conclusion

A systematic approach and methodology for developing a microgrid business case has been presented in this chapter. Here, key elements of the microgrid business case and how they fit together to develop a business case are outlined and discussed. It could be deduced from the work that, regardless of the audience of the business case, a better understanding of how key elements and models of the microgrid business case fit together is important to developing a stronger case. The work further demonstrated how an advance planning strategy with the right technology mix could advance business cases for both grid connected and remote microgrids. Also, the reliability of individual microgrid technologies is observed to have influence on the microgrid business case especially for remote community where repair works could take some days to complete. Applications to practical microgrids are discussed, including remote communities, remote mining sites and grid connected critical distribution grids. Results and analysis from the studies will aid and inform policy makers in drafting microgrid incentive policy and programs.

Chapter 5

Harnessing Flexibility of Microgrid Energy Resources for its Operational Planning

5.1 Introduction

This chapter discusses an energy centric operational planning strategy that seeks to harness identified benefits of flexibility provided by DER resources in a microgrid, to match the dynamics of uncertainty within the microgrid. The chapter explains the *power and energy centric* concept of microgrid planning and seeks to highlight the flexible value of microgrid resources under uncertainty. Application of the proposed strategy to a representative microgrid and its comparison to a traditional operational planning dispatch are discussed. Results obtained from the application are analyzed and discussed in this chapter.

5.2 Quantifying the Energy Based Flexibility Requirement

The main sources of uncertainty within microgrids are variable load and intermittent resources. Careful analysis is required to model these uncertainties and estimate the flexibility requirement of a microgrid in order to meet its real time energy dynamics. From an energy centric perspective, two approaches have been outlined by authors in [105] to quantify these requirement: one that simply integrates the traditional power-based operating reserve requirements to obtain the energy-based operating reserve requirements and a second approach that first integrates the net load power time series to obtain the net load energy time series. After integrating the net load power, statistical analysis is applied to the net load energy time series to obtain the energy-based operating reserve requirement. The former is adapted to the microgrid context and transformed to serve the purpose of the thesis work.

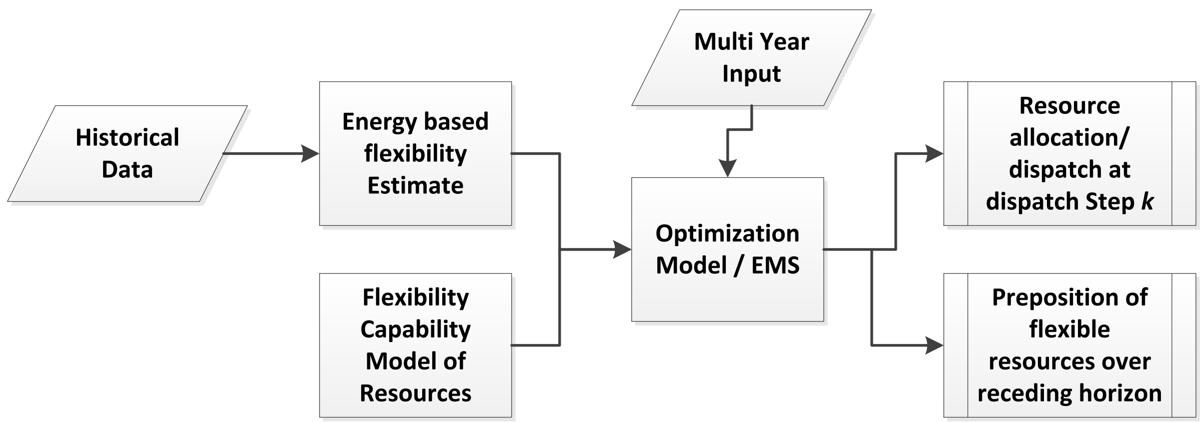

Figure 5.1. Schematic outline of operational strategy

Thus, we start with an estimate of the energy reserve requirement as outlined in Fig. 5.1. To estimate the energy reserve requirement, the power based reserve requirement is initially modeled in the form of an envelope [106, 107]. Here, historical intra-hourly data of the net load (load minus intermittent resources) are gathered. The net load ($\mathcal{L}(q)$) at the present dispatch step q is assumed to be known and used as reference for upcoming operational horizon. It is by deviating from the present net load level that a need to deploy operating reserve over an operational horizon arises.

The deviation $\Delta\mathcal{L}(\tau, q)$ from the reference net load, τ units of time later (here in mins) is computed in (5.1) as a step change in the net load at units of time τ as seen from the present dispatch step q, $q = 1, ..., Q$.

$$\Delta\mathcal{L}(\tau, q) = \mathcal{L}(\tau + q) - \mathcal{L}(q) \tag{5.1}$$

By fixing τ and sweeping through q, we obtain many realizations of the net load step change $\Delta\mathcal{L}(\tau, q)$ as a function of only τ. These realizations can then be used to obtain the standard deviation σ_p as a function of τ. From this, the power-based operating reserve requirements can be defined as a multiple of the standard deviation , depending on the desired percentile coverage of reserve requirements.

Once the traditional power based reserve requirement is modeled, the energy centric reserve requirement is obtained by directly integrating the power based reserve model as given in (5.2).

$$\sigma_{\sum p}(\tau) = T\sum_{j=1}^{\tau/T}\sigma_p(j) \tag{5.2}$$

5.2.1 Flexibility Capability Model of Energy Resources

Inspired by the pretext in the previous section, this section details the flexibility capability/availability of a microgrid as an energy quantity. Here, the available flexibility from flexible energy resources such as thermal generating units, ESS and DR is estimated as the deviation ($\Delta P(\tau, k)$) of the resource power level from its scheduled (present) power level as outlined in (5.3):

$$\Delta P(\tau, q) = P(\tau + q) - P(q) \tag{5.3}$$

where $P(q)$ the power output level at present dispatch step q. The step change in the energy quantity is then obtained by integrating (5.3):

$$\Delta E(\tau, q) = \mathcal{T}\sum_{j=1}^{\tau/\mathcal{T}} P(q + j) - \tau P(q) \tag{5.4}$$

where ($\Delta E(\tau, q)$) represents the amount of energy a resource can deliver τ units of time later, as seen from the present dispatch step q. Hence, the energy centric envelope determines the energy content of the resource while its first and second derivative provides information about the power and ramp capability of the resource. Models of energy centric envelopes for specific microgrid resources are considered in subsequent section.

5.3 Mathematical Formulation of the Operational Planning Strategy

The proposed operational planning strategy is formulated in a way to harness identified benefits of a microgrid's flexibility. The formulation is equivalent to an energy centric EMS solving a combined energy and reserve scheduling problem of a microgrid. The energy levels of energy constrained resources and power levels of conventional resources are continuously dispatched to balance the net load forecast of the microgrid. Concurrently, the resulting energy-based flexibility capability/profile of the resources are made to match the estimated energy-based flexibility requirements modeled in the previous section and projected over the receding horizon of operations. For the sake of clarity and to maintain consistency in units, ramp constraints are in MW/minute, power constraints are in MW, and energy constraints are in MWh.

The problem is a simplified form of the lower level operation problem in chapter three of this thesis and cast as a multi–objective MILP. The main objective is to minimize the dispatch cost of flexible resources, given fuel and emission costs (first term), the costs of providing heat from a non CHP resource (second term) and the maintenance cost of the DERs. Thus, for a dispatch step q, the objective function is defined by (5.5), where x_i in this model is known a priori and C^{CO2} is the emission cost per tCO_2 emitted.

$$\min_{P} \sum_{i \in I_G} (C_i^f + C_i^{CO2}) P_i^e(q) + \sum_{i \in I_H} (C_i^f + C_i^{CO2}) P_i^h(q) + \sum_{i \in I_B} C_i^o x_i \tag{5.5}$$

The objective function is constrained by electrical and thermal load balance at every dispatch step q. The electrical load balance is provided by (5.6):

$$\sum_{i \in I_G} P_i^e(q) + \frac{60}{T} \sum_{i \in I_S} \Big(\eta_i^e [\mu_i(q) s_i(q-1) - s_i^{\downarrow}(k)] + 1/\eta_i^e [(1-\mu_i(q)) s_i(q-1) - s_i^{\uparrow}(q)] \Big)$$
$$+ \frac{60}{T} \left(\left[\mu_r(q) E_r^e(q-1) - E_r^{e\downarrow}(q)\right] + \left[(1-\mu_r(q)) E_r^e(q-1) - E_r^{e\uparrow(q)}\right] \right) = l^e(q) \tag{5.6}$$

while the thermal load balance is ensured by (5.7):

$$\sum_{i \in I_H} P^h_{y,i}(t) + \frac{60}{T}\left([\mu_r(q)E^h_r(q-1) - E^{h\downarrow}_r(q)] + [(1-\mu_r(q))E^h_r(q-1) - E^{h\uparrow}_r(q)]\right) = l^h(q) \tag{5.7}$$

Here s_i denote energy level of a storage resource i at dispatch step q while $s_i^{\downarrow}$ and $s_i^{\uparrow}$ define the charging and discharging energy levels respectively. Also, $E^{e\downarrow}_r$, and $E^{e\uparrow}_r$ denote decreasing and increasing levels of energy available for elctrical DR and $E^{h\downarrow}_r$, and $E^{h\uparrow}_r$ denote that of thermal DR respectively.

The objective is further constrained by maximum and minimum limits of the dispatchable generating resources including a CHP unit, and their ramp rates, given by (5.8) and (5.9):

$$P_i^{\min} \leq P_i^e(q) \leq P_i^{\max}, \qquad \forall i \in I_G \tag{5.8}$$

$$-\mathcal{R}_i \leq P_i^e(q) - P_i^e(q-1) \leq \mathcal{R}_i, \qquad \forall i \in I_G \tag{5.9}$$

The thermal output of the CHP unit is given by:

$$P_i^h(q) = \frac{P_i^e(q)}{\varsigma_i}, \forall i \in I_N \tag{5.10}$$

Also, the dispatch of ESS is constrained by maximum and minimum energy level of the ESS and their rated power output (5.11)–(5.14). Here, ESS is modeled differently due to the need to show the upward and downward projections of the horizon. Nonetheless, the model is within the same context as outlined in chapter two of the thesis. The binary variable μ_i ensures that charging, $s_i^{\downarrow}$, and discharging, $s_i^{\uparrow}$, remain mutually exclusive. The analogy holds for DR as well. The constant ν_i in (5.14) is dependent on the type of storage technology installed as explained in the previous chapters.

$$s_i(q) = s_i^{\uparrow}(q) + s_i^{\downarrow}(q), \forall i \in I_S \tag{5.11}$$

$$\mu_i(q)E_i^{min} \leq s_i^{\downarrow}(q) \leq \mu_i(q)s_i(q-1), \forall i \in I_S \tag{5.12}$$

$$(1-\mu_i(q))s_i(q-1) \leq s_i^{\uparrow}(q) \leq (1-\mu_i(q))E_i^{max}, \forall i \in I_S \tag{5.13}$$

$$-\nu_i E_i^{max} \leq \frac{60}{T}(s_i(q) - s_i(q-1)) \leq \nu_i E_i^{max}, \forall i \in I_S \tag{5.14}$$

Similarly, the dispatch problem is subject to limits on energy available for both electrical (5.15)–(5.18) and thermal DR (5.19)–(5.22). The electric and thermal power available for DR for each dispatch step q is constrained by (5.18) and (5.22) respectively. Likewise, parameters κ_r^e and κ_r^h are dependent on the DR technology/strategy implemented. The electric-side DR has to satisfy (5.16)–(5.19):

$$E_r^e(q) = E_r^{e\uparrow}(q) + E_r^{e\downarrow}(q) \tag{5.15}$$

$$0 \leq E_r^{e\downarrow}(q) \leq \mu_r(q)E_r^e(q-1) \tag{5.16}$$

$$(1-\mu_r^e(q))E_r^e(q-1) \leq E_r^{e\uparrow}(q) \leq (1-\mu_r^e(q))w_r^e L^{emax} \tag{5.17}$$

$$-\kappa_r^e w_r^e L^{emax} \leq \frac{60}{T}(E_r^e(q) - E_r^e(q-1)) \leq \kappa_r^e w_r^e L^{emax} \tag{5.18}$$

while the thermal DR is constrained by (5.19)–(5.22)

$$E_r^h(q) = E_r^{h\uparrow}(q) + E_r^{h\downarrow}(q) \tag{5.19}$$

$$0 \leq E_r^{h\downarrow}(q) \leq \mu_r(q)E_r^h(q-1) \tag{5.20}$$

$$(1-\mu_r^h(q))E_r^h(q-1) \leq E_r^{h\uparrow}(q) \leq (1-\mu_r^h(q))w_r^h L^{hmax} \tag{5.21}$$

$$-\kappa_r^h w_r^h L^{hmax} \leq \frac{60}{T}(E_r^h(q) - E_r^h(q-1)) \leq \kappa_r^h w_r^h L^{hmax} \tag{5.22}$$

Besides the operational constraints of the resources, the reserve profile of the flexible energy resources must match the estimated flexibility requirement of the microgrid over the projected receding horizon. Thus additional constraints are included in the optimization problem to ensure this.

Consequently, the energy based flexibility capability of generators $i \in I_G$ and for $m = 1, ..., M$ is provided by (5.23)–(5.28). The constraints determine two power output trajectories for each generator, one upward and one downward , bounded by the generators' capacities and ramp rates. Here, equations (5.23) and (5.26) set the initial condition of the power output trajectories to the step dispatch levels, while equations (5.25) and (5.28) set the bound of the trajectories to their minimum and maximum generator capacity at the end of the receding horizon. Constraints (5.24) and (5.27) enforce the ramping limitations over the duration of the receding horizon.

$$g_i^{\downarrow}(0) = P_i(q) \tag{5.23}$$

$$-\frac{1}{T}(g_i^{\downarrow}(m) - g_i^{\downarrow}(m-1)) \leq R_i \tag{5.24}$$

$$g_i^{\downarrow}(M) = P_i^{min}(q) \tag{5.25}$$

$$g_i^{\uparrow}(0) = P_i(q) \tag{5.26}$$

$$\frac{1}{T}(g_i^{\uparrow}(m) - g_i^{\uparrow}(m-1)) \leq R_i \tag{5.27}$$

$$g_i^{\uparrow}(M) = P_i^{max}(q) \tag{5.28}$$

Likewise, the flexibility projection of ESS resource $i \in I_S$ is governed by (5.29)-(5.34). Two trajectories are determined here just as in the previous cases, one upward and the other downward. The initial conditions of the ESS flexibility projection are set by equations (5.29) and (5.32). The maximum projected power available from ESS within the period $m \in M$ is constrained by (5.30) and (5.33).

$$a_i^{\downarrow}(0) = s_i(q) \tag{5.29}$$

$$-\frac{60}{T}(a_i^{\downarrow}(m) - a_i^{\downarrow}(m-1)) \leq \nu_i E_i^{max} \tag{5.30}$$

$$a_i^{\downarrow}(M) \geq E_i^{min} \tag{5.31}$$

$$a_i^{\uparrow}(0) = s_i(q) \tag{5.32}$$

$$\frac{60}{T}(a_i^{\uparrow}(m) - a_i^{\uparrow}(m-1)) \leq \nu_i E_i^{max} \tag{5.33}$$

$$a_i^{\uparrow}(M) \leq E_i^{max} \tag{5.34}$$

In the same way, the projected flexibility from electrical DR resources is given by (5.35)–

(5.40). Similarly, two trajectories are determined while the initial conditions are set by (5.35)–(5.38). The maximum projected available power for DR within the projected period $m \in M$ is constrained by (5.36) and (5.39).

$$z_r^{\downarrow}(0) = E_r^e(q) \tag{5.35}$$

$$-\frac{60}{T}(z_r^{\downarrow}(m) - z_r^{\downarrow}(m-1)) \leq \kappa_r^e w_r^e L^{emax} \tag{5.36}$$

$$z_r^{\downarrow}(M) \geq 0 \tag{5.37}$$

$$z_r^{\uparrow}(0) = E_r^e(q) \tag{5.38}$$

$$\frac{60}{T}(z_r^{\uparrow}(m) - z_r^{\uparrow}(m-1)) \leq \kappa_r^e w_r^e L^{emax} \tag{5.39}$$

$$z_r^{\uparrow}(M) \leq w_r^e L^{emax} \tag{5.40}$$

The projected trajectories or anticipatory flexibility provision by the flexible microgrid resources, diesel generators, CHP, energy storage and energy from electric DR must balance the energy centric flexibility requirement of the net load ($\mathcal{W}^{\uparrow}(m)$ *and* $\mathcal{W}^{\downarrow}(m)$). This is ensured by (5.41) and (5.42) for both upward and downward trajectories within the projected period $m \in M$.

$$\frac{T}{60}\sum_{j=1}^{m}\sum_{i\in I_g}\Big(g_i^{\uparrow}(j) - P_i^e(m)\Big) + \sum_{i\in I_S}\Big(s_i(m) - a_i^{\downarrow}(m)\Big) + \big(E_r^e(m) - z_r^{e\downarrow}(m)\big) = \mathcal{W}^{\uparrow}(m) \tag{5.41}$$

$$\frac{T}{60}\sum_{j=1}^{m}\sum_{i\in I_G}\Big(P_i^e(m) - g_i^{\downarrow}(j)\Big) + \sum_{i\in I_S}\Big(a_i^{\uparrow}(m) - s_i(m)\Big) + \big(z_r^{e\downarrow}(m) - E_r^e(m)\big) = \mathcal{W}^{\uparrow}(m) \tag{5.42}$$

5.4 Case Study

The proposed operational planning strategy is applied to the operation of the energy system of a remote mine. The characteristics and parameters of the remote mine are the same as those found in previous case studies of chapter three and chapter four. Here the microgrid consists of conventional diesel generators, CHP, wind turbine, ESS and DR. Unlike the cases in the previous chapters, the capacities of the DERs x_i are known a prior. Four operational planning scenarios are considered here: The first scenario is a myopic deployment of the microgrid energy resources without anticipating their future use or flexibility provision. The second scenario anticipates the future use of the flexible resources and plan their projected flexibility provision. In the third scenario, we consider the use of energy storage without any DR implementation while the fourth case considers having DR resource with no energy storage system. Traditional economic dispatch of the mine's energy resources with no microgrid capabilities is taken as the base case.

We begin by determining the flexibility requirement of the remote mine's energy system as indicated in section 5.2 and [105]. Here, the dispatch step q is taken to be $1, ..., 12$ within an hourly unit commitment so that the sampling period will be $\mathcal{T} = 5$ minutes. The initial idea here, was to have a longer projected horizon or anticipate the flexibility requirement for the next 24 hrs as shown in Fig. 5.2.

However, a rippling or cyclic effect is observed in the modeled envelope in Fig. 5.2,

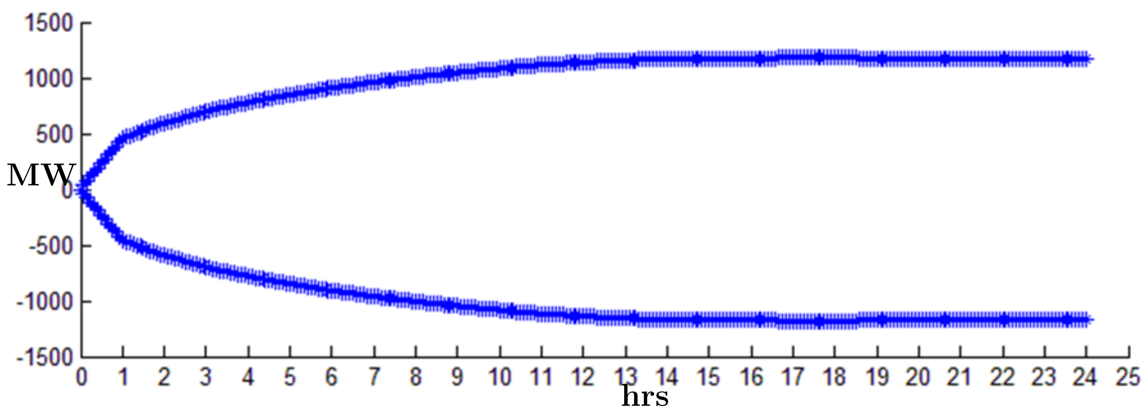

Figure 5.2. A 24hr anticipatory horizon

prompting us to reduce the horizon. Reducing the receding horizon to a 12 hr (720) minute model still showed some ripples as can be observed in Fig. 5.3. This cyclic effect could trigger a research interest in analyzing the long term flexibility requirement for microgrid planning. Nonetheless, the horizon is further reduced to an hourly projection (where we have the highest deviation before the rippling effect). In this way, M is considered to be 12 such that $m = 1, ..., 12$ and $\tau = 5, 10, ..., 60$ or $\tau = m\mathcal{T}$ minutes. Here, assuming the present demand is known to be 8 MW, the power based flexibility requirement projections for an hour is obtained as illustrated in Fig. 5.4. This is then integrated to give the energy

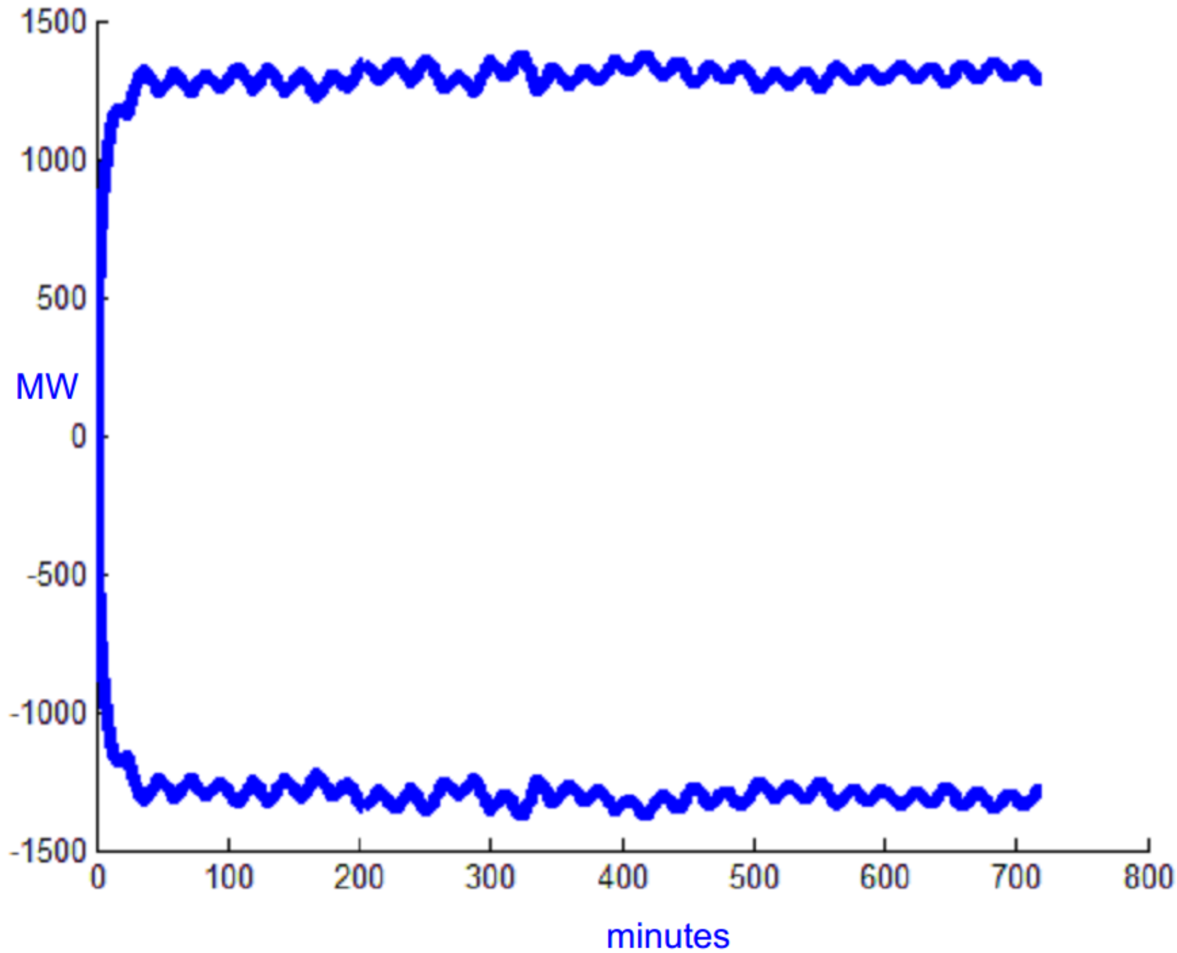

Figure 5.3. A 720 minute anticipatory horizon

centric flexibility requirement shown in Fig. 5.5.

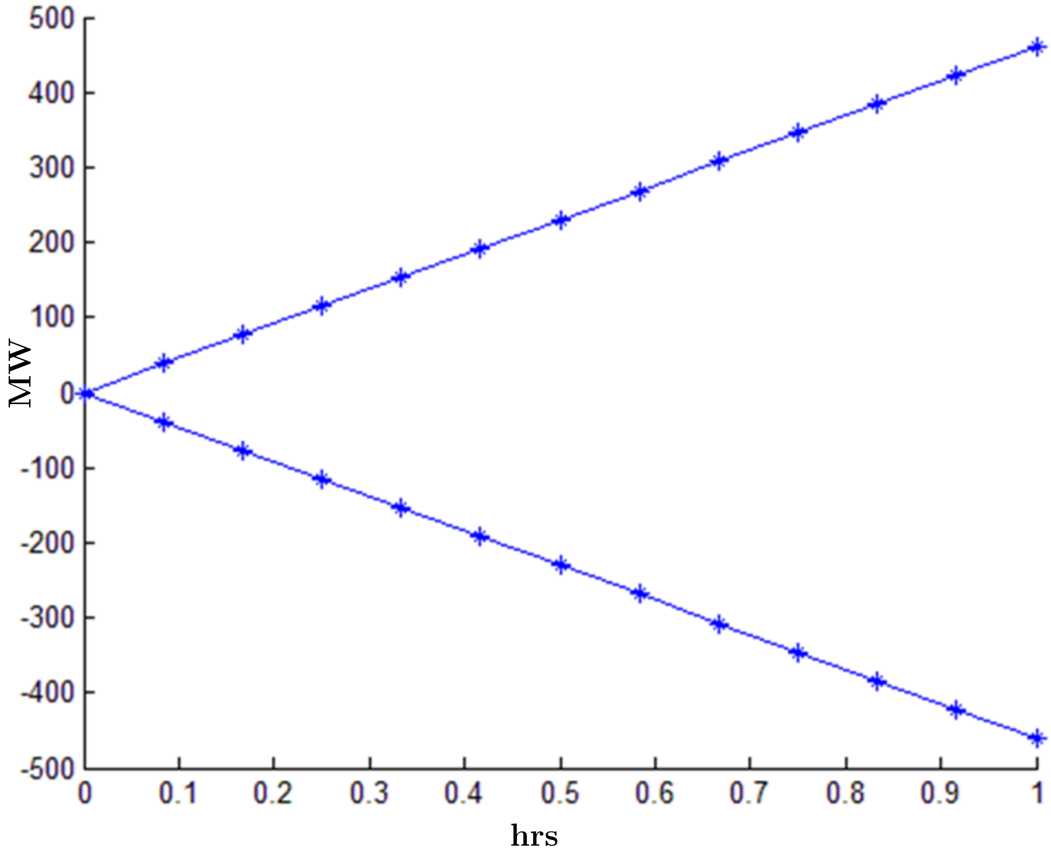

Figure 5.4. Power based flexibility requirement projections for an hour

Once the flexibility requirement is determined, the microgrid energy resources are dispatched to meet the present demand and the flexible resources are preposition to satisfy projected flexibility requirement as outlined in the previous sections and in Fig. 5.1. A hundred one-hour realizations are generated, simulated, and the resulting MILP solved with GAMS CPLEX Solver. Parameters of the microgrid resources are provided in Table 5.1 and Table 5.2.

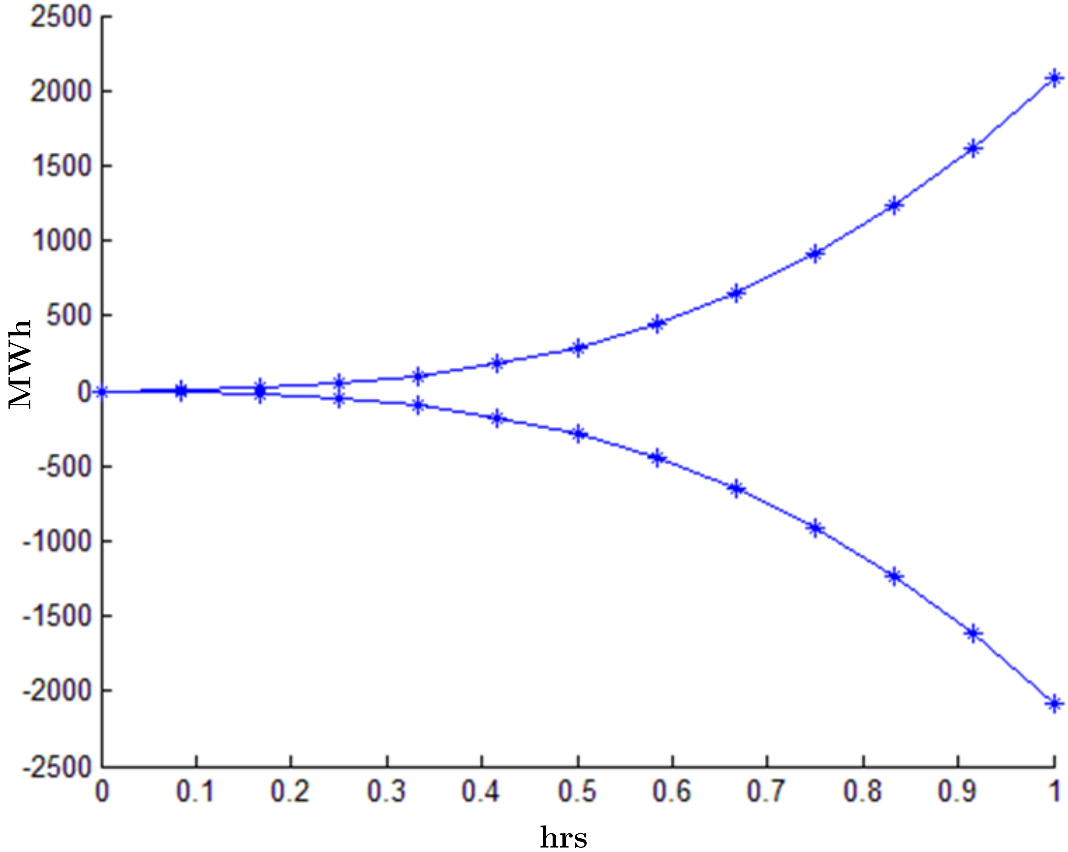

Figure 5.5. Energy centric flexibility requirement projections for an hour

Table 5.1
Parameters of Microgrid Conventional Energy Resources

Resources	P_i^{max}(MW)	P_i^{min}(MW)	$\mathcal{R}_\rangle$(MW/minute)	C_i^f
Diesel I	6	0	1	0.76($/L)
Diesel II	2	0	0.4	0.76($/L)
Diesel III	2	0	0.4	0.76($/L)
CHP	1.047	0	0.2	3.1($/GJ)

Table 5.2
Parameters of Microgrid Electrical Energy Storage System

Storage Type	E_i^{max}(MWh)	E_i^{min}(MWh)	η_i^e	ν_i
CAES	1.82	0	0.9	0.25

5.5 Results

Simulations of hundred realization of the mine's net load variation are run for all the microgrid planning strategies and the expected or mean value of the levelised cost of energy (LCOE) for each planning strategy determined. The LCOE will serve as a metric of comparison for each of the cases. Several realizations of the net load are considered to preserve the validity of results obtained. The results are in two parts as can be observed in Table 5.3 and Table 5.4. The first part provided by Table 5.3 compares the myopic dispatch strategy and the proposed energy centric flexibility planning strategy. They are both bench-marked against the base case where microgrid resources/infrastructure are not considered. In other words, the base case here, is a traditional economic dispatch of the mine with no microgrid capabilities. Here, it can be observed from Table 5.3 that the base case has the highest LCOE, followed by the myopic dispatch strategy, with the energy centric strategy having the least LCOE. The LCOE of the two planning alternatives compared to that of the base case, justify the narrative that microgrid offer several benefits including flexibility which is a service the microgrid can provide to the main grid. It can also be observed that, the proposed approach of anticipating future energy requirement will inform a better use of microgrid resources that could yield some energy cost savings as shown in Table 5.3. The per unit values in the second row of Table 5.3 have a base unit equal to the cost in the base case.

Table 5.3
Levelised Cost of Energy for the Different Planning Strategies

	Base case	Myopic	Energy Centric
LCOE	0.2179	0.1936	0.1542
Per Unit	1.0000	0.8884	0.7076

The second aspect of the results given in Table 5.4 simply compares cases where storage is the only available flexible non generating microgrid resource to a case with DR resource as the only non generating flexible resource. The results show more savings in LCOE of the storage only case than the DR only case. This indicates that ESS is better placed to provide flexibility within the microgrid compared to DR resources. However, one should note that, energy available for DR is comparative lower than the ESS capacity in our analysis. The result can also inform a microgrid operative's choice to operate either a ESS or a DR resource, for such purposes. There is inherent benefit to the microgrid planner who gets to know which DERs are better positioned to offer flexibility related services that may translate to revenue for a microgrid stakeholder.

Table 5.4
Levelised Cost of Energy for the Different Planning Scenario

	Base case	Storage Only	Demand Response Only
LCOE	0.2179	0.1587	0.1593
Per Unit	1.0000	0.7283	0.7311

5.6 Conclusion

This chapter analyses microgrid's flexibility and how it can be utilized for the benefit of the power system and advance the microgrid business case. Models of flexibility requirement of the net load and flexibility capability of microgrid resources are clearly laid out. An energy centric energy management formulation that optimizes the use of these flexible energy resources while anticipating future energy needs is outlined. The proposed operational planning strategy is applied to the operation of the energy system of the remote mine in previous chapters of the thesis. Results from the application compared to that of other identified operational planning strategies show relative cost savings.

The lower LCOE of the proposed strategy compared to the myopic approach, demonstrates that, harnessing flexibility capability of microgrid energy resources this way, can better advance the microgrid business case. Further analysis of the results also informs a microgrid operator's choice of utilizing a ESS or a DR resource to provide flexibility.

Chapter 6

Conclusion and Future Work

6.1 Disertation Overview

The thesis researches advanced microgrid planning and operation strategies. The thesis work seeks to propose a planning solution that seek to maximize the financial and operational benefits of microgrids. To achieve this, DER models, microgrid ownership models, stakeholders and concepts are put together to develop the general framework for advance planning of microgrids. Subsequently, bi–level models/formulation that characterize microgrid planning scenarios are proposed. Firstly, a bi–level formulation that couples microgrid planning and operational problems is proposed. Convexity of the primal formulation and other conditions that guarantee the existence of a solution to the proposed formulation are established. An algorithm available to solve coupled bi–level microgrid planning and operational problems is researched. Consequently, it was concluded that the strong duality theorem presents a more efficient approach to solving the bi–level problem compared to the KKT conditions. Alternate bi–level formulation that fits the narrative of an emerging DSO paradigm is also proposed and algorithm to solve it researched. Within the general framework developed in the early part of the work and in reference to the use case paradigm, the thesis work investigated dependency of microgrid business cases on its generation technology mix. Given the importance of the optimization strategy in the development of microgrid business cases, the thesis looked at how the proposed optimization models, DER models and key element of a business case can be assembled together to make a stronger microgrid case. It also assessed the economic viability of microgrid investments by using standard budgeting techniques and economic metrics. In an attempt to answer questions on application dependency of microgrids, the research work is extended to wide application of microgrids (remote, commercial and industrial microgrids) to develop business cases. Sensitivity analyses are carried out to determine the most important parameters influencing microgrid feasibility.

The work further exploited the operational level problem of the coupled microgrid planning and operation problem to propose an operational planning strategy that directly integrates energy into the flexibility/reserve planning of microgrids. The proposed work directly incorporates energy from storage systems and DR scheduling into the operational strategy of a microgrid. The proposed operational strategy is modeled as an energy centric energy management system solving a dispatch problem of microgrid resources.

The main contribution of the thesis to the best of the author's knowledge can be itemized as follow:

1. The thesis work proposes an optimal design approach for microgrids acknowledging the wide array of technologies available to microgrid designers– generation, energy storage, combined heat and power, and demand response–, and which can represent their operations with good fidelity over a microgrids lifetime [65].

2. A bi-level optimization model for a coupled microgrid planning and operations problem, involving a two way hierarchical interaction between the microgrid designer and an EMS which acts as a proxy system operator is also developed. The problem is further transformed into an equivalent MILP problem that can be solved systematically by commercially available MILP solvers [66].

3. A bi-level formulation for a coupled microgrid power and reserve capacity planning problem. The model is cast within the context of a distribution system operator(DSO) whose duty is to ensure reliable power supply and may request reserve capacity from a microgrid planner whose interest is to minimize its planning and operational cost [67].

The proposed solutions outlined in this thesis work and supporting analysis are aimed to develop a techno-economic tool that will aid in building microgrid business cases, and support power system planners configure new and existing networks into microgrids. Though not all microgrid applications are covered by the thesis, the work outlined in this research can be extended to other applications of microgrid.

6.2 Conclusion

The thesis work is motivated by recent interest expressed by key industrial players and stakeholders in microgrid implementation and policy aimed at reducing greenhouse gas emission. The evolved concept of microgrid required extensive studies and planning strategies which fit the current context of a more active microgrid (advanced Microgrid). Furthermore, analysis outlined in the thesis work are also required by utilities and business owners to develop business cases for a given technology. The conclusion of the thesis can be itemized as follows:

Bi–level Planning Models of Microgrids

Clearly, if one is attempting to choose and size the components of a microgrid, there is a need to have a reflection of the expected operations into the design problem. At the same time, it is clear that past microgrid design decisions can have a direct effect upon the operating costs and space. Therefore, there is a need to find a way to unify these two with the objective of finding the *best microgrid design* which would provide the *best operating costs* over the microgrid's assets lifetime. Coupling the microgrid design problem with the operation through the bi–level formulation would serve these two objectives.

Also, as new roles are defined for a future DSO in a new DSO construct, microgrid operational strategies, controls and communications, when better integrated in the planning stages of microgrids through a bi–level model, can contribute not only to the optimization of generation and load in the microgrid but can also provide services to the benefit of the distribution system.

Business Cases for Isolated and Grid Connected Microgrids: Methodology and Applications

Regardless of the audience of the business case, a better understanding of how key elements and models of the microgrid business case fit together is important to developing a stronger case

Economic analysis of microgrid investment is also necessary to justify the cost associated with the additional complexity inherent in microgrids. From an economic perspective, this line of argumentation is quantified by attaching monetary values to the cost of the additional complexity, weighed with the monetized benefits that are realized through these enhancements.

Sensitivity analysis are needed to determine the important parameters influencing microgrid implementation. Conditions under which the microgrid makes economic sense is also determined through sensitivity analysis in the thesis work.

Harnessing Flexibility of Microgrid Resources for its Operational Planning

Microgrid operational planners need a shift in paradigm from the traditional *power focus* operational and reserve planning to harness maximum benefits microgrid flexibility can provide. This is vital because, majority of flexible microgrid resources capable of managing uncertainty within the microgrid are energy constrained (ESS and DR resources). In furtherance to this point, chapter five of the thesis proposes an operational strategy that seeks to match the dynamics of uncertainty within the microgrid. The formulation is equivalent to an energy centric EMS solving a combined energy and reserve scheduling problem of a microgrid. Application of the proposed strategy to a representative microgrid, highlights the benefits of microgrid flexibility for the advancement of the microgrid business case.

6.3 Recommendations for Future Work

This thesis proposes solutions to a microgrid planning and operational problem. Logical continuation can be considered as follows:

1. The optimal microgrid design approach though proposed within the context of microgrids, could be easily extended to storage planning/sizing and operation. Here, it would be of interest to assess several energy storage technologies depicting different rated energy to rated power ratios.

2. The storage model of the bi-level formulation proposed in the thesis work, assumes a constant charging and discharging rate and negligible charging/discharging losses. However, one may consider a variable charging and discharging rate as well as some losses. Making such modification to the storage model presented, could result in a

non-linear bi-level formulation which could be an interesting extension to the thesis work.

3. Another research area that could be of interest is an extension of the thesis to planning of other representative microgrids such as military microgrids. Military bases and camps in remote locations are usually temporal. Their infrastructure including power supply system often require seamless mobility, quick deployment and should be reusable. It would be of interest to asses how the mobility and re-usability of these infrastructure will impact on the microgrid planning problem.

4. The cyclic effect observed in the initial estimate of the flexibility requirement could trigger a research interest in analyzing benefits of microgrid flexibility for long term microgrid planning (wider planning horizon).

5. Real time implementation of the proposed *energy centric* energy management system will be an interesting extension of this work. Here, the modeled DERs can be loaded onto a real time simulator processor and interface with the energy management system and a physical controller (acting as a remote terminal unit).

Appendix A

A.1 Technical Specification CHP Systems

Typical performance parameters of CHPs found in the manufacturer's datasheet or the system's passport is provided in Table A.1. The data set is taken from [68] for different manufacturers and system capacity. It is important to note that manufacturers quoted heat rates in terms of the lower heating value (LHV) of the fuel. However the purchase price of fuels is measured on a higher heating value basis (HHV).

Based on the table, we can observe that an increase in engine size increases the electrical efficiency of the system. However, as electrical efficiency increases, the absolute quantity of thermal energy available to produce useful thermal energy decreases per unit of power output. This largely affect the economics of the system.

Given the generic picture of different CHP systems, the curve fitting method is used to estimate the power output or system efficiency of a 1.1 MW GEJ system at any loading point. The system's electrical efficiency for four loading points are provided in Table A.2.

Based on the given data and the curve fitting method explained in chapter two, the Matlab function *interp* is used to obtain the polynomial expression (A.1) for all $i \in I_N$ that gives the electrical efficiency for any loading point of the system, and subsequently the power output.

$$\eta_i^e = 1.7766\exp(-5)\ell_i^{f3} - 0.0023\ell_i^{f2} + 0.1556\ell_i^f + 0.1252 \tag{A.1}$$

The electrical efficiency of the system for any load point is shown in Fig. A.1.

Table A.1
CHP Engine Specification and Performance Parameters

Performance Characteristics	**System Type**				
	Tecogen 100	GE Jenbacher (GEJ)-312C65	GEJ-416B85	GEJ-620F01	Wärtsilä-20V34SG
Baseload Electric Capacity (kW)	100	633	1,121	3,326	9,341
Electrical Heat Rate (MJ/kWh), HHV	13.33	10.44	9.77	8.92	8.66
Electrical Efficiency (%), HHV	27.0%	34.5%	36.8%	40.4%	41.6%
Engine Speed(r/min)	2,500	1,800	1,800	1,500	720
Fuel Input (MMBtu/hr), HHV	1.26	6.26	10.38	28.12	76.66
Required Fuel Gas Pressure(psig)	0.4-1.0	> 1.16	> 1.74	> 1.74	75
Form of Recovered Heat	H2O	H2O	H2O	H2O	H20 steam
Total Efficiency (%)	80.0	78.9	78.4	78.3	76.5
Thermal Output / Fuel Input (%)	53.0	44.4	41.6	37.9	35.0
Power / Heat Ratio	0.51	0.78	0.89	1.06	1.19
CHP Specification					
Exhaust Flow (kg/s)	0.51	0.99	1.75	5.06	15.12
Exhaust Temperature (Fahrenheit)	1,200	941	797	721	663
Heat Recovered from Exhaust (kW)	61	434	586	1474	2931
Heat Recovered from Cooling Jacket (kW)	135	211	378	477	1251
Heat Recovered from Lube System (kW)	-	79	129	328	1465
Heat Recovered from Intercooler (kW)	n/a	91	173	847	2210
Total Heat Recovered (kW)	196	815	1,266	3,126	7857

Table A.2
CHP Engine specification and performance parameters

System loading (%)	Fuel Input(MMBtu/hr), HHV	Electrical Efficiency (%), HHV
30	2.965	34.4
40	3.588	37.9
60	4.857	42
80	6.044	45

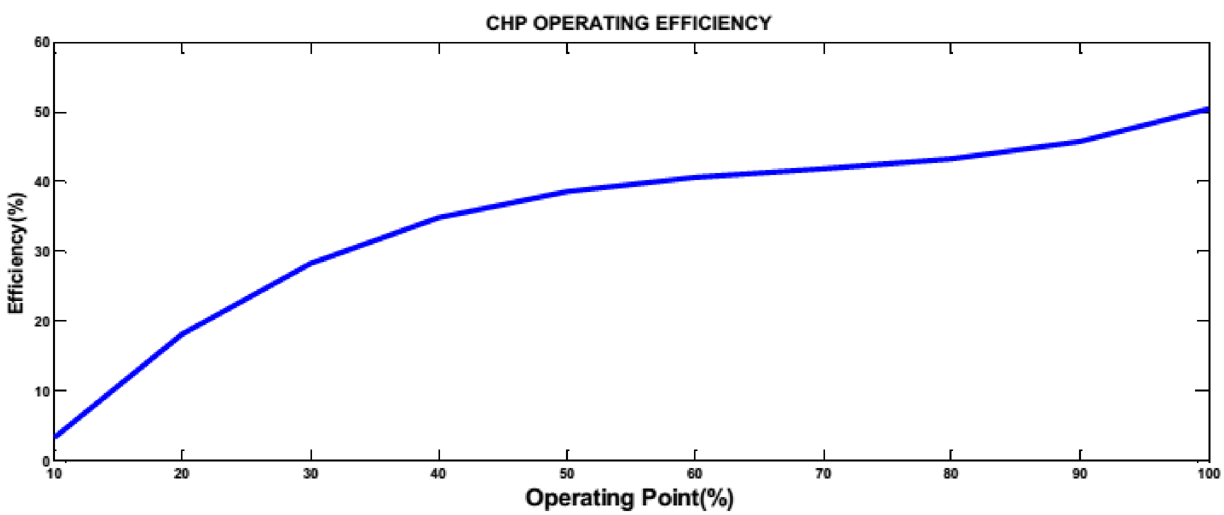

Figure A.1. CHP efficiency curve

A.2 Snapshot of the Microgrid Planning Tool

As explained in the introductory chapter and other chapters of the thesis work, the developed DER models and other components of the thesis work are put together to develop a planning tool that will aid power system planners justify investment in microgrids. A snapshot of the front-end user interface of the tool in *Microsoft VBA-Excel* is shown in Fig. A.2.

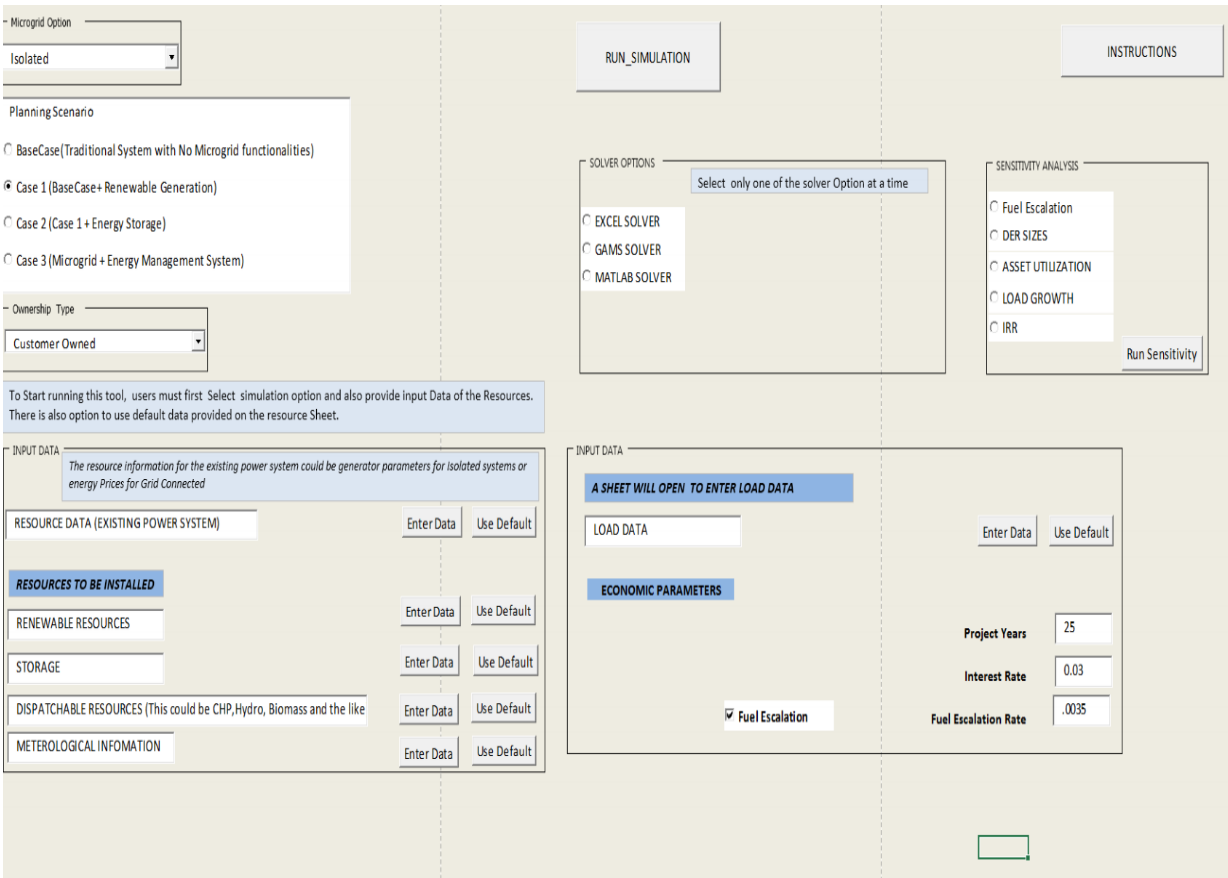

Figure A.2. Snapshot of microgrid planning tool

The user interface allows you to select the type of microgrid (*microgrid option*), the planning option or case to run (*planning scenario*) and the type of ownership model (*ownership type*). The tool also allows you to select energy resources to be included in the analysis and enter their corresponding parameters or use default parameters. Required economic parameters can also be entered or the default parameters can be retained. Data entered by the user are passed on to the optimization engine through the back-end *VBA*. The optimization engine can be *GAMS*, *Matlab* or the *Excel solver*. Solutions from the optimization are pass back to the front-end user interface in the same manner.

The tool can be run as stand alone with the *excel solver* or interface with GAMS or Matlab. The *excel solver* can however handle limited number variables. The user can also select additional sensitivity analysis to run.

Appendix B

B.1 Geometric Description of the Bi-level Problem

To demonstrate how non-convexity arise when the two problems are coupled into a bi–level problem and the non-triviality of the proposed problem, the geometric nature of the proposed formulation is outlined here. For the sake of clarity, a two dimension graph is considered where constrains associated with the ESS are looked at. ESS is chosen because the constraints associated with other resources are reflected in the group of constraints related to the ESS. Fig. B.1 illustrates the set of (P, x) satisfying the constraints associated with ESS for both problems. For illustration purposes, equation (3.6) is rewritten as (B.1) below for all $i \in I_S$:

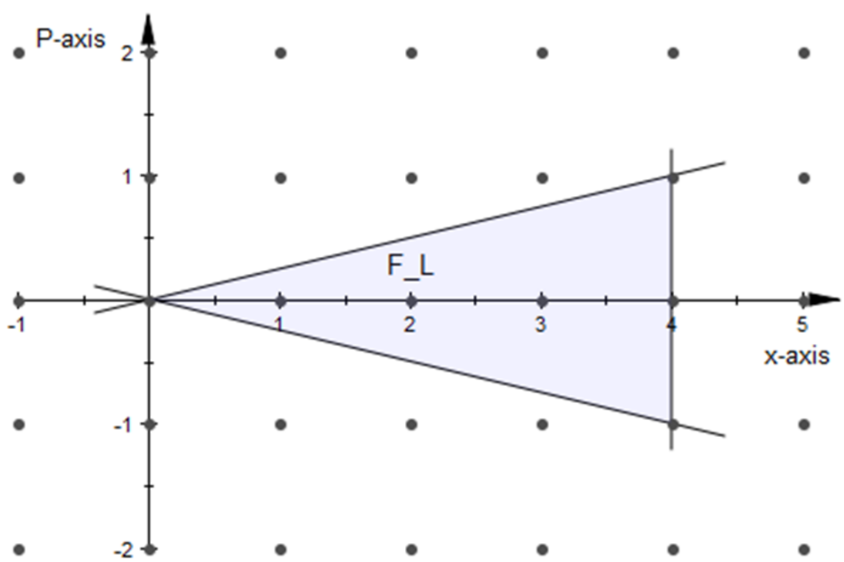

Figure B.1. Feasible set of the lower level problem

$$\sum_{i \in I_S} P_i^e(y,t) = L^e(y,t) \tag{B.1}$$

Then the feasible set $\mathcal{H}$ of the lower level problem for a fixed value of x_i will be the shaded region F-L or $\mathcal{H}$ in Fig. B.1. So if equation (3.5) is to be minimized on this set $\mathcal{H}$, we will arrive at a point (thus an optimal of the lower level problem) on the brown thick line in Fig. B.2 for a fixed value of x_i. If this is repeated for all values of x_i satisfying equation (3.5), assuming x_i is constrained by a maximum value X_i^{max}, all points on the thick brown lines in Fig. B.2 is obtained. Thus the thick lines gives us the set of feasible solution to the upper level problem. It is on this set that the upper level objective (3.1) will be minimized and thus the inducible region of the bi–level problem which is non-convex.

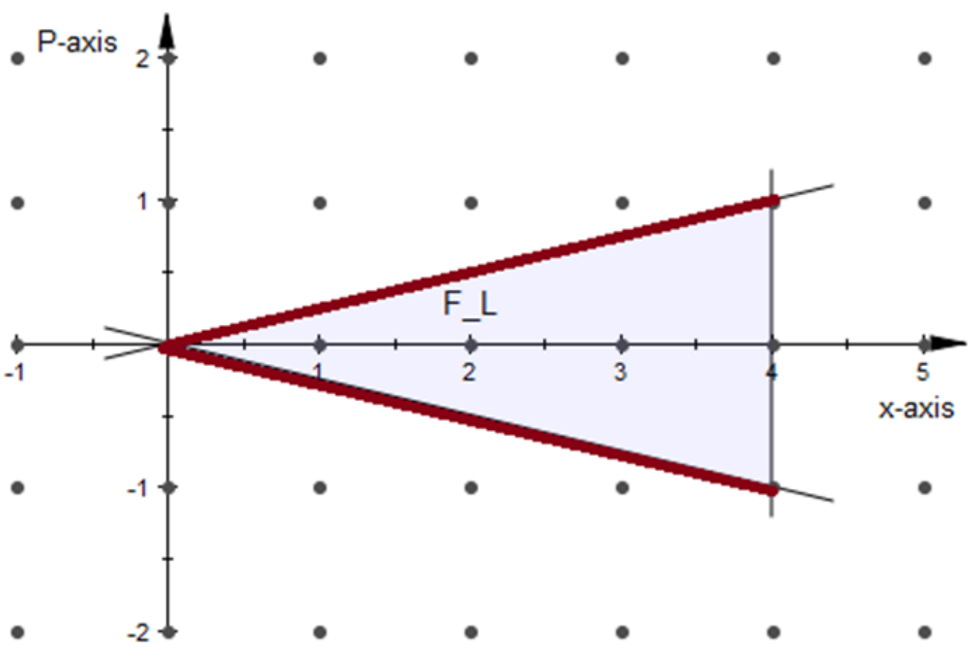

Figure B.2. Feasible set/inducible region of bi-level problem

Appendix C

C.1 Linearization of KKT Complementary Slackness conditions

The complementary slackness conditions (3.46)–(3.61) related to the KKT transformation of the bi–level problem in chapter three are linearized by the Fortuny-Amat and McCarl [85] proposed disjunctive constraints as follows:

$$\alpha_i^{\min}(y,t) \leq \mathbf{M}\underline{\alpha}_i^{\min}(y,t) \quad \forall i \in I_D \tag{C.1}$$
$$(P_i^e(y,t) - P_i^{\min}) \leq \mathbf{M}(1-\underline{\alpha}_i^{\min}(y,t)) \quad \forall i \in I_D \tag{C.2}$$
$$\alpha_i^{\max}(y,t) \leq \mathbf{M}\bar{\alpha}_i^{\max}(y,t) \quad \forall i \in I_D \tag{C.3}$$
$$(P_i^{\max} - P_i^e(y,t)) \leq \mathbf{M}(1-\bar{\alpha}_i^{\max}(y,t)) \quad \forall i \in I_D \tag{C.4}$$
$$\delta_i^{\min}(y,t) \leq \mathbf{M}\underline{\delta}_i^{\min}(y,t) \quad \forall i \in I_{\bar{B}} \tag{C.5}$$
$$P_i^e(y,t) \leq \mathbf{M}(1-\underline{\delta}_i^{\min}(y,t)) \quad \forall i \in I_{\bar{B}} \tag{C.6}$$
$$\delta_i^{\max}(y,t) \leq \mathbf{M}\bar{\delta}_i^{\max}(y,t) \quad \forall i \in I_{\bar{B}} \tag{C.7}$$
$$x_i - P_i^e(y,t) \leq \mathbf{M}(1-\bar{\delta}_i^{\max}(y,t)) \quad \forall i \in I_{\bar{B}} \tag{C.8}$$
$$\pi_i^{\min}(y,t) \leq \mathbf{M}\underline{\pi}_i^{\min}(y,t) \quad \forall i \in I_S \tag{C.9}$$
$$E_i^e(y,t) \leq \mathbf{M}(1-\underline{\pi}_i^{\min}(y,t)) \quad \forall i \in I_S \tag{C.10}$$
$$\pi_i^{\max}(y,t) \leq \mathbf{M}\bar{\pi}_i^{\max}(y,t) \quad \forall i \in I_S \tag{C.11}$$
$$x_i - E_i^e(y,t) \leq \mathbf{M}(1-\bar{\pi}_i^{\max}(y,t)) \quad \forall i \in I_S \tag{C.12}$$
$$\xi_i^{\min}(y,t) \leq \mathbf{M}\underline{\xi}_i^{\min}(y,t) \quad \forall i \in I_S \tag{C.13}$$
$$(P_i^e(y,t) + v_i x_i) \leq \mathbf{M}(1-\underline{\xi}_i^{\min}(y,t)) \quad \forall i \in I_S \tag{C.14}$$

$$\xi_i^{\max}(y,t) \le \mathbf{M}\bar{\xi}_i^{\max}(y,t) \quad \forall i \in I_S \tag{C.15}$$

$$\upsilon_i x_i - P_i^e(y,t) \le \mathbf{M}(1-\bar{\xi}_i^{\max}(y,t)) \quad \forall i \in I_S \tag{C.16}$$

$$\vartheta^{\min}(y,t) \le \mathbf{M}\underline{\vartheta}^{\min}(y,t) \tag{C.17}$$

$$E_r^e(y,t) \le \mathbf{M}(1-\underline{\vartheta}^{\min}(y,t)) \tag{C.18}$$

$$\vartheta^{\max}(y,t) \le \mathbf{M}\bar{\vartheta}^{\max}(y,t) \tag{C.19}$$

$$w_r^e L_r^{e,max} - E_r^e(y,t) \le \mathbf{M}(1-\bar{\vartheta}^{\max}(y,t)) \tag{C.20}$$

$$\varphi^{\min}(y,t) \le \mathbf{M}\underline{\varphi}^{\min}(y,t) \tag{C.21}$$

$$(P_r^e(y,t) + \kappa_r^e w_r^e L^{e,max}) \le \mathbf{M}(1-\underline{\varphi}^{\min}(y,t)) \tag{C.22}$$

$$\varphi^{\max}(y,t) \le \mathbf{M}\bar{\varphi}^{\max}(y,t) \tag{C.23}$$

$$\kappa_r^e w_r^e L^{e,max} - P_r^e(y,t) \le \mathbf{M}(1-\bar{\varphi}_i^{\max}(y,t)) \tag{C.24}$$

$$\theta^{\min}(y,t) \le \mathbf{M}\underline{\theta}^{\min}(y,t) \tag{C.25}$$

$$E_r^h(y,t) \le \mathbf{M}(1-\underline{\theta}^{\min}(y,t)) \tag{C.26}$$

$$\theta^{\max}(y,t) \le \mathbf{M}\bar{\theta}^{\max}(y,t) \tag{C.27}$$

$$w_r^h L_r^{h,max} - E_r^h(y,t) \le \mathbf{M}(1-\bar{\theta}^{\max}(y,t)) \tag{C.28}$$

$$\psi^{\min}(y,t) \le \mathbf{M}\underline{\psi}^{\min}(y,t) \tag{C.29}$$

$$(P_r^h(y,t) + \kappa_r^h w_r^h L^{h,max}) \le \mathbf{M}(1-\underline{\psi}^{\min}(y,t)) \tag{C.30}$$

$$\psi^{\max}(y,t) \le \mathbf{M}\bar{\psi}^{\max}(y,t) \tag{C.31}$$

$$\kappa_r^h w_r^h L^{h,max} - P_r^h(y,t) \le \mathbf{M}(1-\bar{\psi}_i^{\max}(y,t)) \tag{C.32}$$

where $\mathbf{M}$ is a sufficiently large positive constant; and $\underline{\alpha}_i^{\min}(y,t)$, $\bar{\alpha}_i^{\max}(y,t)$, $\underline{\delta}_i^{\min}(y,t)$, $\bar{\delta}_i^{\max}(y,t)$, $\underline{\pi}_i^{\min}(y,t)$, $\bar{\pi}_i^{\max}(y,t)$, $\underline{\xi}_i^{\min}(y,t)$, $\bar{\xi}_i^{\max}(y,t)$, $\underline{\vartheta}^{\min}(y,t)$, $\bar{\vartheta}^{\max}(y,t)$, $\underline{\varphi}^{\min}(y,t)$, $\bar{\varphi}^{\max}(y,t)$, $\underline{\theta}^{\min}(y,t)$, $\bar{\theta}^{\max}(y,t)$, $\underline{\psi}^{\min}(y,t)$, $\bar{\psi}^{\max}(y,t)$ are binary variables.

C.2 Linearization of the Strong duality equation

The strong duality equality (3.76) includes four nonlinear expressions: $\delta_i^{\max}(y,t)x_i$, $\upsilon_i\xi_i^{\max}(y,t)x_i$, $\nu_i\xi_i^{\min}(y,t)x_i$ and $\pi_i^{\max}(y,t)x_i$. The first non-linearity is linearized as provided in (C.33)–(C.37) where $X_i^{\max}$ is the maximum available capacity of resource i. Here, the nonlinear expression $\delta_i^{\max}(y,t)x_i$ is linearized by introducing an auxiliary variable $\mathbf{z}_i = \delta_i^{\max}x_i$ and a big value $\mathcal{Y}$ as the upper limit of the dual variable δ_i. Here, the term $\delta_i^{\max}x_i$ is replaced by

$\mathbf{z}_i$ and additional constraints (C.33)–(C.37) based on McCormick's relaxation [60, 88, 89]

$$\mathbf{z}_i(y,t) \geq X_i^{\max}\delta_i^{\max}(y,t) + \mathcal{Y}x_i - \mathcal{Y}X_i^{\max} \tag{C.33}$$

$$\mathbf{z}_i(y,t) \leq X_i^{\max}\delta_i^{\max}(y,t) \tag{C.34}$$

$$\mathbf{z}_i(y,t) \leq \mathcal{Y}x_i \tag{C.35}$$

$$0 \leq x_i \leq X_i^{\max} \tag{C.36}$$

$$0 \leq \delta_i^{\max}(y,t) \leq \mathcal{Y} \tag{C.37}$$

The other non-linear expressions are linearized based on the same concept and not repeated for brevity.

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