DISSERTATION

A SYSTEMS ENGINEERING APPROACH TO COMMUNITY MICROGRID ELECTRIFICATION AND SUSTAINABLE DEVELOPMENT IN PAPUA NEW GUINEA

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ABSTRACT

A SYSTEMS ENGINEERING APPROACH TO COMMUNITY MICROGRID ELECTRIFICATION AND SUSTAINABLE DEVELOPMENT IN PAPUA NEW GUINEA

Electrification of remote communities worldwide represents a key necessity for sustainable development and advancement of the 17 United Nations Sustainable Development Goals (SDGs). With over 1 billion people still lacking access to electricity, finding new methods to provide safe, clean, reliable, and affordable energy to off-grid communities represents an increasingly dynamic area of research. However, traditional approaches to power system design focused exclusively on traditional metrics of cost and reliability do not provide a sufficiently broad view of the profound impact of electrification. Installation of a single microgrid is a life-changing experience for thousands of people, including both residents who receive direct electricity service and numerous others who benefit from better education, new economic opportunities, incidental job creation, and other critical infrastructure systems enabled by electricity. Moreover, an electrification microgrid must directly satisfy community needs, be sensitive to local environmental constraints, mitigate possible risks, and plan for at least a decade of sustainable operations and maintenance. These considerations extend beyond the technical and optimization problems typically addressed in microgrid design.

An enterprise system-of-systems framework for microgrid planning considering technical, economic, environmental, and social criteria is developed in response to the need for a comprehensive methodology for planning of community electrification projects. This framework spans the entire systems engineering discipline and incorporates elements from project

management, risk management, enterprise architecture, numerical optimization, and multi-criteria decision-making, and sustainable development theory.

To support the creation of the systems engineering framework, a comprehensive survey of multi-objective optimization formulations for planning and dispatch of islanded microgrids was conducted to form a baseline for further discussion. This survey identifies that all optimizations studies of islanded microgrids are based on formulations selecting a combination of 16 possible objective functions, 14 constraints, and 13 control variables. A sufficient group of decision-making elicitees are formed from the group of nearly 250 publications surveyed to create a comprehensive optimization framework based on technical, economic, environmental, and social attributes of islanded microgrids. This baseline enables the formulation of a flexible, computationally lightweight methodology for microgrid planning in consideration of multiple conflicting objectives using the simple multi-attribute ranking technique exploiting ranks (SMARTER).

Simultaneously, the identified technical, economic, environmental, and social decision criteria form a network of functional, operational, and performance requirements in an enterprise system-of-systems structure that considers all stakeholders and actors in the development of community electrification microgrids. This framework considers community capacity building and sustainable development theory as a hierarchical structure, where each layer of the hierarchy is mapped both to a set of organizational, financial, and physical subsystems and to a corresponding subset of the 17 SDGs. The structure presents the opportunity not only to integrate classical project management and risk management tools, but also to create a new lifecycle for planning, funding, executing, and monitoring multi-phase community infrastructure projects.

Throughout the research, a case study of the Madan Community in Jiwaka Province, Papua New Guinea is used to demonstrate the systems engineering concepts and tools developed by the research. The community is the center of multi-phase community capacity building project addressing critical needs of the deep rural community, including electricity, education, water, sanitation, healthcare, and economic opportunities. The researcher has been involved as a pro-bono consultant for the project since 2013 and helped raise over $1M USD in infrastructure materials, equipment, and consulting. The structure of the community-based organization and numerical optimization of a series of islanded microgrids are used to illustrate both the system-of-systems hierarchy and microgrid planning techniques based on both single-objective optimization using linear programming and the SMARTER methodology for consideration of multiple qualitative and quantitative decision criteria.

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Finally, the entire topic, scope, and focus of this dissertation would not have been possible without the decades of humanitarian work by Dr. Larry Hull, who dedicated the last 15 years of his life to improving the lives of the people residing Madan Community. The establishment of the Madan Coffee Mill, construction of the Madan Medical Clinic, donation of tens of thousands of textbooks, and launch of the community-wide infrastructure program were led entirely by the boundless passion, enthusiasm, and visionary dreams of Dr. Hull and his wife Aarlie. I am deeply indebted to the inspiration and kindness passed on to me by Dr. Hull. Despite his untimely passing in 2018, his legacy will continue to live on through this dissertation and the thousands of people that he empowered.

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F	Hourly energy cost	(\$/hr)
HDI	Human development index	
I_{ESS}	Battery current	(A)
LCOE	Levelized cost of energy	
n	Payback period	(yr)
NGO	Non-governmental organization	
P	Real Power	(W)
PNG	Papua New Guinea	
Q_{PV}	PV generation capacity	(W)
Q_{ESS}	Battery capacity	(kWh)
r	Capital depreciation rate	(%)
SDG	Sustainable Development Goal	
SOC	State of charge	(%)
SoS	System of systems	
t	Time	(hr)
V_{ESS}	Battery voltage	(V)

Subscripts:

$base$	Base kVA system rating
$conv$	Converter (DC-AC and DC-DC)
cl	Digital classroom
cr	Capital recovery cost
ESS	Energy storage system
$load$	Load
$loss$	System losses
ll	Lost load
max / min	Maximum or minimum
PBK	Portable battery kit
ph	Cell phone
pu	Purchase cost
PV	Photovoltaic
$ship$	Shipping cost
$start$ / end	Starting / ending time of simulation cycle

CHAPTER 1

INTRODUCTION

1.1.Motivation

The motivation of this research is to develop, quantify, and demonstrate the effectiveness of an enterprise system-of-systems (SoS) approach to community electrification, capacity building, and sustainable development. Worldwide, over 1 billion people still lack access to electricity, which is a prerequisite for numerous critical infrastructure systems. Safe, reliable, and affordable energy serves as a catalyst for creating numerous economic development opportunities that can help eradicate poverty for remote communities across the globe. As a result, it is important that the planning, design, optimization, construction, and commissioning of community power systems consider not only technical parameters, but also economic, social, and environmental parameters as well.

The effects of electrification can be observed in many sectors, including agriculture, healthcare, education, water, sanitation, and information & communications technologies (ICT). These positive impacts can be best examined within the United Nations (UN) 17 Sustainable Development Goals (SDGs), which were adopted in 2015. Table 1, included at the end of this section, lists several of the targets associated with the first eight SDGs and how those targets are directly addressed by community electrification. For the sake of brevity, the numerical indicators adopted by UN for each sustainable development target are omitted [1].

Table 1: Impact of electrification on the 17 UN SDGs and associated targets

UN SDG	Targets from 2030 Agenda [1]	Contribution of Electrification
Goal 1: "End poverty in all its forms everywhere" 	**Target 1.1:** "By 2030, eradicate extreme poverty for all people everywhere, currently measured as people living on less than $1.25 a day"	Create new income sources directly (power system installation, operation, and maintenance) and indirectly (new jobs and businesses enabled by energy access)
	Target 1.4: "By 2030, ensure that all men and women, in particular the poor and the vulnerable, have equal rights to economic resources, as well as access to basic services, ownership and control over land and other forms of property, inheritance, natural resources, appropriate new technology and financial services, including microfinance"	Support other critical infrastructure Provide energy required by ICT systems to enable electronic records, mobile banking, and financial transaction
Goal 2: "End hunger, achieve food security and improved nutrition and promote sustainable agriculture" 	**Target 2.3:** "By 2030, double the agricultural productivity and incomes of small-scale food producers, in particular women, indigenous peoples, family farmers, pastoralists and fishers, including through secure and equal access to land, other productive resources and inputs, knowledge, financial services, markets and opportunities for value addition and non-farm employment"	Enable electrically-powered agricultural equipment for processes including grain grinding, preservation and packaging of food, refrigeration of perishable items Accelerate market access through electric transportation, digital financial services, and online aggregated bidding for supply contracts through community cooperatives
Goal 3: "Ensure healthy lives and promote well-being for all at all ages"	**Target 3.1:** "By 2030, reduce the global maternal mortality ratio to less than 70 per 100,000 live births"	Provide reliable power for lighting, vaccine refrigeration, medical scopes, powered tools, and other medical equipment requiring electricity
	Target 3.2: "By 2030, end preventable deaths of newborns and children under 5 years of age, with all countries aiming to reduce neonatal mortality to at least as low as 12 per	

	1,000 live births and under-5 mortality to at least as low as 25 per 1,000 live births”	Provide access to digital patient education, reference libraries for medical staff, and AI-powered diagnostics assistance Provide ICT for digital medical records, national-scale patient health information, and supporting patient services
	Target 3.4: “ By 2030, reduce by one third premature mortality from non-communicable diseases through prevention and treatment and promote mental health and well-being”	
	Target 3.9: “By 2030, substantially reduce the number of deaths and illnesses from hazardous chemicals and air, water and soil pollution and contamination”	Significantly reduce indoor air pollution by eliminating kerosene, candles, and wood fires used for lighting and cooking
Goal 4: “Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all”	**Target 4.1:** “By 2030, ensure that all girls and boys complete free, equitable and quality primary and secondary education leading to relevant and effective learning outcomes”	Provide lighting, digital classroom technologies, electronic copies of government textbooks / curricula, and supplemental learning materials
	Target 4.4: “By 2030, substantially increase the number of youth and adults who have relevant skills, including technical and vocational skills, for employment, decent jobs and entrepreneurship”	Supply power for lighting, ICT, light industrial equipment, and other loads for technical, vocational, and entrepreneurial training programs
Goal 5: “Achieve gender equality and empower all women and girls”	**Target 5.b:** Enhance the use of enabling technology, in particular information and communications technology, to promote the empowerment of women”	Deliver power for homes, mobile phones, communications networks, and digital education centers
	Target 6.1: “By 2030, achieve universal and equitable access to safe and affordable drinking water for all”	Support electric pumps for wells, header tanks, and water distribution systems

Goal 6: "Ensure availability and sustainable management of water and sanitation for all"	**Target 6.2:** "By 2030, achieve access to adequate and equitable sanitation and hygiene for all and end open defecation, paying special attention to the needs of women and girls and those in vulnerable situations"	Provide lighting, power for safely managed sanitation centers Enable digital education of water, sanitation, and hygiene (WASH) practices
Goal 7: "Ensure access to affordable, reliable, sustainable and modern energy for all"	**Target 7.1:** "By 2030, ensure universal access to affordable, reliable and modern energy services"	Supply electricity to homes, business, schools, and other shared community infrastructure and services
	Target 7.2: "By 2030, increase substantially the share of renewable energy in the global energy mix"	Eliminate kerosene, candles, and other fossil fuels used in lamps and portable generators
Goal 8: "Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all"	**Target 8.2:** "Achieve higher levels of economic productivity through diversification, technological upgrading and innovation, including through a focus on high-value added and labor-intensive sectors"	Supply electricity and ICT needed for lighting, power tools, refrigeration, and other electrical process equipment
	Target 8.3: "Promote development-oriented policies that support productive activities, decent job creation, entrepreneurship, creativity and innovation, and encourage the formalization and growth of micro-, small- and medium-sized enterprises, including through access to financial services"	Foster creation of micro-scale entrepreneurial businesses within the community through access to critical infrastructure and financial services

	Target 8.6: By 2020, substantially reduce the proportion of youth not in employment, education or training	Provide electricity and ICT for K-12 education, as well as technical, vocational, and entrepreneurial training
	Target 8.9: "By 2030, devise and implement policies to promote sustainable tourism that creates jobs and promotes local culture and products"	Create village homestay businesses with electricity and internet to attract tourists interested in preserving local environments and cultures Enable local artisans and entrepreneurs access to the global market through local marketplaces and online distribution

As can be observed from Table 1, community electrification has a much broader scope and impact than simply eliminating kerosene or providing a certain number of kWh of electricity. As a result, it is important that the planning, design, optimization, construction, and commissioning of community power systems include not only technical aspects, but also social, environmental, and economic components. Inclusion of the positive social impacts and additional opportunities created by access to safe, reliable, and affordable energy will enable designers, engineers, project managers, funding agencies, and local stakeholders to understand the electrification process in a more holistic manner. Additionally, it could create a new category of interdisciplinary studies, technical designs, and research areas focused on maximization of the social benefits and opportunities for cross-cutting between SDGs and infrastructure programs.

However, the success of an electrification project does not depend just on if a power system was properly designed, correctly installed, and commissioned in a timely manner. For it truly to achieve sustainability, it is critical that the entire life cycle of the project be considered, including operation, maintenance, replacement, and disposal of the system. Furthermore, there exist numerous non-technical factors that determine whether an electrification project will succeed. The first is that any humanitarian technology transfer must respond directly to the needs, potential opportunities, and desires of the target community. This is best facilitated by requiring local community NGOs and entrepreneurs to shape the strategy, vision, and planning of the project. This includes the second factor that the community must be an equal participant in “co-design” of the project, which enables local technicians to operate, maintain, and replicate the system. Thirdly, technical knowledge and skills must be transferred to the community through train-the-trainer and other capacity building processes. Creation of the socio-economic and organizational framework for management of the project represents the fourth component, which enables the project to develop the financial, technical, administrative, and human resources needed to holistically sustainable. Finally, the project must create a steady revenue stream through customer billing and energy tariffs that will enable the operators of the power system to pay for staff, fuel (if the system includes thermal backup generation), replacement parts, and maintenance of the system for at least a decade.

To the best of the researcher's knowledge, a comprehensive framework for modeling and analysis of community electrifications systems from a holistic standpoint has not be developed to this date. Although several studies have attempted to create standardized methods for the technical design process, none of these address the social, environmental, and economic factors involved.

The research is examined in the context of a case study of a community electrification project in rural Papua New Guinea (PNG). The PNG project represents the current phase of a 15 year ongoing community empowerment and capacity building program centered at the Madan Community, located on the border between Jiwaka and Western Highlands Provinces. The program was founded in 2003 by retired orthopedic surgeon Dr. Larry Hull as medical mission to provide critically-needed healthcare services for infectious diseases in PNG, including malaria, tuberculosis, hepatitis, typhoid, cholera, and a generalized HIV epidemic. In 2007, the Hulls built the Madan Medical Clinic and Birthing Center, which has expanded over the decade to provide not only medical services, but a broad range of community needs, including adult literary, women's empowerment, family counseling, and K-12 education.

Recognizing the need for a means to provide a means to finance the local healthcare initiative (including salaries for nurses, travel for humanitarian doctors, vaccines, and other medical supplies), Dr. Hull and his wife purchased a nearby coffee and tea farm, establishing a social business using the classic "triple bottom line" of "people, planet, and profits" to subsidize the medical outreach and provide fair wages to hundreds of community members. In 2016, the coffee farm was certified by Rainforest Alliance as the fourth greenest in the world.

The social infrastructure and organization capacity created by the Madan Medical Clinic, coffee farm, and series of partnering non-governmental organizations (NGOs) enabled the launch of a community-wide water and sanitation project funded by a series of Global Grants by The Rotary Foundation. A detailed community-based survey was organized and facilitated in early 2013 by volunteers from Rotary Clubs in Western Highlands Province, PNG; Washington State, USA; and Queensland, Australia. The survey examined the status, stakeholders, and institutions in a 10 km radius, serving approximately 40,000 people and 30 schools with an average of 275 children each. The results were assembled into a Rotary program planning and performance (PPP) evaluation report, which served as a baseline for creating an overall community development strategy [2], [3].

The author of this dissertation, hereinafter called the researcher, joined the program in 2013, serving as a design engineer assisting with the design, fundraising, and procurement tasks associated with the construction of a rainwater harvesting and distribution system providing over one million liters of clean water per year to 5000 people in the Madan Community. The system was constructed in a series of phases from 2014 to 2016, providing piped water service to the medical clinic and new community centers. The installation was complemented by pilot installations of water and sanitation systems at several schools in close proximity to the medical clinic, as well as a community sanitation center at one of the community centers.

In 2015, Dr. Hull and the researcher developed the concept for a community-wide electrification program to help solve the critical need for access to safe, reliable, and affordable power throughout PNG. Across the country, over 90% of the population lack any form of electric grid connection, with over 99% of population lacking access in some provinces, as can be seen from Table 2.

Table 2: Electricity access in Papua New Guinea, by province [4]

Province	Population with Electricity	Population without Electricity	Percentage of Population without Electricity
Autonomous Region of Bougainville	570	174,590	99 %
Central	3,182	180,801	98 %
East New Britain	6,496	213,637	97 %
East Sepik	2,380	340,801	99 %
Eastern Highlands	5,445	427,527	98 %
Enga	1,396	293,635	99 %
Gulf	411	106,487	99 %
Madang	3,297	361,809	99 %
Manus	3,353	40,034	92 %
Milne Bay	1,340	209,072	99 %
Morobe	12,136	527,268	97 %
National Capital Dist.	41,766	212,392	84 %
New Ireland	1,202	117,148	98 %
Oro	961	132,104	99 %
Sandaun	1,070	184,671	99 %
Simbu	1,721	257,982	99 %
Southern Highlands	1,131	545,134	99 %
West New Britain	1,982	182,526	99 %
Western	652	152,652	99 %
Western Highlands	6,175	433,850	98 %

Figure 1: Map of generators and transmission lines in Papua New Guinea, taken from [4]

As a result, the majority of communities subside on kerosene, candles, fuelwood, and disposable batteries to supply their energy needs. For the few customers with access to the national grid, blackouts can last for weeks due to generation capacity shortages and transmission-related events. The PNG power grid is composed of 19 diesel microgrids and three islanded networks serving the highlands, capital city, and island of New Britain, which are depicted in Figure 1. The combined generation capacity of all systems is 580 MW, which is far less than the amount needed to serve the country's 8.1 million residents.

Despite the presence of abundant oil, solar, hydro, and coastal wind energy resources, energy projects in PNG have demonstrated mixed success, and unfortunately, reports of failed projects can be found throughout the literature. Challenges to project success largely stem from the high cost of transmission and distribution systems due to rugged terrain across the country, a shortage of engineers and technicians, and a lack of organizations capable of operating and maintaining power systems.

As a result, it was determined necessary to develop a combined socio-economic and technical framework that could create a practical model for community-based projects that could be replicated across the country to provide access to electricity and other critical infrastructure. The need for a comprehensive analytical and numerical model formed the motivation for this dissertation work.

1.2. Objective

The objective of this research is to develop an enterprise SoS methodology for planning electrification projects, designing community microgrids with maximal social impact, siting and sizing renewable generation, evaluating electrical network topologies in regard to their ability to support other critical infrastructure, and optimizing the system with respect to both qualitative and quantitative criteria reflecting the actual needs and desires of the community. The anticipated result is that the developed framework could serve as a template for successful community capacity building projects across the globe for resource-constrained communities without access to reliable electricity.

A related set of objectives focus on implementing the developed framework for guiding the ongoing electrification program in the Madan Community in PNG. To advance the combined system of infrastructure systems (including electricity, education, water, sanitation, and healthcare), a new community-based organization was created, PNG Community Transformation Centres, Inc. This new NGO is now employing the conceptual framework described in this work to create the social, technical, financial, and organizational structure needed to commission, operate, maintain, and expand the installations funded by IEEE Smart Village with contributions of $120,000 USD from the IEEE Nuclear & Plasma Sciences Society, $50,000 USD in education equipment from the IEEE Power & Energy Society, and an equivalent of $250,000 of pro-bono consulting and in-kind services provided by the project team and local community members.

Coupled closely with the conceptual and administrative research objectives described above is the goal to create a modeling environment for translating design, functional, and performance requirements (expressed in both qualitative and quantitative terms) into a series of optimization techniques for planning and operating the installed systems. This numerical objective aims to satisfy the observed need for method for optimal design, sizing, and siting of electrification microgrids from a broader perspective than that offered by traditional power system optimization methods focused on levelized cost of energy (LCOE) and reliability.

In summary, the objectives of this research are to

- Develop a framework for describing community capacity building programs as an enterprise SoS hierarchy, composed of multiple layers of physical infrastructure and organizational structures

- Translate factors in technical design and project planning affecting the success of the community electrification project into quantitative and qualitative criteria

- Formulate a set of numerical objective functions expressing the benefits and costs of design decisions with respect to technical, social, economic, and environmental considerations

- Demonstrate the application of these design methodologies to optimize a series of islanded power systems of varying sizes, load profiles, nominal voltages, and topologies for pilot installations in the Madan Community, PNG.

1.3.Scope

The scope of this research comprises a combination of conceptual analyses and numerical studies focused on the development of the framework for planning community-based electrification projects that consider the broader impact of energy access upon capacity building and advancement of the other UN SDGs. Due to the array of factors influencing the design of a holistically sustainable program, a systems engineering approach is chosen to model the problem. Consequently, the themes of the Systems Engineering discipline were selected to set the bounds of the dissertation scope.

However, a brief introduction of the wider scope of the Systems Engineering discipline will be included before further discussion of the scope of this research. Systems Engineering is a broad discipline that not only includes elements of electrical, mechanical, and civil engineering, but also integrates technical design with social, management, human, regulatory, and business domains. It provides a holistic perspective, which is needed to guide the analysis, design, testing, integration, and deployment of complex systems formed from numerous interrelated components working together to achieve a common goal – arguably a description of any power system. In Systems Engineering, the traditional project management definition of success in terms of scope, schedule, and budget is expanded to provide a balanced viewpoint seeking an optimal tradeoff between performance, cost, customer satisfaction, stakeholder requirements, business opportunities, and individual technical attributes. Systems engineering simultaneously extends the engineering design process to include client needs, use cases, operational scenarios, technological maturity, risk analysis, functional requirements, performance specifications, subsystem interfaces, production, deployment, operations, maintenance, and disposal.

Meanwhile, the scope of this dissertation work can be divided into two complementary components, which represent the qualitative and quantitative aspects of community electrification. The first area of focus develops an enterprise SoS life cycle to model the stages, requirements, considerations, documentation, and processes involved in bringing a community electrification program from the concept stage to being a sustainable, scalable, region-wide program capable of bring socio-economic empowerment to thousands of people. The discussion is framed around a series of factors which have been identified as critical elements to the success of a project. In this context, one of the most salient characteristics is that initiatives focusing on humanitarian technology transfer must be organized as locally-owned entrepreneurial businesses that derive revenue from utility service tariffs, as well as productivity increases and value added to products created by village industries. Structured as social enterprises, profits from utility tariffs are reinvested into the community to provide social services and expand the population served. The combined financial, organizational, and physical structure of the conceptual village program is demonstrated to form a hierarchical SoS

Subsequently, the numerical components of the research translate the technical, social, economic, and environmental impact of the project into a series of objectives that may be implemented in a multi-objective optimization problem created to provide a holistic view of electrification. The foundation for the numerical work is established through a comprehensive literature survey of objective functions, constraints, optimization variables, renewables forecasting techniques, and multi-criteria decision-making methods for islanded microgrids. The results form the basis for optimization studies for three microgrid installations in the Madan Community.

The first examines the simplest case of a single DC microgrid powering community center comprising a digital classroom and charging kiosk. The system consists of a single solar array, battery energy storage system, and set of loads connected by inverters and DC-DC converters, without any significant distribution network. However, it is demonstrated that even systems of such a small scale can benefit from optimization studies. The second is a hybrid PV-diesel industrial microgrid to supply critical agricultural processing loads of the community coffee mill during frequent, extended blackouts of the PNG power grid. A timeline for the publications and presentations related to this research is presented in Figure 2.

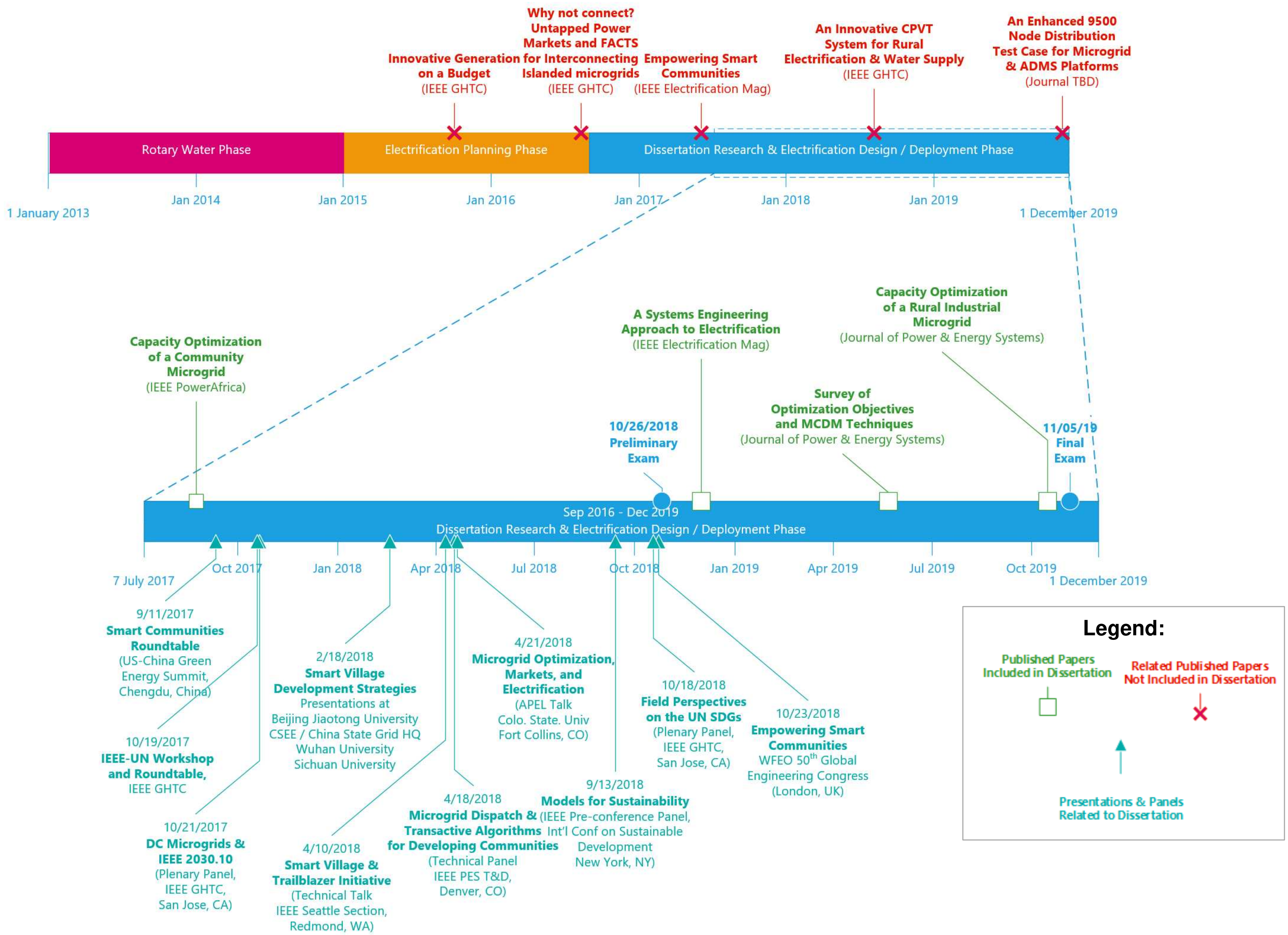

Figure 2: Timeline of publications and presentations relevant to the scope of the dissertation work.

1.4.Tools

Since this dissertation work integrates aspects from project management and technical design, a combination of conceptual, analytical, and numerical tools is selected. The research first examines the organization and administrative framework needed to develop an enterprise SoS hierarchy and new lifecycle model for planning, deployment, commissioning, and expansion of community electrification projects. The developed framework provides the structure for multi-objective optimization of microgrid systems considering technical, social, economic, and environmental objectives, which are prioritized and combined using multi-criteria decision-making (MCDM) tools, including the simple multi-attribute rating technique exploiting ranks (SMARTER). Numerical studies are conducted for three pilot installations in the Madan Community using multiple analytical and software tools.

The remainder of this dissertation is organized as follows: Chapter 2 provides a comprehensive review of optimization of optimization formulations for islanded microgrids, including objective functions, constraints, and optimization variables. Chapter 3 continues the survey with forecasting techniques, conflicts between optimization functions, and MCDM techniques (including both utility theory and outranking methods). Chapter 4 develops the conceptual management framework and enterprise SoS hierarchy for community capacity building programs. Chapter 5 presents a system planning study and capacity optimization for one of the Madan community centers with a digital classroom and battery charging kiosk. Chapter 6 applies the results of Chapters 2 and 3 to build a generalized framework for microgrid planning optimization using the SMARTER technique, which is demonstrated through a generation planning case study for the Madan Coffee Mill, which is a 100kW industrial microgrid that serves as the economic hub for the Madan Community. Chapter 7 summarizes future work.

CHAPTER 2

A COMPREHENSIVE REVIEW OF ENERGY MANAGEMENT AND PLANNING OF ISLANDED MICROGRIDS – PART 1: OPTIMIZATION FORMULATIONS

This survey paper provides the first comprehensive, critical overview of optimization formulations for planning and operation of islanded microgrids, including optimization objectives, constraints, control variables, forecasting techniques, socio-economic factors, and multi-criteria decision making. The optimization approaches reviewed address methods both for increasing the resiliency of advanced distribution systems and electrification of remote communities. This paper is organized into two parts: Part 1 examines over 120 individual optimization studies and discovers that all optimization studies of islanded microgrids are based on formulations selecting a combination of 16 possible objective functions, 14 constraints, and 13 control variables. Each of the objectives, constraints, and variables are discussed exhaustively both from the perspective of their importance to islanded microgrids and chronological trends in their popularity. Part 2 builds on the results of part 1, first briefly discussing forecasting methods for supplying load and renewables data needed for both planning and dispatch studies. It then continues to examine conflicts between the objectives identified in Part 1, socio-economic utility functions, and multi-criteria decision making (MCDM) techniques required to create multi-objective optimization formulations combining numerical criteria with social, environmental, and human factors parameters.

This chapter is a verbatim copy of an article submitted by the researcher for publication in the Journal of Power and Energy Systems and is currently under review.

2.1. Introduction

Within the fifteen years since the emergence of the microgrid concept, a large amount of literature has been dedicated to optimization of these systems. Likewise, multiple review papers [1] – [20] have been written to summarize advances in optimization algorithms. However, these reviews have each focused on only a few of the aspects necessary for building an optimized energy management system for microgrids. A summary of previous literature surveys is presented in Table 3.

As can be observed from Table 3, a comprehensive literature survey covering all aspects of optimization and multi-criteria decision making for islanded microgrids has not been published. This paper aims to fulfill this need by providing a systematic overview of objective functions, constraints, control variables, solvers, forecasting, and multi-criteria decision making methods used in operation of islanded microgrids.

This paper is organized as follows: Section 2.2 provides an overview of microgrid control and topologies. Section 2.3 examines the two categories of problems that are solved in optimization of islanded microgrids. Section 2.4 surveys common objective functions and their formulation. Sections 2.5 and 2.6 outline constraints that must be enforced and optimization variables commonly used in both planning and dispatching problems.

Reference [21] presents Part 2 of this paper, which continues with a discussion of forecasting methods used for loads and renewables, pairwise relationships between the most common objective functions found in multi-objective optimization, and multi-criteria decision making methods suitable for combining numerical and social criteria.

Table 3: Summary of topics covered in current literature reviews

Ref	Year	Type of Review								Configuration		Focus	
		OF	CR	CV	SR	SW	FT	MCDM	APP	Island	Grid	Sched	Plan
[1]	2018	✓	–	–	–	–	–	–	✓	–	✓	✓	–
[2]	2018	–	–	–	–	✓	✓	–	–	✓	–	–	✓
[3]	2017	✓	–	–	✓	–	–	–	–	✓	✓	✓	–
[4]	2017	–	–	–	–	–	–	✓	–	–	–	–	✓
[5]	2017	✓	✓	–	✓	–	–	–	–	–	✓	✓	✓
[6]	2017	–	–	–	✓	–	✓	–	–	–	–	✓	–
[7]	2017	–	–	–	–	–	–	✓	–	–	–	–	✓
[8]	2016	–	–	–	–	–	✓	–	✓	–	✓	✓	–
[9]	2016	–	✓	–	✓	–	–	–	✓	✓	✓	✓	–
[10]	2016	✓	✓	–	✓	✓	–	–	–	✓	✓	✓	–
[11]	2015	✓	–	✓	–	–	–	–	–	–	–	✓	✓
[12]	2015	–	–	–	✓	–	–	–	✓	–	–	–	✓
[13]	2015	✓	–	–	✓	–	–	–	–	–	–	–	✓
[14]	2014	✓	✓	✓	–	✓	–	–	✓	✓	✓	–	✓
[15]	2014	–	–	–	–	–	✓	–	✓	–	✓	✓	–
[16]	2011	–	–	–	✓	–	–	–	✓	–	–	–	✓
[17]	2011	–	–	–	–	–	–	–	✓	–	✓	–	–
[18]	2010	–	–	–	–	–	✓	–	✓	–	–	✓	–
[19]	2009	–	–	–	–	–	–	✓	–	–	–	–	–
[20]	2004	–	–	–	–	–	–	✓	–	–	–	–	✓

OF = Objective functions, CR = Constraints, CV = Control variables, SR = Solver, SW = Software, FT = Forecasting, MCDM = Multi-criteria decision making, APP = Applications, Island = Islanded, Grid = Grid-connected, Sched = Scheduling / operations, Plan = Planning

2.2. Microgrid Topologies and Control

First proposed by [22], [23], a microgrid can be defined as a smaller scale version of an electric power system containing its own generation, distribution, and loads integrated into a decentralized structure with numerous distributed generators (DG), energy storage systems (ESS), controllable loads, reconfigurable network topology, and hierarchical control. Depending on whether the microgrid is connected to the main power grid at a point of common coupling (PCC), the microgrid is classified as either grid-connected or islanded.

Grid-connected microgrids use the main power grid to supply any power mismatches between loads and local distributed energy resources (DER), which include DGs, ESS, and renewable generation. The grid coupling is also used to regulate the voltage and frequency of the distribution network. Multiple grid-connected microgrids can be connected at a medium voltage (MV) feeder to form an advanced distribution network, or multi-microgrid.

Islanded microgrids usually appear in two use cases. The first is isolated operation of a typically grid-connected system by opening the PCC switch during major system disturbances or for economic reasons. The second is electrification of remote communities, for which small autonomous power systems have been the preferred method for decades, typically through scalable fossil-fuel generation [24] and more recently, renewables [3].

In both islanded operating scenarios, the energy management system (EMS) is responsible for matching generation to load, controlling voltage and frequency, and ensuring that system constraints are not violated. As a result, the EMS of an islanded microgrid is responsible for primary, secondary, and tertiary control of the system.

Primary control is typically handled by distributed generators, smart inverters, energy storage, and loads with high-speed autonomous controllers driven by power electronics. Secondary control and automatic generation control (AGC) are commonly performed in a distributed manner by local droop controls [25]. Tertiary control and reliability related tasks are handled by an energy management system and microgrid central controller responsible for active and reactive power flow, economic dispatch, renewables forecasting, unit commitment, and network topology reconfiguration. In multi-microgrids and larger advanced distribution networks, an intermediate controller may be introduced to regulate each feeder branch.

2.3. Microgrid Optimization Problems

Microgrid optimization problems can be classified into two categories: scheduling and planning. Scheduling problems examine optimum dispatch of DER within the microgrid – and occasionally network topology reconfiguration – to minimize various objectives, such as cost, peak load, emissions, and losses. Planning problems examine siting and sizing of new DG and ESS units to accomplish various objectives, including minimum cost and maximum reliability. Frequently, objectives selected are mutually conflicting, resulting in a multi-dimensional optimization problem requiring use of MCDM methods discussed later. The remainder of this section will next discuss each of the common applications of microgrid optimization for scheduling and planning in detail.

2.3.1. Scheduling: Economic Dispatch

Economic dispatch describes the process of minimizing the cost of generation in a power system by optimizing the power output of each generator. In the operation of a typical power system using fossil fuel generation, the cost of each generator is approximated as a quadratic function of its power production. As a result, economic dispatch is usually treated as a classic Lagrangian multiplier problem [26]. The economic dispatch formulation is typically solved every five to fifteen minutes during real-time operations, and also as part of day-ahead unit commitment decisions (to be discussed in the next section).

However, in a microgrid with high penetration of distributed renewables, this straightforward approach is no longer effective. The variability of renewable generation must be considered, requiring accurate forecasting techniques to be included in the optimization. The presence of energy storage capacity introduces another variable: The microgrid can choose to buy or generate extra power for use during periods of peak loads and higher market prices. Finally, the transition from grid-connected to islanded modes may represent a significant topological change, and so the microgrid central controller may solve two different optimization problems depending on the status of the PCC [27].

2.3.2. Scheduling: Unit Commitment

If the economic dispatch problem is expanded to consider startup and shutdown of generators, the optimization is termed unit commitment (UC). UC problems can be classified as security-constrained unit commitment (SCUC) and price-based unit commitment (PBUC). SCUC optimizations are typically performed by an independent system operator (ISO) or microgrid distribution network operator (DNO) to ensure that sufficient generation and spinning reserve are online to ensure secure operation of the power system in the event of loss of the largest generator and other contingencies [26], [28]. Meanwhile, operators of individual generators will often perform a PBUC optimization to determine whether it will be profitable to bring a particular generator online based on load and price forecasts [26]. SCUC formulations for microgrids with high penetration of wind typically require accurate day-ahead forecasts of wind speed, wind power, and load to provide estimates of the amount of conventional generation needed to meet load and compensate for wind variations [29].

2.3.3. Planning: DER Siting and Sizing

In the planning stage of a microgrid, optimal siting and sizing of DG units is essential to ensure secure, economic, and reliable operations, as well as decreased losses, greater reliability, and improved voltage profiles in the network.

Siting problems address the impact of generator location within the microgrid. Unlike traditional radial distribution feeders, microgrids often have a meshed network topology with power flows that can reverse direction depending on renewable generation profiles. As a result, the location of new DG units can have a significant impact on the losses and reliability of the system. Sizing optimization considerations are highly dependent on the location and renewable resource distribution of the microgrid, and so will not be emphasized in this review.

Sizing problems determine the optimum amount of generation needed to meet load and the desired level of reliability. Typically, the goal is to determine an optimum mix of different generation options including wind, solar, thermal (diesel and microturbine), and combined heat and power (CHP) units, considering capital costs, operations, emissions, and reliability. Frequently, the sizing problem is converted into a scheduling optimization that is solved over a rolling time horizon using seasonal forecasts of loads and generation.

Multiple commercial tools, such as HOMER, DER-CAM, EAM, RETScreen, H2RES, and HYBRID2, have been developed and utilized widely for siting and sizing optimizations [10], [12],

[14]. Most of these software tools, especially HOMER, focus on rendering the sizing results in an understandable graphic user interface, but use simple first degree linear equations for system components that decrease the accuracy of the results [30]. Most of these tools use proprietary algorithms that are hidden in "black box" code.

2.3.4. Planning: ESS Siting and Sizing

Proper planning of ESS is essential for secure, reliable, and economic operation of islanded microgrids. ESS resources are able to significantly reduce energy costs due to the ability of the ESS to be dispatched, provide ancillary services, absorb the variability in renewable generation, reduce governor wear and fuel costs associated with ramping of thermal units [69].

As with DG units, the location of ESS within the system plays a significant role in its effectiveness, and many studies have been dedicated to comparing the benefits of central versus distributed storages. Likewise, proper sizing of ESS is necessary to establish an optimum trade-off between reliability and capital cost [113] [147].

2.4.Objective Functions

As discussed in the previous section, there exists a common set of objective functions and formulations that are used throughout optimization of islanded microgrids. Each of the objective functions commonly used throughout the literature is summarized in Table 4 and discussed in detail below.

Table 4: Summary of common objective functions used in scheduling and planning optimization problems

Objective Function	Components / Formulation	2013 and prior	2014	2015	2016	2017	2018 – 2019
Minimize cost / Maximize profit	Fuel cost of thermal units	[27] [31] – [40]	[28] [41] – [45]	[46] – [52]	[53] – [64]	[65] – [83]	[84] – [102]
	Renewable DG costs	[25] [27] [103]	[104] [105] [106]	[49] [107] [108]	[54] [109] [110] [111]	[66] [71] [75] [81] [82] [83]	[86] [86] [91]
	Startup / shutdown costs	[25] [27] [31] [36] [39]	[41]	[46] [49] [51] [52]	[53] [55] [57] [62] [64]	[69] [71] [75] [79] – [81]	[89] [90] [98] [99] [100] [112]
	O & M costs	[27] [33] [35] [37]	[44] [105] [106]	[47] [48]	[113] [55] [63] [110]	[68] [69] [70] [71] [73] [83] [114]	[85] [88] [95] [101] [102]
	Reserve costs		[104]	[52] [108]	[64]	[75] [81] [83] [114]	[91] [92] [94] [102]
	ESS cost	[25] [27] [31] [37] [103] [115]	[41] [105] [106]	[47] [51] [116]	[113] [55] [57] [63] [117] [118]	[69] [66] [78] [79] [82] [83] [114]	[92] [94] [98] [99] [101] [102] [119]
	Load shedding / DR costs	[27] [31] [36] [38] [103] [120] [121]	[28] [105]	[46] [47] [49] [52] [108] [122]	[56] [57] [62] [63]	[66] [68] – [70] [72] [73] [75] [79] [81] – [83] [123]	[86] [89] [91] [93] [99] [101] [102] [112]
	Revenue from loads	[32] [40]			[111] [56] [117]	[70] [73] [75]	[91] [124]

	Installation capital cost	[35] [37] [120] [125]	[44] [105] [106] [126]	[47] [48] [122]	[113] [58] [61] [63] [109] [110] [117]	[68] [69] [70] [73] [83]	[86] [88] [95] [97] [102] [119]
	Cost of losses	[120]	[43]	[48] [50] [51] [116] [122] [127] [128]	[109] [59] [129]	[66] [77] [83] [130] [131]	[95] [97] [102] [132]
Minimize voltage deviations		[133]	[134] [135]	[48] [50]	[59] [111] [129] [136]	[83] [137] [138] [139]	[102] [132]
Minimize frequency deviations		[121]	[104] [140]	[49] [107]	[113] [53] [60] [61] [136]	[77] [83]	[87] [89] [102]
Minimize emissions		[25] [31]	[43] [44]	[48] [107]	[58] [61] [109] [110]	[67] [68] [70] [71] [83] [130]	[85] [93] [95] [96] [102]
Minimize renewable curtailment		[38] [115]		[46]	[57] [61] [118]	[65] [83]	[93] [99] [101] [102]
Maximize load served		[121]	[42] [141]		[111]	[130] [131] [141] – [143]	[93] [119] [144]
Maximize reliability		[37] [115] [146]	[106] [126] [122] [146]	[47] [50] [46]	[61] [63] [110]	[72] [73]	[87] [95]

2.4.1. Minimization of cost or maximization of profit

A majority of work to date has been based on variations of the cost-based optimization. The objective function is expressed as the sum of all the individual components of generation cost, including direct fuel costs, capital recovery costs of DER investments, and penalties for emissions, ramping, and losses.

2.4.1.1. Fuel cost of thermal units

The optimization problem related to nearly all microgrids with a diesel generator or microturbine will include an expression for minimizing the cost of operating the generator [31] – [77], [87] expressed as a linear or quadratic function of the power output, multiplied by the heat rate and fuel cost.

Fuel cost is rarely used as the only objective function, except in scenarios when the only the available generation is from thermal units [45]. All other microgrid optimization formulations in recent literature combine the generation cost with other objectives, either as a multi-objective formulation, such as cost versus emissions [43], [44], [67], or combined into a single objective function composed of multiple types of costs, such as fuel cost and load shedding cost [27], [28], [46], [47], [56], [68], [70], [72].

2.4.1.2. Power from renewable DER

DERs can be treated as either dispatchable or non-dispatchable resources. As a result, optimization studies can be grouped into two categories depending on which classification is used.

The first group of studies include all DER (especially wind turbines) as dispatchable units that have a different cost of generation [25], [27], [54], [83], [109] – [111]. This approach assumes that although the output of these units cannot be ramped up to supply additional load, photovoltaic (PV) and wind generators can be curtailed and held below full output to enable load-following control.

The second category of optimization studies treat all DER as non-dispatchable units whose output cannot be controlled, leaving thermal units and ESS the responsibility of AGC and frequency control [33], [46], [66], [72]. Some formulations set the price of DER power at zero cost, so that power from these units is dispatched first [41], [46], [72].

2.4.1.3. Startup and shutdown costs

If the optimization formulation considers unit commitment, in which the binary states of generator online/offline status is included, the objective function will generally include the startup and shutdown cost of DGs [25], [27], [69], [31], [33], [41], [53], [55], [81], [91]. Startup and shutdown costs are additional costs incurred by the DG owner in bringing the unit online (or taking it offline), and include the cost of auxiliary power, fuel, and special operations, as well as capital recovery costs for the impact on generator lifespan from cycling and additional maintenance [148].

Similar to startup and shutdown costs, ramping costs are an additional cost above the simple cost of fuel to recover the capital and maintenance costs of cycling the plant to follow load. The costs of ramping tend to be ignored and rather modeled as a constraint representing the maximum rate at which the output of DGs can be ramped up or down. Minimization of DG ramping occasionally appears as a separate objective function, as in [145].

2.4.1.4. Cost of ESS

Energy storage systems represent a substantial portion of the construction cost of a microgrid, and so numerous formulations included capital recovery costs or methods for measuring the impact of ESS cycling. The cost of battery storage can be based on an hourly capital recovery cost [83], [117], [149], the depth of discharge reached during a load cycle [27], [55], [66], [71], or the expected lifespan of the ESS [55], [102].

2.4.1.5. Cost of demand response and load shedding

Load shedding and demand response (DR) represent two philosophies that are necessary for reliable and economic operations. DR programs compensate consumers for the ability of the distribution EMS to control the consumption of loads through the use of Smart Grid technologies. In this regard, customer loads can be broken down into three categories [57]:

- Controllable or curtailable loads include heating ventilation and air conditioning (HVAC), refrigeration, lighting, and household appliances [150]. These loads can be reduced through DR control systems to reduce power consumption for a certain time period.

- Deferrable loads, such as electric vehicle charging, can be shifted to a later time period as long as the consumer receives the same total amount of energy by a stipulated time [66].

- Critical or must-run loads must be supplied their full power demand during all grid conditions, even at the expense of load shedding in other parts of the system. Examples include hospitals, communications, emergency services, and data centers [123].

Controllable and deferrable loads allow the system to match load to forecast generation [79], as well as respond to variations in renewable generation without the need to bring high cost and typically "dirty" generation online. Meanwhile, load shedding is used to resolve more significant mismatches between load and the capacity of generation and ESS, such as when the microgrid is islanded unexpectedly or a significant drop in generation exceeds the ESS inverter limits and the ramp rates of thermal units [123]. Load shedding can be performed manually or by under-frequency load shedding (UFLS) protection schemes. Loads interrupted by demand response or UFLS are typically treated as an additional cost formed from DR incentives paid by the utility [66], [102], customer comfort level [102] (or alternatively, customer nuisance cost [38]), or a penalty based on the priority of load shed [111], or the value of lost load (VOLL) [49], [91], [93], [102], [112].

2.4.1.6. Revenue from loads

An alternative to minimization of generation cost is maximization of the profit of the microgrid. In such formulations, the objective function is expressed as the difference between revenue obtained from serving customer loads and the cost of generation, storage, emissions, etc. [32], [40], [56], [70], [73], [111] [91]. Inclusion of load revenue in the optimization enables the use of a transactional market structure with tiered customer pricing based on ability-to-pay and other demand-side bidding strategies [52], [75], [117].

2.4.1.7. Cost of Reserves

In order for the microgrid to respond to variations in load, fluctuations in DER output, and possible loss of any generating units, it is necessary that online generators have a certain amount of margin by which they can increase or decrease their output. Otherwise, if all generators in the microgrid are operating at the maximum output, load shedding will be necessary to resolve any increases in load or decreases in output from non-dispatchable units. This margin is referred to as system reserves, and can be classified as spinning and non-spinning.

Spinning reserve is defined as the total available generation from all synchronized units, minus the power consumed by loads and losses [151], and can be provided by fast-responding ESS [39] [52] or dispatchable generators [75] synchronized to the system. Non-spinning reserve consists of quick-start thermal generators (such as diesel and microturbine units), most hydro units, and power electronics-based DGs, which can be synchronized and brought to full capacity within minutes.

Due to the importance of reserve for regulation of system voltage and frequency [51], [102], the cost of spinning and non-spinning reserves is sometimes included in objective function formulations as an ancillary service provided by generator operators. The objective is typically formulated as the amount of spinning reserve provided by each unit multiplied by a linear cost factor [52], [64], [75], [104], [108], [91], [114]. A small amount of renewable curtailment can also be used so that the curtailed amount can be treated as spinning reserve to increase system security [28].

2.4.1.8. Capital cost of installation

Capital cost of equipment is a primary consideration in many studies involving planning [70] or expansion [73] of power systems. Typical costs include the purchase and installation of thermal generation, PV and wind DGs, energy storage, inverters, controllers, feeders, and substation equipment [34], [55]. The capital cost can be converted into an hourly amortized cost through the use of a depreciation rate based on the lifetime of the system [44], [68], [86], [95], [97] or a desired payback period [117]. Alternatively, the cost of installation can be expressed as a separate objective, formulated as the total cost of all components [125].

2.4.2. Minimization of voltage deviations

Optimizations that expand the unit-commitment / economic dispatch problem into a full optimal power flow sometimes consider the voltage profile of the network. Significant voltage deviations can result in unsatisfactory operation of equipment, tripping of protective relays, and circulating reactive power flows in the network [146]. Simultaneously, the ability of the system to keep all nodes within desired voltage limits (such as those set in ANSI C84.1-2016 [152]) is affected by line flows, DG reactive power capabilities, and network topology [34], [137].

Unlike grid connected systems that benefit from reactive control devices (such as static var compensators or shunt capacitors/reactors [153]) or tap-changing transformers [154], at the MV substation level, islanded microgrids must rely on generation dispatch, voltage setpoints [71], and droop characteristics of local DGs to control voltages within the network [155].

Although minimization of voltage deviations is most often addressed in control studies of droop-based inverters [134], [156], it can be expressed as an independent function in a multi-objective economic dispatch problem, as the sum of either the absolute value [59], [111], [129], [133], [137] or square [48], [50], [138] of the deviation of voltage from 1.00 pu across all nodes in the network.

Related objectives are optimization of the voltage stability index (VSI) [59] and voltage unbalance factor (VUF) [134], [139], which represent the voltage stability of the overall system and imbalance of the *dq* voltage components at a particular node, respectively. These two objectives are considered both in dispatch [129] and control [134], [138] problems.

2.4.3. Minimization of frequency deviations

Depending on whether the line impedances of the islanded microgrid are primarily reactive or resistive, mismatches between generation and load will result in either frequency or voltage deviations, respectively. For primarily reactive networks, minimization of frequency deviations is a central concern for management of load shedding [121]. Minimization of frequency variations can also appear as an objective included in optimization formulations to supplement automatic generation control (AGC) if large imbalances between generation and load exist, including immediately after the transition from grid-connected to islanded modes [27], or when the actual renewable output deviates significantly from the forecasted values [118]. Frequency deviations can be resolved through generation dispatch, demand response [104], load shedding [121], or ESS sizing [113].

Frequency deviation can be treated as a penalty cost [60] or as a separate objective formulated as either the difference between actual and nominal frequency [49], [121], [104] or the MW generation-load mismatch [61], [140]. Minimization of frequency deviations can also be examined from the standpoint of small signal stability analysis, in which the optimization objective is to minimize the any real positive eigenvalues and maximize the damping coefficient of all other eigenvalues [87].

2.4.4. *Maximization of load served*

Closely related to the concept of frequency and voltage deviation minimization is the maximization of load served. Islanded systems have limited dispatchable generation capacity, especially if the microgrid has a high penetration of renewables. Maximization of load served appears in optimization problems related to both planning [131] and operations [42], [130]. It is typically formulated as the weighted sum of each load's power consumption and priority ranking [141], [142].

In planning, one of the concerns is the amount of the load that can be served without causing voltage collapse. This problem can be addressed through optimal placement of generators [131], sizing of ESS, network topology reconfiguration [34], or examination of the loadability of particular buses [42], [130], [142], [144].

In operations, mismatches between generation and load will require frequency excursions and possible load shedding, as a result of forecasting errors, insufficient reserves, or sudden islanding of the system [111]). It can also be used as an objective in system restoration after the occurrence of various contingencies to energize loads in order of priority [141], [143].

Maximization of load served (or conversely, minimization of energy not served (ENS) [72], [83], [102], [121], [144]) can be used as an objective function in a multi-criteria formulation [42] to provide more detailed information on the impact of load on system performance than a simple constraint stating that all critical loads must be served. It can also appear when dealing with design and construction of actual systems that are subject to budget constraints [72]. As a result, designers of rural electrification systems are faced with the objective of trying to electrify the maximum number of customers without exceeding the maximum construction cost available to the project.

2.4.5. *Minimization of emissions and pollutants*

One of the widely recognized benefits of microgrids is their potential ability to reduce emissions through a high a penetration of renewable DER [14]. As a result, many optimization formulations seek to minimize the emissions and pollutants emitted by the power system [67] – [71]. Commonly considered emissions include carbon dioxide (CO_2), sulfur dioxide (SO_2), and nitrogen oxides (NO_X).

Typically, two approaches are taken to modeling emissions of thermal DGs used in the microgrid. The first is to measure emissions directly in tons per unit time (or an equivalent rate) [25], [43], [44], [107], [110], and subsequently use this value as a separate objective that is minimized through a multi-objective optimization. The second method is to convert DG emissions into a penalty function that is treated as an additional cost based on the output of thermal units [67], [68], [83], [95], [102].

2.4.6. *Minimize curtailment of renewables*

Following the same emphasis on the environmental benefits of microgrids are objectives seeking to maximize the use of renewables. Common formulations include adding curtailed generation as an additional penalty cost [38], [46], [57], [65], [83], [93], [99], [101], [102], [118], or minimizing it as a separate objective function [37], [61]. Another approach [41], [72] is to set the cost of renewables to zero so that the cost optimization will accept all renewable generation first in both UC and ED problems.

2.4.7. Minimization of network losses

Optimization formulations that expand the economic dispatch problem into a full optimal power flow (by including an AC power flow calculation) may include minimization of network losses as one of the objective function components [77], [83], [102]. In microgrids, losses in the distribution network are affected not only by generation output [131], but also by network topology [141] and the locations of DER [129]. As a result, minimization of losses is found both in planning [48], [120], [129], [131] and operations settings [59]. Network losses can be expressed as a separate objective [43], [48], [131], but are typically not expressed as a cost objective since it is already included in the cost of generation. Some formulations with a strong emphasis on ESS units in the microgrid will include the losses involved in charging and discharging the ESS [41], [51], [46].

2.4.8. Maximization of reliability

System reliability is a frequent consideration in microgrid planning studies, and several technical indices have been used. In most cases, the optimization is built as a cost-vs-reliability tradeoff study to determine the optimum system configuration given various economic and technical constraints.

The first group of reliability indices are those derived from reliability studies of conventional power systems. The first is expected energy not served (EENS), which is the total amount of energy that would have been consumed if the interruption had not occurred [34], [50], [72], [105], [95]. The system average interruption frequency index (SAIFI) and system average interruption duration index (SAIDI) are another pair of measures, expressed as the total number of customer interruptions over a certain time period divided by the total number of customers and as the total duration of customer interruptions divided by the total number of customers, respectively [50], [146]. Another popular index is loss of load probability (LOLP) or loss of load expectation (LOLE), defined as probability that available generation output will be less than demand, and load shedding will be necessary [61], [95], [99], [110], [115], [146].

However, it has been pointed out [157] that some traditional reliability indices (such as SAIFI and SAIDI) are not as useful for islanded systems, or lead to unnecessary oversizing of designs [126]. As a result, special reliability indices specific to islanded microgrids have been introduced, including loss of power supply probability (LPSP) [37], [106], [56] and energy shortfall probability (ESP) [126].

2.5. Constraints

Nearly all optimization formulations include a set of constraints that model the physical and technical limitations of microgrid equipment. Safe, secure, and economic operation of the system requires that all constraints relevant to equipment damage, system collapse, or disruption of service to critical loads are respected. All commonly used constraints are discussed in detail below and summarized in Table 5.

2.5.1. Power balance and power flow

The most common set of constraints found across nearly all optimization formulations are those for power balance and power flow. The first constraint states that the total amount of real power consumed by all loads in the islanded system must be equal to the sum of the real power supplied by all DER and total network losses. This constraint is found in most optimization formulations [53] – [59], [64] – [76], [85] – [89], except those studying load shedding [105] or frequency regulation [60], [61], [77], [83], [102], [107], [140].

Table 5: Summary of common constraints used in scheduling and planning optimization problems

Constraints	2013 and prior	2014	2015	2016	2017	2018 – 2019
Power balance	[25] [27] [31] [33] [36] [38] [39] [103]	[28] [42] [43] [104] [140] [141]	[47] [49] [51] [52] [108] [127] [128]	[53] – [59] [63] – [65] [111]	[69] [66] – [70] [72] – [76] [78] – [81] [145]	[85] – [89] [92] – [97] [100] [101] [112] [144]
Generator limits	[25] [27] [31] [33] [35] [40] [103]	[28] [41] – [44] [104] [140] [141]	[46] – [51] [108]	[53] – [57] [61] [64] [111]	[65] – [71] [74] – [77] [80] [81]	[85] [86] [88] – [98] [100] [144]
DER VAr limits	[25]	[43]	[50]	[59] [111]	[67] [71] [74] [142]	[85] [86] [93] [96] [97] [132] [144]
Generator ramp rates	[27] [38]	[28] [41] [104] [140]	[46] [49] [51] [52]	[53] [57] [58] [62] – [64]	[65] [66] [67] [69] [71] [82] [145]	[90] [93]
Generator min on / off times	[38]	[41] [104]	[46] [49] [51] [52]	[53] [55] [57] [58] [62] [64]	[69] [67] [71] [80] – [82]	[90] [98] [102]
ESS state-of-charge limits	[27] [35] [38] [40] [103] [115]	[41] [44] [106] [140]	[46] [47] [51]	[53] – [55] [57] [58] [61] [63]	[65] – [69] [73] [78] [79] [80] [82] [145]	[86] [90] [92] [93] [94] [96] [100] [112] [124]
ESS (dis)charging power limits	[35] [38] [39] [40] [103] [115]	[43] [44] [140] [156]	[47] [51]	[113] [53] [55] [57] [58] [62] [63]	[66] [68] [69] [74] [78] [79] [80] [145]	[88] [90] [92] – [96] [112] [101] [124]
Critical loads / DR limits	[27] [38] [121]	[28] [105] [140]		[56] [63]	[66] [69] [73] [75] [81]	[89] [93] [112] [101]

Voltage limits	[25] [34] [120]	[42] [43] [105] [156]	[46] [48] [50] [122]	[56] [59] [62] [111]	[71] [74] [80] [83] [142]	[87] [88] [93] [96] [97] [102] [112] [132] [144]
Frequency limits	[121]	[104]	[107] [128]	[113]	[74] [83] [142]	[88] [89] [97] [98] [102] [132] [144]
Line thermal ratings	[25] [34] [120]	[105]	[52] [127] [128]	[57] [59]	[74] [76] [142]	[85] [87] [89] [97] [102] [112] [144]
Reserve (spin & non-spinning)	[31] [38] [39] [149]	[104]	[49] [51]	[53] [55] [58] [62] [64]	[69] [65] [67] [68] [75] [79] [81]	[88] [90] [92] [94] [98] [112]
Emissions limits	[31]	[104]	[49]		[70]	[85]
Total system cost	[34]		[47]		[69] [68] [70] [72]	
System reliability	[31] [35] [37] [146]	[42] [106]	[47]	[63]	[68]	[124]

The second related constraint is that the classic power flow equations must solve. This constraint is found in all optimal power flow (OPF) formulations [52], [57], [59], [63], [74], [76], [85], [97], [120], [128], [142] and all problems considering voltage violations as an objective or constraint [25], [34], [42] [43], [46], [48], [50], [87], [88], [93], [96], [97], [102], [105] [112], [120], [122], [132], [144], [156]

2.5.2. Generator limits

The second constraint that is nearly universally found in microgrid optimization is that the real power output of DGs must stay between the unit's minimum and maximum operating limits [46] – [51], [53] – [57], [64] – [76], [92] – [98]. If spinning reserve is considered, then the constraint should state that the sum of scheduled output and spinning reserve from a particular unit must be within the unit's rating [68], [75]. Inverter-based DER may specify the limit in terms of current injection capabilities of the inverter, rather than power output of the generator [27], [35], [66], [142].

A related constraint that is increasing in popularity is that DERs must also stay within reactive power generation / absorption limits. This constraint can be expressed in terms of the DG real-reactive capability curve [25] or a fixed minimum and maximum [43], [50], [59], [67], [71], [74], [85], [86], [93], [96], [97], [111], [132], [142], [144].

2.5.3. Generator ramp rates

The ability of a microgrid to respond to variations in load and output from non-dispatchable DER is significantly affected by the rate which controllable generators are able to increase or decrease their power output. This ability is defined as the ramp rate of the DG (measured in

MW/min or kW/min) and set by the physical operating restrictions of each generator [158]. Generally, hydro plants and new gas turbine units have the fastest ramp rates (up to 100 MW/min), while steam-boiler plants have the lowest rates (less than 5% of capacity per min).

The ramping capability of dispatchable generators can be subdivided into two categories for scheduling optimizations [63]. The first is for load following, in which the all controllable DG and ESS units are ramped to an optimized value, based on hourly load and availability of renewables forecasts. The second is frequency regulation, which is determined by the units' ability to provide 1 minute ramping to match short-term deviations in generation and load, in addition to ramping to meet the overall schedule.

Ramp rates are specified as ramp-up and ramp-down limits for each unit that must be followed by the optimization [27], [28], [69], [38], [41], [46], [49], [51] – [53], [57], [62], [63], [65] – [67], [71], [104], [140], [145]. If the change in load or renewable generation is greater than the ramp rate of DGs and ESS, then the microgrid must shed load or curtail renewables to maintain generation-load balance [28].

2.5.4. Generator minimum online / offline times

The final set of constraints related to the physical operation restrictions of DGs is the minimum time that a unit can be online or offline before it can be shut down or started again, respectively. This constraint is usually only found in UC formulations [69], [38], [41], [46], [49], [51] – [53], [55], [57], [58], [62], [64], [67], [71], [104].

2.5.5. *ESS state of charge limits*

The lifetime of ESS units is strongly correlated to the depth of discharge experienced on a regular basis: the lower the state of charge (SOC) experienced by the ESS, the shorter the lifespan of the battery will be. Additionally, ESS units have limited storage capacity and cannot be charged beyond 100% SOC without incurring damage to the unit. As a result, minimum and maximum SOC limits are found in numerous optimization formulations, and are typically set near 50% for the minimum and 100% for the maximum SOC [27], [69], [35], [38], [40], [41], [44], [46], [47], [51], [53] – [58], [61], [63], [65] – [68], [73], [79], [103], [106], [115], [140], [145]. Additionally, the SOC at the end of a scheduling horizon (such as a daily load cycle) may be required to be equal to the SOC at the start of the cycle [88].

2.5.6. *ESS charging / discharging power limits*

The second common constraint applied to ESS is the maximum amount of charging and discharging current that can be applied to the unit without causing damage to the internal cells. This constraint is found in both planning [69], [113], [35], [44], [47], [58], [63], [68] and operations [40], [43], [51], [53], [55], [57], [62], [66], [74], [79], [145] problems. The maximum power that can be supplied from the unit strongly affects the cost of the ESS [113] and its suitability for providing frequency regulation [63].

2.5.7. *Critical loads and DR / shedding limits*

As discussed earlier, microgrid loads can be categorized into critical loads (which cannot be interrupted except during a system blackout), deferrable loads (which can rescheduled to a later time), and curtailable loads that can be interrupted without significant impact on consumers.

Optimizations that include load shedding and demand response (DR) as parameters often place constraints on the maximum amount or percentage of controllable loads that can be interrupted [27], [28], [69], [63], [73], [75], [81], [105] or deferred [38], [66] and the requirement that critical loads must be satisfied [56], [57].

2.5.8. Voltage limits

To prevent possible equipment damage and voltage collapse, the microgrid energy management system must maintain the voltage magnitude of all buses within acceptable limits. This requirement is typically expressed as an inequality constraint that the per-unit voltage of each bus must remain between a minimum and maximum value [25], [42], [43], [46], [48], [50], [56], [59], [62], [71], [74], [105], [97], [111], [120], [122], [142], [156].

2.5.9. Frequency limits

If the islanded system includes microturbine generators or other equipment that could be damaged by frequency excursions, then minimum and maximum limits on system frequency can be added as additional constraints [113], [74], [104], [97], [107], [121], [142] [144]. However, in islanded systems, larger frequency swings are permissible than in grid-connected systems [89].

2.5.10. Thermal ratings of lines

Optimal power flow (OPF) formulations that consider the power flow through the microgrid network may include thermal ratings of feeders and lines. The constraint typically states that the flow of real power [52], [57], [63], [76], apparent power [97], [120], or current [59], [74], [85], [102], [128], [142] on a particular path between two buses (as calculated by the classic power flow equations) must stay below the rated value of the line.

2.5.11. Spinning and non-spinning reserve

Sufficient spinning and non-spinning reserves are essential for system security, for reasons discussed earlier in this paper. The minimum amount of spinning reserve required to cover fluctuations in load and DER output are set as a constraint that can be expressed as:

- 5% of overall load [31]
- 10% of load [38], [53], [103]
- 20% of load [51], [68]
- 20% of load + PV output [55], [58], [79]
- Error / uncertainty in loads and DER [69], [49], [64], [94]
- Loss of largest generator [39], [65]
- Load, PV, and wind output [62], [67]

As can be observed from the list of common formulations, the amount of PV and wind generation is frequently included as part of the reserve requirement. This reflects the trend that higher levels of renewable penetration and greater forecasting uncertainty require larger amounts of spinning reserve to maintain grid stability.

2.5.12. Total system cost

The design and construction of actual systems (as opposed to research on theoretical test cases, such as the IEEE distribution test feeders [159]) must consider the construction cost of the system and budget constraints. System cost constraints typically state that the sum of the cost of all microgrid components must be less than a fixed maximum amount [69], [47], [68], [70], [72].

2.5.13. System reliability

Finally, the system may be constrained to provide a minimum level of system reliability, which may be expressed through a number of measures, including loss of load probability (LOLP) [31], [35], [42], [47] [63] [68], loss of power supply probability (LPSP) [35], [37], [106], [124], and the margin from dynamic instability [146] or voltage collapse [42].

2.6.Optimization Variables

Optimization variables, also referred to as control variables and decision variables, represent the set of parameters that are varied by the solution algorithm to determine the optimal or near-optimal DER schedules or system configuration that satisfies all constraints. A summary of commonly used optimization variables is presented in Table 6.

2.6.1. Power output of generating units

In microgrids with diesel, microturbine, or other thermal generating units [31] – [79], the power output of each thermal unit is taken as an optimization variable that can be varied between the minimum and maximum capacities of the unit. If ramp rates are considered [62] – [67], then the available range over which the output can be varied is the product of the maximum ramp rate and scheduling interval. If renewable generators are considered dispatchable, then the power scheduled from wind and PV units will be treated as an additional optimization variable [25], [27], [28], [43], [53], [54], [67], [71], [74], [75], [104] – [111], [145].

Table 6: **Summary of common optimization variables used in scheduling and planning optimization problems**

Optimization Variables	2013 & prior	2014	2015	2016	2017	2018 – 2019
Power output of thermal units	[27] [31] - [35] [36] – [40]	[28] [41] – [45]	[46] – [52]	[53] – [64]	[65] – [79]	[90] – [92] [94] [96] [97] [100]
Power output of renewables	[25] [27] [33]	[43] [28] [104] [105]	[107] [108] [50]	[53] [54] [109] [110] [111]	[67] [68] [71] [74] [75] [145]	[97] [98]
Curtailment of renewables	[38]		[47]	[57]	[69] [73] [83] [145] [65]	[93] [99] [101] [102]
Operating state (on/offline)	[25] [27] [31] [33] [36] [38] [39]	[41] [104]	[46] [49] [51] [52]	[53] [55] [57] [58] [62] [64]	[67] [69] [71] [74] [75] [81]	[91] [90] [100]
Spinning reserve		[104]	[52] [108]	[64]	[69] [75] [81] [114]	[91] [92] [94] [98]
DR & load shedding	[27] [37] [38] [121]	[28] [104]	[46]	[57] [63]	[65] – [67] [69] [73] [74] [123]	[89] [112]
ESS power output	[38] [39] [40] [103]	[41] [105]	[46] [47] [51]	[113] [63] [53] [62]	[66] [74] [78] [79] [83] [145]	[90] [92] [94] [97] [98] [102] [112]
DG voltage setpoints	[27]	[41] [42]	[46]	[111] [59]	[74] [83] [142]	[102] [144]
Droop constant		[42] [134] [156]	[127] [128]	[53] [59]	[83] [139]	[87] [96] [102] [132]

Thermal generation capacity		[44]	[47]	[61] [63] [110]	[68] [72]	[86] [88] [119]
Installed solar generation capacity	[35] [37]	[44] [106] [126]		[58] [61] [110]	[68] [72]	[86] [119]
Installed wind generation capacity	[35] [37] [125]	[44] [106]	[47]	[61] [110]	[68] [72]	[86]
Installed ESS capacity	[35] [37] [115] [125]	[44] [105] [106] [126]	[46]	[113] [58] [61] [63]	[68] [69] [72] [73]	[86] [88] [119] [124]

2.6.2. Operating state of generators

Unit commitment formulations [25], [27], [69], [31], [33], [36], [38], [39], [41], [46], [49], [51] – [55], [57], [58], [62], [64], [67], [71], [74], [75], [104], which examine the impact of generator startup and shutdown, include a set of binary state variables to represent whether a particular unit is scheduled to provide power during a particular hour. This parameter is typically set to a value of one if the unit is online and zero if offline, and causes the objective function to become discrete, rather than continuous.

2.6.3. Renewable curtailment

If renewable generation is greater than load and the charging ability of ESS units, then the excess generation will need to be curtailed. In formulations that seek to maximize use of renewables or explicitly model the amount of curtailment, this parameter will be included as an optimization variable that can be varied between zero and the total output from renewable DER [69], [38], [57], [65], [73], [83], [101], [102], [145]. Alternatively, curtailment can be expressed as the amount of power directed to a sink or dump load [33], [35], [47], [57].

2.6.4. DR and load shedding

Conversely, if renewable output is less than demand at any time, then either thermal generation will need to be dispatched or load can be curtailed. This choice is reflected through two optimization variables related to DR and load shedding, namely the quantity of load shed or deferred and the priority of the load. Some optimization problems choose to use the product of load quantity and priority [141] – [143], but the majority use the total real power deferred or interrupted.

2.6.5. ESS charging / discharging power

Since ESS units are fully controllable, the real power absorbed or supplied by each storage unit is common control variable [113], [38] – [41], [46], [47], [51], [53], [62], [63], [66], [74], [79], [105], [103], [145] used to achieve optimal operations, considering both current and forecasted demand and generation. Some formulations [38], [51], [66], [79] choose to introduce an additional set of binary state variables to indicate whether the ESS is charging or discharging.

2.6.6. Voltage setpoints and droop constants of DGs

Optimization studies that include network voltage deviations [27], [83], [102], [105], [111], reactive power flow [41], [46], voltage stability [59], and system load limits [42], [142], [144] may select the voltage setpoint of DERs as a control variable. By adjusting the terminal voltages of DG and ESS units, the microgrid EMS is able to provide reactive power support to heavily loaded feeders and adjust power flows in networks with P-V/Q-f droop characteristics. This variable lies at the secondary control layer and is adjusted through a control signal issued by the microgrid controller [142]. Related optimization variables are DG reactive power output [41], [74], optimum placement of shunt capacitors [120], and droop controller gains [42], [53], [59], [83], [87], [102], [127], [128], [134], [139], [156].

2.6.7. Installed generation capacity

Generally, planning problems seek to determine the optimum size and location of DER assets [70]. As a result, the capacity of generation units is an optimization variable in many formulations. The capacity parameter for thermal [44], [68], [110] and renewable DGs is typically expressed in terms of the optimal rated kW capacity of the generator [44], [47], [68], wind rotor /

PV surface area [106], or in terms of the number of individual solar panels and wind turbines [35], [37], [68], [110].

2.6.8. Installed ESS capacity

Similarly, nearly all optimization problems involving planning and installation of ESS will include the capacity of each unit as a decision variable, which can be expressed in terms of the kWh or Ah capacity [69], [113], [44], [46], [106], [115], kW power rating [69], [113], [44], [47], [115], or the number of individual batteries [35], [37], [68], [105].

2.7. Discussion

This paper provides a detailed examination of all the aspects of common optimization formulations for islanded microgrids, including objective functions, constraints, and variables. The papers surveyed have been classified both by the particular set of modeling decisions and chronologically. This approach enables the reader to gather valuable insight into both different approaches, but also trends as certain criteria have increased in popularity significantly within the last few years.

Objective functions based on cost are by far the most popular approach: Of the 120 individual optimization studies of islanded microgrids reviewed, 103 chose an objective function formed from the sum of various costs. Within that category, fuel cost of thermal DGs is easily the most popular cost component with 74 papers (about 2/3 of all papers) selecting this objective. There are no significant changes chronologically in popularity between different types of costs, with all usage of all 8 types of costs growing equally as the number of microgrid optimization papers published each year rises. A summary of the popularity of each objective function over the last ten years is presented in Figure 3.

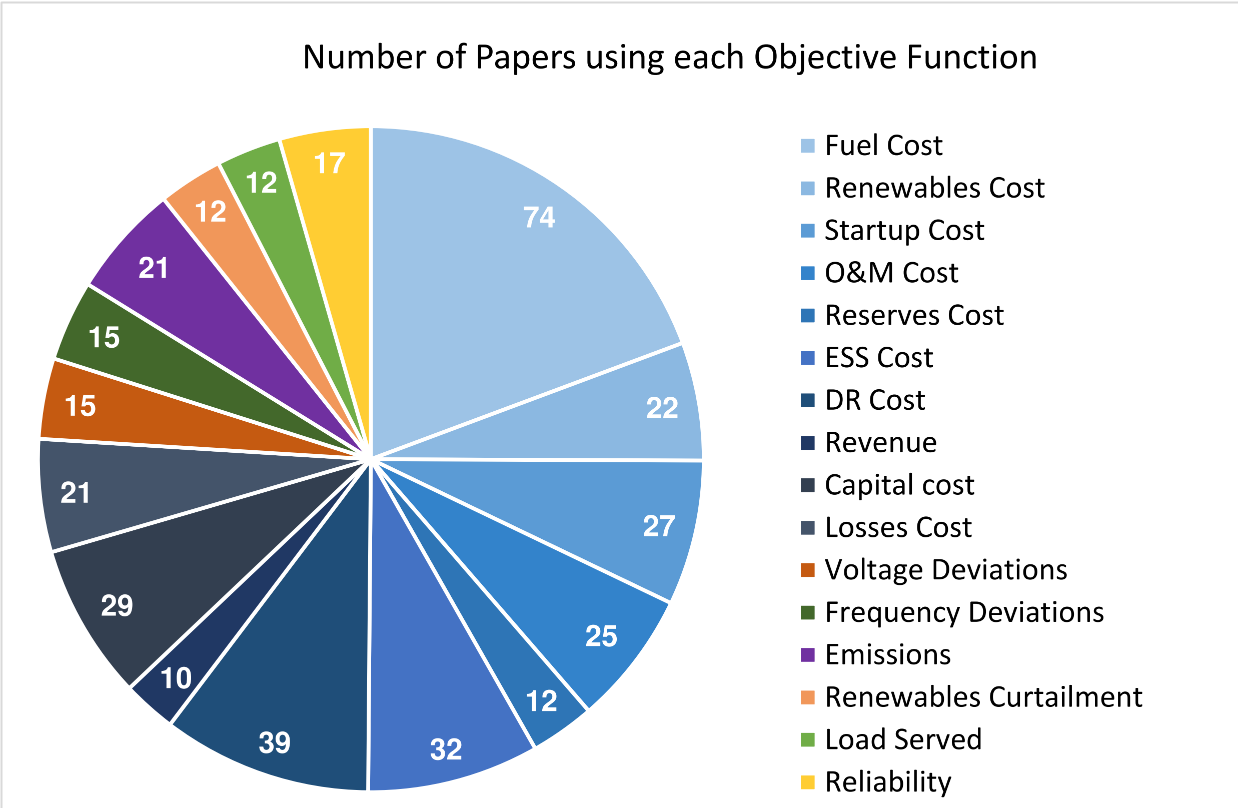

Figure 3: Number of papers dealing with islanded microgrids using each category of objective function over the last 10 years. Note that most papers use multi-objective formulations, as in the case of cost-based objectives (illustrated in blue shades) which were selected 291 times by 103 papers (out of a total of 120 individual optimization studies reviewed).

In contrast, there is a much more even distribution of preference for optimization constraints. Power balance and generator output limits stand out as the two most popular limits since they represent fundamental operating requirements that a planning or dispatch algorithm must find a way to supply load demands and must also not exceed the maximum or minimum output settings of all DGs. A close second in popularity are SOC and output limits of ESS units since violating these constraints will significantly reduce the lifespan or even damage the ESS. Two constraints that have received an exponential increase in interest are voltage and frequency limits. As can be observed from Table 5, voltage limits were considered by four papers in 2016, five papers in 2017, and nine papers in 2018. Likewise, frequency limits were considered by one paper in 2016, three papers in 2017, and seven papers in 2018. A possible explanation for this trend is the growing awareness that the frequency of islanded microgrids can be allowed to wander over a much greater range, especially in small systems that lack of any steam turbines or gas turbines that could be damaged by frequency deviations. In these small systems, it is possible to simply let voltage and frequency swing slightly out of bounds in the event of a generation-load mismatch, rather than shedding load or curtailing renewables. A summary of the number of papers using each of optimization constraints examined in Section 2.4 is presented in Figure 4.

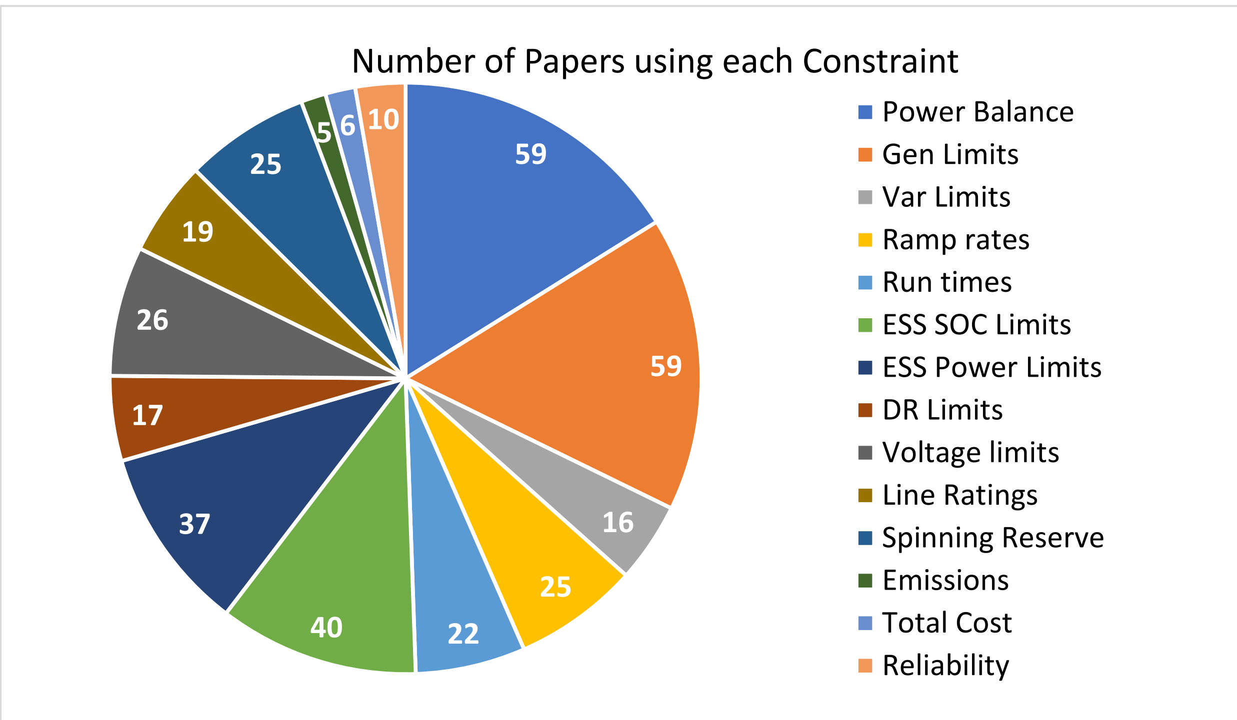

Figure 4: Number of papers dealing with islanded microgrids using each type of optimization constraint.

Finally, a few interesting trends can be observed in preference for solution variables. Basic variables (such as power dispatched from thermal DGs, unit commitment on/off states, and ESS output) have been used at a relatively constant rate in the past decade. Also of note is that variables that are used by both planning and scheduling optimization problems (such as ESS output and DG output) are used much more extensively than variables exclusive to planning problems, such as DG and ESS capacity. All of the variables discussed earlier are summarized in Figure 5.

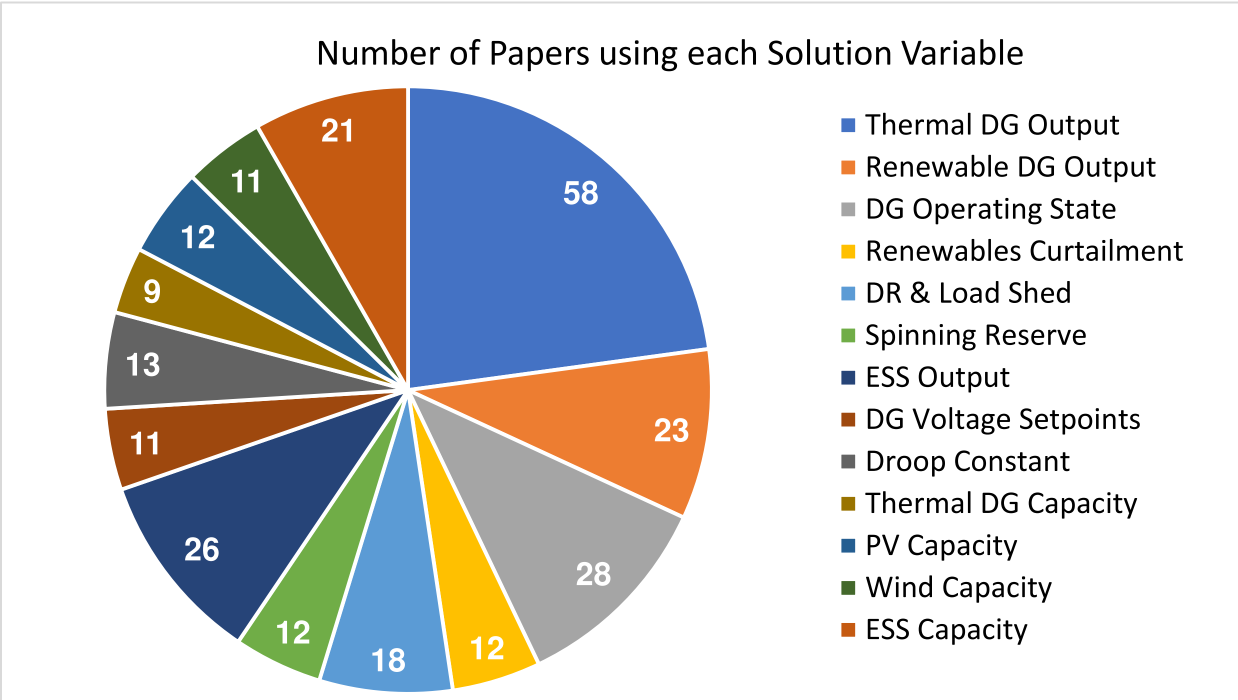

Figure 5: Number of papers dealing with islanded microgrids using each solution variable

2.8. Conclusion

This chapter provides several key findings regarding optimization of islanded microgrids. All referenced papers selected formulations from a combination of 8 categories of objective functions, 15 types of constraints, and 13 possible solution variables. Each choice of objective, constraint, and solution variable was discussed exhaustively earlier in this paper, with a list of common formulations as selected by each group of previous works in the literature.

It is anticipated that this survey will be useful to several groups of researchers, including developers of off-grid electrification microgrids, power systems engineers examining methods for increasing the resiliency of islanded microgrids during emergency operation of advanced distribution networks, and students studying optimization problems. In the author's opinion, community electrification is the most urgent and rewarding application of this paper, especially when complemented by the social impact factors discussed in Part 2 [21]. With around 1 billion people worldwide still lacking access to electricity, islanded renewables-based microgrids stand out as the most viable solution from the standpoints of sustainability, cost-effectiveness, scalability, and reliability. The urgent need for more research in this area is reflected by the targets of United Nations Sustainable Development Goal (SDG) #7 and related target indicators of ensuring universal access to affordable and reliable energy to all people by the year 2030. In the past, any electric service in remote communities was delivered by dirty, inefficient diesel generators. However, billions of US dollars of funding are now available through numerous public-private-venture capital partnerships to create solar-powered "mini-grids" ranging from 20 to 200kW of PV generation capacity. Planning and installation of these microgrids will require development of new, more effective planning and optimization tools for siting and sizing of PV and ESS resources, as well as smarter dispatch algorithms focused on providing a balance of reliability, operating cost, and level of electric service provided. Moreover, the demands of many communities are rapidly growing past simple lighting needs, and are focusing on equipment related to productive uses of energy.

This survey is continued in Chapter 3, which will focus on techniques for renewables forecasting and load forecasting, as well as methods for identifying and resolving conflicts between technical, economic, social, and environmental objective functions. Nearly all multi-objective optimization problems will contain some individual objectives which complement each other and some which directly conflict. Moreover, obtaining a holistic view of the transformative impact of microgrids (both for off-grid communities and critical loads in advanced distribution grids) requires consideration of a wide variety of factors beyond levelized cost of energy, such as land use, noise, job creation, and social benefits. However, a set of specialized tools are needed in order to combine both technical and human factors into a single optimization problem.

CHAPTER 3

A COMPREHENSIVE REVIEW OF ENERGY MANAGEMENT AND PLANNING OF ISLANDED MICROGRIDS: PART 2 – RENEWABLE ENERGY FORECASTING AND MULTI-CRITERIA DECISION MAKING

This survey paper provides the first comprehensive, critical overview of optimization formulations for planning and operation of islanded microgrids, including optimization objectives, constraints, control variables, forecasting techniques, socio-economic factors, and multi-criteria decision making. The optimization approaches reviewed address methods both for increasing the resiliency of advanced distribution systems and electrification of remote communities. This paper is organized into two parts: Part 1 examines over 120 individual optimization studies and discovers that all optimizations studies of islanded microgrids are based on formulations selecting a combination of 16 possible objective functions, 14 constraints, and 13 control variables. Each of the objectives, constraints, and variables are discussed exhaustively both from the perspective of their importance to islanded microgrids and chronological trends in their popularity. Part 2 builds on the results of part 1, first briefly discussing forecasting methods for supplying load and renewables data needed for both planning and dispatch studies. It then continues to examine conflicts between the objectives identified in Part 1, socio-economic utility functions, and multi-criteria decision making (MCDM) techniques required to create multi-objective optimization formulations combining numerical criteria with social, environmental, and human factors parameters.

This chapter is a verbatim copy of an article submitted by the researcher for publication in the Journal of Power and Energy Systems and is currently under review.

3.1. Introduction

Within the fifteen years since the emergence of the microgrid concept, a large amount of literature has been dedicated to optimization of these systems. Likewise, multiple review papers [1] – [20] have been written to summarize advances in optimization algorithms. However, these reviews have each focused on only a few of the aspects necessary for building a complete optimization formulation. A summary of previous literature surveys is presented in Table 7, repeated from Part 1 of this survey [21]. As can be observed from Table 7, a comprehensive literature survey covering all aspects of optimization and multi-criteria decision making for islanded microgrids has not been published.

Additionally, fundamental modeling differences exist between islanded and grid-connected systems, most importantly that islanded systems cannot use the point of common coupling (PCC) for voltage / frequency stabilization and balancing. As a result, islanded systems must resort to load shedding and curtailment of renewables, which are control strategies typically not implemented in grid-connected systems. Consequently, results and techniques from surveys of optimization of grid-connected microgrids cannot be transferred to islanded systems. An extensive discussion of microgrid topologies and control schemes is provided in Part 1 [21], along with a comprehensive discussion of the different types of optimization problems encountered in planning and dispatch of islanded microgrids.

This paper aims to fulfill this need by providing the first systematic overview of all tools and techniques required to create a holistically formulated optimization problem considering the transformative impact of electrification, which is not reflected by traditional approaches to power system design focused on cost and reliability criteria. Furthermore, the economic sustainability

Table 7: Summary of topics covered in current literature reviews

Ref	Year	Type of Review								Configuration		Focus	
		OF	CR	CV	SR	SW	FT	MCDM	APP	Island	Grid	Sched	Plan
[1]	2018	✓	–	–	–	–	–	–	✓	–	✓	✓	–
[2]	2018	–	–	–	–	✓	✓	–	–	✓	–	–	✓
[3]	2017	✓	–	–	✓	–	–	–	–	✓	✓	✓	–
[4]	2017	–	–	–	–	–	–	✓	–	–	–	–	✓
[5]	2017	✓	✓	–	✓	–	–	–	–	–	✓	✓	✓
[6]	2017	–	–	–	✓	–	✓	–	–	–	–	✓	–
[7]	2017	–	–	–	–	–	–	✓	–	–	–	–	✓
[8]	2016	–	–	–	–	–	✓	–	✓	–	✓	✓	–
[9]	2016	–	✓	–	✓	–	–	–	✓	✓	✓	✓	–
[10]	2016	✓	✓	–	✓	✓	–	–	–	✓	✓	✓	–
[11]	2015	✓	–	✓	–	–	–	–	–	–	–	✓	✓
[12]	2015	–	–	–	✓	–	–	–	✓	–	–	–	✓
[13]	2015	✓	–	–	✓	–	–	–	–	–	–	–	✓
[14]	2014	✓	✓	✓	–	✓	–	–	✓	✓	✓	–	✓
[15]	2014	–	–	–	–	–	✓	–	✓	–	✓	✓	–
[16]	2011	–	–	–	✓	–	–	–	✓	–	–	–	✓
[17]	2011	–	–	–	–	–	–	–	✓	–	✓	–	–
[18]	2010	–	–	–	–	–	✓	–	✓	–	–	✓	–
[19]	2009	–	–	–	–	–	–	✓	–	–	–	–	–
[20]	2004	–	–	–	–	–	–	✓	–	–	–	–	✓

OF = Objective functions, CR = Constraints, CV = Control variables, SR = Solver, SW = Software, FT = Forecasting, MCDM = Multi-criteria decision making, APP = Applications, Island = Islanded, Grid = Grid-connected, Sched = Scheduling / operations, Plan = Planning and social benefits provided by a microgrid power system strongly depend on numerous socio-economic factors that bracket the engineering design process.

Part 1 of this paper provided several key findings regarding optimization of islanded microgrids. All referenced papers selected formulations from a combination of 8 categories of objective functions, 15 types of constraints, and 13 possible solution variables. Each choice of objective, constraint, and solution variable was discussed with a list of common formulations as selected by each group of previous works in the literature. A summary of the results of Part 1 is provided in Table 8.

The classification of surveyed papers both chronologically and by shared characteristics in Part 1 [21] of this paper enabled identification of several trends in microgrid optimization formulations. The first was a significant increase in attention given to management of VAr / reactive power capabilities of DGs and inverters, along with a substantial increase in the number of publications considering the voltage and frequency of islanded microgrids as both optimization objectives and constraints. A second was a trend towards hybrid AC-DC microgrids and multi-microgrids with planning and scheduling tasks treated by multi-objective optimization, often with separate objectives for each portion of the microgrid and with conflicting objectives requiring resolution through various multi-criteria decision making methods, which will be discussed in detail in this paper.

Part 2 of this survey focuses on techniques for renewables forecasting, as well as methods for identifying and resolving conflicts between technical, economic, social, and environmental objective functions. Nearly all multi-objective optimization problems contain some individual objectives which complement each other and some which directly conflict. Moreover, obtaining a

Table 8: Summary of common optimization objectives, constraints, and variables reviewed in Part I [21]

Objective Functions	Constraints	Solution Variables
Minimize cost / Maximize profit		
Fuel cost of thermal units	Power balance	Power output of thermal units
Renewable DG costs	Generator limits	Power output of renewables
Startup / shutdown costs	DER VAr limits	Curtailment of renewables
O & M costs	Generator ramp rates	Operating state (on/offline)
Reserve costs	Generator min on / off times	Spinning reserve
ESS cost	ESS state-of-charge limits	DR & load shedding
Load shedding / DR costs	ESS (dis)charging power limits	ESS power output
Revenue from loads	Critical loads / DR limits	DG voltage setpoints
Installation capital cost	Voltage limits	Droop constant
Cost of losses	Frequency limits	Thermal generation capacity
Minimize voltage deviations	Line thermal ratings	Installed solar generation capacity
Minimize frequency deviations	Reserve (spin & non-spinning)	Installed wind generation capacity
Minimize emissions	Emissions limits	Installed ESS capacity
Minimize renewable curtailment	Total system cost	
Maximize load served	System reliability	
Minimize ramping		
Maximize reliability		

holistic view of the transformative impact of microgrids (both for off-grid communities and critical loads in advanced distribution grids) requires consideration of a wide variety of factors beyond levelized cost of energy, such as land use, noise, job creation, and social benefits. However, a set of specialized tools are needed in order to combine both technical and human factors into a single optimization problem.

3.2. Forecasting Methods for Renewables

Accurate forecasting of PV and wind generation is essential for energy management of islanded systems since ESS and thermal units must supply any differences between renewable generation and demand. Excessively large forecasting errors can lead to thermal units reaching their ramp rates [22], as well as ESS units and inverters reaching SOC and charging / discharging current limits. Simultaneously, forecast-based dispatch can reduce the cost of generation in islanded systems by 2% to 7%, depending on the accuracy of the forecast [23]. Forecasting techniques and historical weather data are commonly integrated into several types of optimization problems, as illustrated in Figure 6, which provides a spatiotemporal comparison of common applications.

Common methods used for modeling the uncertainty of weather on planning and scheduling include probability density functions (PDF) [24], numerical weather prediction (NWP) [25], artificial neural networks (ANN) [26], time series models [27], scenarios based on historical data [28], and fixed approximations of the maximum error [29]. Figure 7 arranges these forecasting methods by their applicability to various spatial resolutions and time frames.

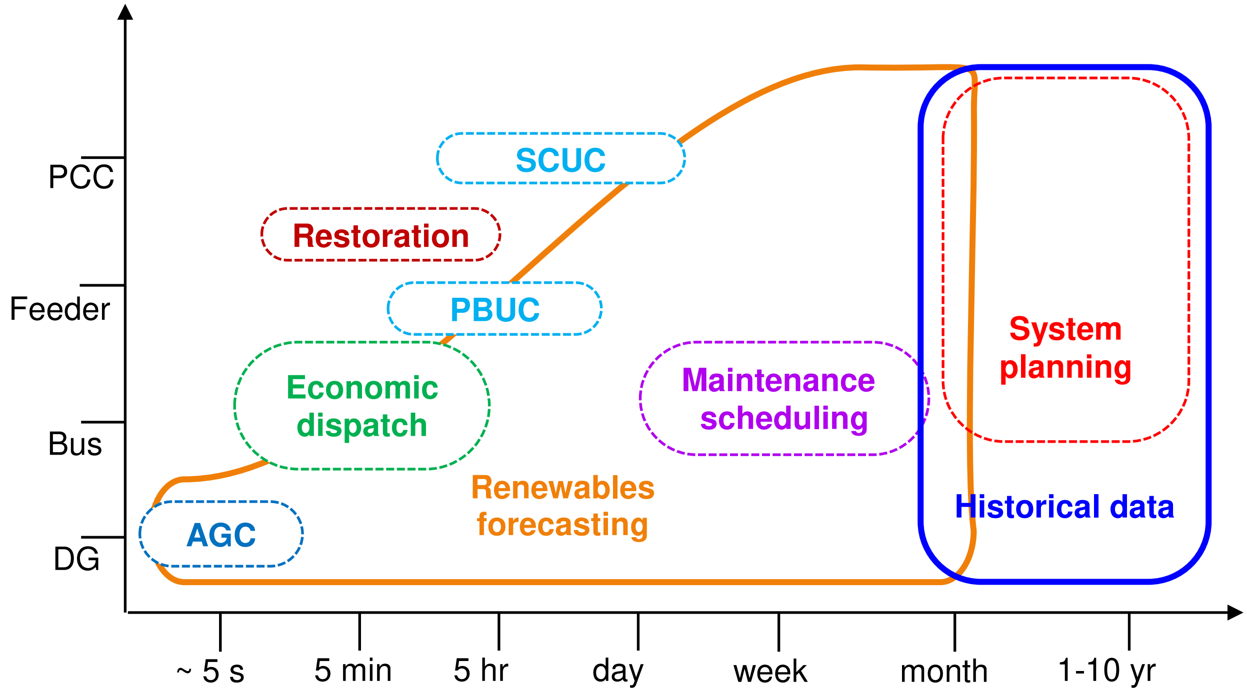

Figure 6: Comparison of common applications requiring forecasting or historical data of renewables output, arranged by increasing scales of forecast time period and network topology

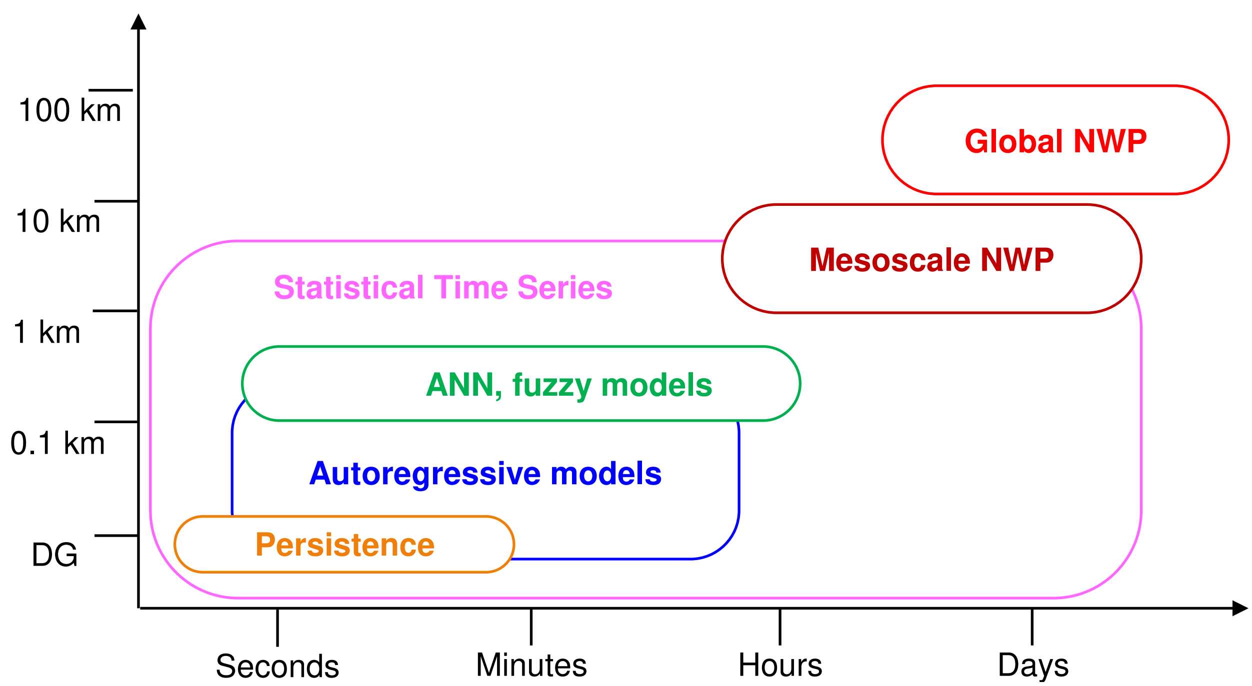

Figure 7: Comparison of common forecasting techniques and their application to optimization problems, arranged by spatial and temporal usage

3.2.1. Classification by forecast timeframe

Long-term forecasts are used to predict the amount of wind generation in the one day to one week timeframe [30]. The results are used for making decisions concerning maintenance schedules, reserve requirements, and approximate unit commitment.

Medium-term forecasts estimate wind speed and power generation in a six hour to one day window [18]. These predictions are used in day-ahead power market bids, as well as security-constrained and price-based unit commitment decisions.

Short-term forecasts are valid for a half-hour to six hour period, and constitute the majority of models created [30]. Statistical models (ANN and time-series models) are the most popular due to their simplicity, ease of computation, and accuracy of results. However, a number of new techniques, such as fuzzy logic networks, are gaining traction.

Finally, very-short-term forecasts estimate power production within a period of a few seconds to half an hour. The benchmark for all models in this range is the persistence method, which states the wind speed and generation output will remain at their current value. Statistical and hybrids methods (e.g. neuro-fuzzy models) can provide absolute errors of less than 4% [18].

3.2.2. Classification by forecasting method

3.2.2.1.Physical models

NWP methods use computational fluid dynamic simulations using measured weathered data, such as temperature pressure, relative humidity, locations of fronts, storm systems, and geographic topology to produce predictions of relevant weather parameters, such as wind speed, wind direction, precipitation, temperature, and humidity [8]. Common models are the MM5, Global Forecasting System (GFS) [25], [31], and European Centre for Medium Range Weather Forecasts (ECMWF) [18].

Disadvantages of NWP methods are complexity, computational cost, introduction of large errors by time shifts in data, and ineffectiveness for short term forecasting [32]. Additionally, physical models cannot provide detailed predictions at the very small resolution corresponding to geographic footprint of an islanded microgrid. For this reason, few examples of NWP methods [25] implemented in actual microgrid optimization tasks can be found in the literature.

3.2.2.2.Time Series Models

Time series models use historical data to predict future trends using statistical methods. The most common of these techniques are autoregressive (AR), moving average (MA), and combinations of these two techniques, such as autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) methods [8], [33]. Due to the simplicity of these models, they are frequently used for dispatch of both islanded microgrids [27], [34] and grid-connected systems [35], [36]. Historical data is used to develop a relationship between parameters representing time, autoregression, moving average, and the order of the autocorrelation function.

Another statistical tool with increasing popularity for dispatch studies is Markov chains [37] – [40], which represent renewable output or customer loads as a finite set of states that change in discrete time steps. These models work can reproduce the probability density function (PDF) for long tem predictions with a high degree of accuracy [41], [42]. However, these models consistently under-estimate the amount of energy storage required for wind-based microgrids [41]. Markov chains can also be used to model outages of DGs and other equipment [39].

3.2.2.3.Artificial Neural Networks

ANN models simulate the operation of the human brain, with many nodes operating in paralleled and communicating through connecting synapses [8]. ANNs have been successfully developed for very short-, short-, medium-, and long-term forecasts of renewable output [26], [38], [43], [44]. ANN networks have also been used for control of wind turbine real / reactive power, pitch control, max power point tracking, voltage / frequency control, power quality, and transient stability studies [44].

As with time series models, ANN networks require extensive training with a data set whose size is optimized to yield the least error. Comparative studies, such as [45], have found that neural networks can achieve lower mean square errors than ARMA techniques.

3.2.2.4.Probability density functions

An additional tool used for modeling wind speed variability in stochastic scheduling and planning problems is simply the probability density function of the site's wind speeds. Typically, a Rayleigh or Weibull [24], [46] – [48] and beta [49] – [51] distributions are used for wind and solar forecasts, respectively. These methods can provide fairly accurate results, such as the multivariate Gaussian regression of [52], which give a root mean square error of 0.0208 for 1 minute ahead forecasts, or about 10% better than the persistence method for the wind data analyzed.

Probability distributions for renewable output can be converted into a randomly generated scenario using a Monte Carlo simulation that creates a random walk for simulating the output of each renewable resource, [24], [53], [54]. A similar method is the roulette wheel mechanism, in which a series of levels of renewable output or forecasting error are assigned to the sectors of a roulette wheel in accordance with the forecast probability distribution function [47].

3.2.2.5.Historical Data

Scenarios built from historical data gathered from the microgrid site are perhaps the most common approach to replicating wind forecast data for development of optimization techniques [22], [25], [28], [37], [48], [53], [55] – [71]. This approach is especially common for system planning studies of actual systems, in which the design must consider the unique site conditions and availability of renewable resources for the planned microgrid.

3.3.Relationships between Objective Functions

A complex set of conflicting and mutually supporting relationships exist between the objective functions discussed exhaustively in Part I of this review [21]. In comparing the results of optimizing with respect to one objective function versus another, the relationship between any two objective functions can be classified as conflicting, weakly conflicting, mutually supporting, and not related.

An example of directly conflicting objectives is maximum reliability and minimum installation cost. Maximization of system reliability can be achieved through installation of more generation capacity, parallel, alternate transmission paths, and larger energy storage. All of these options directly increase the installation cost of the system. Meanwhile, an example of mutually supporting objectives is minimization of network losses and minimization of operations cost since decreases in the losses of the network generally translate to decreases in fuel use by thermal DGs, and in turn lower generation cost.

Figure 8 presents a summary of the pairwise relationships between all the objective functions discussed earlier. The remainder of this section will examine the relationships between the most popular pairs of objective functions, which were summarized in Table 8. A detailed discussion of the other objective functions (resulting in over 120 pairwise combinations) will be omitted from this paper for the sake of brevity.

3.3.1. Operating cost vs installation cost

Generally, the hourly generation cost of a system can be decreased through the installation of distributed renewables and ESS, thereby decreasing the need for thermal generation and associated fuel, operations / maintenance, and startup / shutdown costs. However, this objective directly conflicts with the objective of minimizing the purchase, installation, and commissioning costs of the microgrid [24], [50], [60], [65], [67], [72] – [77].

3.3.2. Operating cost vs ESS SOC

Scheduling problems may seek to maximize the lifespan of ESS units by restricting the depth of discharge through an objective cost function related to the minimum SOC during a particular time interval, [27], [49], [54], [78]. This objective conflicts with the goal of minimizing operating costs since higher cost thermal units will be dispatched more often to maintain a higher value of SOC.

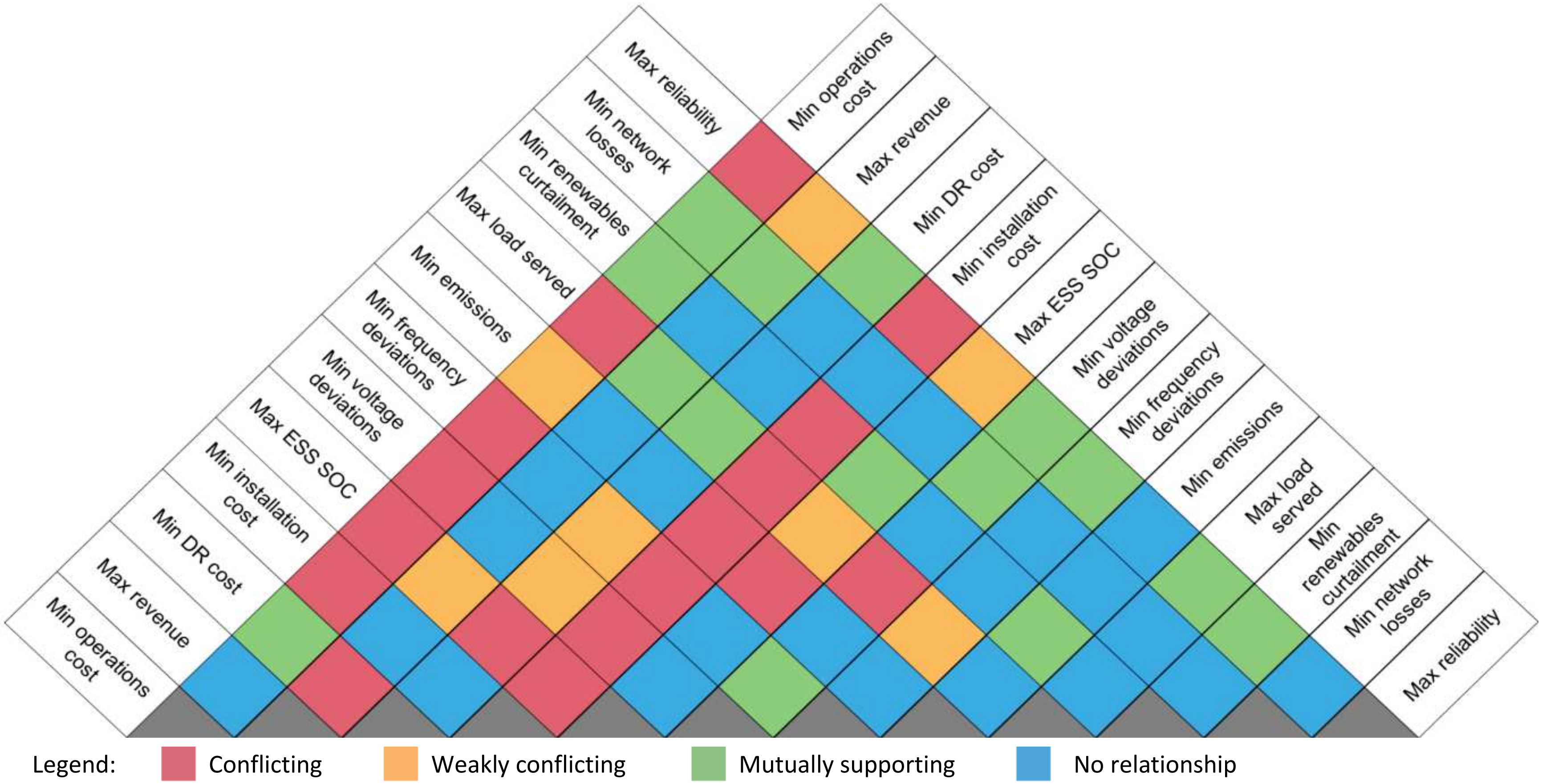

Figure 8: Relationships between common microgrid planning and scheduling objective functions. Whether two objectives are conflicting or supporting can be read from the square at the intersection of the diagonals corresponding to each optimization objective.

3.3.3. *Operating cost vs voltage or frequency deviations*

Minimization of voltage [74], [79], [80] and frequency [61], [76], [81] – [85] deviations in joint scheduling–control problems conflicts with the objective of minimizing operating costs since more generation will need to be dispatched (or curtailed in over-frequency situations) and provide fast ramping for real-reactive regulation.

3.3.4. *Operating cost vs reliability*

Maximization of reliability requires that as much generation be dispatched as necessary to meet all demand [24], [53], [67], [73], [76], [77], [79]. This conflicts with the goal of the minimizing operating costs, which may prefer load shedding to startup of high cost peaker units. Maximization of reliability also conflicts with minimization of installation cost [24], [67] [71], [76], [77], [86], [87], since increasing the desired level of reliability increases the amount of generation and ESS capacity required, which increases the capital cost of the system.

3.3.5. *Operating cost vs emissions*

Minimization of emissions and operating cost is one of the most popular multi-objective formulations for scheduling problems [88], [37], [59], [64] – [78], [85], [89]. If the incremental cost of renewable DER is less than that of thermal generation, then the two objectives can be mutually supporting, and the solution will be that which maximizes use of low-cost non-polluting DGs. Otherwise, the two objectives will conflict. Conflicts between emissions and operating cost / installation cost also appear in planning problems seeking to add renewable generation to isolated microgrids [60], [74] – [76], [86] [90].

3.4.Multi-Criteria Decision Making

As can be observed from the optimization studies surveyed [88] – [91], most formulations have expanded beyond traditional single parameter economic dispatch problems [92] to combine several objectives (such as operating costs, installation costs, emissions, and reliability). Additionally, microgrid planning and scheduling directly affects many parties, and so it is essential that the optimization considers the needs, interests, and criteria of all stakeholders in an energy project [93]. To help resolve these issues, a series of multi-criteria decision making (MCDM) methods have been developed.

MCDM techniques are a branch of operations research models designed for resolving conflicting objectives and criteria under high uncertainty, and can be defined in two categories [4]. Multi-attribute decision making (MADM) methods focus on choices between a small number of discrete alternatives, typically evaluated against a set of attributes that are difficult to quantify [93]. Meanwhile, multi-objective decision making (MODM) techniques search for an optimal solution within a set of continuous alternatives constrained by limits placed on decision variables and related system parameters. MODM is also known as multi-objective programming. Multi-criteria decision making generally follows five basic steps [93]:

1) Definition of the problem, alternatives, and criteria

2) Assignment of criteria weights

3) Construction of an evaluation matrix formed from the criteria, weights, and alternatives

4) Selection of an MCDM method

5) Ranking of the alternatives

MCDM techniques can be classified into

- Utility theory methods, including the Analytical hierarchy process (AHP), multi-attribute utility theory (MAUT), and simple multi-attribute rating technique (SMART)

- Outranking methods, such as elimination et choices expressing reality (ELECTRE) or preference ranking organization method for enrichment evaluation (PROMETHEE)

- Miscellaneous techniques, such as discrete choice experiment (DCE), discrete compromise programming (DCP), and technique for order of preference by similarity to ideal solution (TOPSIS).

The remainder of this section will describe the advantages, disadvantages, implementation process, and applications in microgrid optimization for each MCDM method. Common techniques and their application in optimization of islanded and grid-connected microgrids is summarized in Table 9.

3.4.1. Weighted Sum

The weighted sum technique is the most straightforward method and is effective for one-dimensional optimization [20]. The overall objective function is the sum of the individual criteria multiplied by a weight assigned to each criterion. The optimization solution is the best alternative that maximizes (or minimizes) the weighted sum objective function. Since the additive utility of the weighted sum is violated if applied to multi-dimensional problems, all criteria to be included in the objective function need to be expressed in the same units [20].

Table 9: Summary of common MCDM techniques used in optimization of islanded and grid-connected microgrids

MCDM Method	2013 & prior	2014	2015	2016	2017	2018 – 2019
Weighted sum	[88] [94]	[60] [95]	[79]	[75] [96] [76] [97]	[64] [98] [99]	[100] [101] [102]
MAUT	[103] [104]		[105]	[106]	[107]	[108] [109]
AHP	[110]	[111]	[79]			[112] [113]
SMART	[114] [115] [116]	[117]		[118]	[119]	
DCE	[120] [121] [122]			[123] [124]	[125] [126] [123] [127]	[125]
ELECTRE	[110] [128] [129]	[130]		[131] [132]		
PROMETHEE	[110] [116]	[111] [133]		[134]	[135] [136]	[137]
TOPSIS	[115] [73] [116]		[138]		[139] [140]	[141] [113]
DCP					[214]	
Pareto-front	[143] [73]	[144] [59] [87]	[74] [75] [80]	[86] [80]	[64] [66] [140]	[89] [141]

As a result, weighted sum methods can only be applied either to cost-based optimization formulations (in which all objectives are direct or penalty costs) or to objective functions that have been normalized by dividing the objective by a base value (such as total system load or a similar parameter with the same units). Due to its simplicity, the weighted sum approach has become increasingly popular, as evidenced below.

Reference [60] minimizes the weighted sum of three normalized objective function with generation cost, use of renewables, and emissions. The emissions objective is formed from the weighted sum of the microgrid's CO_2, CO, SO_2, NO_X emissions, and dust pollutants. The weights for the first objective function are chosen arbitrarily and are varied in the interval [0, 1/3, 1/2, 1].

Reference [63] creates a ranking of lines for network topology configuration using the weighted sum of the normalized power loss in the line and risk of the line being unavailable.

Reference [64] compares results obtained from 1) a single objective of operating cost, 2) cost of emissions, 3) the sum of fuel and emissions, 4) a pareto-optimal solution between fuel cost versus emissions, and 5) the weighted sum of the deviation of cost and emissions from ideal values. The last two methods achieve the best tradeoff between cost and emissions.

Reference [75] adjusts the weights for three objective functions (operating cost, capital cost, and emissions) to determine a pareto-front solution using an adaptive direct search algorithm.

Reference [76] presents a two level optimization in which the first objective function is the sum of fuel cost, emissions cost, and a penalty for real power imbalance. The second objective function is the weighted sum of LOLP, renewable curtailment (expressed as a percentage of total load), and installation cost.

Reference [79] combines a pair of weighted sums. The first is a reliability objective function formed from the sum of the EENS and SAIFI reliability indices, with the weights determined using AHP. This objective function, in turn, is used in a weighted sum composed of reliability, operations cost, network losses, and voltage deviations.

Reference [86] obtains a set of pareto-optimal solutions with respect to installation cost, emissions, and LOLP. The results are then evaluated using a decision function formed from the weighted sum of the three individual objectives. The weights are chosen based on objective preference, as determined by non-numerical ranking.

Reference [88] presents an objective function formulated as the weighted sum of dispatchable DG costs, emissions, and ESS use. The effect of different objective weightings are examined by creating nine sets of weights for use in each simulation scenario.

Reference [95] examines technical, economic, environmental, social, and institutional factors with multiple evaluation criteria in each category that are summed to create a score in each category that is subsequently combined with a second set of weighted sums to evaluate multiple electrification options for communities in the Brazilian Amazon. Weighting factors for each criteria and the overall category weights were determined by surveys of community members.

Reference [96] sums the real power of DR-adjustable loads, load shedding, curtailed renewables diverted to a dump load, and ESS SOC. The weights of each objective are chosen arbitrarily.

Reference [97] uses equal weights to form an objective function with the power output rating and installation cost of an ESS unit.

Reference [99] treats the sum of revenue obtained from serving customers, cost of generation and EENS, and risk of system security violations as the objective function.

Reference [100] applies two sets of weighted sums to a day-ahead dispatch optimization. The first sum ranks the priorities of customer loads for demand response. The result forms a term in a second weighted sum combining fuel cost, renewables curtailment, VOLL, and emissions.

Reference [114] combines the power losses in the network and the square of voltage deviation at each bus to determine optimal droop coefficients for DGs placed throughout the network for voltage and frequency support

3.4.2. Multi-attribute utility theory

Utility theory describes the set of relationships between the costs and utility of a particular decision, and can be extended to decisions involving multiple objectives, criteria, and alternatives. The preference given to various attributes is expressed in the form of a utility function that varies between zero and one to reflect the level of satisfaction of a particular criterion [20]. Common criteria found in MCDM energy problems are summarized in Table 10

The utility function reflects the importance of criteria under uncertain conditions by assigning function values so that more preferable criteria will have a higher utility than less preferable ones. The utility function is also able to indicate the decision-maker's tolerance of risk: linear functions indicate neutral risk, convex functions indicate a preference for risk, and concave functions indicate risk aversion [93]. The best alternative is then chosen by either adding or multiplying the utility function scores for each of the alternatives, and the alternative with the overall highest utility score is selected.

Table 10: Common criteria used in MCDM energy planning problems

Category	Criterion	Reference
Technical	Reliability	[73] [93] [95] [112] [114] – [117] [124] – [126] [145] – [147]
	Safety	[108] [117]
	Technical maturity	[110] [112] [117] [133]
	Energy efficiency / losses	[110] [112] [114] [116] [117] [134]
	Resource potential	[95] [110] [111] [132] [133] [135] [147] [137]
	Scalability	[95] [112] [133]
Economic	Fuel / operations cost	[73] [93] [95] [103] [104] [112] [117] [119] [133] [140] [147]
	Installation cost	[93] [103] [104] [110] – [112] [116] [117] [120] [122] [132] – [135] [137] [147]
	Maintenance cost	[93] [95] [103] [104] [109] [112] [115] – [117] [120] [132] – [135] [137]
	Equipment lifespan	[109] [112] [117] [116] [119] [140]
	Customer monthly cost	[93] [120] [121] [122] [123] [124] [145] [146]
	Payback period	[93] [122] [132]
	Financing	[95] [132] [147]
Environmental	CO2 emissions	[103] [104] [109] [115] – [117] [119] [122] [123] [133] [135] [134] [148]
	SO2 emissions	[117] [148]
	NOx emissions	[103] [104] [134] [148]
	Other emissions	[95] [112] [116] [117] [132] [147]
	Noise	[117]
	Environmental	[95] [108] [111] [114] [117] [132] [133] [147]
	Land use	[95] [109] [112] [115] [116] [123] [133] [134] [147]
	Renewables utilization	[73] [121]
Social	Social acceptability	[93] [112] [117] [134]
	Jobs creation	[93] [95] [109] [112] [117] [132]–[135] [147]
	Ease of use / maintenance	[117] [133]
	User (in)convenience	[112] [119] [120] [125] [126]
	Community services provided	[95] [112] [133] [147]
	Energy policy	[133] [135] [137]
	Socio-economic benefits	[93] [95] [111] [133] [135] [137] [147]

Unlike AHP (discussed next), MAUT methods are able to consider uncertain factors in the decision analysis in a consistent manner [103]. Uncertainties can be classified as external (which can affect the decision outcome) and internal (relating to the decision-maker's preferences). Common uncertainties in energy system planning include physical conditions (such as technology assets and consumer demand), economic variables (fuel prices and installation costs), and regulatory policy.

Due to the complexity of formulating utility functions and computing scaling constants, MAUT is applied much less frequently than AHP and other MCDM methods for planning and scheduling problems [20].

References [103] and [104] consider operating cost, investment cost, CO2 emissions, NOx emissions, and wasted heat as five attributes to evaluate different system expansion alternatives. The formulation uses an exponential utility function with overall utility scores as the weighted sum of each alternative's satisfaction of possible user. Criteria weights are determined by questionnaires asking the decision-maker's priorities regarding various evaluation criteria.

Reference [105] creates a MAUT-based platform to assist selection of new DGs for inclusion in microgrids using a combination of economic, environmental, and social criteria.

Reference [106] examines a decision making process for distribution line restoration considering four main goals: minimize travel of the line crew to the next fault location, complete repairs as soon as possible, restore higher priority loads first, and minimize impacts of other contingencies on the repair process. The utility function of each possible repair is formulated as the sum of binary values corresponding to whether a particular line crew is able to perform the repairs alone. The order of restoration is then determined while seeking to minimize two objective functions of minimizing total repair time and minimizing total lost load.

3.4.3. Simple multi-attribute rating technique (SMART)

To overcome the difficulty in applying MAUT, SMART was introduced by in the 1970's [149], [150]. SMART uses linear approximations of utility functions and an additive aggregation model for weighted sums of utility values [117]. Criterion weights are ranked in order of importance, and successively more points are assigned to each attribute with ten points for the least important criterion. The final weights are then obtained by normalizing the values so that all individual weights sum to unity [151].

Errors in the original SMART formulation from the need to consider the range of utility values were corrected with swing weights (SMARTS) and justifiable rank weights (SMARTER) [151]. The overall process in applying this MCDM method follows nine steps [151]:

1) Identify decision makers' objectives

2) Create a value tree of criterion hierarchy

3) Determine objects of evaluation using attribute structure and elicitation results

4) Formulate matrix of alternatives and criteria. Entries are scores, preferably physical measures.

5) Eliminate dominated alternatives, often through visual inspection

6) Convert matrix entries of performance scores to single–dimension utility function values ranging from 0 (relative worst) to 1 (relative best)

7) Choose swing weighting of criteria considering both importance and the range of utility function values (not a relative 0-1 ranking).

8) Calculate multi-attribute utilities / rank order centroid (ROC) of alternatives

9) Select alternative with best weighted sum utility

Despite its ease of use and high applicability to the combined social, economic, and technical aspects of power systems, SMART has found relatively little use in microgrid planning and operations optimization.

Reference [117] considers eight alternatives for renewable generation (hydro, PV, wind, biogas, fuel cell, geothermal, and wave) with respect to 15 attributes covering technical, economic, environmental, and social parameters. Decision weights are based on a subjective ranking of criterion preferences, which is then normalized into ROC weights and then overall weighted sum multi-attribute utility scores using the nine step SMARTER process discussed above.

Reference [114] applies SMART to resolve equipment overloads for a distribution system in Kenya using the criteria of capacity constraints, reliability, energy losses, and environmental impact.

References [115] and [116] examine optimal sizing of grid-tied PV and wind DGs for 11 configurations of PV and wind. The alternatives are evaluated against the criteria of power supply probability (LPSP), capacity factor, emissions, share of renewables, installation cost, maintenance cost, land use, and social acceptance. Objective weights are formulated as the weighted sum of the scores obtained from SMARTER and the more objective entropy weighting method. The results are then compared to those from the TOPSIS [115], ELECTRE, and PROMETHEE [116] methods.

Reference [119] optimizes DR planning in five cities of the northwest USA with SMARTER, achieving elicitation of user preferences with better accuracy and speed than AHP and DCE [118]. The study seeks to minimize thermal discomfort, energy cost, emissions, user inconvenience, and equipment degradation. Ranking of weighting factors was determined by online user preference surveys regarding the relative importance of six evaluation criteria: carbon emissions, adequacy of hot water, financial savings, delay of clothes washing, delay of dishwashing, and air temperature.

3.4.4. Analytical Hierarchy Process (AHP)

AHP decomposes complex problems into a hierarchy with the overall goal at the top, decision criteria (and sub-criteria) at the next lower level, and available alternatives at the bottom of the structure [20]. Alternatives are compared in a bottom-up pairwise manner to create relative rankings based on the decision-maker's information and experience [152]. AHP generally follows a four step process [93]:

1) Arrangement of the goal, criteria, and alternatives into a hierarchical structure

2) Determination of criteria weights through pairwise comparisons and computation of the consistency index of the decision-maker's preferences from the maximum eigenvalue of the weighting matrix

3) Compilation of a matrix of performance scores of the alternatives for each criterion

4) Calculation of the final priorities of the alternatives as the weighted sum of each performance score, multiplied by the local priority of the corresponding criterion

The primary advantage of AHP is a straightforward ranking that is mathematically and rationally justifiable, especially with a small number of criteria and decision makers, incorporating all viewpoints of decision maker [110]. However, scaling depends on the elements compared, ordering can be erroneously introduced when none actually exists, and indifferent criteria (i.e. criteria for which all alternatives score equally) can disrupt aggregated priorities.

AHP is widely used for energy planning, possibly due to its simple hierarchy, flexibility, intuitive structure, and ability to handle both qualitative and quantitative criteria simultaneously [20]. An exhaustive survey of its use for microgrids is presented in [152].

3.4.5. Discrete Choice Experiment

Based on theory of demand, welfare theory, and consumer theory, DCE methods are very effective in modeling choices of consumers. Individuals complete a survey with n discrete alternatives, and consumer will pick 1 alternative which maximizes his/her utility function (i.e. personal preference) [153]. DCE provides a high level of detail for modeling uncertain choices of consumers by breaking down selection of alternatives into two parts: 1) a systematic component related to characteristics of alternatives and 2) random variations in preferences [154]. DCE finds extensive use in the early planning stage of power system design as a tool to determine user requirements and willingness-to-pay (WTP) for electricity:

References [125] and [126] examine WTP of 22 rural communities in Uttar Pradesh, India for various levels of reliability and electric service from a solar microgrid. It is observed that customer satisfaction is much greater from an islanded PV system than for grid power, and that customer criteria for service are (in decreasing priority) the amount of energy provided (measured in hours of appliance use), reliability, and overall price.

Reference [120] studies consumer choice and customer WTP for micro-generation technologies based on the criteria of capital cost, maintenance cost, monthly savings, contract length, and inconvenience.

Reference [127] examines customer WTP for difference sources of energy on the basis of regional location and percentage of renewables among 780 German households, with highest customer preference for a mix of hydro and solar electricity generated locally within each region.

Reference [123] summarizes an EPRI study on the factors relating to adoption of residential PV systems using a DCE survey that can be implemented by utilities. Pretesting of the tool determined that supplier, ownership method (purchase/lease/community-based), location, monthly payment, cost savings, and emissions were the primary drivers of customer choice. Peer effects, discounts, and appearance did not strongly affect consumer preferences. Similar DCE studies were conducted by [155] of 835 owners of PV systems in the Italian market, by [121] of customers in Spain, and by [122] of households in Canada.

Other applications of DCE include customer WTP for system reliability [124] – [146] through surveys ranking various levels of energy pricing with frequency, duration, and time of interruptions, and preferences of 259 steam plant operators regarding boilers and cogeneration [156].

3.4.6. Preference ranking organization method for enrichment evaluation (PROMETHEE)

Unlike the utility theory MCDM techniques discussed above, PROMETHEE is an outranking method. Although outranking methods also perform pairwise comparisons, they differ from AHP in that pairs of *alternatives* are compared against each other or a fixed standard [157], rather than pairwise comparisons of the evaluation criteria. Additionally, the comparisons are directly used to create a ranking of optimal alternatives, rather than just a set of weights indicating the relative importance. PROMETHEE II applies the outranking strategy using a five step process [93]:

1) Definition of the decision maker's preference function, categorizing evaluation criteria into six types
2) Pairwise comparisons of alternatives and calculation of the preference index for each pair
3) Assembly of comparisons into a decision matrix and outranking graph with two variables, incoming and outgoing flow. The larger the former, the more a particular alternative dominates the others; the smaller the latter, the less the alternative is dominated.
4) Partial ranking preordering alternatives by which other alternatives they outrank, are indifferent to, or are incomparable.
5) Final ranking using the difference of the incoming and outgoing flows for each alternative

Advantages of PROMETHEE include the ability to accept poorly shaped stakeholder inputs, handle both qualitative and quantitative data, and separate incomparable alternatives [133]. It is most effective on problems with a finite number of alternatives using several criteria, although modifications have been made to improve its suitability for other problems, as can be seen from the list of versions presented in Table 11.

Table 11: Advances in PROMETHEE techniques [103]

Version	Characteristics
PROMETHEE I	Partial ranking
PROMETHEE II	Complete ranking
PROMETHEE III	Interval-based ranking
PROMETHEE IV	Continuous problems
PROMETHEE V	Integer linear programming
PROMETHEE VI	Human brain characteristics

Due to its main suitability to discrete problems, PROMETHEE is typically applied to energy planning rather than scheduling optimizations, as illustrated below.

Reference [110] considers three alternatives (a grid-connected PV system with subsidies, a grid-connected PV system without subsidies, and an islanded PV microgrid with subsidies) using the criteria of technology maturity, installation cost, efficiency, local potential, and social acceptance. Results are compared from ELECTRE, PROMETHEE, and AHP.

Reference [111] ranks five possible locations for a new substation in Bangladesh using PROMETHEE II using 13 technical, economic, social, and environmental criteria identified using the Delphi method and structured using AHP. Incoming and outgoing flows are evaluated using seven different preference functions to evaluate the impact of varying DM preferences.

Reference [133] studies ten sites of large electrification microgrids in India using micro-hydro, wind, PV, and biogas generation. Ten socio-technical and economic criteria were ranked in priority through stakeholder surveys. The results were evaluated with PROMETHEE II, which ranked micro-hydro and biogas plants as the most suitable technologies for village-scale electrification.

Reference [134] compares geothermal, solar, wind, hydro, biomass, nuclear, and conventional thermal generation for electrification of a hypothetical country using cost, efficiency, social, and environmental criteria. PROMETHEE II is observed to give nearly identical results as TOPSIS and is easier to use than ELECTRE since none of the generation alternatives can be eliminated.

Reference [135] examines optimal integration of rooftop solar in Zhejiang, China using ten socio-technical criteria and four preference functions. Incoming and outgoing flows are determined for ten alternative installation sites, and the final decision is made with a genetic algorithm search.

Reference [136] evaluates the sustainability and economic value of energy investment portfolios using PROMETHEE II with criteria including net present value, risk, and employment provided.

Reference [137] applies PROMETHEE II to create an optimized portfolio of investments in rooftop solar installations considering renewable resource availability, economic viability, risks, and carbon reduction. The selected criteria were ranked in priority using AHP and subsequently used to evaluate ten project alternatives.

Reference [138] formulates an economic dispatch problem seeking to minimize fuel cost, emissions, distance of DGs, and line loading using a fuzzy AHP process to rank the priority of the four objectives.

3.4.7. Elimination et choices expressing reality (ELECTRE)

Another outranking method is ELECTRE, designed to compare a large number of alternatives using just a few criteria [110]. Its main advantages are the ability to compare alternatives with no clear preference and that an alternative with a particularly high score for one criterion will not dominate others. However, the decision algorithm is complicated and intuitively appealing elements (such as thresholds) may not have physical significance [110]. A comprehensive review of ELECTRE and its applications is provided by [157].

The popularity of ELECTRE for energy optimization problems peaked in the 2000's, especially among European researchers. Prior to 2010, it was applied to policy strategy and large scale renewables site planning in Greece [128] – [158], Armenia [159], Italy [160], [161], Turkey [162], and France [163], as well as to manufacturing of thin-film solar panels [129]. However, its popularity has dropped significantly in the past decade. Since 2012, it has only been implemented in two study to determine optimal planning of a solar farm in Spain [130], [131] and wind farm in China [132] using technical, economic, and environmental criteria.

3.4.8. Technique for order of preference by similarity (TOPSIS)

Like AHP and SMART, the TOPSIS method also uses subjective rankings to build criteria weights. The approach is based on the concepts of an ideal alternative (with the best scores for all criteria) and negative ideal alternative (with the worst possible scores) [19]. The alternative selected will have the longest geometric distance to the negative ideal alternative and the shortest distance to the positive ideal, as shown in Figure 9. It can be observed that the approach is closely related to the concept of the Pareto-front, and the two methods are often applied together [73], [140].

Reference [73] evaluates six design alternatives of an islanded system using fuzzy TOPSIS using the criteria of operating cost, installation cost, unmet load, and renewable curtailment. Objective weights are varied to examine the sensitivity to the effect of decision-maker preferences.

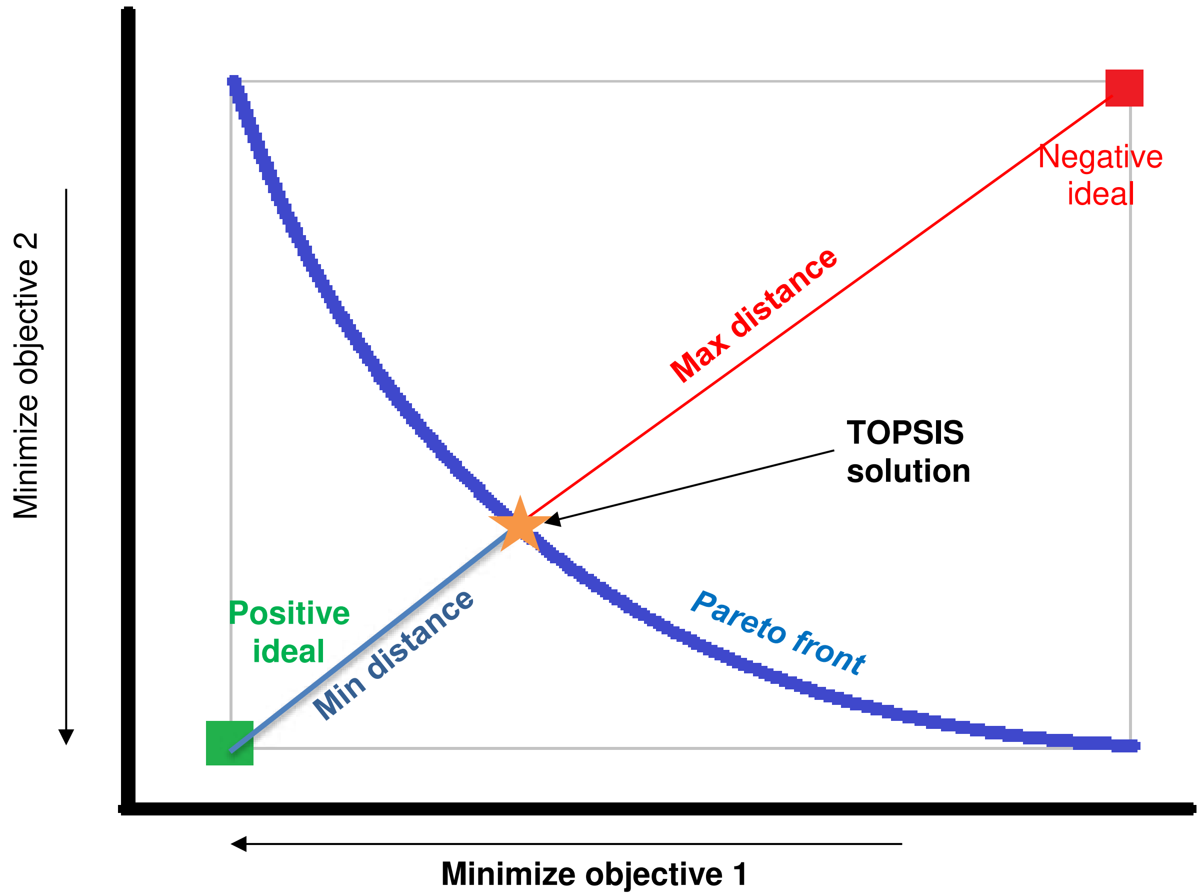

Figure 9: Hypothetical example of TOPSIS illustrating positive and negative ideals.

Reference [140] approaches optimal scheduling of a PV-wind-diesel microgrid, seeking to minimize the conflicting constraints of diesel cost and ESS degradation cost. The positive and negative ideals are taken as the corners opposite the pareto front with the minimum and maximum values of battery and fuel cost, in a method similar to the hypothetical TOPSIS solution shown in Figure 9. The weightings of the two objectives are varied to create a ranking of the different alternatives.

References [139] and [115] apply TOPSIS to solve daily dispatch and sizing problems for grid-connected systems with a high penetration of wind, seeking to minimize total operating cost and emissions.

3.4.9. Pareto-front optimization

Although not an MCDM method, a survey of multi-objective optimization would not be complete without a discussion of pareto-front optimization, which is one of the most commonly used techniques for resolving conflicting objectives. Unlike MCDM techniques that combine multiple criteria and goals into a single objective function (such as the weighted sum method), pareto-front optimization keeps each objective function intact and seeks the set of solutions for which variation of any parameter to improve one objective results in a decrease in optimality of one or more objective functions. This set of solutions is known as the Pareto front [164].

Pareto based techniques are applied both in planning and scheduling problems for microgrids, seeking optimal tradeoffs between two or three conflicting objectives including

- Fuel cost vs emissions [64]
- Fuel cost vs emissions vs energy loss [59]
- Fuel cost vs emissions vs installation cost [74]
- Fuel cost vs installation cost vs reliability [73]
- Fuel cost vs load served [144]
- Fuel cost vs voltage deviation [80]
- Installation cost vs emissions [75]
- Installation cost vs reliability [66], [86]

- Installation vs emissions vs reliability [87]
- Load shedding vs frequency deviations [143]

3.5.Discussion

This paper provides a detailed examination of additional tools and techniques needed to create complete optimization formulations for islanded microgrids. The focus is not just on numeric objective functions, but expanding the scope of the optimization formulation to include the full range of technical, economic, environmental, and social benefits provided by islanded microgrids, both for increasing the resiliency of existing distribution systems constraints and for providing new electric service to off-grid communities. The papers surveyed have been classified both by the particular set of modeling techniques and chronologically. This approach enables the reader to gather valuable insight into both different approaches, but also trends as certain criteria have increased in popularity significantly within the last few years.

The first observation is that historical data is the most popular method for including the impact of variable renewable output, as can be seen from Figure 10. This method provides accurate results if local weather data is available for the microgrid site. However, it is important that seasonal variations are taken into consideration.

Each of the renewables forecasting techniques for islanded microgrids used by the individual optimization studies reviewed in Part 1 [21] of this survey seem to be used equally. An exception is numeric weather prediction, which is likely the result that NWP forecasts cover an entire region cannot provide the level of detail needed by an islanded microgrid affected by local variations in renewable generation.

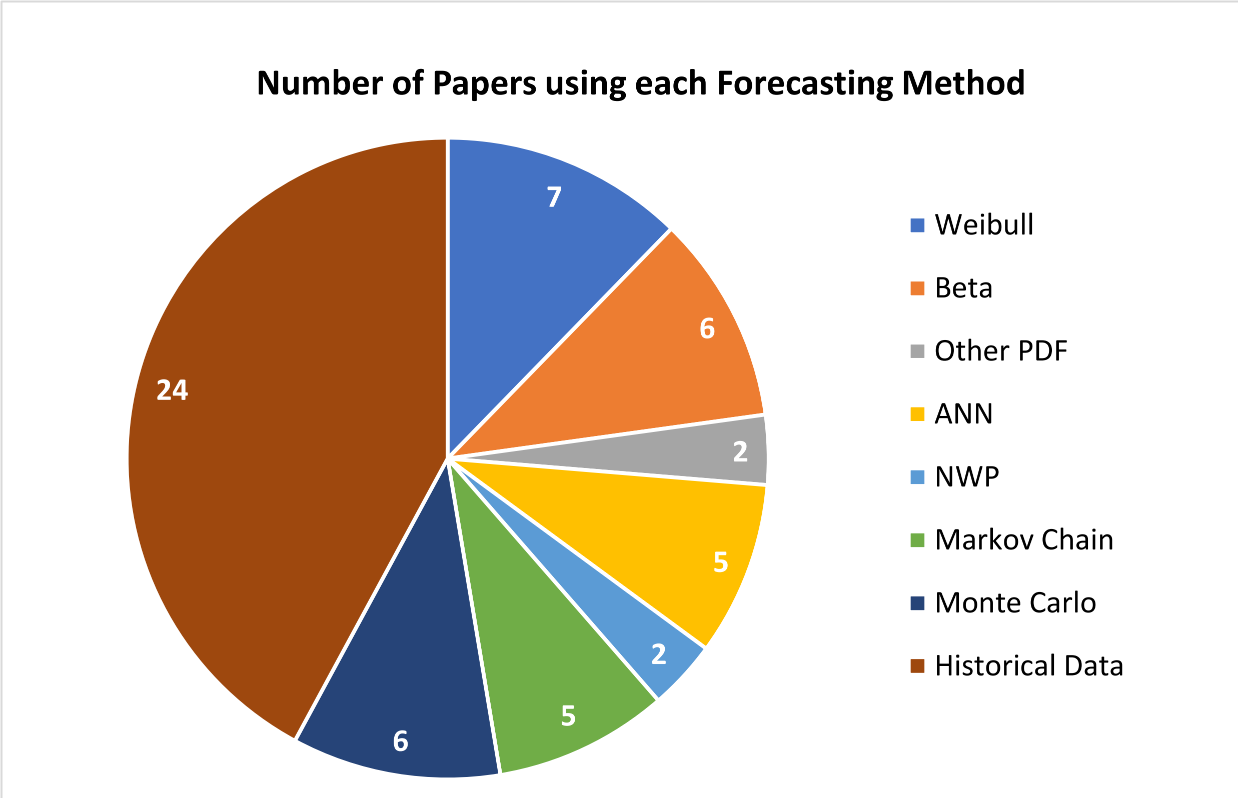

Figure 10: Number of paper using each forecasting method. About half of the papers reviewed in Part 1 [21] inlcuded renewables forecasting or historical data as part of the optimization formulation.

Among the qualitative technical decision criteria for microgrid planning, reliability was the most popular measure, as illustrated in Figure 11. This statistic correlates to the trend of upgrading distribution systems to enable formation of islanded microgrids is to provide greater reliability for critical loads or feeders frequently affected by outages and sever weather. Secondly, installation cost and maintenance cost were the most frequently chosen economic criteria. This reflects the fact that any real-world project is limited in the amount of funding available, and that project management decisions often use a cost-to-benefit analysis. Moreover, installation cost and maintenance cost are arguably the two largest factors in determining the net present value (NPV) of a project. Thirdly, emissions were chosen by over half of studies considering the environmental impact of microgrids. Renewable DERs play a major role in microgrid design, and emissions are

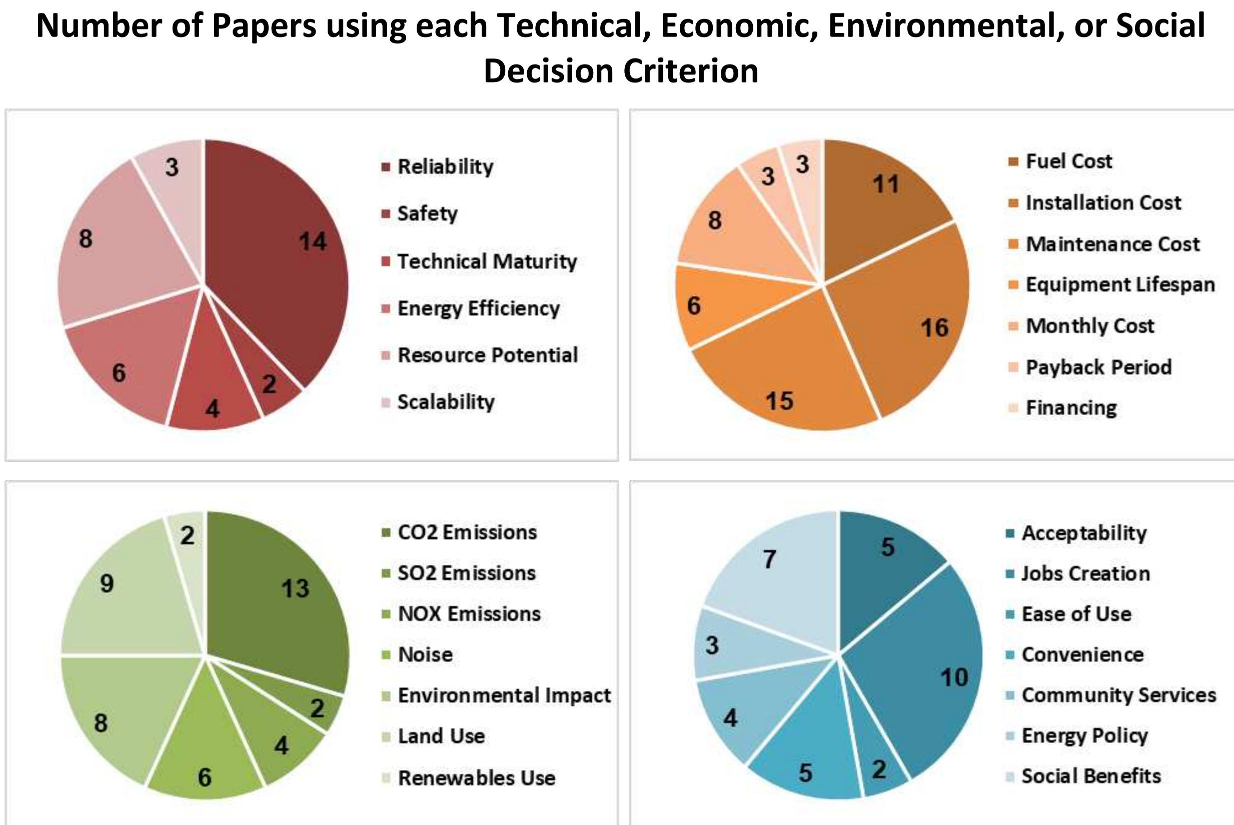

Figure 11: Number of papers using each category of technical, economic, environmental, and social impact criterion as part of an optimization formulation including both qualitative and quantitative objectives.

one of the easiest measures of the environmental benefit, both in urban and off-grid sites. Simultaneously, land use represents one of the major environmental drawbacks, and so is frequently an issue. Finally, jobs creation represents one of the most transformative impacts of islanded microgrids for community electrification. In the past, any electric service in remote communities was delivered by inefficient, expensive, polluting diesel generators. However, billions of US dollars of funding are now available through numerous public-private-venture capital partnerships to create solar-powered “mini-grids” ranging from 20 to 200kW of PV generation capacity. As the electrical demands of many communities are rapidly growing past simple lighting needs, many microgrid projects are now focusing on powering equipment related to productive uses of energy and job creation.

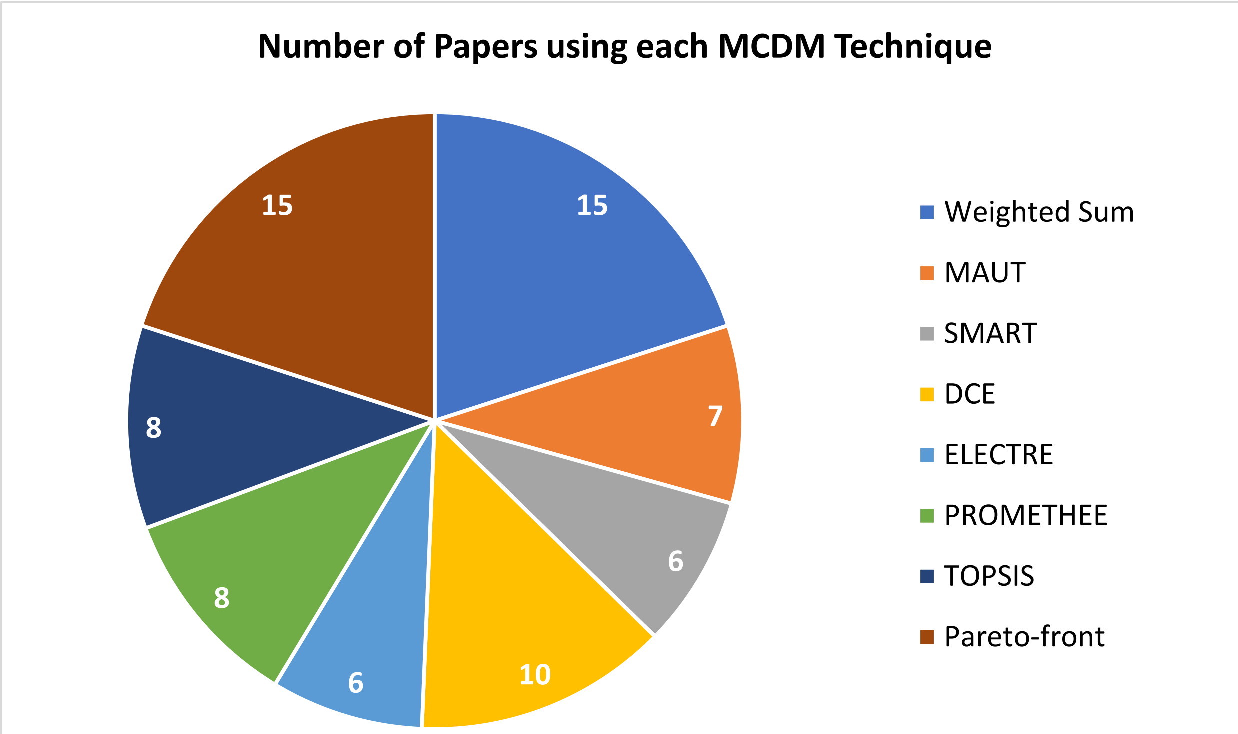

Figure 12: Number of papers dealing using each multi-criteria decision making technique to determine priorities and resolve conflicts between multiple objectives

The last portion of this survey examined tools available to combine the quantitative criteria discussed in Part 1 [21] and qualitative technical, economic, environmental, and social decision criteria summarized in Table 10. The analytical hierarchy process (AHP) is by far the most popular method, with dozens of studies and entire survey papers [152] dedicated to application of this technique to microgrid optimization.

As a result, the concluding discussion will focus on the other less common MCDM techniques (summarized in Figure 12) as there still exists space for new contributions and innovations. The weighted sum process is the easiest of these methods, and does not require any special analysis once weighting factors are chosen. Utility theory techniques (such as MAUT, SMART, and AHP) present great flexibility in combining both numerical and qualitative decision criteria. However, some of the analyses required to determine relationships and priority between objectives can be quite arduous. DCE and PROMETHEE provide an excellent framework when choosing between discrete alternatives, such as siting options, microgrid investment portfolios, and customer preferences. TOPSIS and Pareto-front optimization can be applied together, and seek a compromise between directly conflicting objective functions, such as those listed in Figure 8.

3.6.Conclusion

This paper surveys the key components of multi-objective optimization for planning and operation of islanded microgrids, including objective functions, constraints, control variables, solvers (covered in Part 1 [21]), forecasting, relationships between objectives, and multi-criteria decision making techniques (covered in Part 2). Optimization tools and evaluation criteria relating to technical, economic, social, and environmental considerations are discussed in the context of microgrids both for electrification of rural communities and for reinforcement of existing distribution systems that may be separated from the rest of grid during major disturbances.

This survey also provides some insight into areas of open research, such as the need for further study of effective ways of integrating social impact indices into optimization problems to provide a more comprehensive view than that provided by traditional measures, such as levelized cost of energy or system reliability. Additionally, some of the MCDM techniques discussed (such as SMARTER) have found relatively little use in microgrid optimization formulations despite their applicability. Integration of more accurate forecasting tools for both renewable generation and customer loads is an area where faster and more accurate models may benefit both power system planning and operations. Interconnection of islanded microgrids and formation of multi-microgrid distribution networks is an emerging field, which will require extensive study of potential conflicts between different microgrid controllers with different control and optimization objectives. Finally, additional tools must be developed to help accelerate electrification of the last billion people worldwide that lack safe, reliable, and clean electricity, and for whom access to renewables-based microgrids will be a life-changing experience. The authors anticipate this survey to serve as reference for research in all of these fields.

CHAPTER 4:

AN ENTERPRISE SYSTEMS ENGINEERING APPROACH TO ELECTRIFICATION

A holistic framework to modeling community electrification projects is presented in this chapter, introducing a new life cycle model for the planning, design, funding, construction, commissioning, operation, and expansion of community microgrids. The discussion the details of each phase in the systems life cycle, including needs analysis, concept development, community validation, decision analysis, deployment planning, in-field demonstration evaluation, engineering design, integration & verification, production & deployment, operations & support, and expansion of the project to reach additional communities. An enterprise system-of-systems hierarchy is also introduced, in which a community-based management structure is broken down into 5 layers spanning the administrative, social, technical, and physical components of a community development program. Each of the layers is also associated with a set of UN Sustainable Development Goals.

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4.1.Introduction

Electrification of remote communities worldwide represents a key necessity for sustainable development and advancement of the 17 United Nations Sustainable Development Goals (SDGs). Additionally, it is a prerequisite to creation of numerous other infrastructure and economic systems, including agriculture, healthcare, education, clean water, sanitation, transportation, and telecommunications. With over 1 billion people still lacking access to electricity, finding new methods to provide safe, clean, reliable, and affordable energy to off-grid communities deserves to be a dynamic area of research. It is for this reason that numerous papers discussing the design, optimization, and construction of electrification microgrids can be found throughout the literature.

However, traditional approaches to power system design focused on cost and reliability criteria do not provide a sufficiently broad view of the profound impact of electrification. Installation of a single microgrid is a life-changing experience for thousands of people, including both residents who receive direct electricity service and numerous others who benefit from better education, new economic opportunities, incidental job creation, and other critical infrastructure systems enabled by electricity. Numerous socio-economic factors, which span the engineering design process in terms of both scale and scope, determine whether the power system will be able to provide these benefits and operate sustainably.

For an electrification program to succeed, the project team must work with the community to satisfy their needs directly, be sensitive to local environmental constraints, mitigate possible risks, and plan for at least ten years of sustainable operations and maintenance. These considerations extend beyond the technical and optimization problems typically addressed in microgrid design. To address this need, a systems engineering life cycle is introduced and discussed in the context of an IEEE Smart Village regional electrification program in the highlands of Papua New Guinea.

4.2.Papua New Guinea Case Study

Located just 300km north of Australia, Papua New Guinea (PNG) is a unique country with 8.1 million residents, 840 languages, and several thousand separate communities. Despite strong growth in the oil, mining, and agricultural commodity sectors, 82% of the population survives on subsistence agriculture in remote villages. The widespread lack of critical infrastructure has stymied growth throughout the country: only 41% of the population has access to proper sanitation, 31% to clean water, 10% to electricity, and 3% to internet connectivity.

Although the only national electricity provider, PNG Power Ltd, is attempting to expand the power grid through installation of small-hydro and thermal plants, progress has been limited by the country's rugged terrain and lack of supporting infrastructure. Three islanded networks and nineteen diesel microgrids account for the country's total generation capacity of 580 MW, composed of 300 MW controlled by PNG Power and 280 MW owned by independent power producers (IPPs). The mainland of PNG is served by the Ramu System in the highlands and Port Moresby System in the capital city, as depicted in Figure 13. Although the capacity of the Ramu System is planned with expansion of the Ramu Hydro plant from 75 MW to 273 MW nameplate capacity along with upgrades to a few other smaller units, it is unlikely that the distribution system will be expanded farther than a range of several kilometers from the Highlands Highway connecting Mount Hagen to Lae. Service to the limited number of customers connected to the grid is highly unreliable, as illustrated in Figure 14, with some customer outages lasting weeks. For this reason, islanded renewables-based electrification microgrids still remain the most viable method for providing safe, affordable, and reliable electricity to all the residents of PNG.

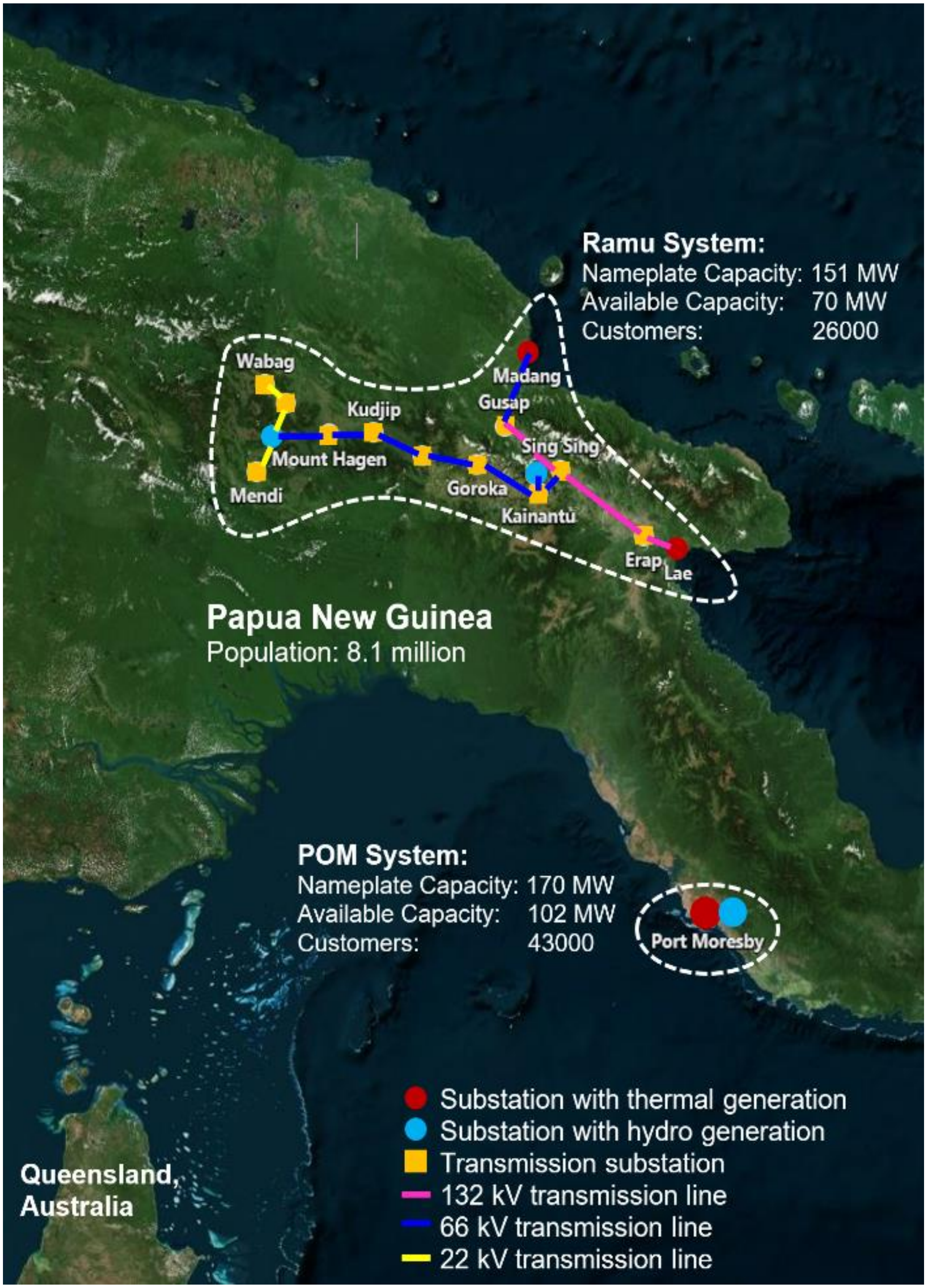


Figure 13: The Port Moresby and Ramu power systems that provide service to the capital and highlands. Not shown is the 42 MW system powering the island of New Britain.

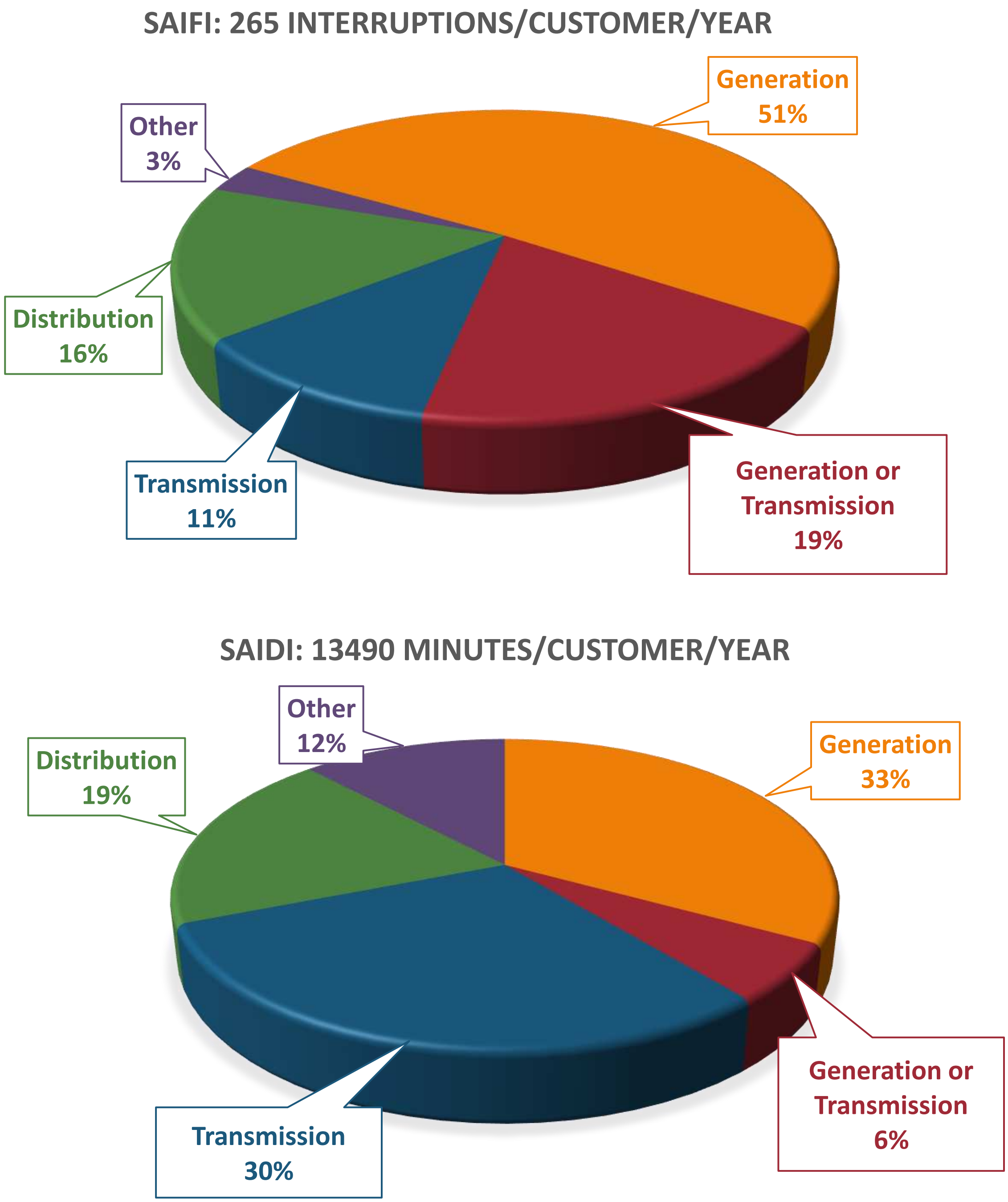


Figure 14: Ramu system reliability statistics for Lae, a seaport on the east coast of PNG. About 60% of generation-related interruptions are caused by system under-frequency events. Reliability figures for customers in the Highlands are even lower. (data source: JICA Study Team)

About 30 km east of Mt Hagen is the Madan Community, which is the center of a capacity building program by PNG CTC, Inc. (a local NGO) and Transform International to provide access to electricity, intranet, education, safe water, proper sanitation, and community empowerment programs. Within the initial 10 km project radius, there are seven tribes with an estimated 44,000 people and 35 schools with an average of 275 students each. The majority of schools lack critical resources including safe drinking water, electricity, sanitation, desks, books, teaching supplies, or access to the government curriculum.

The Madan CTC program builds upon 15 years of capacity building work focused initially on the critical healthcare needs of PNG, which has both the highest infant and child mortality rate and highest HIV incidence rate in the Pacific. To address these needs, the community and late Dr. Larry Hull, MD built the Madan Medical Clinic and Birthing Center in 2007, which is entirely off-grid and serves over 10,000 patient visits, 5000 vaccinations, and hundreds of births every year. In 2013, the community launched the current sustainable development program, which has made great progress in creating the community capacity to build, install, maintain, operate, and expand infrastructure systems. A series of Rotary Global Grants has successfully constructed a set of rainwater harvesting and distribution systems providing a million liters of clean water a year and safe sanitation to 5000 people in the community. The program has also provided over 175,000 textbooks to local schools and established three new community centers that function as hubs for

Figure 15: Community members gather to celebrate the construction of a new water and sanitation facility at Papen Elementary School in the Madan Community.

ongoing adult literacy, women's empowerment, and vocational training programs. In collaboration with IEEE Smart Village, the program will also provide electricity, community intranet, digital education, and entrepreneurial opportunities with regional expansion planned to reach all 700,000 residents of Jiwaka and Western Highlands Provinces.

4.3.IEEE Smart Village Approach to Sustainability and Scalability

IEEE Smart Village (ISV) is the member-led, not-for-profit, humanitarian outreach program of IEEE and one of the four priority initiatives of the IEEE Foundation. ISV enables community entrepreneurs to empower their communities through capacity building projects focused on three pillars of energy, education, and enterprise. With a focus on field implementation of the Sustainable Development Goals, ISV has created a network of experienced partners and village leaders engaged in community micro-utility infrastructure projects, humanitarian technology transfer, community-based education, and holistically sustainable enterprise. ISV aims to empower 50 million people by 2025 with plans for expansion in Africa, India, South America, and Asia.

ISV has been acting as the catalyst for socio-economic and technological change with eight years of successful projects by simultaneously taking bottom-up and top-down participatory development strategies. Each new project builds upon an on-the-ground network of partners and village leaders who have previously led community infrastructure projects addressing other Sustainable Development Goals, including clean water, proper sanitation, affordable healthcare, quality education, sustainable agriculture, and gender equality. Access to safe, clean, secure, and affordable sources of electricity have been the limiting factor in economic growth and poverty eradication.

The ISV business model is based on establishment of long-term collaboration with in-country community entrepreneurs, who in turn are expected to build relationships at both the local and national level with financial, social, and governmental institutions. This approach eliminates conflicts of interest with national utilities, raises awareness and support for ISV initiatives, enables creation of complementary infrastructure, and promotes opportunities for increasing the prosperity of villages surviving on less than $2 USD per day of per capita income. Open sharing and standardization of technology, business models, education, vocational training, community-wide enterprise, and approaches to funds leveraging have allowed the ISV model to be implemented worldwide, reaching over 100,000 people in 2017 with a 50% annual growth rate.

4.4.Achieving Sustainability

Success of electrification projects extends far beyond the design, installation, and commissioning of a microgrid. To provide real benefits to a community, a power system must also be complemented by an equally complex array of social infrastructure and community-based organizations that will assure that the system and its components are properly maintained, operated, and replaced at the end of their lifespan. Prior to the start of the design process, a network of local stakeholders, customer user-groups, financial mechanisms, and community organizations must be established. During the installation and commissioning phase, it is essential that the community is an equal participant and that core knowledge is transferred to full-time staff through train-the-trainer processes.

In creating a holistically sustainable electrification program, arguably only 20% of the work is technology; the remaining 80% is development of community relationships, inclusive education, and business development practice. Due to the complexity of the process required to create a truly sustainable project, advanced design and project management tools are necessary and can be found in the discipline of systems engineering.

4.5.Systems Engineering

Systems engineering is a broad discipline that not only includes elements of electrical, mechanical, and civil engineering, but also integrates technical design with social, management, human, regulatory, and business domains. It provides a holistic perspective, which is needed to guide the analysis, design, testing, integration, and deployment of complex systems formed from numerous interrelated components working together to achieve a common goal – arguably a description of any power system.

The traditional project management definition of success in terms of scope, schedule, and budget is expanded to provide a balanced viewpoint seeking an optimal tradeoff between performance, cost, customer satisfaction, stakeholder requirements, business opportunities, and individual technical attributes. Systems engineering simultaneously extends the engineering design process to include client needs, use cases, operational scenarios, technological maturity, risk analysis, functional requirements, performance specifications, subsystem interfaces, production, deployment, operations, maintenance, and disposal. This sequence of analyses and considerations leads to the development of a systems engineering life cycle, of which the project management life cycle is a subset.

A number of standards have been developed to model the activities involved in systems engineering, including MIL-499B, IEEE-1220, EIA-632, and ISO-15288. The first three standards in this list focus more on individual processes and systems analysis/control, and so are of less relevance to the current discussion. However, ISO-15288 integrates technical processes with a set of enterprise management and project planning tasks. Although these elements are not presented in sequential order, they form a foundation for creating a life cycle for electrification systems.

4.6.Community System-of-Systems Enterprise

Although a microgrid typically represents a single system, it actually forms part of a system-of-systems hierarchy spanning social, economic, and technical levels, not unlike Maslow's hierarchy of needs. Arguably, the final mission of electrification projects is to increase the quality of life for the residents of the community, which can be represented by community enterprise. This abstraction integrates all the elements that contribute to eradicating poverty in a community and can be expressed through the 17 UN SDGs, as depicted in Figure 16.

More specifically, community enterprise represents the organizations, entrepreneurs, processes, systems, technologies, stakeholders, community members, and other resources that contribute to the holistically sustainable development of the community. The scale of community enterprise is far broader than merely providing electricity service. Creation of reliable access to electricity enables information communications technology (ICT), water, and other critical infrastructure that will transform the previously remote community into a regional hub that attracts new businesses, education programs, and further investment. The goal of community empowerment and capacity building drives the enterprise development and management strategy, including infrastructure, services, business opportunities, training, ICT investments, and operations.

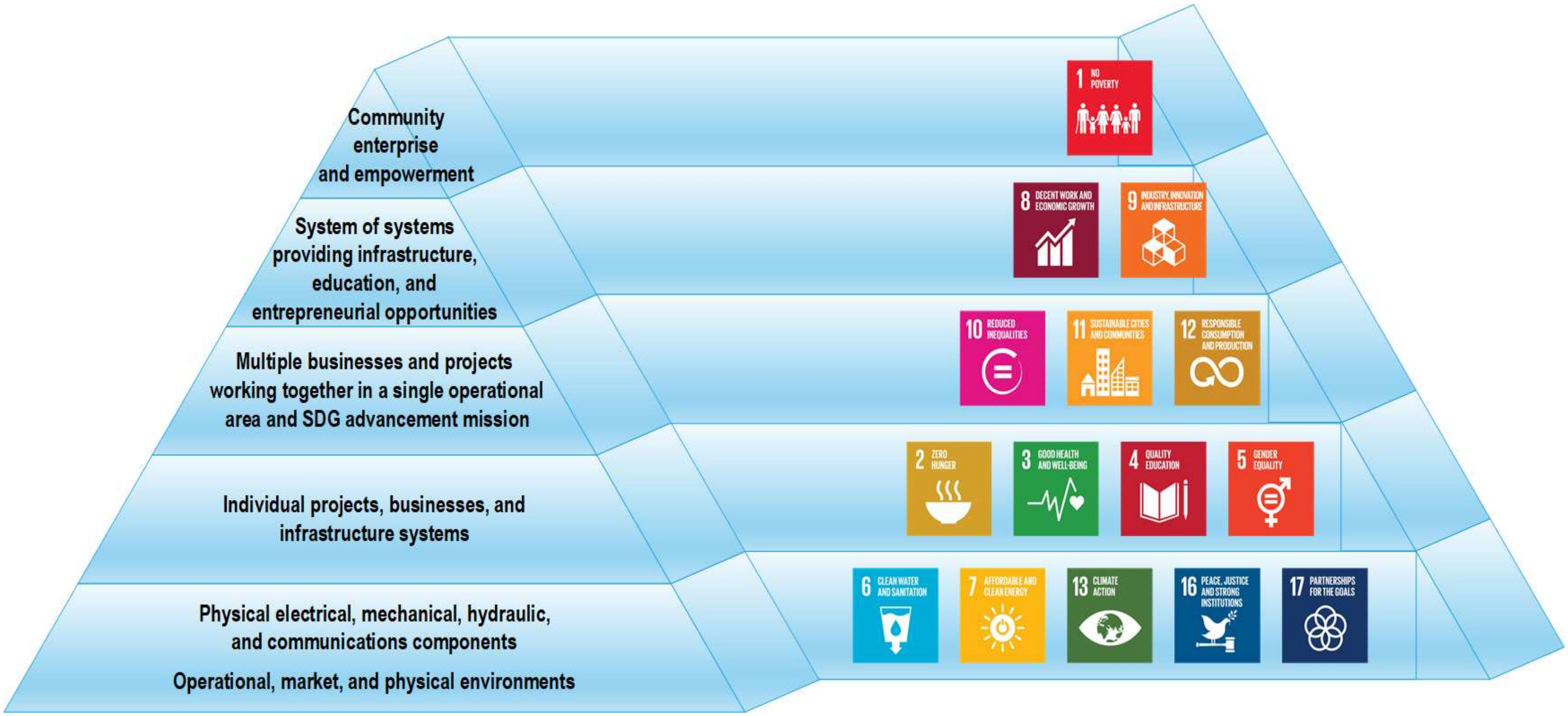


Figure 16: Hierarchy of elements forming the community infrastructure system-of-systems, with a mapping of UN Sustainable Development Goals corresponding to each system level (i.e. system, subsystem, component, etc.)

A community infrastructure program is composed of a series of partially interdependent projects and systems forming a system-of-systems (SoS) that cooperate to support and promote sustainable economic growth and social empowerment throughout the community. The second layer of the enterprise systems hierarchy represents the interfaces and collaboration between a microgrid and other water, sanitation, electrical, information technology, and wireless telecommunications systems that may be present. The lower layers of the hierarchy represent multiple businesses that may be providing the same service (such as multiple islanded microgrids or service kiosks), individual systems, and their respective components.

The SoS structure of a community electrification and infrastructure can be explained in terms of the seven characteristics of SoS originally outlined by Sage and Cuppan:

- *Operational Independence:* An electrification microgrid forms the foundation for other infrastructure systems and community services that are independent and individually useful.
- *Managerial Independence:* The microgrid and other community systems not only can be, but typically are operated and managed independently. The entities responsible for design, construction, operation, and maintenance of various systems (including electricity, water, or communications technologies) may be unrelated, but contribute towards the overall mission of the SoS.
- *Geographic Distribution:* The systems typically are dispersed over a wide region of a community. Through advancement of communications access and Internet of Things (IoT) humanitarian technologies, exchange of information between systems is becoming increasingly common.

- *Emergent Behavior:* The overall goal of the SoS to enable sustainable development and capacity building is not related to the direct functions of an individual microgrid or other system
- *Evolutionary Development:* The development of the community SoS evolves continuously, with each new system not only changing the structure, mission, and role of the SoS, but also enabling the addition and modification of other systems.
- *Self-Organization:* The SoS represents a dynamic organization structure that is able to respond in an agile manner to its environment and objectives of the community program.
- *Adaptation:* The entire community enterprise (at the pinnacle of the SoS) is itself responsive to changing community needs, technological acceptance, success of current projects, stakeholder inputs, and an array of socio-economic factors.

In the case of the Madan program, the highest level of community-based infrastructure enterprise is organized and guided by the Madan CTC management authority (the local non-profit responsible for construction, maintenance, and managerial oversight of the program) and small entrepreneurial businesses supported by the new infrastructure. The Madan CTC is additionally responsible for providing the forum for community members, sponsors, and other stakeholders to establish the continuous feedback loop necessary to keep the community enterprise SoS agile and adaptive.

The community centers and maintenance monitoring staff operate at the second level, ensuring proper coordination of operations and maintenance of the systems. At the third level are the individual systems and their operators who run small entrepreneurial businesses providing safe drinking water, charging services for cell phones, operation of portable battery kits, collection of waste, and distribution of tablets and computers to community workshop participants at schools and community centers. Finally, at the lowest two levels are the individual solar-power, digital classroom, community intranet, water, and sanitation subsystems and the individual components of each system, such as solar panels, batteries, computers, and wireless routers.

4.7.Electrification Systems Engineering Life Cycle

Several life cycles have been created for the development of defense technologies, software, and other complex projects, including the waterfall, spiral, agile, rapid prototyping, and incremental models. Although models derived for other applications share many of the same phases as those of an electrification program, the primary emphasis of most models is initially upon development of specifications and subsequently upon integration and testing since these phases are essential for successful deployment and production of new technologies and software.

However, these phases are of less importance for the success of community electrification programs. Few microgrid projects implement unproven, cutting edge technologies (as are required for defense systems), but rather focus on design and operation of robust, durable, and reliable commercially-off-the-shelf (COTS) generation, energy storage, and controller components that have already been integrated and tested by the manufacturer. Likewise, the extreme differences between various custom software systems are not seen in the functional and performance requirements between one microgrid and another. The complexity of community electrification lies in attaining financial, technical, and operational sustainability of the microgrid so that it can successfully reach its 20 year design lifespan.

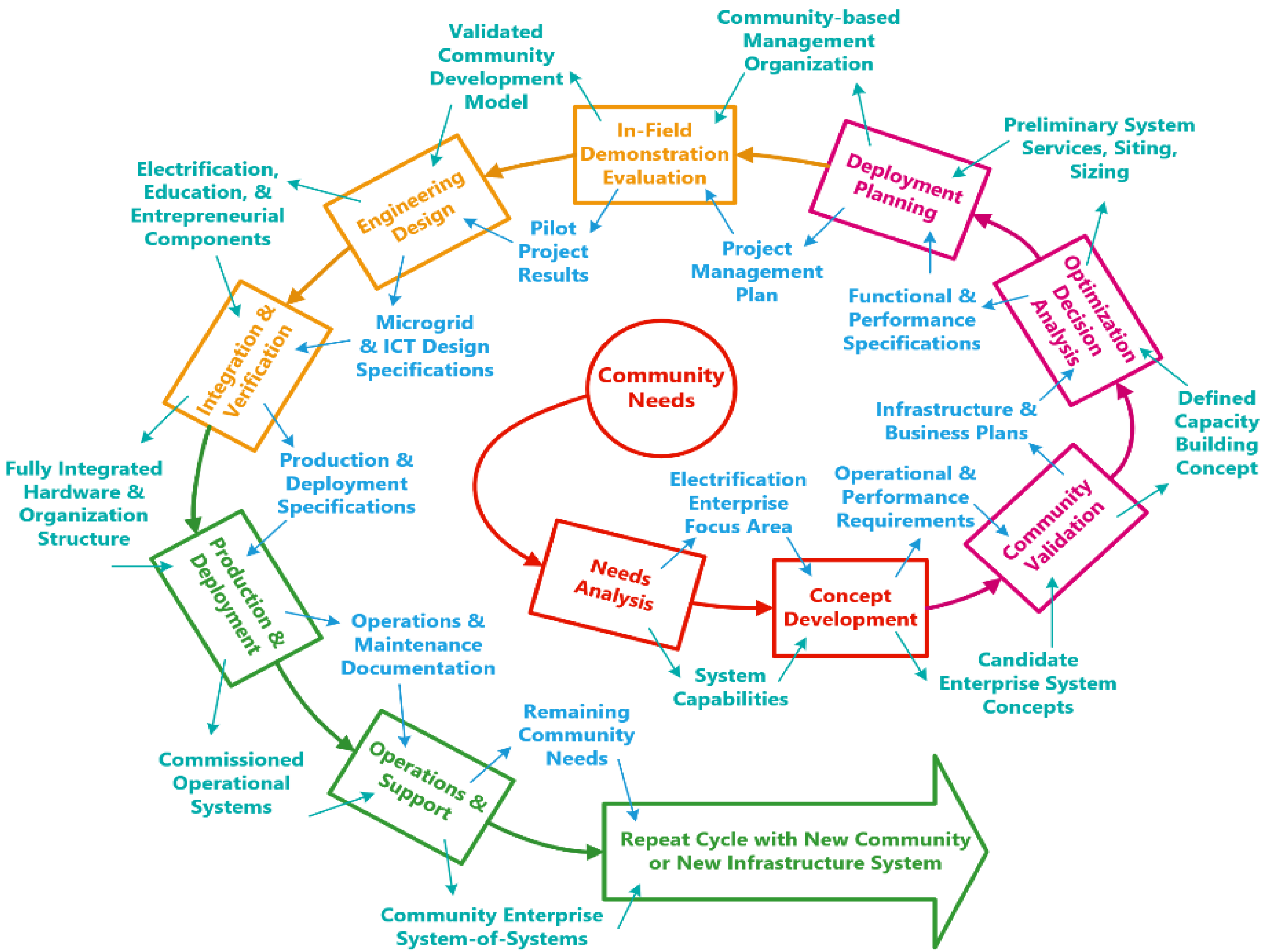


Figure 17: Spiral of community-based infrastructure: this systems life cycle model has been developed to address the unique challenges and considerations involved in electrification projects

To address the need for a simple description of the process for establishing the technical, financial, and organizational support subsystems needed, a new electrification systems engineering life cycle is proposed. This model targets project planners, pro-bono consultants, and in-country engineers seeking to collaborate with a series of communities to establish a community-based infrastructure program capable of regional scaling. The life cycle proposed follows a spiral pattern, as shown in Figure 17, due to the cyclical nature of building successive infrastructure programs within a single community and when expanding to additional communities. Each of the phases of the lifecycle will be discussed and illustrated using the Madan community empowerment program.

4.8.Needs Analysis and Concept Development

The needs analysis process is possibly the most important step for understanding the required project scope, establishing a relationship with the community based on mutual trust, and creating the foundation for a successful regional program. This phase comprises far more than a simple survey of how many people in a village lack electricity, what they are willing to pay, and how much kerosene they burn. It is a comprehensive process that includes

- establishing relations with community leaders
- identifying potential local technical contributors
- categorizing key stakeholders
- recognizing factors that have limited electricity access
- researching publications and records of prior project successes and failures
- evaluating availability of supporting information/communications technology
- assessing access to education and vocational training
- gauging the familiarity of the community with microgrid technologies

- appraising past records of maintenance, operation, and materials availability
- compiling community income generation sources and local access to finance
- estimating new jobs and entrepreneurial opportunities that will be created by electrification
- mapping existing assets for infrastructure and shared community services
- selecting candidate sites for preliminary in-field demonstration systems

A detailed assessment covering the technical, social, geographical, financial, cultural, and organizational aspects of the community enables the development of a project baseline justifying the need in both qualitative and quantitative terms. The needs analysis phase is concluded by an operations analysis that defines the general approach, value delivered to the community, and list of operational objectives for the planned electrification program.

Figure 18: Madan community members, who had never seen a tablet computer before, gather around a Rotary volunteer conducting a site survey. (Photo courtesy Aarlie Hull)

Figure 19: A typical household in the PNG Highlands (Photo Courtesy Maureen Yalde)

The subsequent concept development phase focuses on converting the identified community needs into a set of candidate enterprise system concepts. The first process is functional analysis, which identifies which new products, services, or features would be delivered to the community by the considered electrification plan. The goal is to translate the operational objectives previously identified into a list of functions to be performed, which are assigned to subsystems. The analysis also identifies operational interfaces both between internal subsystems and with external stakeholders. These interfaces can be summarized in a context diagram, as depicted in Figure 20.

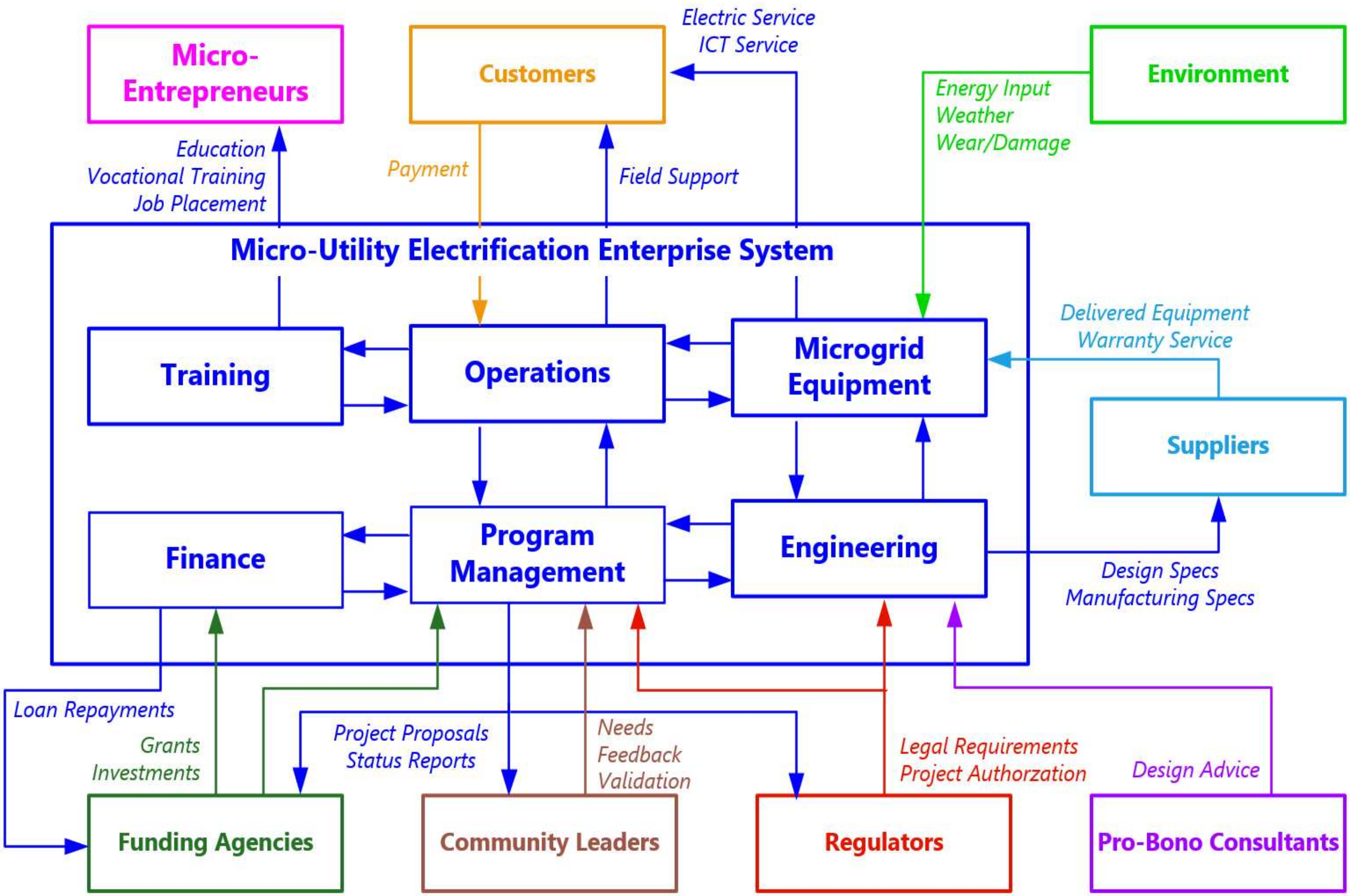


Figure 20: A context diagram depicting some of the interfaces of the electrification enterprise system with its internal subsystems and external stakeholders.

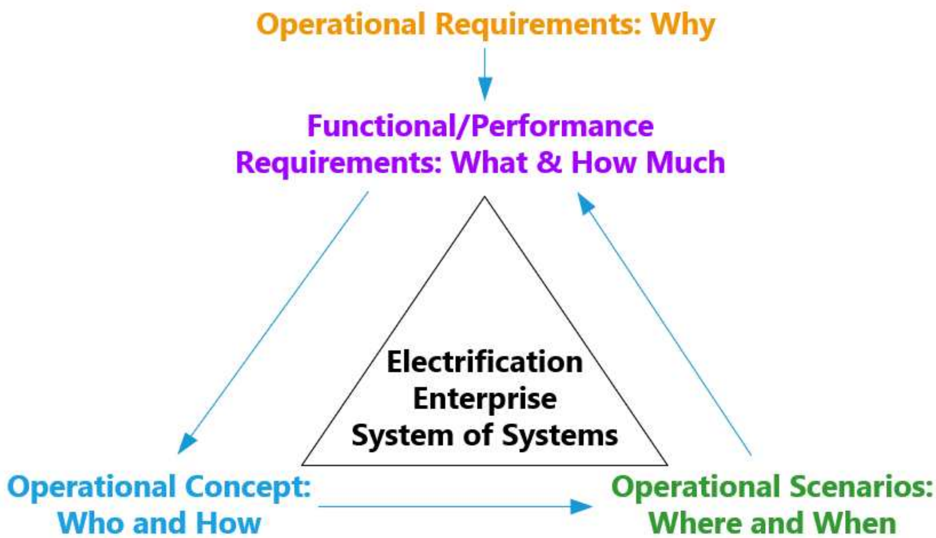


Figure 21: The triumvirate of conceptual design is a useful tool for defining the concept of operations and system requirements as answers to seven simple interrogatives.

A complete functional analysis enables the identification of the operational, functional, performance, and physical requirements for the system, leading to the creation of a detailed concept of operations. A useful systems engineering tool for this process is the triumvirate of conceptual design, which is illustrated in Figure 21. The operational context, operational scenarios and system requirements are answers to seven simple interrogatives (*why*, *what*, *how much*, *who*, *how*, *where*, and *when*) and form the overall electrification enterprise system concept. It is important that community leaders and key stakeholders are closely involved in this process to ensure that the resulting concept of operations is relevant to community needs, culturally acceptable, and actually feasible.

In the case of the Madan project, the needs analysis process (conducted in 2015) resulted in three parallel operational concepts for the first set of electrification systems that would serve as technology demonstration platforms and provide maximum initial social impact. The operational concepts focused on electrification of existing shared community infrastructure, starting with

1) formation of digital learning and empowerment hubs at the three Rotary community centers
2) creation of electricity and education access for the 35 schools within the project radius
3) electrification of the Madan Medical Clinic for vaccine refrigeration and power of critical medical equipment
4) improvement of electric supply reliability at the community coffee mill, which provides fair employment to 800 workers and was certified as the world's fourth greenest coffee operation by Rainforest Alliance.

The operational concept created for the Madan community consisted of a community-based organization following the proven enterprise model of a rural electric cooperative that would be responsible for stakeholder management, customer relations, commissioning, operation, and maintenance of the electrification infrastructure. The local micro-utility would also be responsible for training of community members, both as staff and as customers. The community organization would continue to manage the Madan water, sanitation, and education infrastructure as separate components of its micro-utility project portfolio. Program management, oversight, and funding would be provided through Transform International, an NGO based in USA and Canada. Costs of staffing, operations, maintenance, upgrades, and expansion would funded by revenue derived from residential and commercial electric service, battery charging services, and technology delivery fees assessed from schools receiving electrification / digital education packages.

The micro-utility operational concept and functional analysis was subsequently translated into a functional series of functional, operational, and performance requirements, which are summarized for the community center deployment strategy in Table 12. The associated concept of operations is depicted in Figure 22.

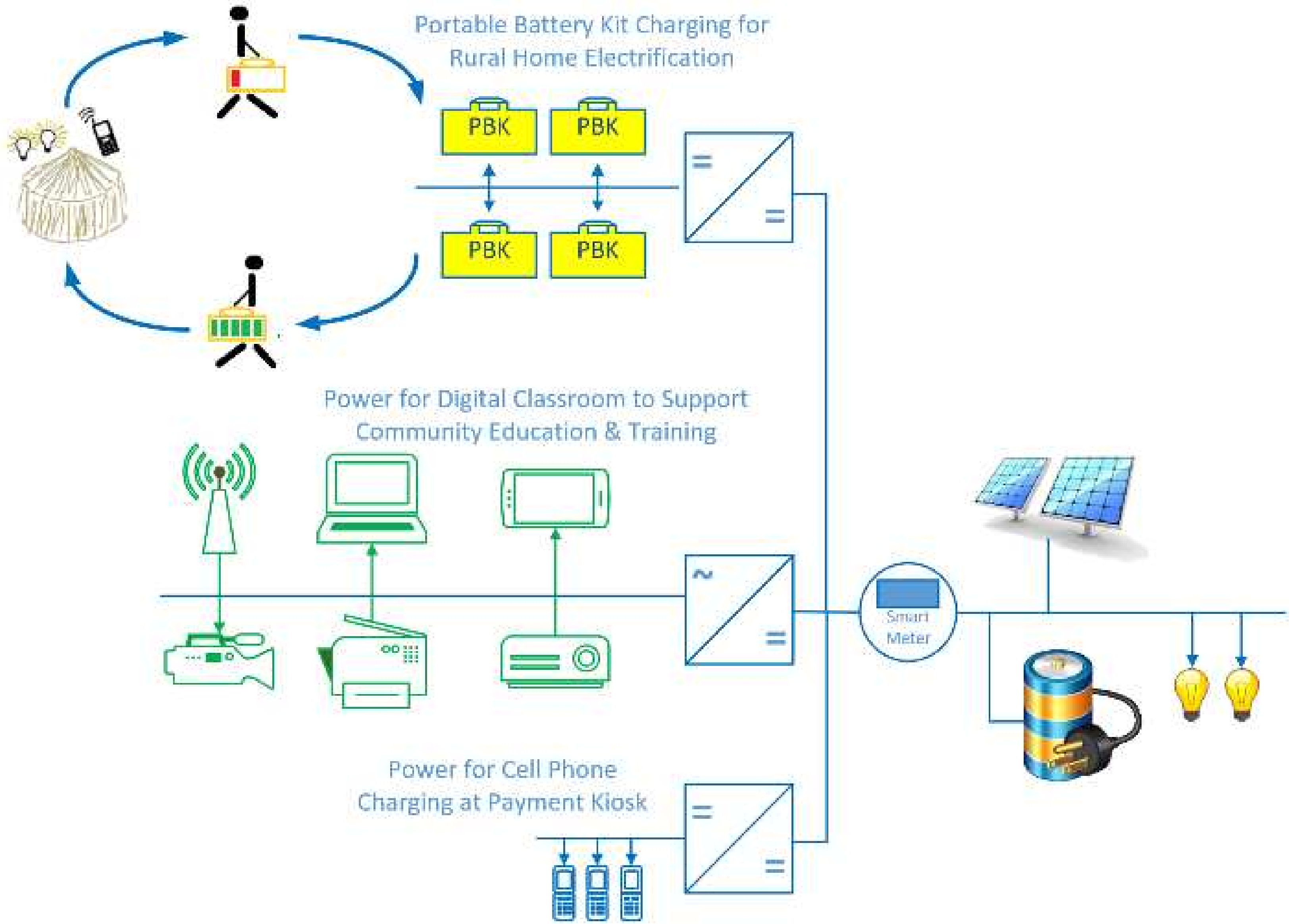


Figure 22: Concept of operations for electric service at the three community centers

Table 12: Concept development results for community center electrification in Madan, one of four parallel operational concepts developed for the program

Functional Requirements	Scalable, robust systems to provide reliable electricity for • LED lighting • digital classroom technologies (computer, projector, camera, digital content server, Android tablets, printer, Wi-Fi router) • paid cell phone charging. • charging of portable battery kits (PBK) for home electrification
Operational Requirements	• Sufficient lighting for operations after dusk and during periods of heavy rain • Delivery of power with sufficient quality and capacity for IT equipment and electronics for digital classrooms • Ability to store sufficient energy to provide at least two days of power during monsoons • Sufficient capacity for cell phone charging • Ability to expand system to allow charging of PBK • Ability to power both AC and DC loads
Performance Requirements	• Ability to power at least 10 LED light bulbs per room with minimum luminosity of 300 lumens each • Ability to power a computer, projector, Wi-Fi modem, and intranet receiver with a maximum power consumption of 50 W each • Ability to operate the system at maximum power for at least 12 hours a day • Ability to charge at least 30 Android tablets with a maximum power use of 10 W for use 3 hours per day • Ability to charge at least 100 cell phones per day with a cell phone battery capacity of 2 Ah each • Ability to charge up 5 laptops per day with a battery capacity of 50 Ah each

4.9.Validation, Optimization, and Planning

The next set of phases in the enterprise systems life cycle bring the initiative from concept to an actionable plan for deployment and operation of the electrification systems. The third phase, Community Validation, evaluates and verifies whether the proposed concept of operations and requirements are not only feasible, but also whether the system will satisfy the needs of the community and sustainable development objectives of the project. The deliverables from this phase are an initial infrastructure and enterprise development plan, as well as a fully defined community capacity building concept.

The validation process must involve all local community stakeholders to assure that the concept will be relevant, acceptable, and practical. An example of a local review meeting with stakeholders is depicted in Figures 23 and 24. If a small amount of ICT access (e.g. 3G cellular service) is available to community leaders, then it is possible to expand the validation phase into a continuous feedback process through email and video-conferencing software. Hosting virtual meetings can enable the involvement of a global team of pro-bono consultants, provide answers to site-specific questions without the need for international travel of experts, and reduce the delay in receiving feedback and project status updates from months to merely hours.

Figure 23: Drafting of system requirements by Madan micro-utility managers with engineering volunteers from USA and Australia

Figure 24: Community validation review with community leaders, local teachers, installers, and other stakeholders

The next phase in the life cycle addresses preliminary optimization of the system and decision analysis for the electric services to be provided, as well as initial microgrid siting and sizing issues. From the SoS standpoint, the broad community impact and empowerment opportunities created by electrification require a much broader perspective than that offered by traditional power system optimization approaches based on levelized cost of energy and system reliability. Fortunately, systems engineering offers a set of tools that have been adapted to modeling, simulation, optimization, and decision analysis of complex systems with both quantitative and qualitative attributes.

Optimal siting and sizing of distributed energy resources in a community microgrid is required to ensure secure, economic, and reliable operations. Unlike traditional radial distribution feeders, electrification microgrids may often have a meshed network topology with frequent power flow reversals depending on variations in renewable generation and load. Suboptimal siting of distributed generators (DGs) and energy storage systems (ESS) can result in higher network losses, unsatisfactory voltage profiles, and poor generator performance due to the unique topology and renewable resource distribution of every site. Optimal DG and ESS sizing is also critical to achieving a balance between system reliability and installation cost.

Optimization for microgrid planning often focuses on solving an economic dispatch or unit commitment problem over a daily, weekly, or seasonal cycle using historical data and predictions of renewable generation and load growth. Multiple software tools, such as HOMER, have also been developed to handle these planning tasks. However, these methods do not have the ability to include non-quantitative measures of system performance that affect the sustainability and scalability of community electrification programs.

Multi-criteria decision making (MCDM) methods are an evaluation tool used in systems engineering for trade-off analyses and selection of system configurations using both quantitative and qualitative decision criteria. The most popular MCDM methods are based on utility theory and include the analytical hierarchy process (AHP), multi-attribute utility theory (MAUT), and the simple multi-attribute rating technique (SMART). Utility theory allows the relation between the costs and benefits (or "utility") of a particular decision to be expressed in terms of multiple objectives, criteria, and alternatives. The amount of preference given to a particular attribute is expressed in terms of a utility function that varies between zero and one. Utility functions and MCDM methods enable a wide variety of technical, economic, environmental, and social

Table 13: Select criteria that can be used in multi-objective optimization of microgrids considering the capacity building and empowerment possibilities of electrification

Technical	**Economic**	**Environmental**	**Social**
Reliability	Fuel / operations cost	Greenhouse gas emissions	Social acceptability
Safety	Installation cost	Land use	Ease of maintenance
Technical maturity	Maintenance cost	Renewables utilization	Ease of training
Energy efficiency	Revenue / profit	Component toxicity	Jobs creation
Renewable resource potential	Customer monthly cost	Other environmental degradation	Community services provided
Scalability	Payback period	Noise	Energy policy
Equipment lifespan	Financing	Support of other nearby infrastructure	Relevance to community needs

objectives to be included in the optimization and decision making process. Table 13 presents a short list of criteria that can be used in evaluation of candidate microgrid configuration alternatives.

Completion of the preliminary optimization process leads to the creation (or revision) of a detailed project management plan that will guide the project through the remaining stages of design, production, installation, commissioning, and training. An effective planning document will include many of the elements of a traditional project management plan, including a project scope, schedule, budget, statement of work, business case, deliverables to the community, work breakdown structure (WBS), organization breakdown structure, risk management plan, supplier management plan, and communications plan.

For the Madan project, a set of detailed optimization studies were performed for each of the parallel microgrid demonstration projects at the three Madan community centers, eight pilot

Table 14: Configurations of the Initial Set of Microgrid Installations in Madan

Installation	PV Capacity	ESS Capacity	Voltage	Site
Community Centers	2 kW	5 kWh	24V DC	
Medical Clinic	5 kW	10 kWh	48V DC 220V AC, 1ϕ	
Madan Mill & Business Center	20 kW	50 kWh	48 or 380V DC 415V AC, 3ϕ (Δ)	
Pilot Schools	0.5 kW	1 kWh	12V DC	
Standalone Sunblazers	2.2 kW	5 kWh	24V DC	

schools, medical clinic, and coffee mill considering the factors listed in Table 13. The selected configurations for each system is summarized in Table 14.

4.10. Demonstration, Design, and Integration

The theme of the next three phases of the electrification enterprise systems lifecycle is risk mitigation. Total system breakdown shortly after a successful "intervention" in a community is unfortunately a very common occurrence worldwide, which can be attributed to failures in earlier phases of the project, such as incomplete needs analysis, lack of community engagement, and the absence of an organizational structure to operate and maintain the commissioned system. However, even if all the planning and validations steps are followed, there still exist a vast array of risks to successful project deployment and long-term sustainability. A sample risk matrix with a few of the risk events considered for the first phase of the Madan electrification project is presented in Table 15.

One of the most effective tools for risk management in sustainable development is the deployment of a series of small-scale demonstration systems that enable evaluation of candidate technologies in the actual community, which is impossible to simulate. Development, deployment,

Table 15: Sample risk matrix for the Madan project

Impact / Likelihood	Low	Medium	High
High	Monsoon, earthquake	Random vandalism	Theft of electrical & ICT equipment
Medium	Late Delivery from Suppliers	Inability to build ICT support systems for operations	Inability of community to maintain system
Low		Misuse of Technology	Inability to hire / train qualified staff

and evaluation of scaled prototype of the actual systems and critical components are essential to gauge whether the defined system concepts and preliminary designs will be technically feasible, cost-effective, and socially acceptable.

Consequently, a series of demonstration systems will be constructed in Madan prior to the design and deployment of the full electrification program in the 10 km project radius. These demonstration systems will be located at the three community centers and will test the effectiveness of portable battery kits, wired distribution, prepaid smart meters, and other technologies. Simultaneously, the ability of local schools to operate digital classroom technologies will be evaluated using the innovative EmpowerPack digital electrification education system developed by the authors, depicted in Figures 25 and 26. Each of the EmpowerPack systems will provide instantly deployable solutions for schools, community centers, and other community

Figure 25: The EmpowerPack electrification education system developed by the authors provides a portable, instantly deployable system for a school, medical clinic, or community center with the latest ICT and power technologies

facilities with solar power, computing, internet connectivity, access to government curricula, adult vocational training resources, and means for local content development.

Figure 26: An EmpowerPack Standard solar ICT kit for a single classroom, capable of bringing the latest digital education technologies to off-grid settings

After the successful deployment and evaluation of the demonstration systems in Fall 2018, a full engineering design will be created for interconnecting nearby demonstration systems, electrifying all remaining schools, and deploying home electrification systems throughout the community with a combination of wired distribution systems and portable battery kits. A map of the first multi-microgrid interconnection in Madan is presented in Figure 27. All of the elements will subsequently be assimilated into the community-based micro-utility enterprise system, which will be responsible for final integration and validation of all system functions.

4.11. Towards Regional Deployment and Sustainable Operations

The last set of phases in the electrification enterprise life cycle focus on the transition of the program from a set of pilot demonstration project into a cohesive regional infrastructure system-of-systems. The process involves an even wider range of stakeholders and considerations, including the establishment of dedicated equipment supply chains, staff training programs, operating procedures, maintenance schedules, customer relations teams, and financial mechanisms. As the Madan CTC progresses towards this phase as an adaptive enterprise system, changes in even the micro-utility organization structure may be necessary, such as the transition from its current rural electricity cooperative model to a community-based independent system operator (ISO) with transactive market mechanisms capable of coordinating a broad network of interconnected islanded and grid-tied microgrids. A conceptual framework for this future model is presented in Figure 28.

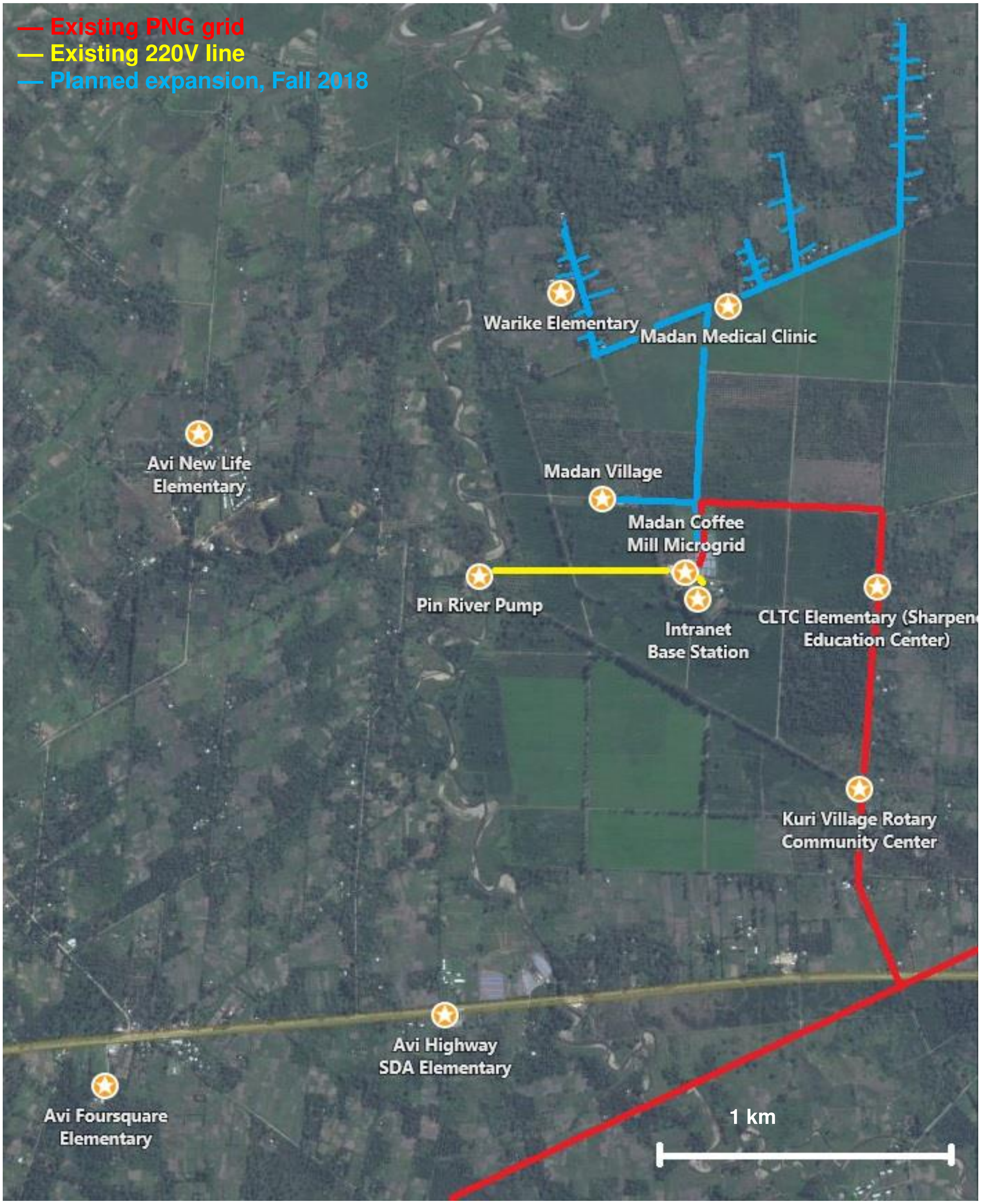


Figure 27: Planned interconnection of Madan pilot demonstration systems and initial distribution system expansion

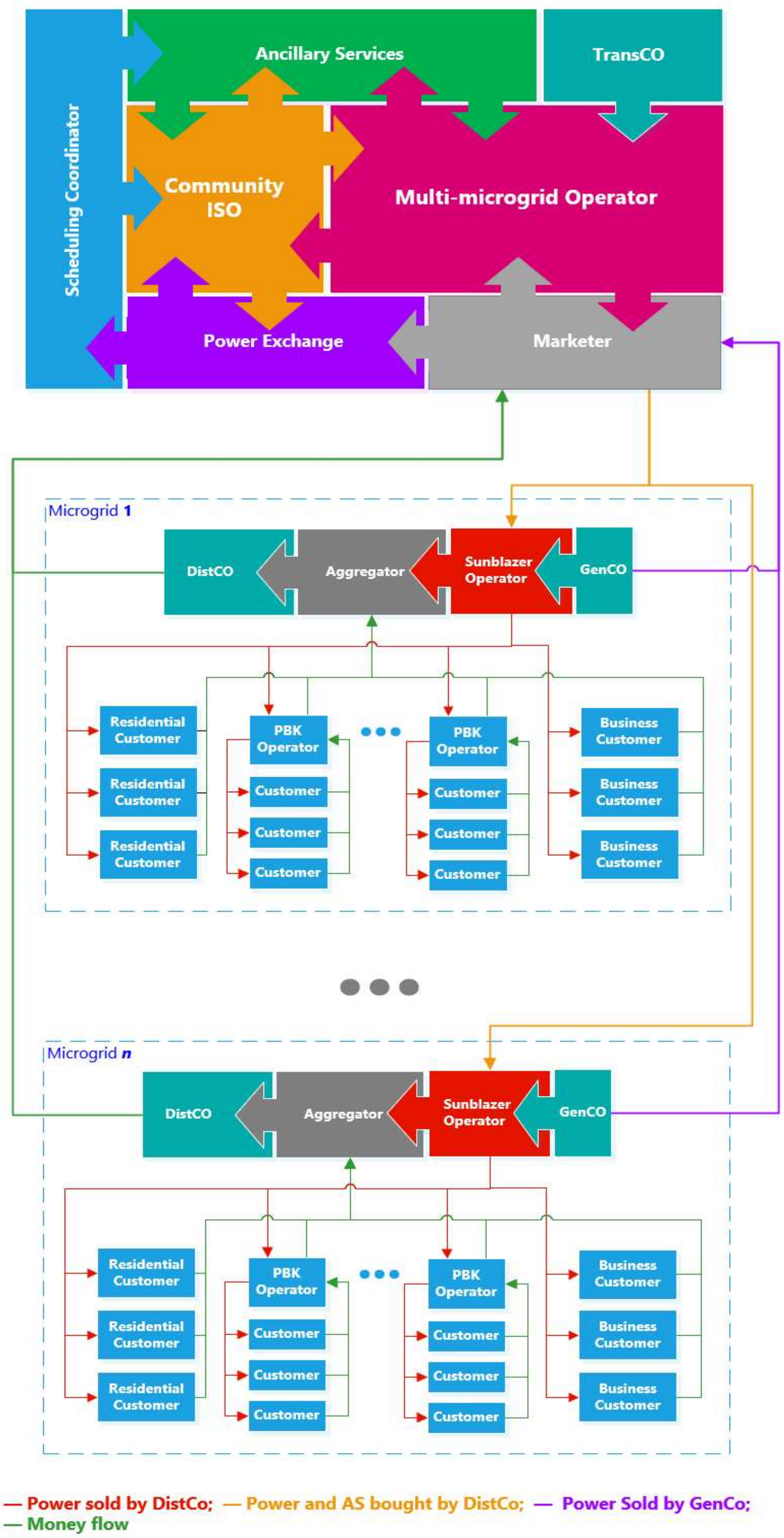


Figure 28: Conceptual framework for a future multi-microgrid transactive market in PNG.

CHAPTER 5

CAPACITY OPTIMIZATION OF A COMMUNITY MICROGRID FOR RURAL ELECTRIFICATION

An algorithm is developed for optimization of photovoltaic and energy storage capacity of small community microgrids for rural electrification without diesel or other thermal backup. The developed algorithm is applied to a case study of the Madan Community in Jiwaka Province, Papua New Guinea. A series of community microgrids are being installed to provide electricity, high speed intranet, and digital education in community centers, schools, and homes. The optimization results will be used to create a set of standardized designs based on the IEEE Smart Village microgrid topology for electrification of communities throughout Jiwaka Province.

This chapter is a verbatim copy of a paper of the same titled published by the researcher in the 2017 IEEE PowerAfrica Conference. A copyright waiver form is provided in Appendix A.1.

5.1. Introduction

Electrification indisputably stands as one of the most effective ways to confront global poverty–a prerequisite to meeting the critical needs of billions of people who currently lack clean water, sanitation, and access to education, medical services, communications technologies, and entrepreneurial opportunities [63]. Furthermore, reliable electric supply can create a foundation for creating community-based infrastructure, sustainable business opportunities, and vocational training programs. Photovoltaic-based microgrids are one of the most successful methods for providing reliable electricity to communities in peri-urban, rural, and deep-rural communities worldwide [177].

Optimization of generation and storage capacity installed in a microgrid is essential for secure and cost-effective operations. As a result, many approaches to optimal planning were developed; these are classified into three categories [14]. The first seeks to optimize the size and type of generation with respect to cost (expressed as installation cost, cost of energy and operations, or payback-period of investment), environmental impact, and reliability [178] - [179]. The second approach solves an economic dispatch problem using anticipated load and renewable generation profiles [180] - [181], seeking a compromise between conflicting objective functions of maximizing profit, minimizing emissions, and maximizing reliability using pareto-optimization [182], discrete compromise programming [183], or a multi-criteria decision making algorithm [184] [185].

The majority of such studies focus on optimal capacity and location of distributed generation and ESS in a distribution-scale network, rather than small DC microgrids typical of electrification in rural and deep-rural communities. However, optimization of the installed capacity is nevertheless important even for islanded DC systems less than 5 kW, especially if the power system will not include any fossil-fuel backup generation. Additionally, the literature does not include any optimization methods for systems using portable battery kits (such as shown in Figure 29 b) for electrification of homes where wired distribution or solar home systems are not practical.

Figure 29: a) A rooftop solar array being installed at the Madan Medical Clinic in Papua New Guinea. b) Energy entrepreneurs in Haiti demonstrate the first generation portable battery kit. Images courtesy Larry Hull, Na Wokabaut and Ray Larsen, IEEE Smart Village.

As a result, it was determined necessary to develop a method for capacity optimization of PV microgrids using the IEEE Smart Village Sunblazer configuration, which is depicted in Figure 30. In this paper, a planning approach for determining optimal photovoltaic and battery energy storage capacity is developed. Two objective functions are presented for 1) maximizing operational profits using time varying generation pricing and tiered load pricing, and 2) minimizing the installation cost of the system. PV and ESS capacity configurations are evaluated by a steady-state simulator of the DC power system that also determines the solution space boundaries set by inequality constraints. Both optimization formulations are solved using linear

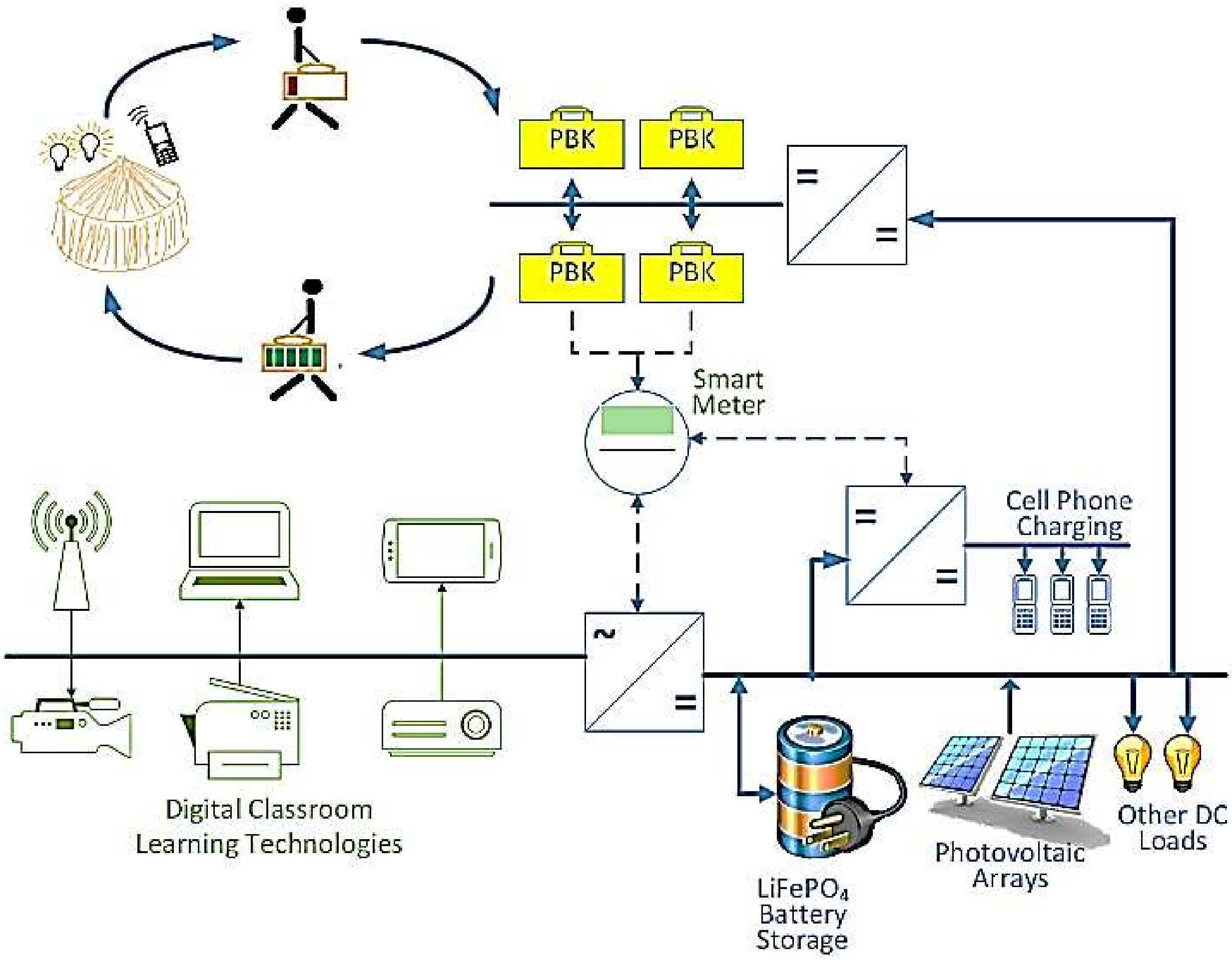


Figure 30: Concept-of-operations of the community center microgrid supplying PBK charging, cell phone charging, and AC digital classroom loads. Residents rent a fully charged PBK from a community center, power DC appliances, and return the PBK when it is discharged.

programming. The rest of the paper is organized as follows: Section 5.3 examines a case study of Madan Community in Papua New Guinea (PNG); sections 5.4, 5.5, and 5.6 define the load modeling, optimization problem, and solution techniques; section 5.7 presents the optimization re1sults for both optimization objectives.

5.2. Case Study: Papua New Guinea

Located 200 km north of Australia, Papua New Guinea has 7.46 million residents, of whom 80% live in rural subsistence-level conditions and 40% on less than a US dollar a day. With the highest child and infant mortality rate in the Pacific and an adult literacy rate of 58%, development throughout rural PNG is stymied by the absence of critical infrastructure, including electricity (90% of the population lacks reliable access), water and sanitation (68% lacks access), and internet (97% lacks access) [63].

Community-based initiatives stand out as the most viable solution to stable community growth and creation of critical infrastructure. A case in point is the Madan Community in Jiwaka Province (lat. -5.807°, long. 144.402°), where a series of community microgrids are being built by a project involving tribal leaders, Transform International, IEEE Smart Village, The Rotary Foundation, Na Wokabaut, and Highlands Arabicas Ltd (a social business operating the Madan Coffee Mill).

The project builds upon the success of a previous initiative [186] that constructed a community rainwater system supplying over a million liters of clean water a year. In spring and summer of 2017, a series of pilot microgrids (depicted in Figure 31) will be established at three Rotary community centers in Madan and Kuri villages, eight primary schools, and the Madan Medical Clinic, which serves 10000 patient visits and provides 5000 vaccinations a year.

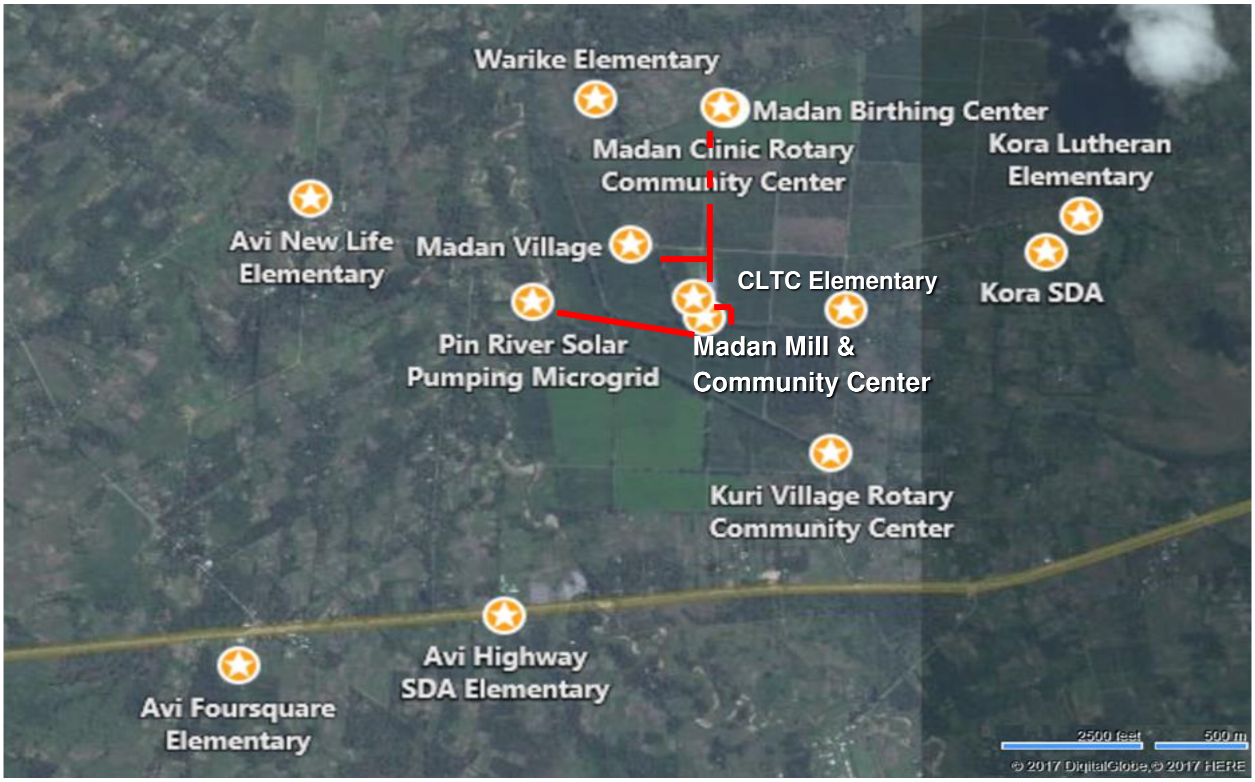


Figure 31: Map of the Madan community and pilot community microgrid installations at three community centers and eight primary schools. Also depicted is the multi-microgrid interconnecting the Madan Mill, Village, Medical Clinic, community intranet base station, and Pin River solar pump.

The project will also construct a multi-microgrid interconnecting five microgrids operating in both grid-connected and islanded modes. The resulting power system comprises the Madan Coffee mill (25 kW PV, 90 kW diesel), Madan Village (5 kW PV), community intranet base station (5 kW PV), Pin River water pump (10 kW PV), and a point of common coupling to PNG power grid. By interconnecting the individual microgrids [63], the power system achieves greater reliability, reduces capacity requirements, shares peak loads, and enables more economic operations.

The first set of demonstration projects at the Kuri Rotary Community Center and Madan Medical Clinic use the IEEE Smart Village Sunblazer topology and operational structure, which is shown in Figure 30. The system can be divided into a 0.5 kW AC section powering a digital classroom for use by community workshops and empowerment programs, a 24 V DC bus for PV and BESS units, and two lower voltage (14 V and 5V) connected by DC-DC converters for charging of cell phones and 12 V portable battery kits (PBK).

Throughout Jiwaka Province, the majority of the population lives in small groups of huts built from grass or bush materials and are frequently scattered beyond the practical service range of a microgrid using traditional power distribution technologies. Additionally, above ground distribution lines frequently become the target of power tapping, while underground cables in other Papua New Guinea projects have failed due to ants eating the PVC insulation [187]. Consequently, electrification of homes is to be accomplished by means of portable battery kits (PBK) developed by IEEE Smart Village, thereby bypassing the challenges of wired distribution lines. A small PBK with a capacity of 120 Wh is shown in Fig 29(b) on the first page and can support LED lighting and charging of small electronics of a single household for a few days.

PBKs are rented on a monthly basis by the community micro-utility to local women entrepreneurs who are trained to become energy traders and resell the electrical energy throughout their communities. Micro-utilities are established throughout the region on a franchise system and use the generated revenues to expand their services to additional communities and fund maintenance and operation of the system. Using this model, the project is anticipated to reach at least 200000 customers in Jiwaka Province and possibly up to a million people throughout PNG.

5.3.Load Modeling

5.3.1. PBK Charging:

12 V lithium-iron-phosphate ($LiFePO_4$) batteries with 25 Ah capacity are chosen for use in the PBK system for home electrification. With an energy density of up to 130 Wh/kg and long life cycle (up to 80% of original capacity after 4500 cycles [188]), a typical PBK would weigh less than 3 kg and provide a service lifetime of at least 15 years.

The charging profile of LiFePO4 batteries typically comprises two constant-current periods followed by a short constant-voltage period to allow the battery to cool, [188] [189], as shown in Figure 32.

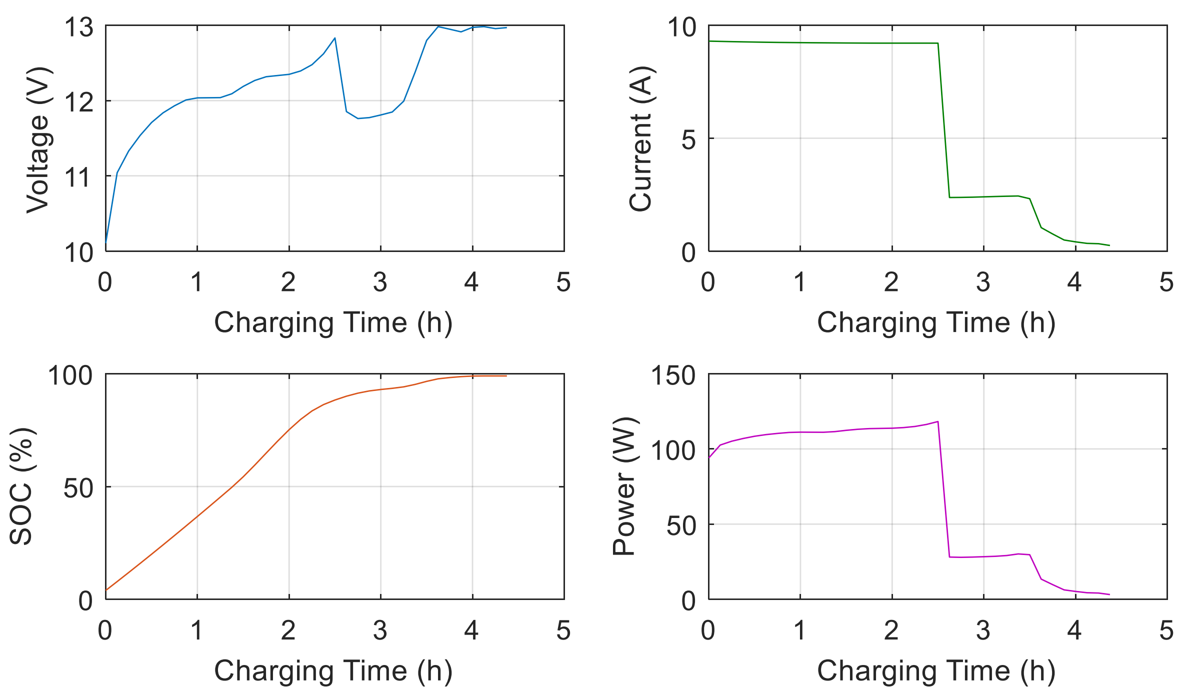


Figure 32: Charging profile of a 12 V, 25 Ah $LiFePO_4$ portable battery with two constant-current and one constant-voltage components.

The power required for PBK charging is obtained by combining the load profile of an individual battery (shown in Figure 32(d)) with the anticipated arrival profile. The frequency distribution of PBK arrivals is modeled by two normal distributions centered at 08:00 and 17:00 whose areas sum to one fourth the number of PBKs currently rented by the micro-utility. The resultant load profile is shown in Figure 26 as a function of number of PBKs charged per day and the time.

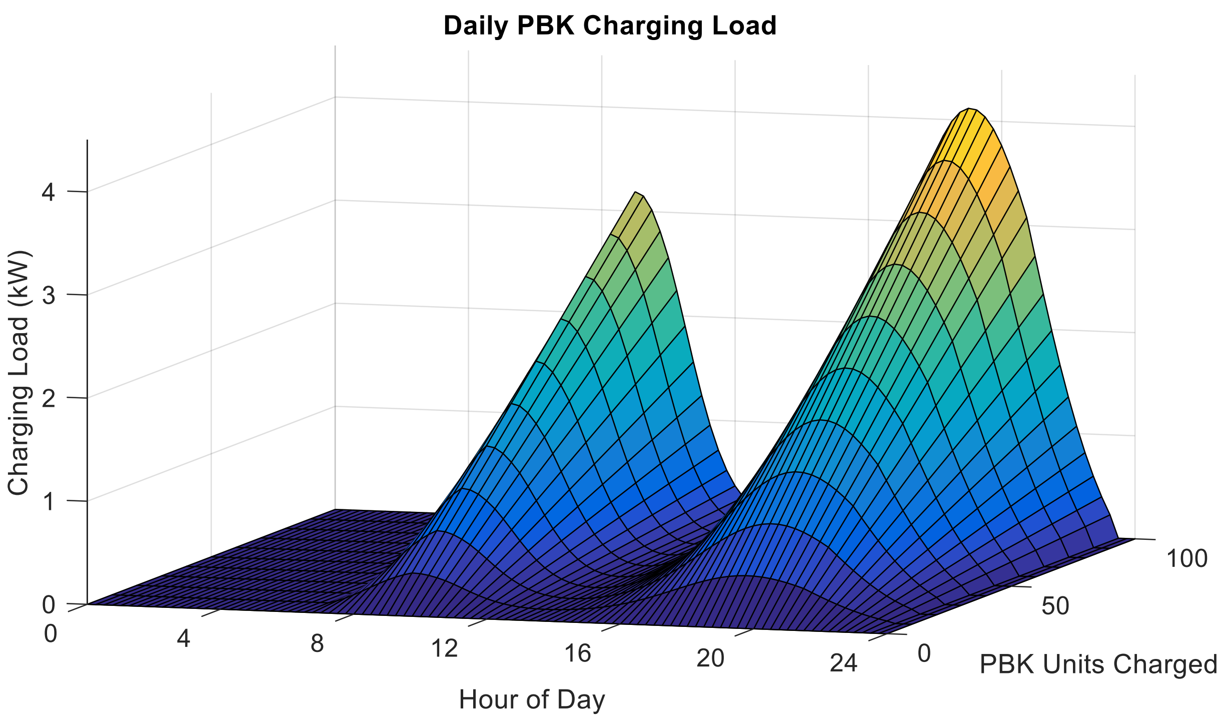


Figure 33: Charging profile of PBKs over a typical load cycle as a function of the number of batteries brought per day.

5.3.2. Cell phone charging:

Cell phones charged at the community center have a charging profile similar to that of the PBKs, but a capacity of only 1.5 Ah (or 5.5 Wh at 3.7 V). The community center will charge 30 to 50 cell phones per day.

5.3.3. AC digital classroom loads:

Equipment included in each digital classroom include 200W of LED lighting, a 30W laptop computer, 200W LED projector, 50W printer, 5W Ligowave DLB-5 WiFi long distance (WiLD) radio receiver, 5W local WiFi router, and 30 android tablet computers. The three load profile components and resulting total AC and DC load are shown in Figure 34.

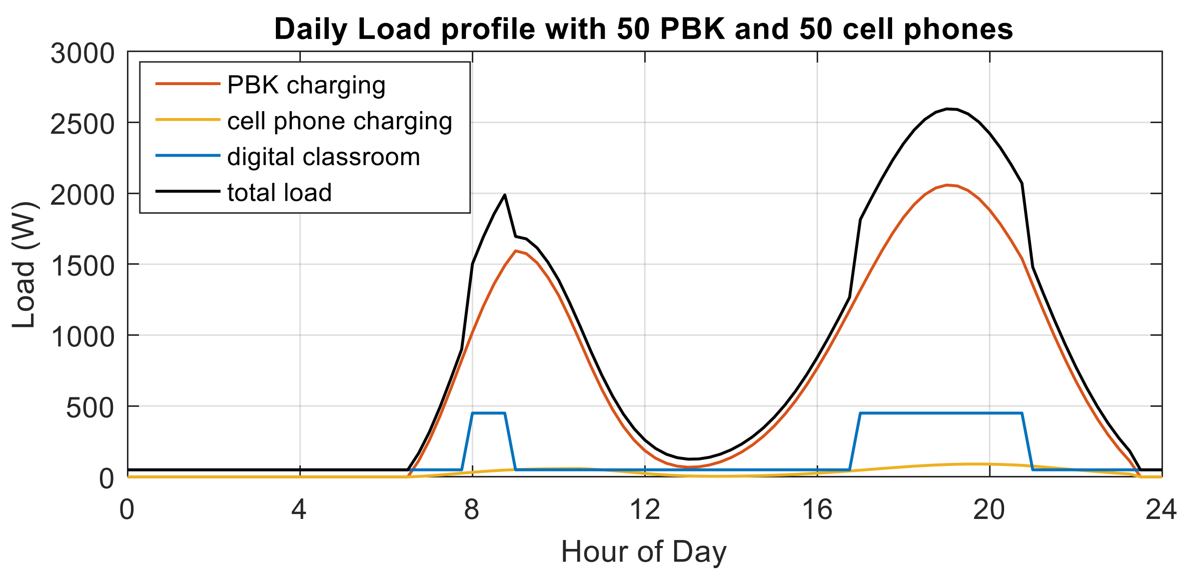


Figure 34: PBK charging, cell phone charging, AC digital classroom, and resultant total load profiles over a typical daily cycle.

5.4.Optimization Problem Formulation

5.4.1. Maximization of Operational Profit

The first optimization formulation focuses on maximization of profit obtained from providing electric services. This is formulated as the revenue obtained from energy sales less the costs of photovoltaics, energy storage, and lost load due to insufficient capacity. In the PNG case study, revenue sources are PBK charging, cell phone charging, and digital classroom power, which are each billed at different rates.

Constraints on operation of the power system include power balance, limits of power dispatched from or absorbed by the energy storage; power flow through DC-AC and DC-DC converters; SOC of the ESS; and network voltages. Line flow constraints are neglected in this optimization since the microgrid is spatially contained within the community center, and wire harness design is based on the maximum expected current draw of all loads. Since the topology does not include any backup thermal generation, an additional constraint is added such that at the end of a load cycle, the final ESS SOC is at least 95% of the initial SOC:

$$max\colon \sum_{t=t_{start}}^{t_{end}} \Big(F_{ph}(P_{ph}) + F_{pbk}(P_{pbk}) + F_{cl}(P_{cl})\Big) - \big(F_{PV}(P_{PV}) + F_{ESS}(P_{ESS})\big) - F_{ll}(P_{ll}) \qquad (1)$$

$$subject\ to\colon \quad P_{PV} + P_{ESS} = P_{load} + P_{loss} \qquad (2a)$$

$$I_{ESS,min} \le I_{ESS,chrg} \le I_{ESS,max} \qquad (2b)$$

$$I_{ESS,min} \le I_{ESS,dsg} \le I_{ESS,max} \qquad (2c)$$

$$P_{conv,min} \le P_{load} \le P_{conv,max} \qquad (2d)$$

$$SOC_{min} \leq SOC \leq SOC_{max} \tag{2e}$$

$$SOC(t_{end}) \geq 0.95\, SOC(t_{start}) \tag{2f}$$

$$V_{min} \leq V_{ESS} \leq V_{max} \tag{2g}$$

The energy cost of PV and ESS are expressed as a variable rate depending on the capital recovery cost (F_{cr}), power balance, and ESS SOC:

$$F_{PV,ESS} = F_{cr}\left(\frac{200}{SOC + 100}\right)\left(\frac{\sum P_{load} + P_{base}}{P_{PV} + P_{base}}\right) P_{PV,ESS}\,, \tag{3}$$

where P_{base} is the system base kVA value and is included to scale the energy price to the capital recovery cost when load and generation are equal or zero.

F_{cr} is expressed as the quotient of the annualized capital cost and actual annual energy production or actual energy cycled through the ESS during a load cycle:

$$F_{cr,PV} = \frac{capital\ cost}{(actual\ annual\ kWh)}\,\frac{r(1+r)^n}{(1+r)^n - 1} \tag{4}$$

$$F_{cr,ESS} = \frac{capital\ cost}{(total\ kWh\ cycled)}\,\frac{r(1+r)^n}{(1+r)^n - 1}\,, \tag{5}$$

where r and n are the depreciation rate and desired payback period of the system. The behavior of the energy cost formulation is summarized in Table 16 below.

Table 16: Energy price characteristics

Change in Microgrid Environment	**Impact on Optimization Parameters**	
	Available Energy	Energy Cost
PV Generation	*Increases*	*Decreases*
Load	*Decreases*	*Increases*
ESS SOC	*Increases*	*Decreases*

5.4.2. Minimization of Installation Cost

The next objective to be examined is minimization of the installation cost of the system, which is expressed as the sum of the installed costs of PV, energy storage, and miscellaneous equipment including regulators, inverters, and other controllers, subject to the same constraints as the first optimization formulation, listed in (2a) - (2g):

$$\text{minimize: } F_{PV}(Q_{PV}) + F_{ESS}(Q_{ESS}) + F_{misc} + F_{Install}\,, \tag{6}$$

where the costs of generation and storage are assumed to be linear functions of the installed capacity Q_{PV} and Q_{ESS}:

$$F_{PV}(Q_{PV}) = F_{pu} \cdot Q_{PV} + F_{ship} \tag{7}$$

$$F_{ESS}(Q_{ESS}) = F_{pu} \cdot Q_{ESS} + F_{ship}. \tag{8}$$

5.5. Solution Technique

A simple steady-state simulator is used to model the behavior of each system configuration and determine the time-varying pricing of energy from PV and ESS. The structure of the simulator is outlined in the flowchart depicted in Figure 35.

Photovoltaic generation is treated as a non-dispatchable unit whose output is proportional to the solar irradiation. For the PNG case study, seasonal variations are negligible due to the country's near equatorial location. The average daily insolation is 4.5 kWh/m^2/day throughout the year.

The power flow through the ESS is determined from the power balance equality constraint (2a) to determine the current and power absorbed by or dispatched from the ESS:

$$i_{ESS} = \frac{1}{V_{ESS}}\left(P_{PV} - P_{loss} - \sum P_{load}\right), \tag{9}$$

where positive current represents charging of the ESS, and negative current represents discharging. Subsequently, the SOC is determined recursively by

$$SOC(t + \Delta t) = SOC(t) + \frac{i_{ESS}\,\Delta t}{Q_{ESS}} \tag{10}$$

If the ESS is fully drained, the SOC is set at zero, and the lost load is calculated as the difference between the total load and the power supplied by the PV and ESS. Similarly, if the ESS is fully charged, the SOC is set at its maximum value of 100, and the curtailed PV generation is determined.

At the end of the simulation period, the SOC and current over the time period are examined for violations of the inequality constraints (2b) – (2f) were violated during the load cycle. If not, the two objective function are calculated using (1) and (6) using the actual amount of solar generation dispatched and energy cycled through the ESS, as determined by the simulation.

The simulation results for a sample configuration charging 50 PBKs and 50 cell phones a day with a 4kW photovoltaic array is depicted in Figure 36. For ESS capacities less than 2 kWh, the microgrid enters periods of generation curtailment and load shedding, which is seen as the vertical surfaces in subplots a), c), and d). The effect of low SOC values corresponds to spikes in the time-varying pricing of energy

The process is repeated for each configuration of PV and ESS capacities under evaluation.

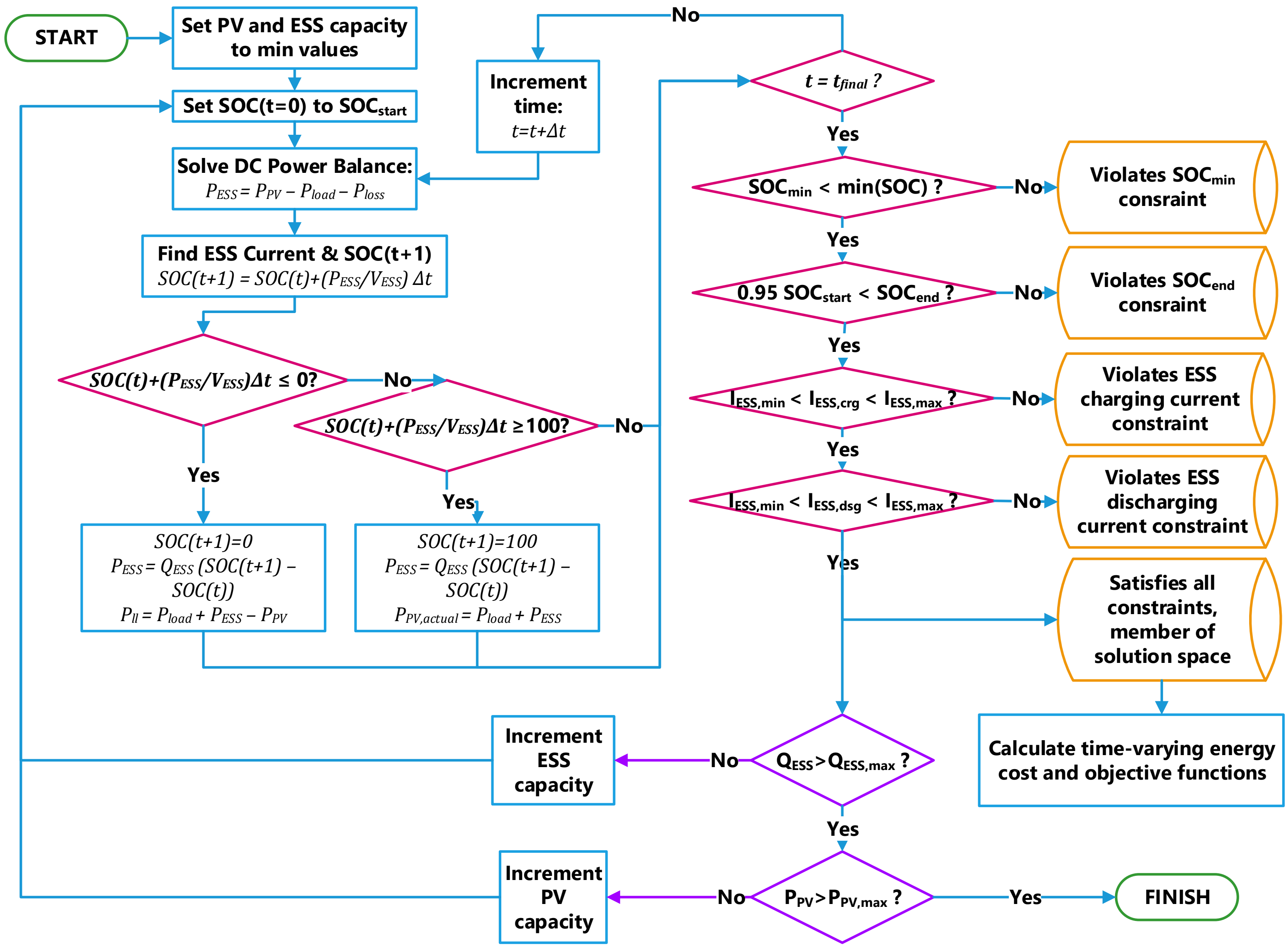


Figure 35: Simulation algorithm for evaluating the performance of different microgrid configurations and determining the boundaries on the solution set by the inequality constraints of the ESS state-of-charge and current limitations

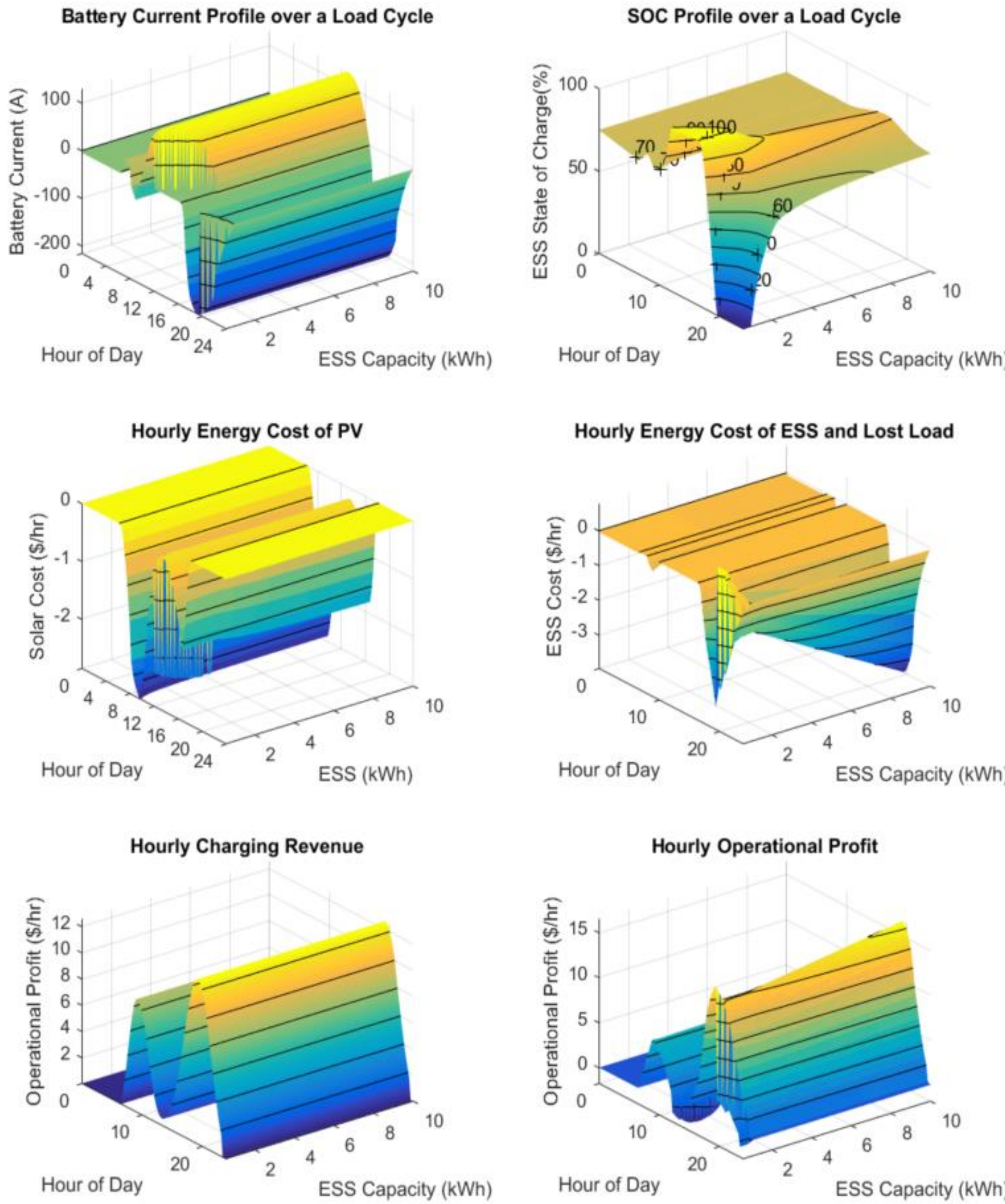


Figure 36: Simulation results for microgrid configurations with 4kW of PV Capacity: a) battery current, b) state-of-charge, c) energy cost of photovoltaics, d) energy cost of ESS and lost load, e) revenue derived from charging services, and f) resultant operational profit. Note areas of photovoltaic and load curtailment between hours for ESS capacities

.

As can be seen from plots of the two objective functions shown in Figures 37 and 38, the operational profit given by (1) and installation cost given by (6) demonstrate monotonic behavior with respect to both PV and ESS capacity within the available solution space. As a result, a linear

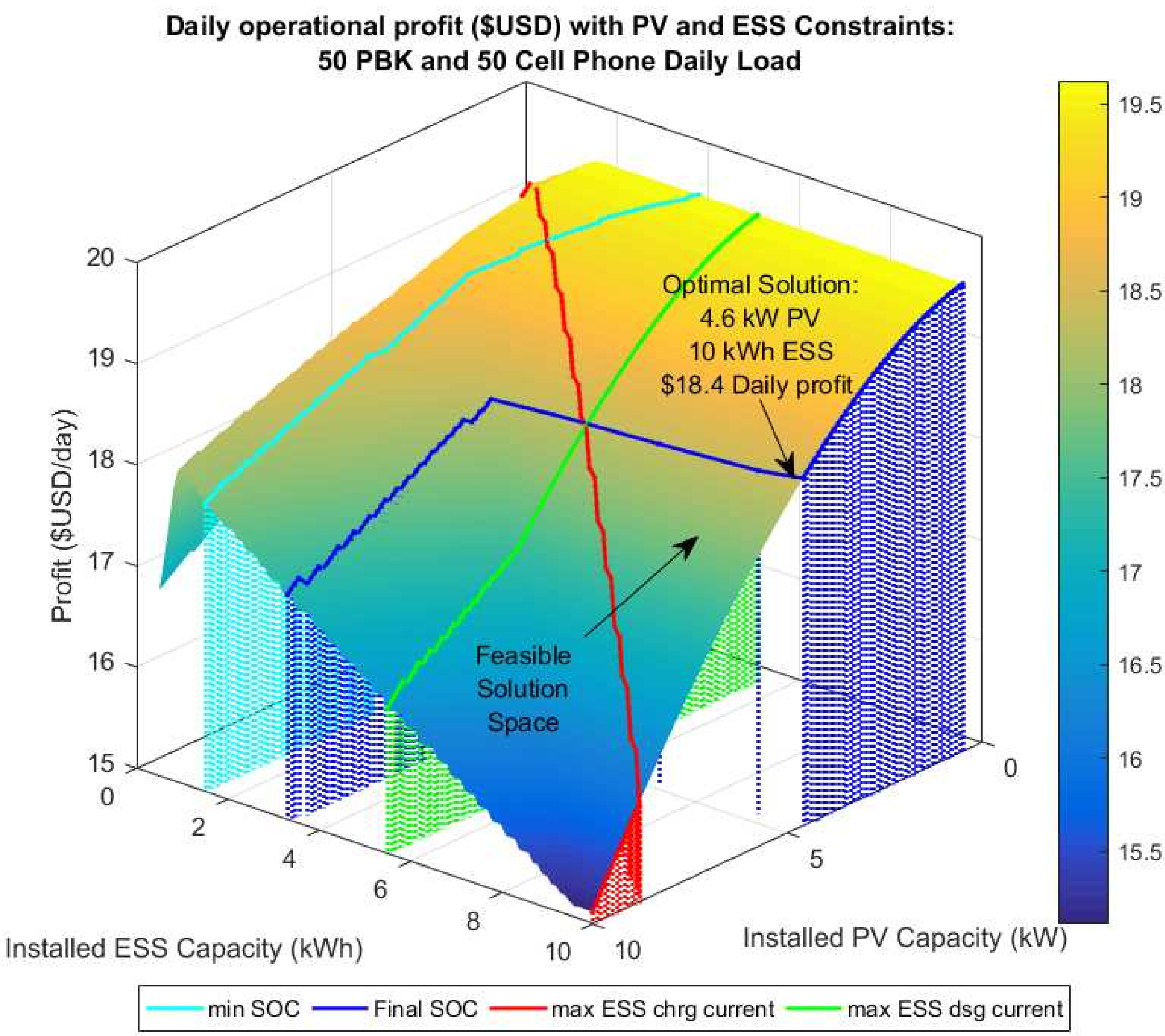


Figure 37: Daily operational profit as a function of installed PV and ESS capacity. For the load profile of 50 PBK and 50 cell phones charged daily, the objective function is maximized by a configuration with 4.6 kW of photovoltaics and 10 kWh of ESS, resulting in a profit of $18.4 per day.

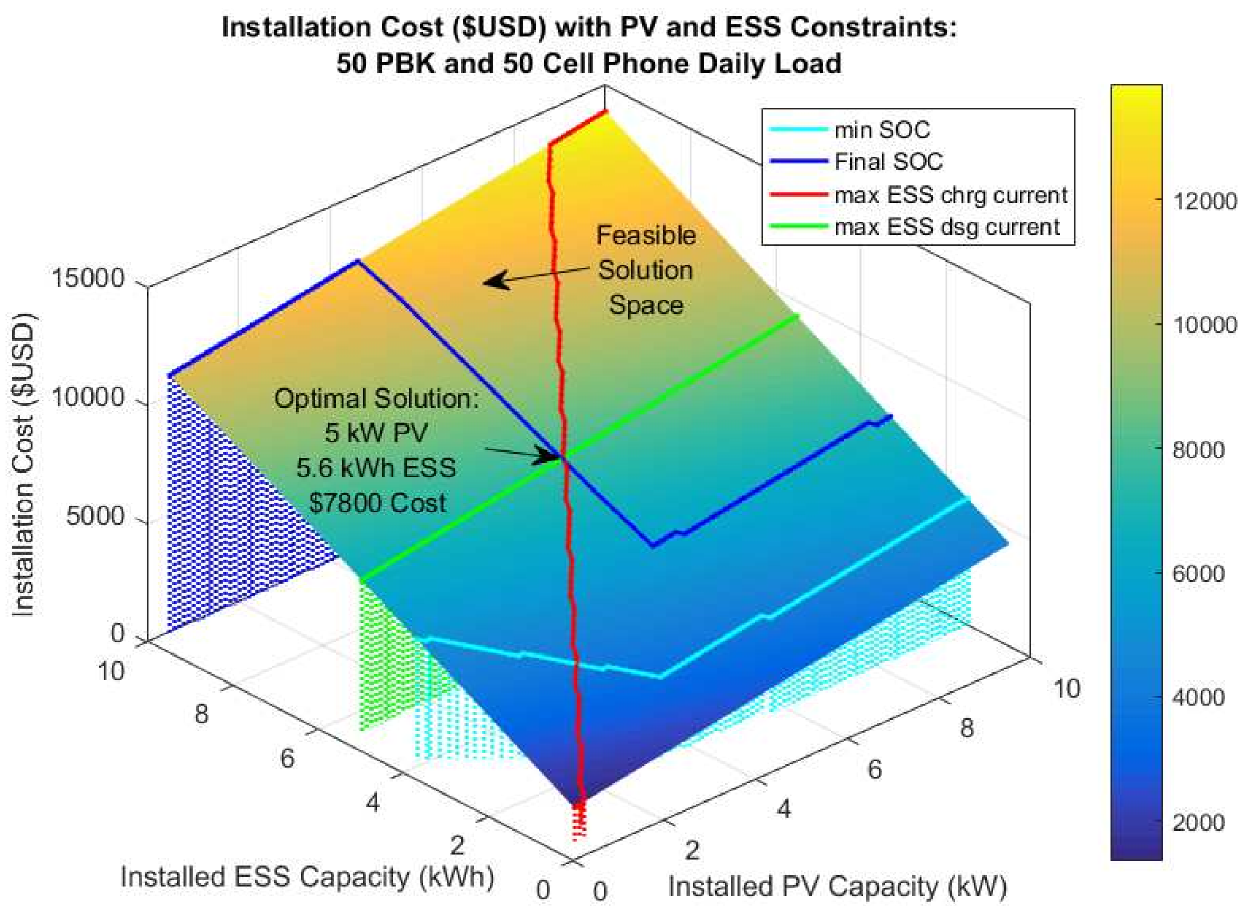


Figure 38: Installation cost as a function of installed PV and ESS capacity. For the load profile of 50 PBK and 50 cell phones charged daily, the objective function is minimized by a configuration with 5 kW of photovoltaics and 5.6 kWh of ESS, with a system cost of $7800 USD.

programming is applied to determine the optimum capacity configuration. The simulation algorithm determines the intersections of the solution space boundaries set by constraints (2b) – (2g). Both objective functions are then evaluated for each PV and ESS configuration corresponding to a corner of the solution space for which no constraint violations occur. The objective function values are compared by a sorting algorithm to yield the solution that maximizes (1) or minimizes (6).

5.6. *Optimization Results*

5.6.1. *Maximization of Operational Profit*

The hourly operational cost of each configuration is summed to produce the first objective function given by (1), which is plotted as a function of the installed PV and ESS capacities. The objective is observed to increase monotonically with decreasing PV and increasing ESS values. This behavior is attributed to the inverse relation between SOC and cost of PV and ESS energy, which causes the algorithm to associate higher ESS capacities with greater operational profits. For the community centers examined in the PNG case study charging 50 PBK and 50 cell phones a day, the operational profit for the possible configurations is plotted in Figure 37 as a function of the installed PV and ESS capacity, along with the boundary constraints set by the SOC and ESS current inequality constraints (2b) – (2g). For the studied scenario, the operational profit is maximized by a system to a value of $18.4 USD / day with 4.6 kW of PV generation and 10 kWh of battery storage.

5.6.2. *Minimization of Installation Cost*

Optimization results for the three community microgrids of the case study for loads ranging from 50 to 100 PBKs per day are presented in Table 17.

Table 17: Optimization results for varying system load sizes

Daily PBKs	Optimized Microgrid Configuration		
	PV Capacity (kW)	ESS Capacity (kWh)	Installation Cost ($USD)
50	5.0	5.6	7800
60	5.7	6.5	9000
70	6.5	7.4	10100
80	7.3	8.2	11200
90	8.0	9.0	12200
100	8.8	9.9	13400

5.7.Conclusion

A method for optimization of generation and storage capacity for planning of small microgrids using the IEEE Smart Village topology is developed. Two objectives of maximization of operational profit and minimization of installation cost, of the microgrid are solved by linear programming. The developed techniques were applied to determine the optimum configuration of a pair of community microgrids in the Madan Community of Papua New Guinea.

Areas of future work include expansion of the algorithm to include additional types of generation such as wind energy, quantitative measures of system reliability, and expansion of the developed algorithm into an optimal power flow formulation with interconnection of multiple community microgrids into a hybrid AC-DC distribution network.

CHAPTER 6

A SMARTER APPROACH TO MICROGRID PLANNING

An optimization framework for microgrid planning based on discrete multi-criteria decision making is proposed using the simple multi-attribute rating technique exploiting ranks (SMARTER) technique. The approach offers greater flexibility in formulating numerical optimization of generation and energy storage capacity, and discrete alternatives of generation mix, controller setpoints, and siting of distributed resources. The proposed technique enables the use of both quantitative and qualitative attributes in planning. The methodology is demonstrated for a simple example and a detailed case study seeking to improve the reliability of a small industrial microgrid in a rural village of Papua New Guinea. Simulations of discrete alternatives are run over a one year horizon, which is then used as input to provide decisions on any set of technical, economic, environmental, or social criteria.

An abridged version of this chapter has been submitted by the researcher for publication in the Journal of Power and Energy Systems and is currently under review.

6.1. Introduction

Since the concept of the microgrid was first proposed by [1], [2], a vast number of optimization tools, techniques, and methodologies have been developed for both planning and dispatch problems. Planning problems examine siting and sizing of new distributed energy resources (DER) and changes to network topology to accomplish various objectives such as minimizing costs, maximizing reliability, or minimizing losses. Dispatch problems seek an optimal schedule of DER in the microgrid to minimize objectives such as costs, emissions, and deviations in voltage and frequency in the network.

The majority of optimization studies in the literature uses a multi-objective formulation seeking to maximize or minimize several objective functions related to costs, reliability, and environmental impact [3]. If all the objectives are formulated to use the same dimensions then a single objective is formed from the sum of each individual objective. Otherwise, conflicts between different objectives must be resolved through pareto-front optimization or multi-criteria decision making (MCDM) techniques [4]. Once formulated, the optimum value of the objective function is found by using optimization solvers such as linear programming, dynamic programming, genetic algorithm, and swarm optimization; some reviews of optimization solvers are given in [5] – [7].

This paper presents an alternative to traditional optimization approaches that is based on a nine-step process focused on stakeholder engagement and maximization of technical, economic, environmental, and social benefits. Based on the simple multi-attribute rating technique (SMART), the methodology used here – simple multi-attribute rating technique exploiting ranks (SMARTER) – is computationally lightweight and scales linearly with the size of the solution space and number of decision criteria. By redefining the optimization functions into elicited attributes and converting the multi-dimensional solution space into a vector of discrete attributes, we can combine multiple conflicting optimization objectives, and include both qualitative and quantitative indicators of the importance of various benefits to key stakeholders and the decision maker.

The rest of this paper is organized as follows: Section 6.2 introduces multi-attribute utility theory (MAUT). Section 6.3 introduces the SMARTER framework for microgrid planning and demonstrates the nine-step process with a simple example. Section 6.4 outlines the numerical case study. Section 6.5 integrates the SMARTER methodology with simulation output to provide rapid decision-making capabilities for any number of technical, economic, environmental, and social objectives. Section 6.6 concludes.

6.2. Multi-Attribute Utility Theory

Originating from game theory and economic theory, utility theory is based on the concept of a *utility function* that expresses the value of an alternative among a set of choices. The decision-maker(s) use their preference ranking to select an optimum with the maximum *utility* among the list of available alternatives. Utility functions are non-dimensional expressions with values ranging from either zero to one or zero to 100, reflecting the extent to which the alternative satisfies the decision-maker's preference for the corresponding decision criterion [8]. The utility function is also able to indicate the decision-maker's tolerance of risk: concave functions indicate risk aversion, convex functions indicate a preference for risk, and linear functions indicate neutral risk [9].

MAUT combines multiple utility functions using either a weighted sum or product to yield the *overall utility*. The alternative with the highest overall utility is then selected. However, MAUT is seldom applied directly to microgrid optimization problems due to the complexity of formulating utility functions and computing scaling constants. Instead, it is typically used as a basis for formulation of other approaches, such as the analytical hierarchy process (AHP) and SMARTER

6.3.Simple Multi-Attribute Rating Technique

SMART was developed in the 1970s to address the formulation difficulties of MAUT and uses linear approximations of utility functions and an additive aggregation model to calculate the overall utility of each alternative as the weighted sum of utility values [10] – [12]. Shortly afterwards, the concept of swing weights was introduced to correct a conceptual error in the original SMART framework, which failed to recognize the impact of the range of values on the meaningfulness of the utility function [13]. Subsequently, justifiable rank weights were developed to yield the SMARTER process, which removed the burden of determining weighting factors from the decision maker [13].

6.3.1. Prior SMART Formulations for Power Systems Problems

Despite its simplicity and ability to consider both technical and socio-economic objectives, SMART has been used by surprisingly few studies of power system optimization.

Reference [14] applies SMARTER to determine an optimal demand response (DR) strategy in five cities of northwestern Unites States, with a goal of minimizing thermal discomfort, energy cost, emissions, user inconvenience, and equipment degradation. The study also observed that SMARTER achieved elicitation of user preferences faster and more accurately than AHP or a discrete choice experiment (DCE) [15].

Reference [12] examines generation mix study considering hydro, photovoltaics (PV), wind, biogas, fuel cell, geothermal, and wave energy with respect to 15 attributes covering technical, economic, environmental, and social parameters.

References [16] and [17] optimize the capacity of grid-tied wind and solar generation for 11 possible configurations. The alternatives are evaluated against the criteria of loss of power supply probability (LPSP), capacity factor, emissions, share of renewables, installation cost, maintenance cost, land use, and social acceptance.

Reference [18] resolves equipment overloads for a distribution system in Kenya while considering capacity constraints, reliability, losses, and environmental impact.

6.3.2. Implementation of the SMARTER Process

As can be seen from the scope of the literature using SMARTER, a systematic framework for applying this technique to microgrid planning has not yet been developed. This section will expand the original nine-step SMARTER decision process with a simple technique for converting microgrid optimization problems into an MCDM formulation integrating all the objectives, constraints, and solution variables selected by the decision-maker. To help illustrate each of the steps in the process, a running example will be used throughout this section. The example will use a subset of the solution space, simulation results, and decision criteria for the case study to be discussed in detail in Section 6.4.

6.3.2.1. Identification of decision makers and their goals

The first step is identification of the purpose of the decision making process (*value elicitation*) and key stakeholders (*elicitees*) involved in the decision process. An explicit and exhaustive list of elicitees is essential for generating a satisfactory list of decision criteria. For the purpose of creating a general process for microgrid optimization using SMARTER, an exhaustive literature survey was conducted by the authors in [3], [4] to acquire a comprehensive list of decision criteria. Nearly 250 papers on optimization formulations for planning and dispatch of islanded microgrids were surveyed to form an acceptable list of elicitees. We found that optimization studies of islanded microgrids are based on formulations selecting from 16 possible objective functions, 14 constraints, and 13 control variables.

6.3.2.2. Creation of a value tree

The second step is to ask the elicitees to create a list of attributes (*criteria*) that are relevant to them in the decision-making process. A common structure and set of labels must be agreed upon by all elicitees participating in the value elicitation process. The criteria submitted by all the elicitees must then be combined into a single list with all duplicates eliminated and overlapping labels merged. Note that the elicitees are not deciding the ranking between criteria; but are generating a comprehensive list of attributes relevant to the decision.

It is recommended by [13] that the total number of attributes be limited to 12 by combining related attributes, redefining attributes that are too specific, and omitting unimportant attributes. After all attributes are categorized, they are combined into a value tree that depicts all the elicited attributes in a simple graphical format.

In creating the microgrid optimization framework proposed by this paper, the optimization objectives, constraints, solution variables, and decision criteria from the papers surveyed by the authors in [3], [4] were categorized, labeled, and tabulated, as shown in Figures 39 and 40, as well as in the value tree depicted in Figure 41. The authors anticipate that the value tree presented in

Figure 41 will provide a comprehensive set of attributes from which other microgrid designers can select decision criteria for microgrid planning formulations using the SMARTER framework.

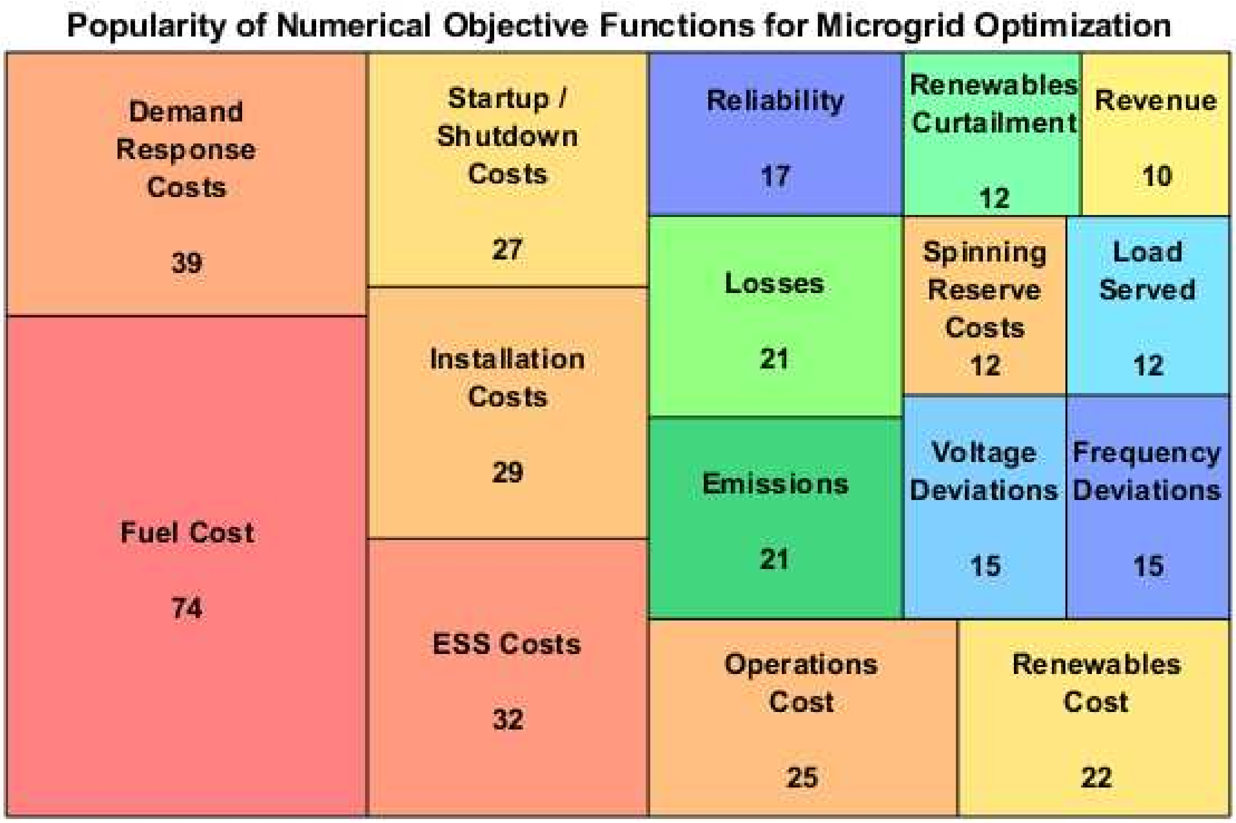


Figure 39: Available objectives and their popularity as observed by [3] in the literature for microgrid optimization

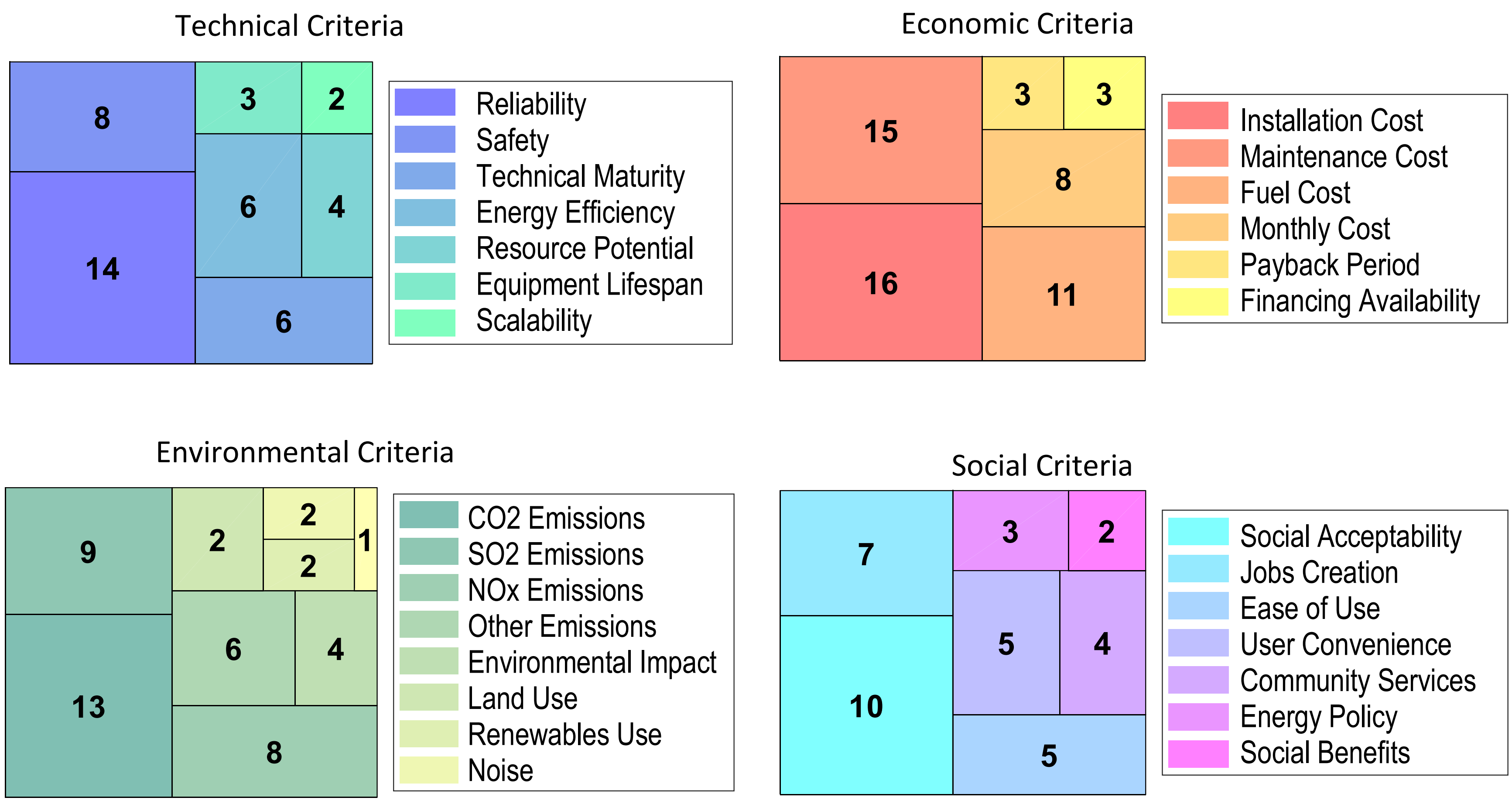


Figure 40: Available technical, economic, environmental, and social criteria and their popularity as observed by the authors in [4] in the literature for microgrid optimization

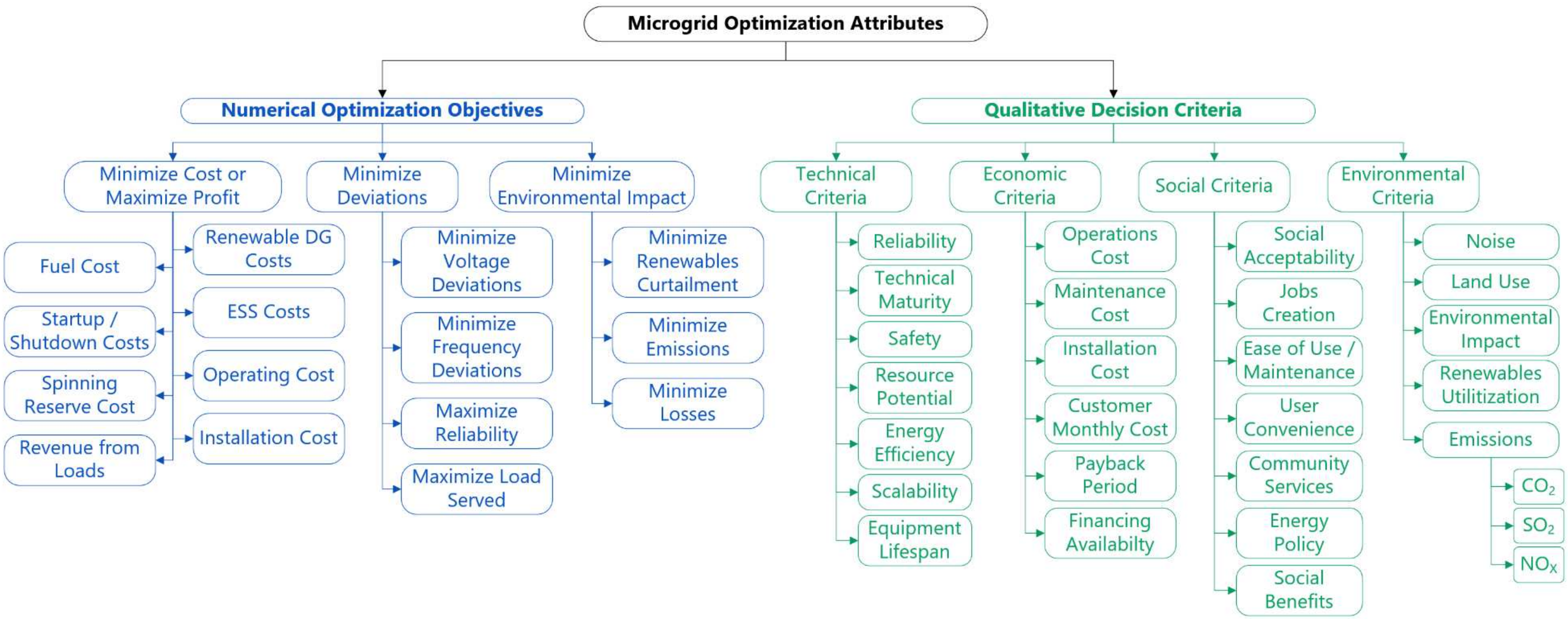


Figure 41: Value tree of microgrid attributes available for use in SMARTER formulations

For the example problem used in this section, five of the available attributes are chosen and presented in Table 18. The formulation and significance of these criteria will be explained in detail during the discussion of the larger case study in Section 6.4 and 6.5.

TABLE 18: SELECTED DECISION CRITERIA FOR THE EXAMPLE PROBLEM

Label	**Category**	**Criterion**	**Dimensions**
C1	Technical	Reliability	MWh not served
C2	Economic	Operations cost	USD
C3	Economic	Installation cost	USD
C4	Environmental	CO2 emissions	tons/yr
C5	Social	Socio-economic benefits	HDI

6.3.2.3.Objects of evaluation

Here we identify the objects of evaluation, i.e. the set of available options from which the decision or solution is chosen. In the case of microgrid optimization, this represents the set of optimization variables and the range of available values for each variable forming the solution space. Each combination of discrete values of the selected solution variables within the solution space represents an alternative.

We observe in [3], [4] that all islanded microgrid formulations use 13 possible optimization variables, which are listed graphically along with their popularity in the literature in Figure 42.

For the simple example problem, three solution variables are chosen: solar generation capacity, energy storage system (ESS) capacity, and usage of existing thermal capacity. A solution space is formed by varying the above variables on the intervals [0, 25, 50 kW], [0, 25, 50 kWh], and [Yes, No], respectively. The solution space is then converted into 15 discrete, feasible alternatives labeled A0 through A14, shown in Table 19, where A0 represents the “do-nothing” option of keeping the existing system without making any changes to the microgrid topology.

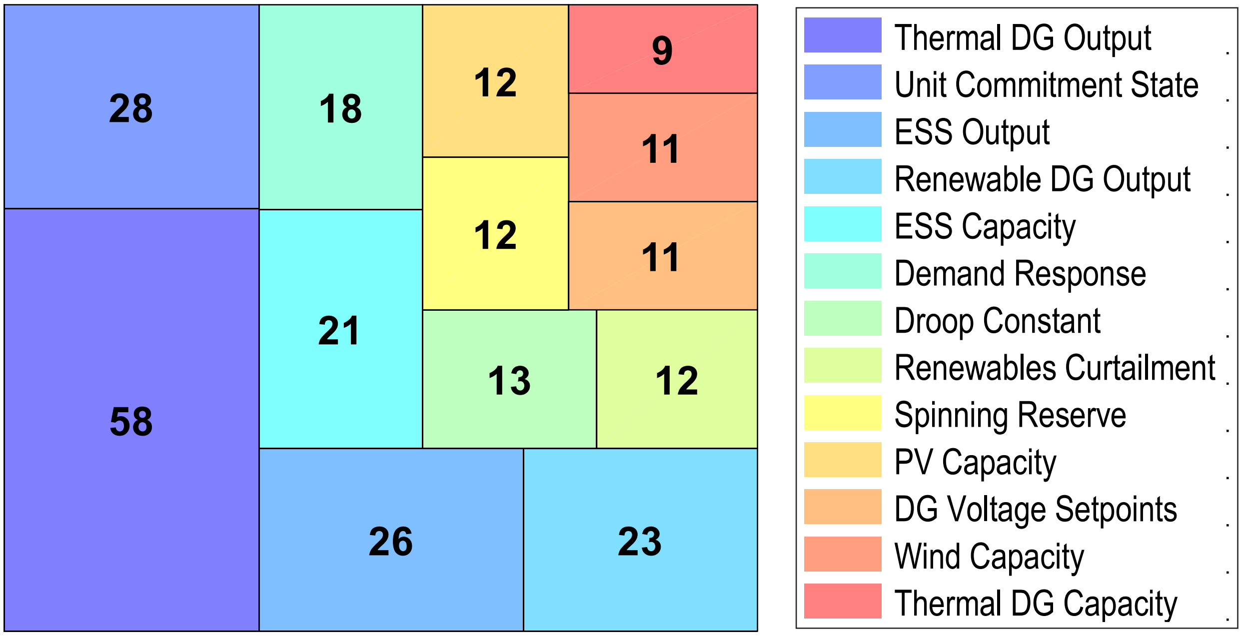


Figure 42: Available objects of evaluation and their popularity as optimization variables as observed by [3] in the literature for microgrid optimization

Table 19: Selected alternatives forming optimization solution space for the example problem

Label	PV Capacity (kW peak)	ESS Capacity (kWh)	Existing Diesel?
A0	0	0	Y
A1	0	25	Y
A2	0	50	Y
A3	0	25	N
A4	0	50	N
A5	25	0	Y
A6	25	25	Y
A7	25	50	Y
A8	25	25	N
A9	25	50	N
A10	50	0	Y
A11	50	25	Y
A12	50	50	Y
A13	50	25	N
A14	50	50	N

6.3.2.4. Objects-by-attributes matrix

The next step is to create a table or matrix whose rows and columns represent the available alternatives and decision criteria, respectively. At this point, a comprehensive set of simulations are performed for each alternative. The physical quantities or attribute scores obtained from simulations are then tabulated to form the objects-by-attributes matrix.

For the example problem, simulations of each microgrid configuration are performed over a one year time period. For the sake of continuity of discussion, the details of the simulation software, load profile, and other numerical details will not be discussed he re, but later in Section 6.5. The direct outputs of the simulation software, including total MWh not served (C1), monthly operating cost (C2), overall installation cost (C3), annual CO2 emissions (C4), and human development index (HDI) (C5) are tabulated in Table 20. The computational method used to obtain each of the physical simulation scores are discussed in Section 6.4.

Table 20: Objects-by-attributes matrix comparing alternatives and decision criteria for the example problem

	C1 (kWh/yr)	C2 (USD)	C3 (USD)	C4 (kg/yr)	C5 (HDI)
A0	3282	21,077	0	33380	0.0000
A1	537	19,076	19,750	20393	0.1816
A2	0	19,128	33,500	16298	0.0908
A3	9962	16,344	-250	0	0.0000
A4	5498	18,361	13,500	0	0.0000
A5	2856	14,628	22,250	24079	0.4678
A6	470	12,626	39,000	12336	0.4227
A7	0	12,780	32,750	9406	0.4100
A8	4967	10,949	19,000	0	0.4041
A9	2117	12,064	32,750	0	0.4041
A10	2605	10,916	41,500	18969	0.5335
A11	347	9,179	55,250	9303	0.5139
A12	0	9,544	69,000	7784	0.5127
A13	3089	7,170	35,250	0	0.5058
A14	1602	7,819	49,000	0	0.5058

6.3.2.5.Elimination of dominated alternatives

Dominated alternatives can often be eliminated by visual inspection. This step is optional since dominated options will be eliminated in course of the subsequent analysis. However, this step is useful if elimination of dominated alternatives reduces the range of one or more evaluation criteria. If the difference between the maximum and minimum values of a criterion is reduced to a small range, then that attribute should be eliminated as well.

Although not a step in the original SMARTER formulation proposed by [13], it is recommended that microgrid planners also use this step to enforce technical constraints on the optimization problem. Alternatives whose simulation results violate any constraint should also be eliminated. A comprehensive list of technical constraints found in microgrid optimization problems is provided in Figure 43.

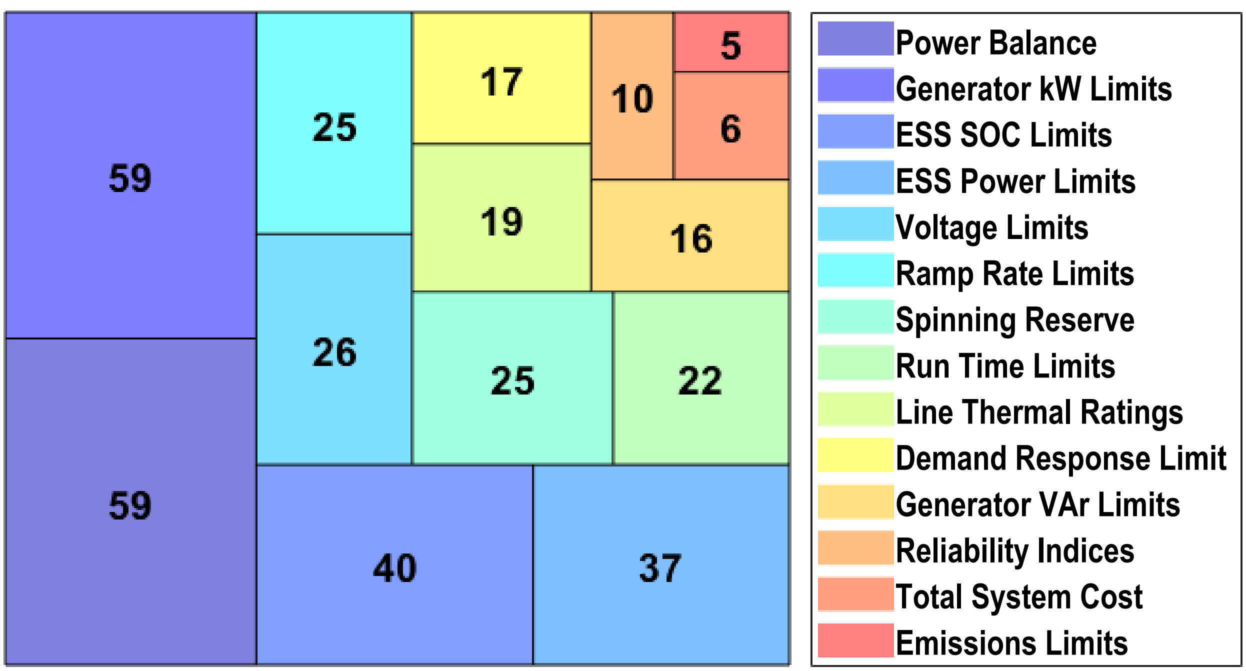


Figure 43: Available constraints and their popularity as observed by [3] in the literature for microgrid optimization

6.3.2.6. Conversion to non-dimensional utilities

The next step is the conversion of the physical measures and scores of each alternative into non-dimensional utility functions. This is performed for each criterion by finding the alternative with the worst score for that single criterion and assigning it a utility of zero. Then, the alternative with the best score for that attribute is assigned a utility of either one or 100. If the decision maker feels that the range of values presented by the alternatives does not correctly represent the best and worst possible alternatives, then it is possible to adjust the bounds of the attribute. The importance of the range of values of the attribute will be discussed further in the next step, which will focus on determining the swing weights for the utility scores determined in the current step. A key assumption is that the relationship between the utility of an attribute and range of scores is linear or at least conditionally monotonic. Specifically, [13] has identified four types of relationships: i) linearly increasing, so that more of an attribute results in a higher utility to the decision-maker; ii) linearly decreasing, so that less of an attribute is better, and the smallest amount possible results in the highest utility; iii) an uncommon situation where a particular value results in the highest utility, and higher or lower amounts of the attribute are less preferable; and iv) strictly judgmental utilities with no underlying single physical variable.

The assumption of linearity is justified for all the attributes listed in the value tree of Figure 41. Moreover, all of the microgrid attributes identified in Figure 41 correspond to the first and second type of relationships listed above, with all optimization formulations seeking to strictly minimize or maximize a particular physical score. For example, the utility function of fuel cost decreases linearly since an alternative with the least fuel consumption has the highest utility, while an alternative with the most fuel consumption has the lowest utility. Likewise, an alternative with the longest equipment lifespan has the highest utility, while an alternative with the shortest equipment lifespan has the lowest utility. A similar analysis can be made for the attributes listed in Figure 41. Note that the discussion of utility linearity only applies to the relationship between one utility function and one criterion or physical attribute, with the values of all other attributes held constant.

The objects-by-attributes matrix presented in Table 20 for the example problem is now converted into non-dimensional utility scores, using the process described above. The resulting in the matrix of utility values is illustrated in Table 21. The utility function values can be best understood by examining alternative A0 (the existing system of a diesel generator with no solar and no battery storage). The five utility scores represent that this alternative lies in the middle of the range of options for reliability (C1), is the worst option for operating cost (C2), is the best option for installation cost (C3), and is the worst option for both the emissions (C4), and is the worst option for and the social benefits (C5).

Table 21: Non-dimensional utility matrix for the example problem

	C1	C2	C3	C4	C5
A0	67.06	0.00	100.00	0.00	0.00
A1	94.61	9.50	71.38	38.91	34.04
A2	100.00	9.25	51.45	51.17	17.02
A3	0.00	22.46	100.00	100.00	0.00
A4	44.81	12.89	80.43	100.00	0.00
A5	71.33	30.60	67.75	27.86	87.68
A6	95.28	40.10	43.48	63.04	79.23
A7	100.00	39.37	52.54	71.82	76.86
A8	50.14	48.05	72.46	100.00	75.75
A9	78.75	42.76	52.54	100.00	75.75
A10	73.85	48.21	39.86	43.17	100.00
A11	96.51	56.45	19.93	72.13	96.34
A12	100.00	54.72	0.00	76.68	96.11
A13	68.99	65.98	48.91	100.00	94.82
A14	83.91	62.90	28.99	100.00	94.82

6.3.2.7.Rank ordering of swing weights

Swing weights are a correction developed in response to a formulation error in the original SMART framework which ignored the relationship between the importance of an attribute and the range of values between alternatives [13]. This intellectual error was resolved by the development of simple multi-attribute rating technique with swing weights (SMARTS) shortly after publication of the original formulation [13].

The term "swing" refers to the process of "swinging" the utility values for each attribute over a range of scores, typically from zero to 100. For the process, a hypothetical alternative is used, which has the worst possible utility for all the criteria. Subsequently, the elicitees are asked to choose a single attribute for which they could swing the utility score from 0 to 100. Next, the respondents are told that they can swing the utility score for any attribute except the one they chose and are asked to select their next preference. The last step is repeated until all the decision criteria have been ranked from most preferred to least preferred for a swing of the utility score of the worst possible alternative. This ranking of preference establishes the basis for determining the swing weights.

For the example of this section, it is determined that for the hypothetical worst possible alternative, swinging reliability to the best available value would yield the best overall utility since the microgrid operator incurs large financial losses during power interruptions. The process is repeated to determine that the ranking of decision criteria from most important to least important is reliability, installation cost, operations cost, social benefits, and emissions.

6.3.2.8.Rank order centroid weighting

The core difference between the SMARTS and SMARTER MCDM techniques is that the former requires the decision-maker to determine the numerical weight given to each decision criteria, while SMARTER presents a framework for assigning weights automatically using the concept of the rank order centroid (ROC).

The convention for weights in any weighted sum formulation is that the sum of all the weights must equal one. The simplest possible method is to assign all the decision criteria equal weights. Consequently, the point representing equal weighting is the centroid of the hyperspace simplex of all weighting variables possible. The SMARTER framework modifies this concept by adding a ranking of importance among the decision criteria. When the geometric coordinate points of the simplex are specified with knowledge of ranking, it is possible to determine the resulting centroid. The resulting weights have a rather convenient computational form. For the series of weights where w_1 corresponds to the highest priority criterion and w_n to the lowest priority criterion, then

$$w_1 = \left(1 + \frac{1}{2} + \frac{1}{3} + \cdots + \frac{1}{n}\right)\left(\frac{1}{n}\right) \tag{11a}$$

$$w_2 = \left(0 + \frac{1}{2} + \frac{1}{3} + \cdots + \frac{1}{n}\right)\left(\frac{1}{n}\right) \tag{11b}$$

$$w_3 = \left(0 + 0 + \frac{1}{3} + \cdots + \frac{1}{n}\right)\left(\frac{1}{n}\right) \tag{11c}$$

$$w_n = \left(0 + 0 + 0 + \cdots + \frac{1}{n}\right)\left(\frac{1}{n}\right) \tag{11d}$$

Multiple numerical studies surveyed by [13] have found that the total loss in overall utility from using ROC weights rather than those determined by manual elicitation is less than 2%.

6.3.2.9.Decision based on highest multi-attribute utility

The last step is calculating the weighted sum of all utility scores multiplied by the associated ROC swing weights to yield the overall multi-attribute utility of each alternative. The alternative with highest overall utility is the best choice. For the short example used in this section, alternative A7 has the highest utility and is selected as the solution best satisfying all five decision criteria.

Table 22: Final multi-attribute utility scores for example problem

Alternative	Multi-attribute Utility Score		Alternative	Multi-attribute Utility Score
A0	56.30		A8	59.85
A1	67.64		A9	66.97
A2	63.90		A10	62.24
A3	33.28		A11	69.59
A4	47.13		A12	65.96
A5	63.77		A13	66.94
A6	70.61		A14	68.15
A7	**75.11**			

6.4.Case Study: An Industrial Microgrid in the Madan Community, Papua New Guinea

Located 300km north of Australia, Papua New Guinea (PNG) is largely unelectrified with a population of over 8.1 million but only 580 MW of generation capacity from three islanded transmission networks and 19 diesel microgrids [19]. Over 90% of the country has no access to any form of electricity, and consequently, the majority of communities subside on kerosene, candles, fuelwood, and disposable batteries to supply their energy needs. For the few customers with access to the national grid, blackouts can last for weeks due to generation capacity shortages and transmission-related events.

The Western Highlands province is one of the few partially electrified provinces with a population of over 440,000 and 6,175 customers served by a 66kV transmission line running along the Highlands Highway [19]. About 20 km east of the provincial capital of Mt. Hagen is the Madan Community, which has been the center of a multi-year capacity building and social empowerment program, funded in part by profits from the Madan Community Coffee Mill. In the past five years, the project has focused on creation of community infrastructure, including digital classrooms in 10 schools, safe sanitation systems, a medical clinic serving over 10,000 patient visits per year, and construction of a rainwater harvesting and distribution system providing over a million liters of clean water annually.

The Madan Community Coffee Mill processes the coffee grown in the Madan Community and by small-holder farmers in neighboring villages. The mill contains a series of large three phase, delta-connected machines that are grouped into a wet mill (pulping the fresh coffee cherries to extract the beans inside), a dry mill (hulling, sorting, and bagging the dry coffee beans), and a water pump in the pin river that supplies water for the wet mill and serves a backup source for the new community water system during times of drought. The mill and pump are located near the Highlands Highway and have access to the PNG national grid. However, operation of the mill equipment and river pump are severely disrupted by frequent power interruptions and prolonged blackouts. A 90kW diesel backup generator was installed, but fuel shortages result in frequent spoilage of the coffee cherries. As a result, a concept was developed to convert the mill into an industrial microgrid supplied by a mix of grid power, local PV arrays, battery storage, and diesel generation [20].

6.4.1. *Modeling of Demand Profile*

Since the only available data from which the model is to be constructed are the electric bills and diesel fuel expenditures over the course of the year 2014 [21], it will be necessary to interpolate and extrapolate this data to create the demand profile. Data from 2015 is excluded from the analysis due to a record drought that ruined the year's harvest and caused extensive failures of the power grid.

Table 23: Grid energy consumption of Madan in 2014 [20]

Date	Days in Billing Cycle	Bill (Kina)	Daily Cost (Kina/day)	Daily Energy Use (kWh/day)
01/28/14	56	3200	57.14	87.91
02/25/14	28	1548	55.29	85.05
03/25/14	28	1632	58.29	89.67
04/22/14	28	3426	122.36	188.24
07/14/14	76	7688	101.16	155.63
09/09/14	64	1943	30.36	46.71
10/07/14	28	2791	99.68	153.35
10/21/14	14	1314	93.86	144.40
12/02/14	42	2193	52.21	80.33
01/13/15	42	2271	54.07	83.19

Table 24: Diesel consumption of Madan, 2014 [20]

Date	Days in Billing Cycle	Bill (Kina)	Daily Cost (Kina/day)	Daily Fuel Use (L/day)	Daily Energy Use (kWh/day)
01/14/14	28	3400	121.43	50.60	202.38
02/11/14	28	3400	121.43	50.60	202.38
03/11/14	28	3420	122.14	50.89	203.57
04/22/14	28	4230	151.07	62.95	251.79
05/06/14	28	4960	177.14	73.81	295.24
06/17/14	42	3888	92.57	38.57	154.29
09/09/14	84	3500	41.67	17.36	69.44
12/02/14	84	3987	47.46	19.78	79.11

Tables 23 and 24 summarize the total expenditure on grid energy and diesel fuel over a year. These costs are used to create an estimated monthly load profile by converting the billed costs to daily costs, which are then modeled by spline interpolation, and finally summed and converted to monthly averages. The process is depicted graphically in Figure 44.

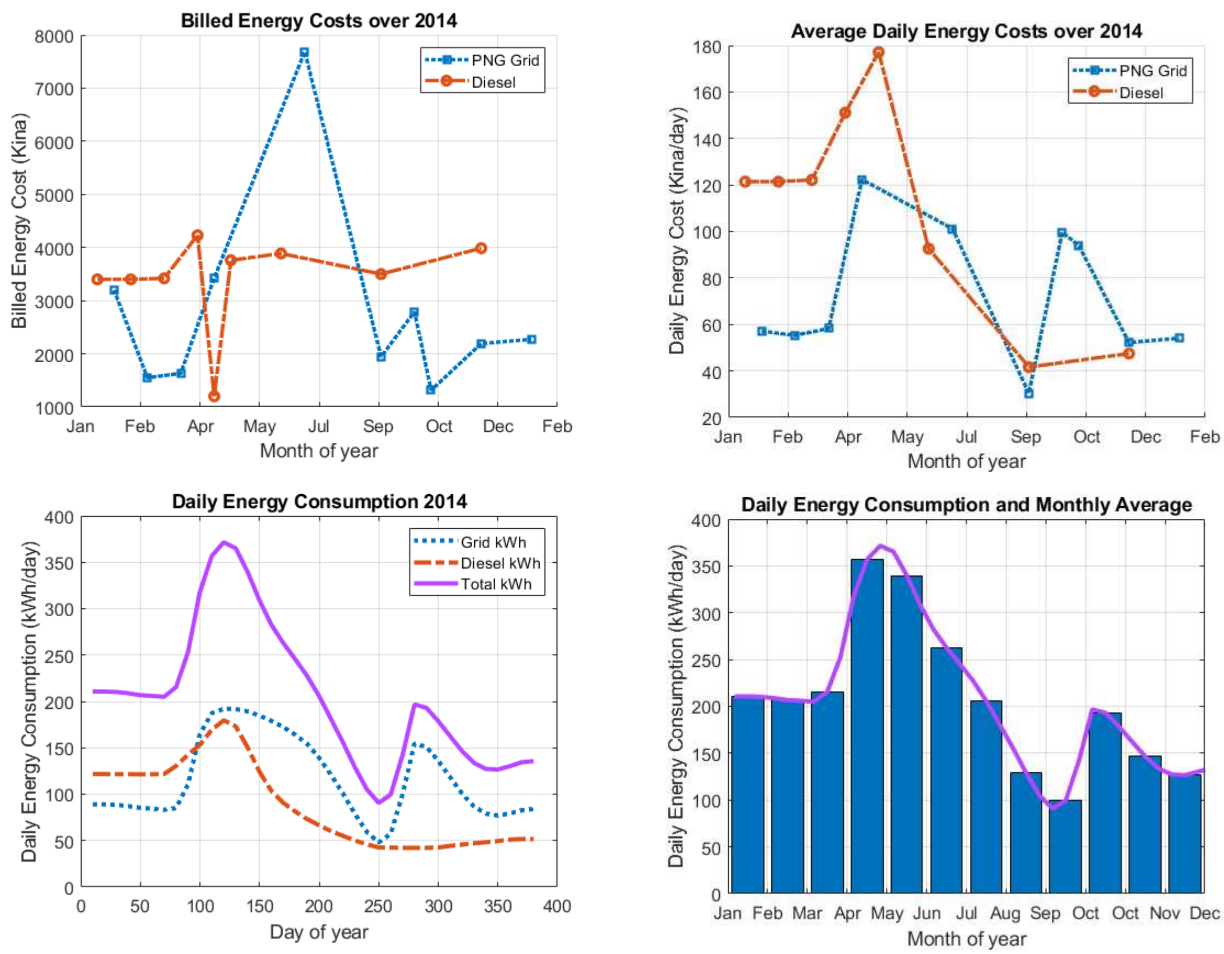


Figure 44: The billed energy costs of the Madan Mill (a) are averaged to yield the daily energy costs (b), which fitted to produce continuous functions that can be summed to yield the total daily energy use over the course of the year (c), which is averaged to yield monthly averages of the daily energy consumption (d).

Since the power is unavailable from the grid for an average of 20 to 30 working hours per week, a large portion of the electric demand is provided by a 90 kW diesel genset installed at the mill. Although the fuel curve of the genset is unknown, the total power generation can be approximated from the total diesel fuel expenditure and the power curve of a standard 100 kW diesel generator, which increases linearly from 4 L/hr at idle to 27 L/hr at full output.

The average daily energy consumption can be converted into an hourly demand profile corresponding to the approximate hours of operation of the mill, which are five days a week, from 8 am to 4 pm for most of the year. In the harvest season (March – June), the mill operates seven days a week during all daylight hours. This increase in operating times is reflected by the spike in energy consumption, especially for April and May. The estimated hourly demand profile can be plotted for each month of the year, as shown in Figure 45.

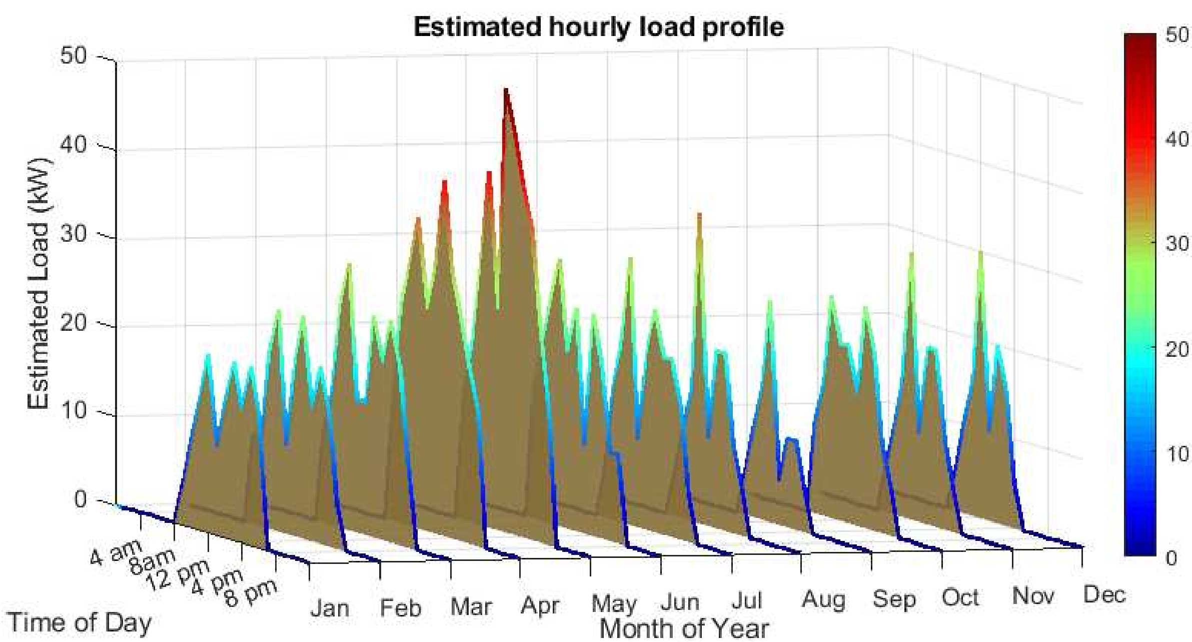


Figure 45: Estimated hourly load profile for each month of the year

6.4.2. Microgrid Modeling in HOMER

HOMER is a commercial software commonly used for solving optimization problems related to microgrid planning. Although the modeling and logic of HOMER are less detailed than that of other microgrid simulators (such as PV-DesignPro or PV*Sol), the software includes a broad array of generation and fuel sources, load profiles, and operation characteristics. HOMER offers three analysis modes:

- Power system simulations in which the software runs a simulation of all possible configurations of the microgrid to analyze feasibility and life-cycle cost over a one year horizon using a one hour time step
- Optimization of the DER configuration to determine the solution that minimizes the levelized cost of energy (LCOE)
- Sensitivity analysis of the design to uncertainty of various parameters beyond the control of the system designer.

When simulating a power system including energy storage, there are two different economic dispatch methods used by HOMER. The first is load-following, in which the ESS is only charged by renewable generation, while the output of generators simply follows the load demand curve. The second economic dispatch strategy is cycle-charging, in which the energy storage system is charged by all available generators. Use of the latter dispatch strategy enables the simulations to include the strategy of buying grid power when it is available and then using the stored energy during grid outages. The latter operating scheme is selected for the simulations to be discussed in Section 6.5.

At the end of each set of simulation runs, HOMER returns aggregated results categorized into groups of economic, environmental, and technical indices sorted by equipment type.

6.4.3. Modeling of Existing System in HOMER

The current system topology consists of the intermittent power grid, the 90 kW diesel genset, and the load. Due to the lack of a net metering policy, the microgrid is modeled as an islanded system with the PNG Power grid treated as a generator with a fixed cost of 0.23 USD/kWh. The intermittency of grid supply is modeled in HOMER as forced maintenance outages at randomly selected times that sum to a power outage of 20 to 30 hours per week. The schedule of grid outages is depicted in Figure 46. Meanwhile, the diesel genset is only operated during the working hours of the mill, and so a daily outage is scheduled from 5 am to 7 am.

As can be observed from Table 25, the simulation results from HOMER match the actual operating parameters from 2014 closely with a maximum error of 0.5%.

Table 25: Comparison of HOMER base case simulation and 2014 actual operations

	Grid Energy Usage (kWh)	**Diesel Fuel Usage (L)**	**Operating Cost (USD)**
HOMER Result	43,062	12,843	21,078
Actual 2014 Value	43,086	12,827	21,165

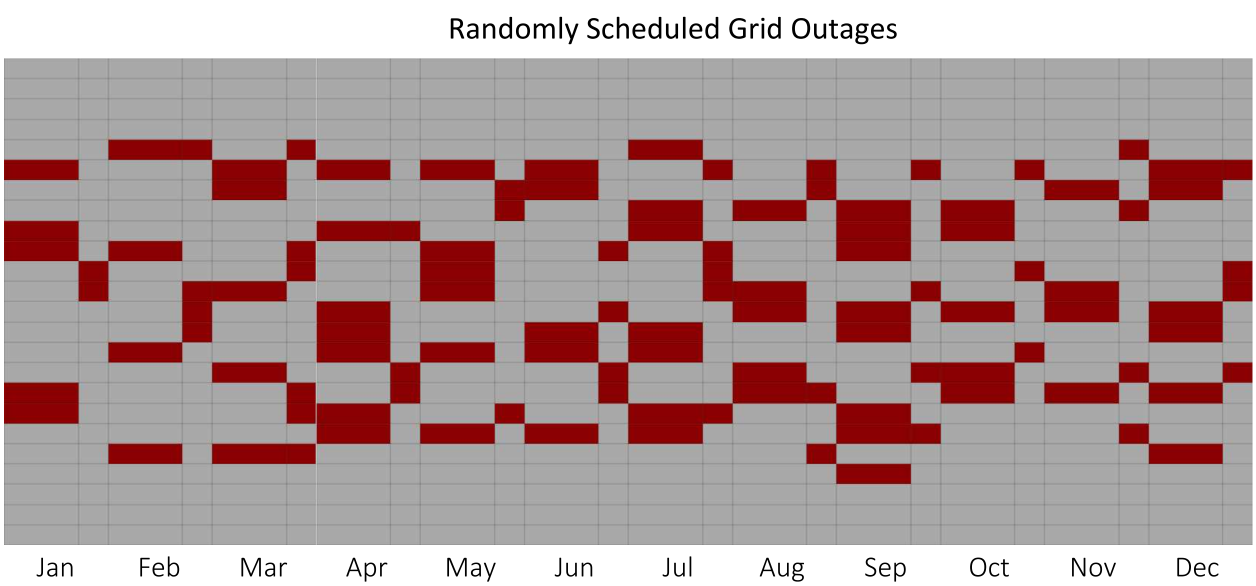


Figure 46: Generator outages scheduled in HOMER to replicate the unreliability of the PNG Power grid.

6.5. Combined HOMER-SMARTER Technique

6.5.1. Optimization and Decision-Making Formulation

The nine step process described in Section 6.3 is now combined with the ability of HOMER to perform high speed simulations for discrete alternatives of system topologies, resulting in a versatile tool for microgrid planning.

6.5.1.1. Identification of decision-makers

Key stakeholders for the case study are the owners of Madan Mill, management of the local community-based organization, tribal leaders, and potential project funding agencies. For the optimization process, first author, who has firsthand knowledge of the system and community, serves as the decision-maker.

6.5.1.2. Creation of a value tree

The general microgrid planning value tree shown in Figure 41 is sufficient for the decision-making process. Six objectives are selected to represent the key interests of each group of stakeholders. The mill owners are interested in 1) reducing losses of raw coffee cherries due to outages (*maximize reliability*) and 2) reducing payments made for diesel fuel and grid power (*minimize operating cost*). The funding agency desires the solution with lowest installation cost (*minimize initial capital cost*) and longest lifespan (*maximize ESS lifespan*). The community-based organization and tribal leaders desire the greatest social benefit (*maximize HDI*) and lowest environmental impact (*minimize CO_2 emissions*).

For social benefits, human development index (HDI) is used instead of job creation since a reliable measure of job creation as function of microgrid capacity has not yet been published. A new set of detailed indices will be released by the World Bank in 2020 with a focus on the impact of productive uses of energy in previously unelectrified communities. Portions of the draft document were distributed to select peer reviewers from IEEE Power & Energy Society (including the primary author), but the full report was not available at the time of paper submission. As a result, the older metric of HDI as a function of kWh per person is used. HDI is an index ranging from zero to one that represents the life expectancy, education, and income of the population. The relationship between HDI and electric consumption was developed in [21] using human development data collected by the United Nations Development Program from 60 countries, including Papua New Guinea:

$$HDI = 0.091\ln(kWh) + 0.0724 \tag{12}$$

For the analysis, it is assumed that all excess generation capacity will be made available for the social benefit of the community through charging of portable battery kits and/or wired distribution to the nearby homes of approximately 250 full-time workers at the mill.

6.5.1.3. Objects of evaluation

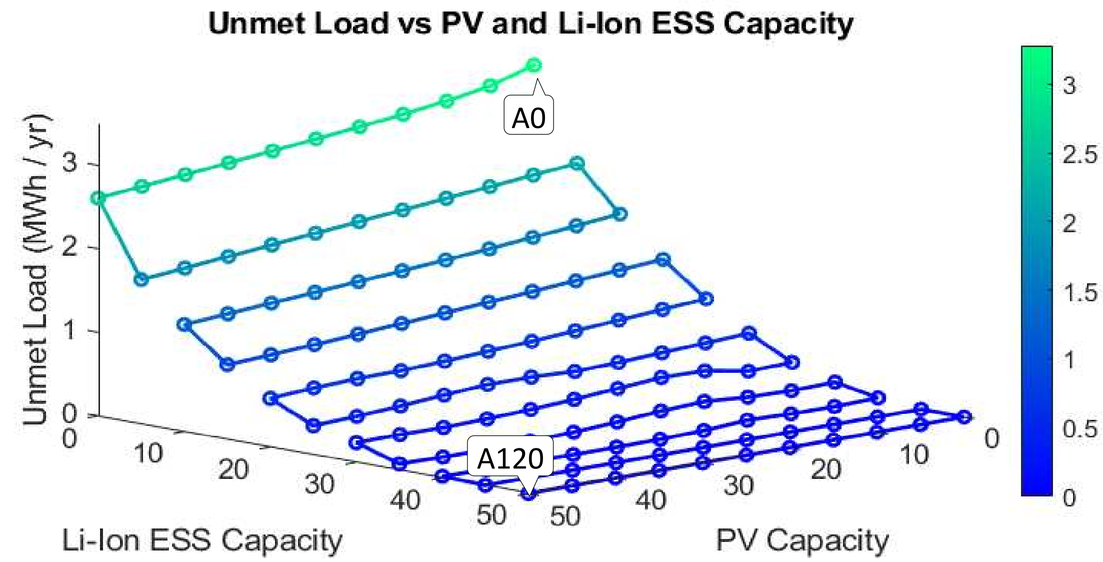
The solution space is formed from five solution variables representing the PV installed capacity, ESS installed capacity, ESS battery chemistry, ESS maximum depth of discharge (DoD), and usage of the existing diesel genset. Each of the capacity parameters are varied between 0 and 50 kW or 0 and 50 kWh in increments of 5 kW or 5 kWh. The resulting solution space is converted into 682 discrete alternatives, as summarized in Table 26.

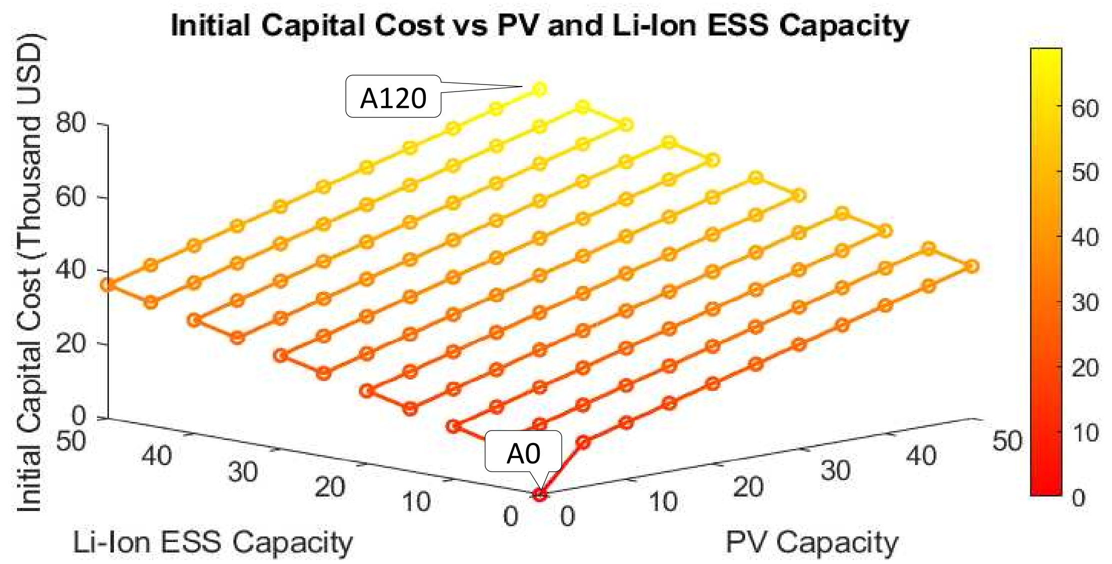
Table 26: Selected alternatives forming optimization solution space for the Madan Mill case study

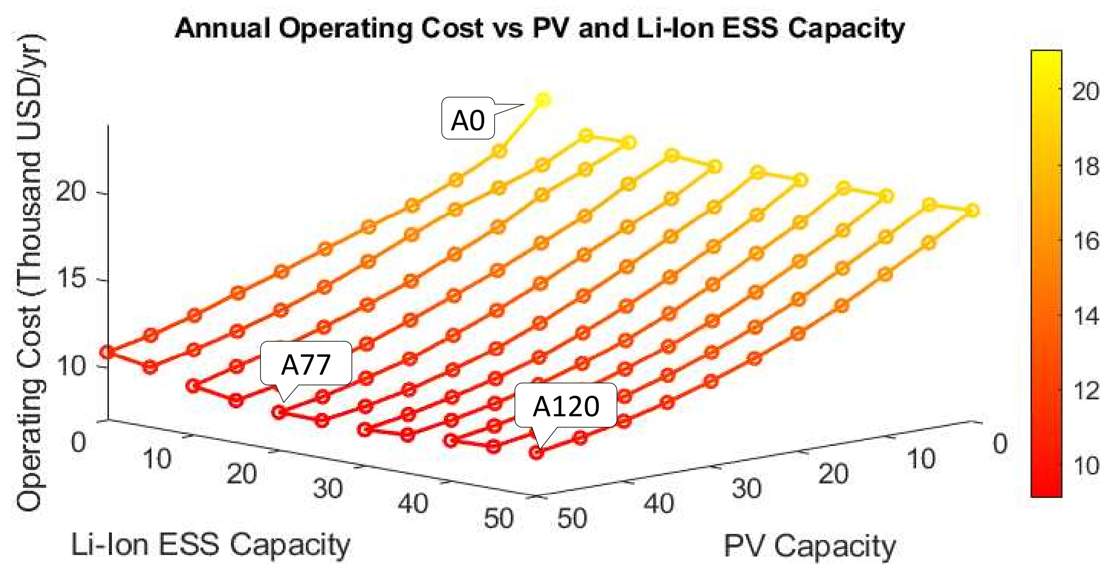
Label	PV Capacity (kW peak)	Li-Ion ESS (kWh)	Lead-Acid ESS (kWh)	ESS Max DoD (%)	Existing Diesel?
A0 – A120	[0 : 5: 50]	[0 : 5: 50]	No	80	Yes
A121 – A230	[0 : 5: 50]	No	[0 : 5: 50]	40	Yes
A231 – A340	[0 : 5: 50]	No	[0 : 5: 50]	60	Yes
A341 – A461	[0 : 5: 50]	[0 : 5: 50]	No	80	No
A462 – A572	[0 : 5: 50]	No	[0 : 5: 50]	40	No
A572 – A682	[0 : 5: 50]	No	[0 : 5: 50]	60	No

6.5.1.4.Objects-by-attributes matrix

HOMER simulations are performed for all 682 alternatives over a one year rolling horizon using a 1 hour time step. Sample plots of the simulation results for five of the decision criteria are presented in Figure 47. Conflicts between the objectives can be observed from the scores of alternative A120, which has the best physical simulation scores for unmet load, operating cost, and emissions. Simultaneously, A120 has the worst score for initial capital cost. The conflicts between the selected attributes illustrates the need for the SMARTER process since it is impossible to select an optimal solution merely by inspection.


Unmet Load vs PV and Li-Ion ESS Capacity
Unmet Load (MWh / yr)
A0
A120
Li-Ion ESS Capacity
PV Capacity
0
1
2
3
10
20
30
40
50
0.5
1.5
2.5


Initial Capital Cost vs PV and Li-Ion ESS Capacity
Initial Capital Cost (Thousand USD)
A120
A0
Li-Ion ESS Capacity
PV Capacity
0
20
40
60
80
10
30
50


Annual Operating Cost vs PV and Li-Ion ESS Capacity
Operating Cost (Thousand USD/yr)
A0
A77
A120
Li-Ion ESS Capacity
PV Capacity
0
10
15
20
12
14
16
18
30
40
50

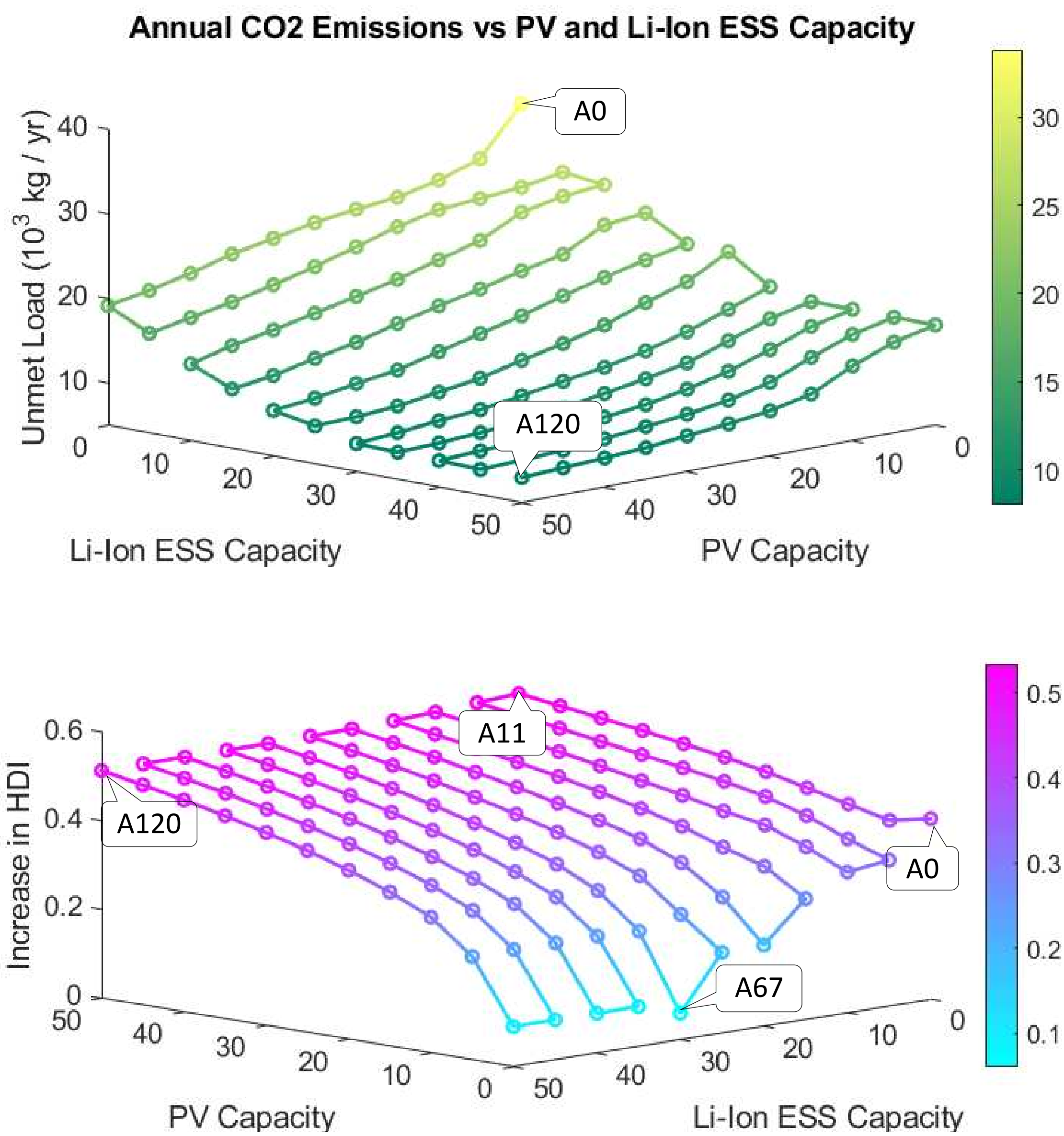


Figure 47: Plots of the direct physical simulation scores for alternatives A0 through A120 for five of the six decision criteria. ESS lifespan is not depicted since the Li-ion battery lifespan is a fixed 15 years and not affected by depth of discharge or capacity. Observe that the plot is not a continuous surface, but rather a sequence of discrete alternatives traversing the solution space.

6.5.1.5. Elimination of dominated attributes

Simulations are performed for all 682 alternatives over a one year rolling horizon using a one hour time step using the HOMER commercial software package. Sample plots of the simulation results for five of the decision criteria are given in Figure 47. Conflicts between the objectives can be observed from the scores of alternative A120, which has the best physical simulation scores for unmet load, operating cost, and emissions. Simultaneously, A120 has the worst score for initial capital cost. The conflicts between the selected attributes illustrates the need for the SMARTER process since it is impossible to select an optimal solution merely by inspection.

6.5.1.6. Conversion to non-dimensional utilities

The minimum and maximum values of the physical simulation scores for an attribute are determined by searching the associated column in the objects-by-attributes matrix. The results are converted into the linear utility functions (Figure 48). The original optimization problem seeks to minimize unmet load, operation cost, capital cost, and emissions. So, the corresponding utility functions decrease linearly with the minimum value for any alternative in the solution space assigned a utility of 100, and the maximum value assigned a utility of zero. The optimization problem seeks to maximize ESS lifespan and HDI, and so the associated utility functions increase linearly. The entries in the objects-by-attributes matrix are then converted into non-dimensional utilities by the process described earlier in Section 6.3.

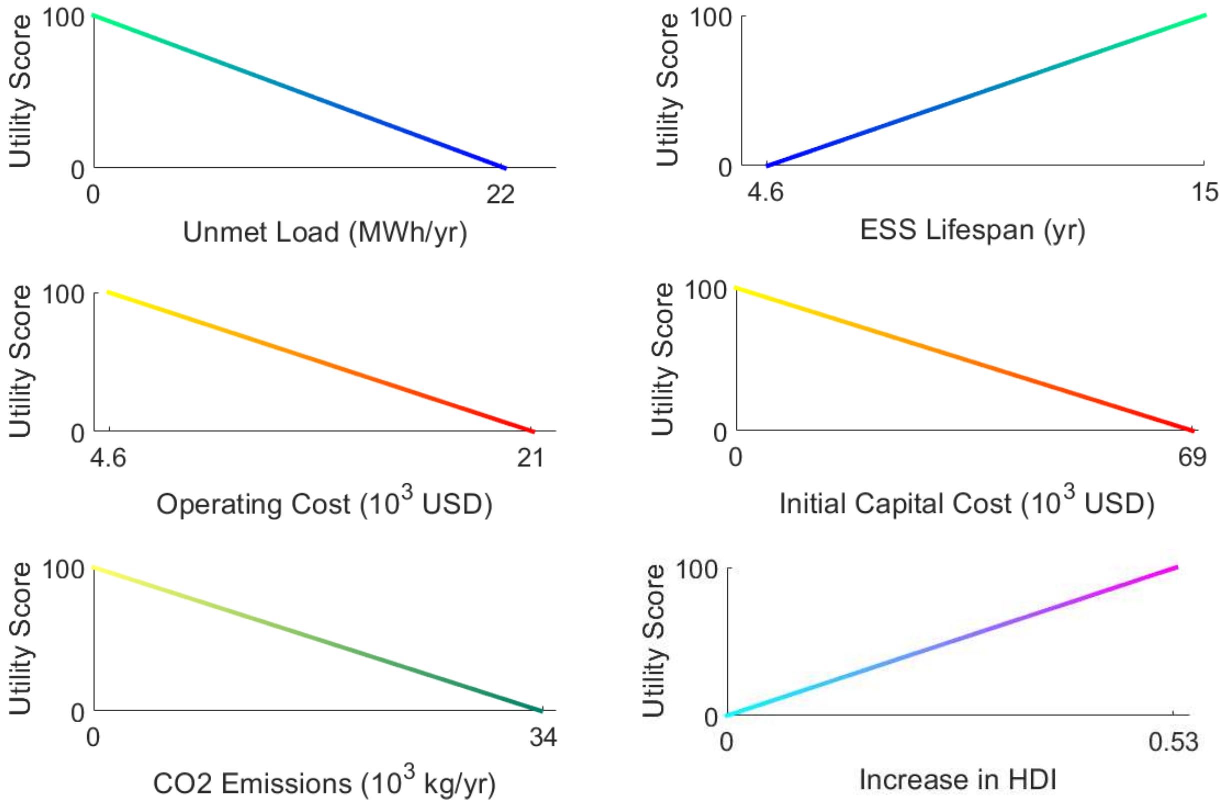


Figure 48: Utility functions for each of the technical, economic, environmental, and social attributes considered in the decision-making process

6.5.1.7.Rank ordering of swing weights

Using the elicitation process described earlier, it is determined that the preference ranking of attributes from most important to least important is reliability > initial capital cost > operating cost > ESS lifespan > HDI > CO_2 emissions.

6.5.1.8.Rank order centroid weighting

The decision process uses six attributes, and consequently the ROC weights for each decision criterion are as shown in Table 27.

Table 27: ROC weights for each decision criterion

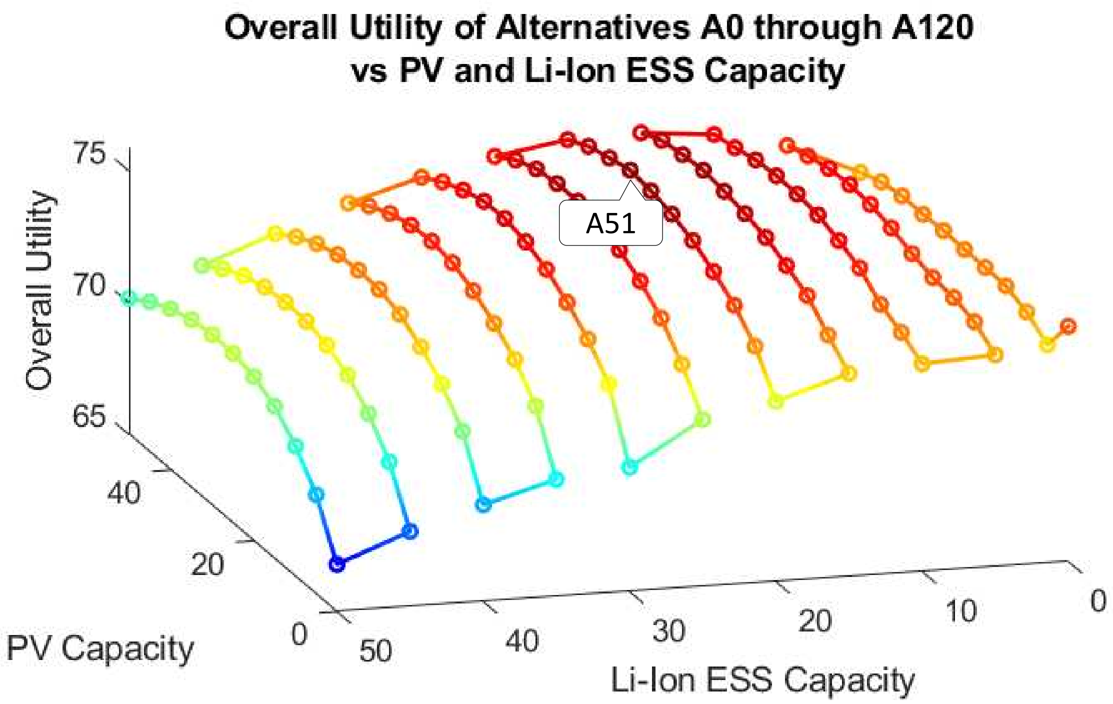
Label	Category	Criterion	ROC Weight
C1	Technical	Reliability	0.4083
C4	Economic	Capital cost	0.2417
C3	Economic	Operations cost	0.1583
C2	Technical	ESS lifespan	0.1028
C6	Social	HDI	0.0611
C5	Environmental	CO2 emissions	0.0278

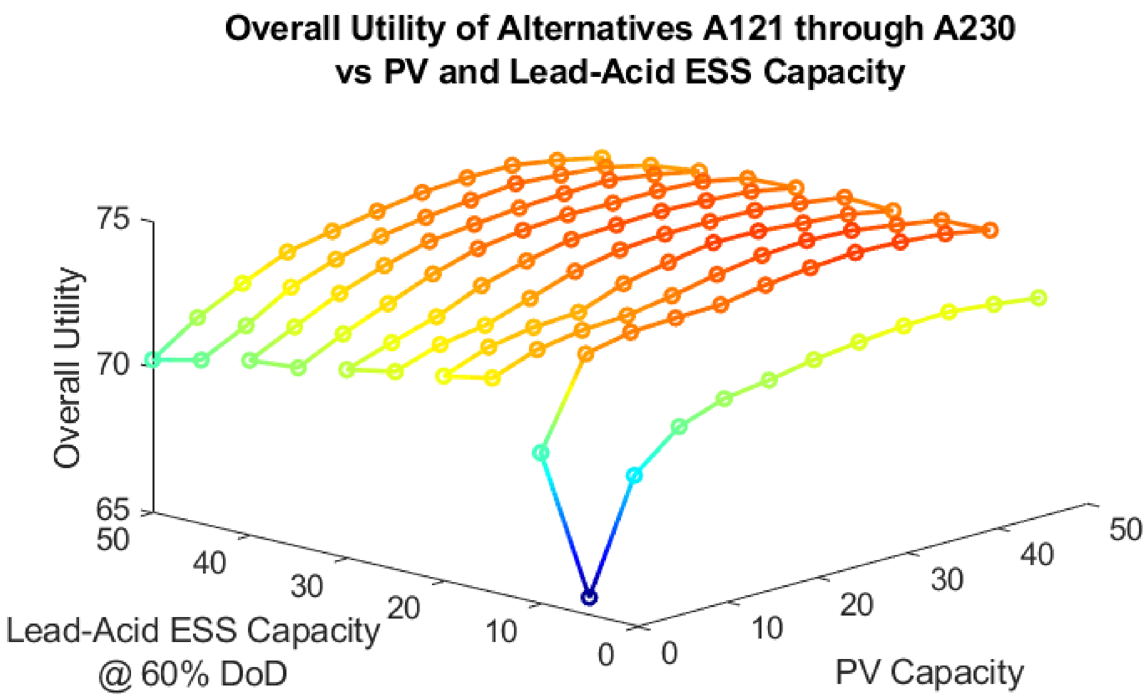
6.5.1.9.Decision maximizing overall utility

The overall utility for the alternatives is calculated as the weighted sum of the utility scores for each alternative using the ROC weights presented in Table 28. Figure 49 shows the overall utility for alternatives A0 through A340. A simple search of the vector of overall utilities reveals that alternative A51 (35kW of PV generation, 20 kWh of ESS storage, and continued use of the diesel genset) has the highest overall utility.

Table 28: Comparison of the existing system vs selected configuration

	C1 (kWh/yr)	C2 (USD)	C3 (USD)	C4 (yr)	C5 (kg/yr)	C6 (HDI)
A0	3282	21,077	0		33380	0.0000
A51	637	10,199	42,750	15	12438	0.1816


Overall Utility of Alternatives A0 through A120
vs PV and Li-Ion ESS Capacity
75
70
65
Overall Utility
A51
40
20
0
PV Capacity
50
40
30
20
10
0
Li-Ion ESS Capacity


Overall Utility of Alternatives A121 through A230
vs PV and Lead-Acid ESS Capacity
75
70
65
Overall Utility
50
40
30
20
10
0
Lead-Acid ESS Capacity
@ 60% DoD
0
10
20
30
40
50
PV Capacity

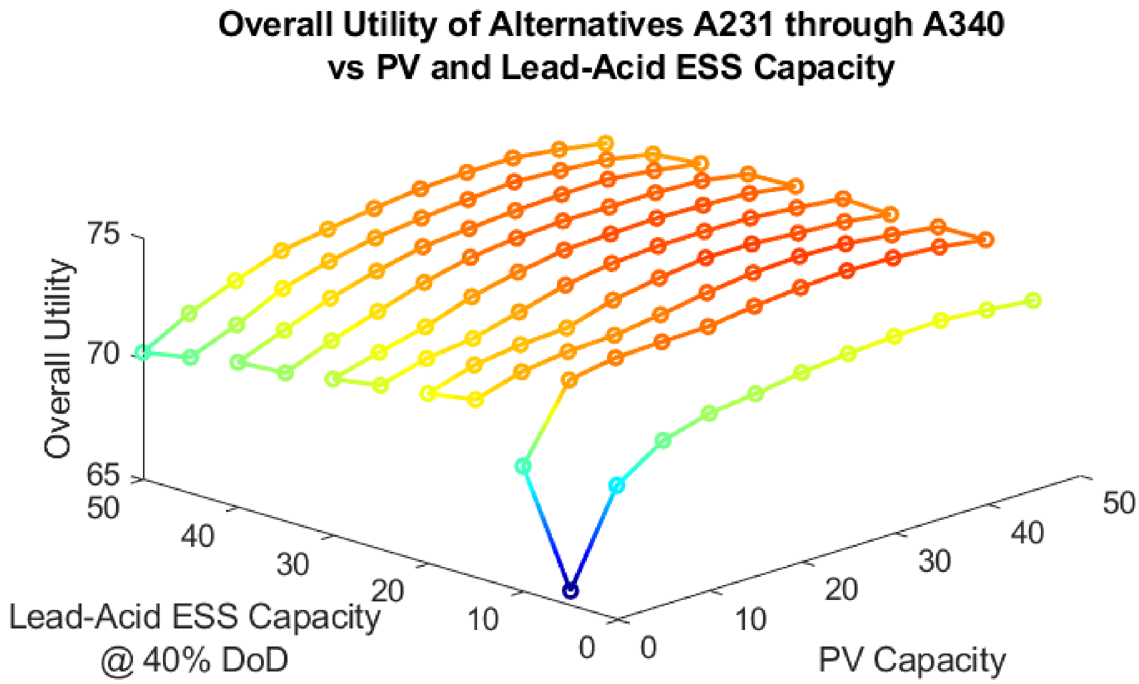


Figure 49: Plots of the overall utility of alternatives A0 through A340, which traverse the solution space of installed PV, Li-ion, and lead-acid capacity.

6.6.Conclusion

This paper has proposed and demonstrated the use of a new framework for formulating and solving optimizations problems for microgrid planning using the SMARTER process. The core concepts of the nine-step process are redefining optimization functions into elicited attributes, converting the multi-dimensional solution space into a vector of discrete attributes, and selecting the alternative that maximizes the overall utility.

The proposed methodology is computationally lightweight and scales linearly with the size of the solution space and number of decision criteria, as shown in Table 29. Computation times are for a machine running MATLAB R2019a with an i7 CPU @ 2.8 GHz and 32GB RAM.

Table 29: Computation time vs number of alternatives

Number of alternatives	HOMER simulation time	SMARTER decision analysis time
15 (25kW resolution)	0.3 s	0.0044 s
682 (5 kW resolution)	12.7 s	0.0048 s
2200 (2.5 kW resolution)	42.0 s	0.0229 s
4400 (1 kW resolution)	92.4 s	0.0502 s

It is anticipated that the SMARTER framework proposed in this paper will lay the foundation for a broad array of future research topics. The ability to combine multiple conflicting quantitative optimization objectives with numerous qualitative technical, economic, environmental, and social attributes will enable the creation of microgrid planning problems that provide much deeper insight into the transformative impact of energy access. Furthermore, the conversion of the solution space into discrete alternatives suggests the framework can be easily extended to consider DER siting, network topology, switch configurations, and load selection considering community capacity building through productive uses of energy.

CHAPTER 7

Conclusion and Future Work

7.1. Conclusion

The problem of microgrid planning for community electrification has been examined in detail from multiple standpoints offered by the Systems Engineering discipline.

The initial survey of microgrid optimization formulations and multi-criteria decision making presented by nearly 250 papers paved a path for creating a set of organizational management techniques and numerical optimization approaches based on a common set of technical, economic, environmental, and social decision criteria. In Chapter 2, the survey identified that all optimization studies of islanded microgrids are based on formulations selecting a combination of 16 possible objective functions, 14 constraints, and 13 control variables. Each of the objectives, constraints, and variables were discussed exhaustively both from the perspective of their importance to islanded microgrids and chronological trends in their popularity. Subsequently, Chapter 3 examined the set of pairwise relationships between each of identified objective functions and classified these relationships as mutually supporting, weakly conflicting, and directly conflicting. Available techniques for combining multiple objectives were also examined with detailed discussions of the combinations of objectives selected by each of the surveyed microgrid optimization studies implementing a particular MCDM method. MCDM techniques based on utility theory (MAUT, SMART, AHP) and outranking methods (PROMETHEE, ELECTRE, TOPSIS) were also compared from the perspective of their applicability and chronological popularity for microgrid optimization.

Next, a holistic framework for modeling community electrification projects was developed in Chapter 4, introducing both a hierarchical enterprise system-of-systems (SoS) framework and a new life cycle model for the planning, design, funding, construction, commissioning, operation, and expansion of community microgrids as part of multi-phase community capacity-building programs. Each of the tiers in the pyramid of organizational, financial, and physical subsystems was mapped to a set of the 17 United Nations Sustainable Development Goals and explained in terms of the seven characteristics of a SoS (operational independence, managerial independence, geographic distribution, emergent behavior, evolutionary development, self-organization, and adaptation). An operational implementation of the proposed hierarchy was illustrated using the structure of the Madan CTC, which is responsible for managing ongoing water, sanitation, education, and healthcare projects, as well as the planned electrification program. Subsequently, a new systems engineering lifecycle was developed to help describe the complex process of planning, funding, executing, and monitoring portfolios of multi-phase community-based critical infrastructure projects. The life cycle identified 10 steps within an expanding cycle, including needs analysis, concept development, community validation, decision analysis, deployment planning, in-field demonstration evaluation, engineering design, integration and verification, production and deployment, operations and support, and lastly, expansion of the project to reach additional communities. Finally, a set of systems engineering tools and operational context diagrams were presented to illustrate the organization management, project management, and risk management approaches recommended to improve the sustainability of community electrification projects.

Chapter 5 argued the necessity of application of microgrid optimization techniques for not only larger microgrids, but also stand-alone energy kiosks providing electricity access in deep rural communities where wired distribution systems are impractical for economic, environmental, or social reasons. A combination of the cost-based objective functions identified in Section 2.4.1 were applied to determine the optimum capacity of PV generation and battery storage as a function of the total number of customers served. A daily dispatch problem was solved using real-time pricing based upon a transactive energy market considering change in PV generation, load, and ESS state of charge.

Chapter 6 combined the contributions of the previous chapters to create a generalized microgrid optimization framework considering not only the entire set of objective functions, optimization constraints, and solution variables, but also decision criteria based on technical, economic, environmental, and social benefits of the microgrid. A key innovation of methodology was redefinition of objective functions into elicited attributes and conversion of the optimization solution space into a vector of discrete alternatives. This approach enabled inclusion of multiple conflicting optimization objectives, and include both qualitative and quantitative indicators of the importance of various benefits to key stakeholders and the decision maker. The resulting framework was demonstrated to be computationally lightweight and linearly scalable with the number of discrete alternatives considered. Finally, a generic MATLAB code was presented to apply the SMARTER decision-making technique automatically to the simulation results generated by the HOMER commercial microgrid simulation software. The included code was able to generate a satisfactory decision using an arbitrary set of decision criteria within tens of milliseconds for solutions spaces using thousands of discrete alternatives.

7.2. Future Work

It is anticipated that the contributions of this research will find numerous future applications, for the planning and dispatch of both electrification microgrids and advanced distribution systems. The enterprise SoS hierarchy is highly replicable and can be applied to sustainable development initiatives across the globe, not only for community electrification projects, but also for other capacity-building programs addressing the array of critical infrastructure needed to eradicate poverty for over a billion people. Likewise, the flexibility of the SMARTER approach to microgrid optimization enables consideration of numerous discrete alternatives, including selection of equipment manufacturers, locations of DERs, routes of distribution lines, operating setpoints of controllers, and types of customer loads.

For the sake of brevity, the following discussion of future work will be limited to three immediate areas building on expansion of the SMARTER process and the next phase of the Madan Community infrastructure program.

7.2.1. Decision-Making Considering Productive Uses of Energy

Funding for community electrification projects has recently demonstrated a significant shift from basic energy services (such as lighting and phone charging) to productive uses of energy (PUE). Field practice has demonstrated that providing access to electricity does not immediately result in increased economic prosperity. Consequently, microgrid planners must actively consider potential entrepreneurial businesses that can be created through electrification.

Several categories of PUE have been identified by IEEE Smart Village through the seed-funding process of a series of community-based entrepreneurs who have established electrification micro-utilities and training centers developing micro-businesses in several PUE categories [1]:

- **Artisan Crafts** – beadmaking, embroidery, leather work, sewing
- **Construction** – brickmaking, carpentry, greenhouse construction, manufacturing, welding
- **Electrical Wiring** – CCTV installation, home wiring
- **Electronics Assembly** - assembly of LED light bulbs, repair of small electronics
- **Electric Transportation** – market-garden produce delivery, mobile water pumping, portable battery kit delivery, taxi services
- **IT Services** – electronics maintenance and repair, internet cafes, IT outsourcing (photo tagging, media editing, etc.), programming and software development
- **Retail Services** – barbershops, cell-phone charging, refrigeration, grocery stands
- **Sustainable Agriculture** – agricultural processing, construction and repair of agricultural equipment, water pumping, mushroom farming, beekeeping, dairy farming, and animal husbandry
- **Tourism** – homestays, managerial team building, training of environmental stewards

The flexibility of the SMARTER decision-making process for microgrid optimization will enable microgrid planners to consider the types of PUE businesses that could be created through electrification considering technical, economic, environmental, and social criteria. Technical impacts of various PUE include shifting of demand curves, higher reliability requirements, and possible power quality issues related to the high startup current of single-phase induction motors. From an economic standpoint, PUE significantly increase the community's willingness and ability to pay for electric service; simultaneously, if the microgrid operator includes some PUE businesses within its own organization, then it is possible to use retained earnings to reduce the payback period of the microgrid by several years. Additionally, elimination of large polluting diesel engines frequently used to power agricultural processing machines in Africa (Figure 50) can provide substantial environmental benefits to the community. Finally, the social benefits provided by job creation through PUE are far greater than those from providing solar home systems or street lighting.

Figure 50: Diesel engines replaced by a solar microgrid in Niger State, Nigeria by GVE in 2018 using seed-grant funding from IEEE Smart Village and private venture capital [2]

7.2.2. SMARTER Optimization using Real-Time Transactive Pricing and Demand Response

The numerical analysis in Chapter 6 used a smooth daily load curve derived from aggregated energy usage over a one year period. However, the load profile of the Madan Mill consists of about 20 delta-connected three-phase machines (Figure 51 and 52) with a total nameplate capacity of 108 kW, which are listed in Table 30. As a result, the load profile for the mill grows in a stepwise manner as each machine is brought online over the course of the day. Modeling of the individual motors enables the hourly economic dispatch algorithm to decide which machines to energize in a transactive market framework. Real-time pricing for loads will include the priority of the load and the potential income generated (or lost). Generation and storage will use the pricing mechanism introduced in Chapter 5.

Figure 51: One of the agricultural processing machines at the Madan Mill [3]. (image courtesy Joanna Gentili, Madan CTC)

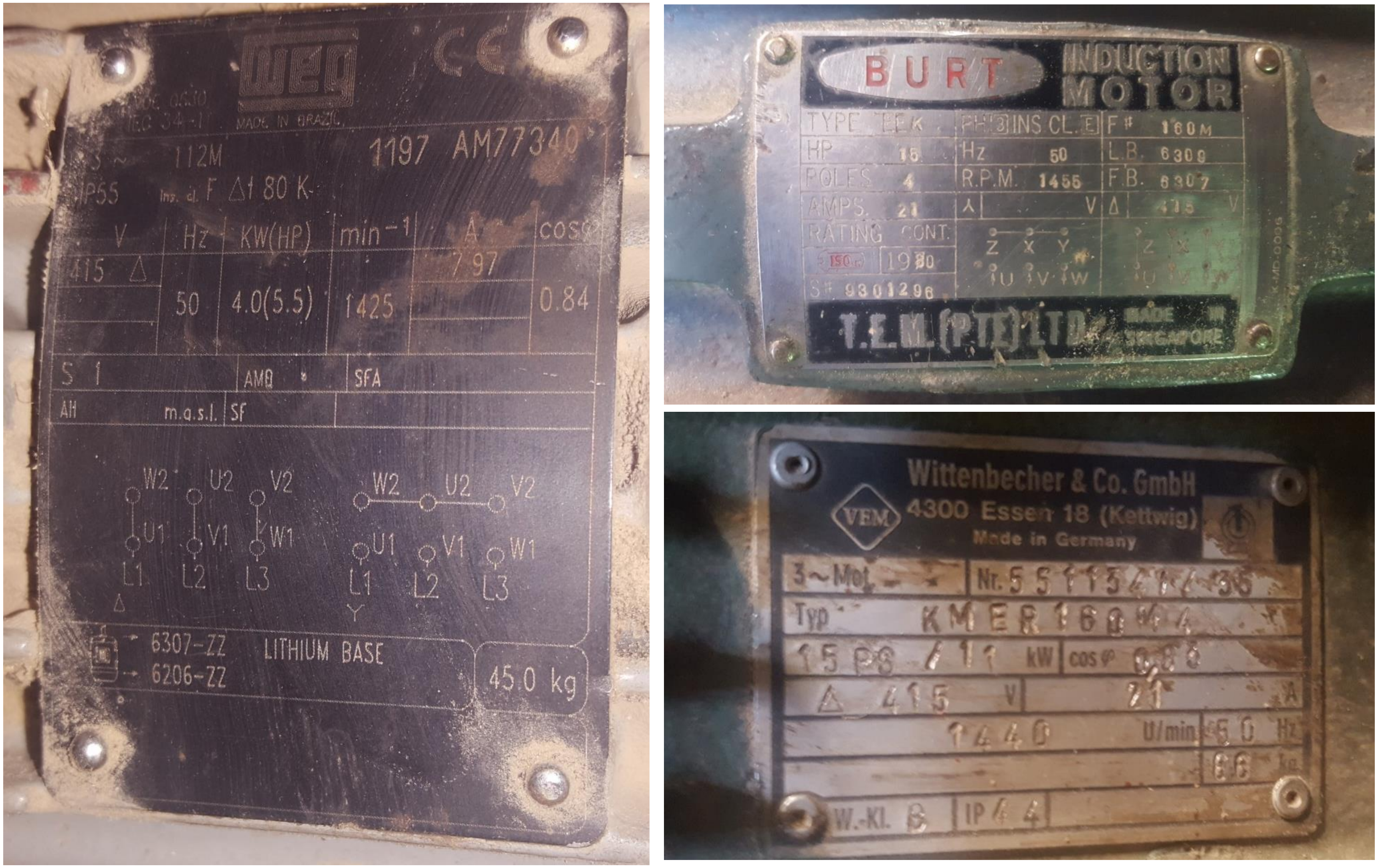


Figure 52: A few of the motor nameplates gathered by the project team to refine the results of the optimization presented in Chapter 6 [3]. (image courtesy Larry Hull, Madan CTC)

Table 30: List of motor nameplates at the Madan Mill

Motor Application	Voltage (V)	Current (A)	Power (kW)	Power Factor (pf)	RPM	Qty	Total kW	Estimated Elec power (kW)	Total kVA
	Δ-connected	Δ-connected					(mechanical)		
Separator	415	3.40	1.50	0.79	1415	1	1.50	1.93	2.44
Elevator	415	3.09	0.75	0.80	1420	7	5.25	12.44	15.55
Dust Remover	415	4.40	1.50	0.82	1415	1	1.50	2.59	3.16
De-stoner Main	415	7.97	4.00	0.84	1425	1	4.00	4.81	5.73
De-stoner Engine	415	3.09	0.75	0.80	1420	1	0.75	1.78	2.22
Huller 1	415	21	11.25	0.86	1455	1	11.25	12.98	15.09
Huller 2	415	21	11.25	0.86	1440	1	11.25	12.98	15.09
Huller 3	415	38.8	22.00	0.80	1450	1	22.00	22.31	27.89
Huller 4	415	38.8	22.00	0.80	1450	1	22.00	22.31	27.89
Huller 5	415	3.26	1.50	0.82	1440	1	1.50	1.92	2.34
Grader 1	415	9.00	4.00	0.77	1440	1	4.00	4.98	6.47
Grader 2	415	3.70	1.50	0.79	1400	1	1.50	2.10	2.66
Dismantling Table	415	7.97	4.00	0.84	1425	1	4.00	4.81	5.73
Dry Mill Total							**90.5**	**108**	**132**

7.2.3. DER Siting and Microgrid Distribution Planning

The second optimization study will examine a larger scale distribution microgrid to provide electricity to over 250 homes, as well as small businesses, churches, schools, and other demands around the Madan Medical Clinic. The system is located outside the range of the PNG national grid, and will be served by PV generation with lithium battery ESS located at the Madan Medical Clinic. Overhead AC lines will be used to serve larger loads within a cost-effective radius of the Clinic; PBKs will serve homes outside the range of the grid. A multi-objective optimization, also using SMARTER, will consider the technical, social, economic, and environmental objectives presented earlier in Table 13. The problem will be formulated as an economic dispatch problem solved over daily and weekly schedules using MATLAB and/or HOMER. If desired, the problem could then be expanded to an optimal power flow considering issues including conductor sizing, voltage profile, and network topology using Open-DSS, GridLab-D, or Xendee. Detailed maps of the system site prepared by community members are presented in Figures 53 through 55. The microgrid will be arranged with two or three feeders and an optional interconnection to the microgrid at the Madan coffee mill about 1km away, as depicted in Figure 56.

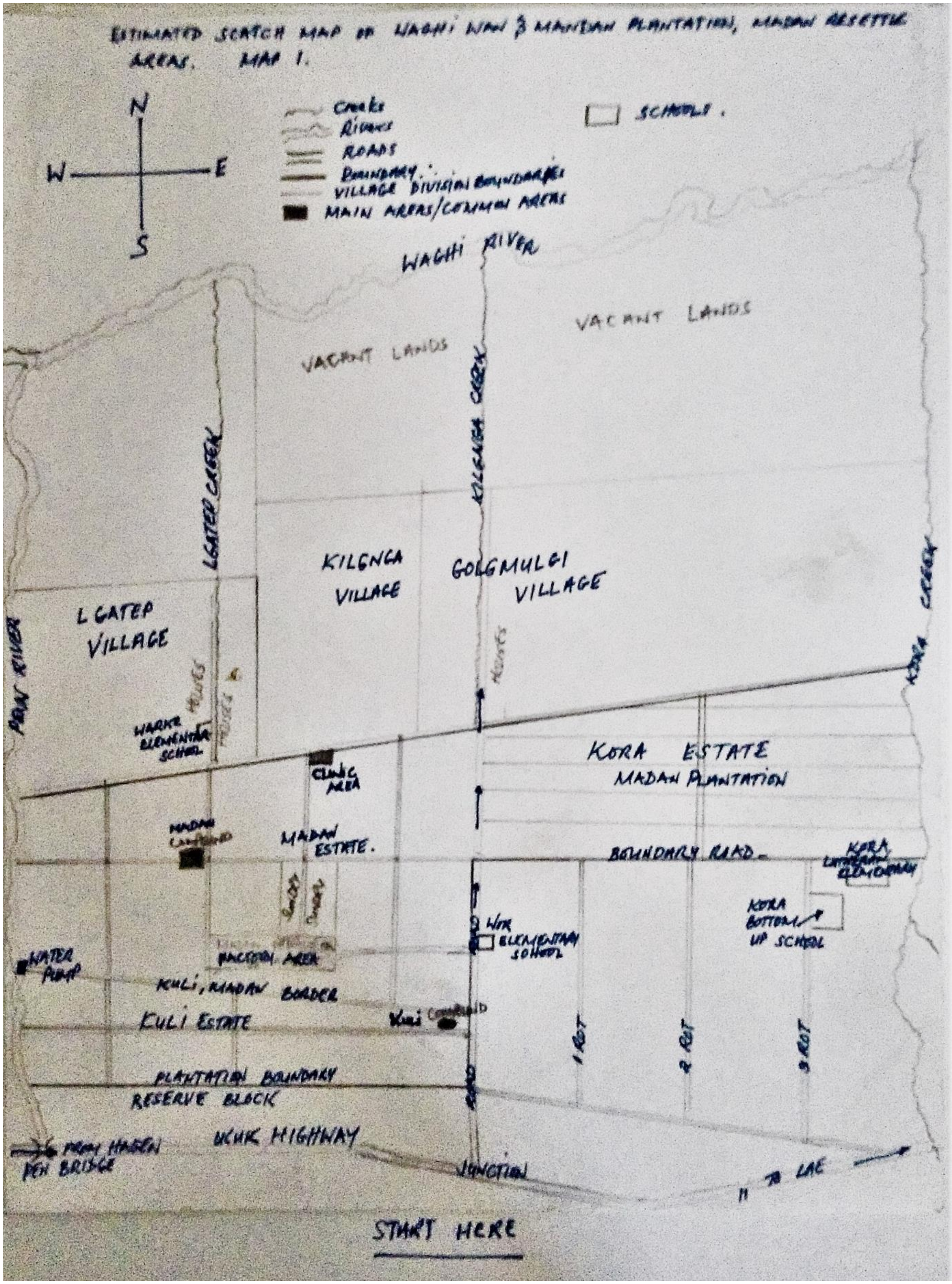


Figure 53: A detailed map of the electrification site prepared by one of the local community members (image courtesy Amos Dalton, Madan CTC)

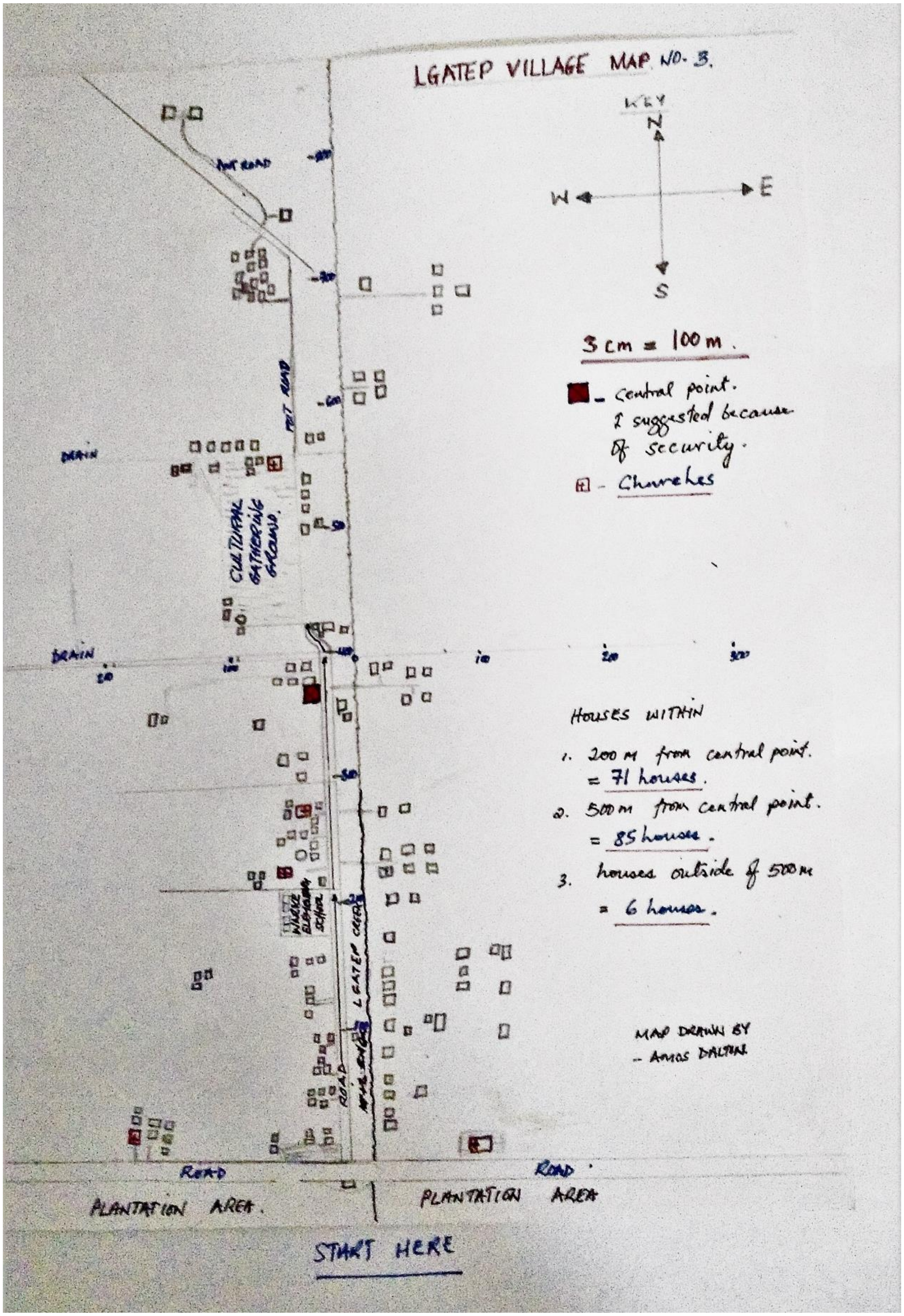


Figure 54: A detailed map of the Lgatep Village electrification site prepared by one of the local community members (image courtesy Amos Dalton, Madan CTC)

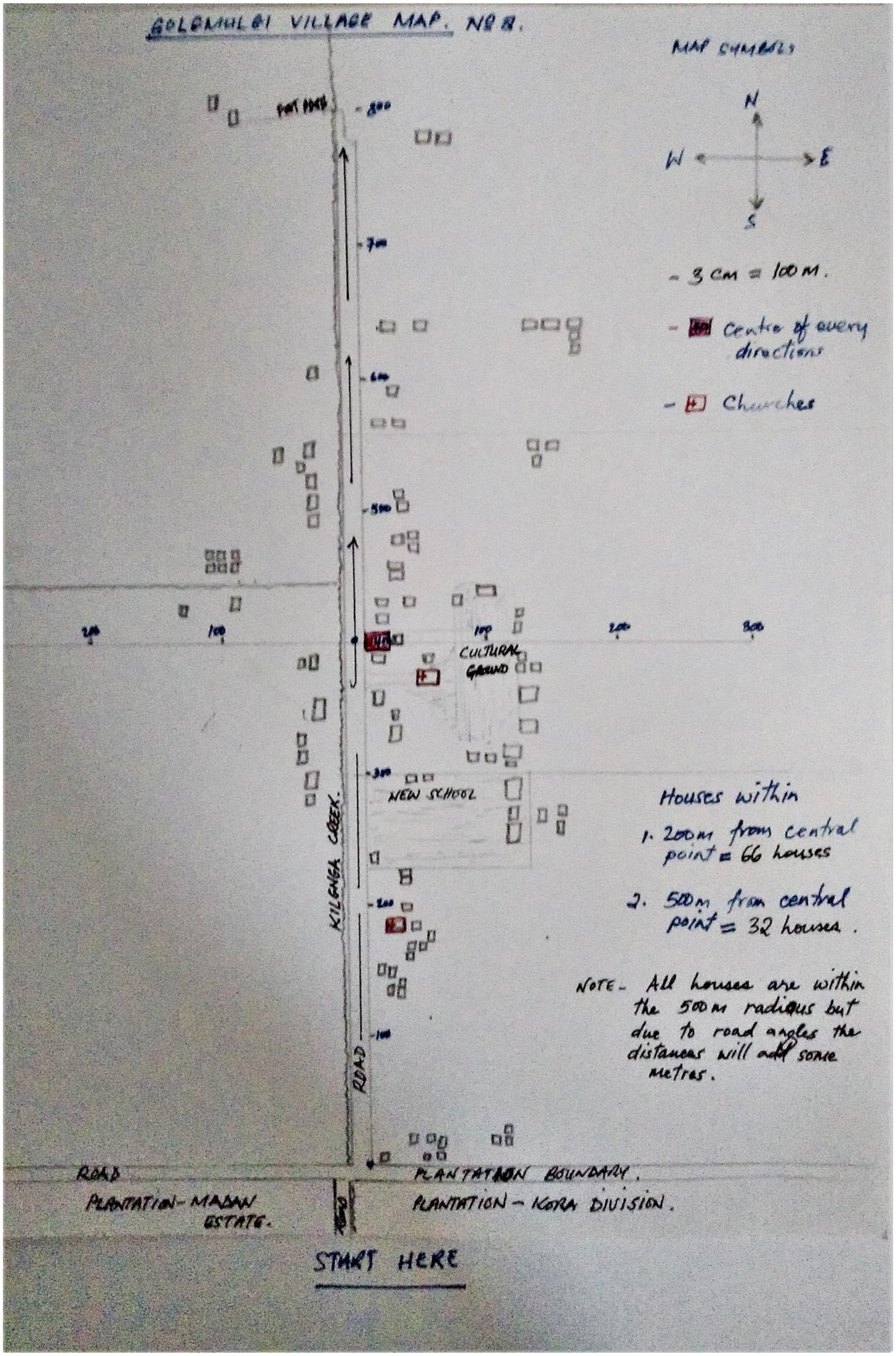


Figure 55: A detailed map of the Golgmulgi Village electrification site prepared by one of the local community members (image courtesy Amos Dalton, Madan CTC)

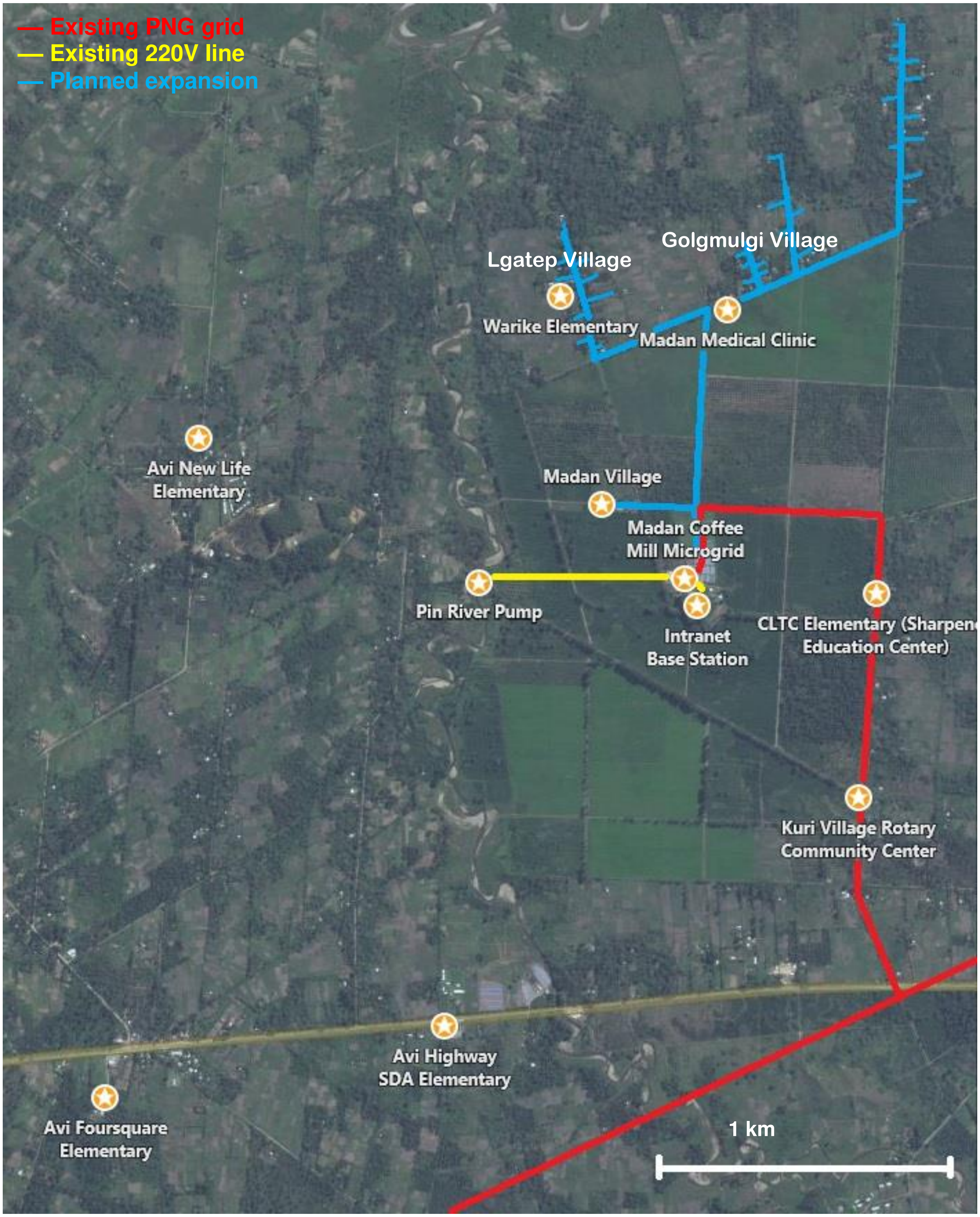


Figure 56: Planned interconnection of Madan pilot demonstration systems and initial distribution system expansion

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R.2. Chapter 2 References

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A.2. SMARTER MATLAB Code

```
function
[best,best_score,utilities]=SMARTER_for_HOMER(homer_data,homer_criteria,custom_criteria,priority,constraint
s)
% Automatically perform a SMARTER decision process for HOMER simulations
%
%% Syntax
%
%
[best,best_score,utilities]=SMARTER_for_HOMER(homer_data,homer_criteria,custom_criteria,priority,constraint
s)
%
%% Input Arguments
%
% The function takes five input arguments, homer_data, homer_criteria,
% custom_criteria, priority, and contraints.
%
% homer_data is a table array created by importing the HOMER simulation
% results CSV file into MATLAB as a workspace variable. An additional
% column named Alternative may be added to serve as an index of the
% discrete alternatives. If homer_data.Alternative is not inlcuded,
% alternative names will be generated automatically by the function
%
% homer_criteria is an n x 2 cell array. The first column
% constains char type names representing each of the physical simulation
% outputs used a decision criterion. The criterion names are case-senstive
% and must match the column names used in the workspace variable passed to
% the function. The second column of the array is either 'min' or 'max'
% depending on whether it is desired to maximize or minimize a particular
% criterion.
%
% custom_criteria is an n x 4 cell array. The first is a character string
% for the name of the criteria. The second The second column of the array
% is either 'min' or 'max' depending on whether it is desired to maximize
% or minimize a particular criterion. The third is the homer simulation
% output attribute used as the input for custom criterion. The last is a
% function handle specifying the criterion as a function of the simulation
% result. At this time, only one simulation output variable can be used as
% an argument for each custom criterion.
```

```
%
% priority is an n x 1 cell array listing of the priority ranking of
% decision criteria from most preferred (highest weight) to least preferred
% (lowest weight). Criteria weights are calculated automatically using the
% Rank Order Centroid method used by the SMARTER process.
%
% constraints is an nx3 cell array. The first is a string for
% the name of the homer criterion to be enforced as the constraint. The
% second is the type of constraint, expressed as a string. Currently
% supported constraint types are 'max' and 'min'. The third column of the
% cell array is numerical value to be used as the maximum or minimum
% acceptable value.
%
%% Output Arguments
%
% The function returns three arguments representing the best alternative,
% its corresponding overall utility score, and the non-dimensional utility
% scores for all alternatives not eliminated due to constraint violations
%% Example 1:
%   homer_criteria={'CostNPC','min';'CostInitialcapital','min';'SystemCOkgyr','min'};
%   custom_criteria={};
%   priority={'CostInitialcapital';'CostNPC';'SystemCOkgyr'};
%   constraints={'CostInitialcapital','max',50000;'SystemCOkgyr','max',25000;'SystemRenFrac','min',15};
%
[best,best_score,utilities]=SMARTER_for_HOMER(homer_data,homer_criteria,custom_criteria,priority,constraint
s);
%
%% Example 2:
%   homer_criteria={'CostOperatingcostyr','min';'CostInitialcapital','min';
%       'SystemCOkgyr','min';'SystemUnmetloadkWhyr','min'};
%   custom_criteria={'HDI','max','SystemExcessEleckWhyr',@(x)max(0.091*log(x/250)+0.0724,0)};
%   priority={'SystemUnmetloadkWhyr';'CostInitialcapital';'CostOperatingcostyr';'HDI';'SystemCOkgyr'};
%   constraints={'CostInitialcapital','max',50000;'SystemCOkgyr','max',25000;'SystemRenFrac','min',15};
%
[best,best_score,utilities]=SMARTER_for_HOMER(homer_data,homer_criteria,custom_criteria,priority,constraint
s);

%% Initialize variables
total_alternatives=size(homer_data,1);
eliminated_alternatives=strings(total_alternatives,1);
```

```
if ~ismember('Alternative', homer_data.Properties.VariableNames)
    homer_data.Alternative=string([repmat('A',total_alternatives,1),num2str((0:total_alternatives-1)')]);
end
%% Calculate Custom Criteria / Attributes
for counter=1:size(custom_criteria,1)
    func_handle=cell2mat(custom_criteria(counter,4));
    homer_data.(cell2mat(custom_criteria(counter,1)))=func_handle(...
        homer_data.(cell2mat(custom_criteria(counter,3))));
end

%% Enforce Constraints
index1=1;
% Iterate through each row of constraints and eliminate alternatives
% violating that constraint
for counter=1:size(constraints,1)
    switch cell2mat(constraints(counter,2))
        case 'max'
            eliminate=find(homer_data.(cell2mat(constraints(counter,1)))>cell2mat(constraints(counter,3)));
        case 'min'
            eliminate=find(homer_data.(cell2mat(constraints(counter,1)))<cell2mat(constraints(counter,3)));
    end
    % Index eliminated alternatives
    total_eliminated=length(eliminate);
    eliminated_alternatives(index1:index1+total_eliminated-1)=homer_data.Alternative(eliminate,:);
    index1=index1+total_eliminated;

    % Eliminate alternatives from data set
    homer_data(eliminate,:)=[];
end

%% Convert to non-dimensional utilities

% Determine best and worst single-attribute scores
% criteria using HOMER simulation results

utilities=table('Size',[size(homer_data,1),length(priority)+2],...
    'VariableTypes',["string";string(repmat('double',length(priority)+1,1))],
     'VariableNames',[{'Alternative'};priority;{'Overall'}]);
utilities.Alternative=string(homer_data.Alternative);
```

```
for counter=1:size(homer_criteria,1)
    % Identify highest and lowest single physical scores
    highest=max(homer_data.(cell2mat(homer_criteria(counter,1))));
    lowest=min(homer_data.(cell2mat(homer_criteria(counter,1))));
    switch cell2mat(homer_criteria(counter,2))
        case 'min'
            utilities.(cell2mat(homer_criteria(counter,1)))=100*(1-...
                (homer_data.(cell2mat(homer_criteria(counter,1)))-lowest)/(highest-lowest));
        case 'max'
            utilities.(cell2mat(homer_criteria(counter,1)))=100*(...
                (homer_data.(cell2mat(homer_criteria(counter,1)))-lowest)/(highest-lowest));
    end
end

for counter=1:size(custom_criteria,1)
    % Identify highest and lowest single physical scores
    highest=max(homer_data.(cell2mat(custom_criteria(counter,1))));
    lowest=min(homer_data.(cell2mat(custom_criteria(counter,1))));
    switch cell2mat(custom_criteria(counter,2))
        case 'min'
            utilities.(cell2mat(custom_criteria(counter,1)))=100*(1-...
                (homer_data.(cell2mat(custom_criteria(counter,1)))-lowest)/(highest-lowest));
        case 'max'
            utilities.(cell2mat(custom_criteria(counter,1)))=100*(...
                (homer_data.(cell2mat(custom_criteria(counter,1)))-lowest)/(highest-lowest));
    end
end

 %% Calculate ROC Weights
  ROC=zeros(length(priority),1);
 for counter=length(ROC):-1:1; ROC(1:counter)=ROC(1:counter)+1/counter; end; ROC=ROC/length(ROC);

 %% Calculate Overall Utility
  utilities.Overall=table2array(utilities(:,2:length(priority)+1))*ROC;
 [best_score,best]=max(utilities.Overall);
 best=utilities.Alternative(best)
```