Evaluation of Energy Systems for Distributed Green Data Centres using Lifetime Cash Flow Analysis

By

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Abstract

Distributed Green Data Centres (DGDC) are micro-data centre collocated with renewable energy generation sources. Multiple DGDCs are networked together to share information and computing processes. In this thesis, a year-long DGDC simulation balances the computing demand and supply each hour with variable renewable energy production and electricity prices. A five-year Net Present Value (NPV) analysis determines the optimal energy system with the lowest lifetime cost of computing (LCC), equal to the net present value divided by the amount of electricity used for computing. The LCC fairly compares alternative energy systems by the ability to provide lowest cost computing.

Grid-isolated DGDCs with 100kW of solar panels have an optimal computing capacity of 20kW and a 20 hour battery capacity. When the optimal grid-isolated DGDC is connected to the Ithaca electricity grid the battery storage is 10 hours and the LCC is $10/MWh less. The NYSERDA Solar PV Program applied to a grid-tied DGDC reduces the panel cost by $76,806 and reduces the LCC by 8.5%. Grid-tied DGDCs in Ontario are not feasible due to the high Feed-in-Tariff incentive to sell electricity.

A grid-isolated DGDC is optimal in Ithaca when the cost of transmission infrastructure upgrades are greater than $8291 or when the value of a generated Renewable Energy Credits (REC) are higher than $38/MWh. Both on- and off-grid DGDCs use equal amount of energy for computing but a grid-tied DGDC is able to sell 26% of electricity from a 100kW solar system with only 10kW of transmission capacity.

Grid-tied DGDCs are active market participants responding to electricity price signals. DGDCs buy low-cost electricity and sell electricity when prices are high. On average the cost of energy used by the DGDC is $19/MWh less than grid electricity. DGDCs provide a reliable source of computing for high-priority applications such as video streaming as well as a low-cost option for time independent tasks such as batch processes or cloud storage.
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<tr>
<td>DGDC</td>
<td>Distributed Green Data Centre</td>
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<tr>
<td>NPV</td>
<td>Net Present Value</td>
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<td>LCC</td>
<td>Lifetime Cost of Computing</td>
</tr>
<tr>
<td>NYSERDA</td>
<td>New York State Energy Research and Development Agency</td>
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<tr>
<td>IT/ITC</td>
<td>Information Technology and Communication</td>
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<tr>
<td>UPS</td>
<td>Uninterruptable Power Supply</td>
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<tr>
<td>PUE</td>
<td>Power Usage Effectiveness</td>
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<tr>
<td>FIT</td>
<td>Feed-In Tariff</td>
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<td>REC</td>
<td>Renewable Energy Credits</td>
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<tr>
<td>RPS</td>
<td>Renewable Portfolio Standard</td>
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<tr>
<td>NERC</td>
<td>North American Electric Reliability Corporation</td>
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<tr>
<td>POD</td>
<td>Performance Optimized Data Centre</td>
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<tr>
<td>AMD</td>
<td>Advanced Micro Devices</td>
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<tr>
<td>HPVCL</td>
<td>High Performance Computing Virtual Laboratory</td>
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<tr>
<td>IESO</td>
<td>Independent Electricity System Operator</td>
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<tr>
<td>NREL</td>
<td>National Renewable Energy Laboratory</td>
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<tr>
<td>LBMP</td>
<td>Locational Based Marginal Pricing</td>
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<tr>
<td>ISO</td>
<td>Independent System Operator</td>
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<tr>
<td>HOEP</td>
<td>Hourly Ontario Electricity Price</td>
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<tr>
<td>AC/DC</td>
<td>Alternation Current/Direct Current</td>
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<tr>
<td>SOC</td>
<td>State of Charge</td>
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<tr>
<td>MILP</td>
<td>Mixed Integer Linear Programming</td>
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<tr>
<td>IRR</td>
<td>Internal Rate of Return</td>
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<tr>
<td>SEARC</td>
<td>Sustainable Energy Applied Research Centre</td>
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<tr>
<td>FERC</td>
<td>Federal Energy Reliability Commission</td>
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<tr>
<td>NPCC</td>
<td>Northeast Power Coordination Council</td>
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<tr>
<td>NYISO</td>
<td>New York Independent System Operator</td>
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<tr>
<td>OPA</td>
<td>Ontario Power Authority</td>
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<tr>
<td>NYPF</td>
<td>New York Power Authority</td>
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<td>HP</td>
<td>Hewlett Packard</td>
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<td>OEB</td>
<td>Ontario Energy Board</td>
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<td>NYSEG</td>
<td>New York State Electric and Gas</td>
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<td>SLC</td>
<td>St. Lawrence College</td>
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<td>TCPL</td>
<td>Tompkins County Public Library</td>
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<td>RRP</td>
<td>Regulated Rate Plan</td>
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<td>PV</td>
<td>Photovoltaic</td>
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Chapter 1. Introduction

1.1. Distributed Generation and Computing

Demand for electricity has increased due to the continuing growth of information technology and computing. Reliance on fossil fuel thermal generation contributes to the production of pollutants and greenhouse gases. It is argued that renewable energy can power information technology and mitigate transmission constraints by collocating renewable energy with modular data centres. Furthermore, the geographically distributed nature of renewable energy is similar to the distributed nature of cloud computing.

A surge in renewable energy development and the growth of information technology presents a synergy for these two industries. Information technology is utilized in all aspects of society, including medical diagnostics, communication, and social media. Personal interactions with computers have shifted from a local personal computer to a mobile and connected experience in a cloud environment. Instead of owning and controlling computing resources in a single location, users communicate, access, and interact from virtually any location. Computing resources and information storage that is widely distributed can be accessed by users on demand.

The Distributed Green Data Centre (DGDC) is a micro-data centre co-located with a renewable energy source. Generated electricity is used on location, thereby eliminating the need for electrical transmission infrastructure to connect to large data centres. Many DGDC are connected together to form a network of micro-data centres that work together to ensure information and computing resources are available somewhere at any time. Lower cost data transmission infrastructure replaces the need for electricity transmission investments [1].
This thesis presents a method of determining the economic value of DGDCs at specific geographic locations. The model considers both grid-tied and grid-isolated DGDC energy systems that embrace renewable energy variability, electricity market design as well as, renewable energy policies. The outputs can be used to compare geographic locations and electricity jurisdictions. In addition, the model can be used to optimize the high level design of DGDC energy system components.

The model enables design and analysis of many possible DGDC arrangements. Grid-isolated DGDC energy systems can be optimized based on the available local renewable generation sources. If the DGDC is located near a transmission resource, the economic value of connecting to the electrical grid can be assessed. Location specific electricity policies, pricing schemes, and regulatory constraints are included in the analysis to understand the value of a grid-tied DGDC with renewable generation.

1.2. Information Technology Growth

Information technology and communication (ITC) has changed the way humans communicate, share information, view media, and stay connected. The number of connected devices has grown exponentially since the development of the internet in the 1970s. Cisco, a leader in networking equipment and operation, estimates there will be 50 billion connected devices by 2020 [2]. The growth in connected devices is fuelling growth in the internet and communication, which is predicted to double in size every 5.32 years [3].

Enabling this growth requires investments in ITC systems. Energy consumed by ITC has also increased drastically. In 2006 an estimated 1.5% of electricity generated in the United States was used to power IT equipment and data centres. This represents 61 billion kWh with an estimated cost of $4.5 billion [4]. Energy efficiency measures reduce the energy demand of data centres but electricity consumption will continue to increase.
Electricity used by computers in data centres represents only a part of the total electricity consumed. A significant portion of the energy consumed is used to remove heat from the data centre and ensure the computing resources remain within the design temperature limits. Additional electricity used for converting/inverting and conditioning electrical power. AC electricity is converted to DC for the uninterruptable power supply (UPS) and battery system. The DC electricity is then rectified to AC for distribution to the computers. Finally it is converted back to DC by the computer power supply. Each conversion/inversion uses electricity and generates heat due to inefficiencies. Overhead energy uses such as lighting and security systems also contribute to the total electricity consumed.

Data centre performance metrics are developed and published by the Green Grid [5]. The Green Grid is a consortium of data centre operator and information technology professionals dedicated to improving data centre efficiency. The metric regarding energy use is the Power Usage Effectiveness (PUE). PUE is a measure of the amount of electricity required to operate a data centre compared to the actual amount used for computing (1.1).

\[
PUE = \frac{\text{Total Facility Power}}{\text{IT Equipment Power}}
\]  

(1.1)

where;

- **PUE** is the Power Usage Effectiveness,
- **Total Facility Power** including computing, cooling, power conditioning, and overhead, and
- **IT Equipment Power** is energy used by the servers, switched and operator workstations.

A PUE of 2 indicates that for each kWh used by the computer, another kWh is used to support the computing. Data centre owners use the metrics to compare performance to similar data centres and determine if upgrades are necessary [5]. A study of 22 data centres indicated that most data centre PUE is between 2 to 3, but with proper design, a data centre can achieve PUE close to 1 [6].

Many efforts are currently being pursued to increase data centre efficiency. For instance changes to the power delivery systems reduce the power losses from conversions/inversion between AC and DC power [7]. Computational fluid dynamics modeling of data centres highlights the importance of server room
layout to maximize server cooling efficiency [8]. Changes to the design of the servers themselves allows
for high efficiency direct water cooling [9]. Radical changes to design and awareness of the energy
efficiency of both the hardware and software environment will eventually decrease energy consumption
of data centres [10].

Server virtualization balances computing loads across many servers eliminating data centre hot spots and
increasing cooling efficiency. Collocation facilities host IT equipment for small companies or
organization to in a common facility which shares cooling and power infrastructure. Cloud computing
moves data storage and computational processing away from individual personal computers to data
centres that are focused to ensure reliable access to information.

Regardless of energy efficiency initiatives, a source of electrical power is required. Greenpeace examined
the power source for data centres of 9 large internet companies (Figure 1.1). The 2011 report found that
over half of the surveyed data centres relied on coal to supply the majority of their power [11].

![Figure 1.1 – Data centre power sources for 9 large internet companies [11].](image)

Subsequently a 2012 a report examined an additional 5 internet companies [12]. Since these reports, some
internet companies have started to take action on mitigating coal use. SalesForce, a cloud based company
made a commitment to increase efficiency and increase the amount renewable energy used in their data
centres [13]. Additionally Facebook announced a new data centre to be developed in Sweden powered by
hydroelectricity and utilizing free cooling for 8 months of the year [14].
Power availability and quality for a data centre influence the choice of location. Data centre reliability is benchmarked by the Uptime Institute’s data centre site infrastructure Tier Classifications. They assess the ability of a data centre to maintain long term operational functionality to indicate the reliability and redundancy of the data centre infrastructure [15]. The higher the Tier, the greater uptime a data centre will have (Table 1.1).

<table>
<thead>
<tr>
<th>Tier</th>
<th>Basic Site Infrastructure</th>
<th></th>
<th>Redundant Site Infrastructure</th>
<th>Concurrently Maintainable Site Infrastructure</th>
<th>Fault Tolerant Site Infrastructure</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>▪ No redundant components</td>
<td>▪ Critical components have redundant capacity</td>
<td>▪ Critical components have redundant capacity</td>
<td>▪ Fully functional redundant system of critical components.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>▪ Site is shut down for service and maintenance</td>
<td>▪ Maintenance on critical infrastructure will disrupt service</td>
<td>▪ Site can be serviced without a disruption in service</td>
<td>▪ Site can be serviced without a disruption in service</td>
<td></td>
</tr>
<tr>
<td></td>
<td>▪ Planned and unplanned events can disrupt service</td>
<td>▪ Planned and unplanned events can disrupt service</td>
<td>▪ Planned and unplanned events can disrupt service</td>
<td>▪ Site is fault tolerant from planned or unplanned events</td>
<td></td>
</tr>
<tr>
<td></td>
<td>▪ Site is susceptible to operational error</td>
<td>▪ Site is susceptible to operational error</td>
<td>▪ Site is protected against operational errors</td>
<td>▪ Site is protected against operational errors</td>
<td></td>
</tr>
</tbody>
</table>

Table 1.1 – Data centre infrastructure reliability based on The Uptime Institute rating system [15].

Even the highest levels of reliability and functionality do not protect against the possibility of local or regional disasters [15]. Data centres must protect against the risk of large scale natural and man-made disasters [16]. Some factors considered when siting a new data centre include:

1. Secure against targeted attacks.
2. Secure against natural disasters. (e.g. earthquakes, flooding, tornados, hurricanes, snow, wildfire)
3. Local climate and data centre cooling.
4. Availability of a high speed communication network.

Current data centre efficiency initiatives reduce but do not eliminate the need for electrical power. Using renewable energy is the next step to the “greening” of information technology. Renewable energy reduces
the production of greenhouse gases but adds an increased risk from generation intermittency and variability. The reliability and redundancy requirements for data centre operation must be considered when using renewable energy power sources.

1.3. Renewable Energy Growth

Renewable energy growth is being driven by the need for an emissions reduced source of energy. Since 2000 energy derived from wind and solar has grown by 27% and 42% per year on average [17]. In 2011, 19% of the world energy demand was supplied from renewable energy sources. Worldwide renewable energy incentives in 2011 were worth $88 billion dollars, a 24% increase from 2010 [17].

In Ontario, renewable energy installations are expected to reach 6,800MW by 2014, which is an increase of 3,200 MW since 2010. The recent growth in renewables is driven by the Ontario Feed-In Tariff (FIT) program as part of the Ontario Green Energy and Green Economy Act. The Ontario FIT incentive is a 20-year contract to purchase electricity at a fixed rate from renewable generation sources [18]. FIT programs provide stability for investors that will provide the financial capital for renewable generation development. As the renewable energy infrastructure develops and markets changes, the incentives for new FIT contracts are adjusted to reflect the new costs [19]. The Ontario FIT incentive has been adjusted 4 times since the beginning of the program in 2009 [20].

Renewable energy growth in New York has been largely focused on the development of hydro power, solar and wind generation technologies. Renewable energy accounted for 22% of New York’s energy production in 2012 and in 2013 there was 6076 MW of installed renewable generation [21]. Renewable energy has the potential to provide 40% of New York’s energy demands by 2030 [22]. Yearly wind energy production has increased from 112 GWh in 2004 to 3,060 GWh in 2012 [23].

The New York renewable energy sector has been driven by the Renewable Portfolio Standard (RPS). The standard mandates that 30% of electricity will be generated from renewable energy sources by 2015 [24].
This is accomplished by collecting a fee from customers to fund incentives for renewable energy development. Depending on the program, incentives for renewable energy projects can offset the capital costs of new installations or are paid for each kWh of renewable energy generated [25].

Renewable Energy Credits (RECs) are another renewable energy incentive common in the United States. Generators are credited a REC for each MWh of renewable energy produced which are bought and sold on a REC market. In some States, utilities are able to purchase RECs to fulfil the state RPS requirements. The requirements for REC qualification varies greatly between states and the source of renewable energy [26].

The distribution of renewable energy resources are often geographically separated from the location of the consumers. In general the solar and wind energy potential in Canada and the United States is greatest in the western half of the continent. The south-west states have the highest solar energy potential in United States. The US mid-west and the Canadian prairies have a large wind potential as well as near large bodies of water (Figures 1.2).
A map of nighttime light sources from settlements in North America approximates the distribution of populations and load centres (Figure 1.3). Many of North American settlements are located on the east and west coast of the continent, which are removed from renewable energy locations. New renewable generation developments often require upgrades to the transmission system to connect the load centres. Because of the intermittent nature of generation, the transmission interconnections can be under-utilized during non-peak generation periods and highly congested during peak periods.
In New York, three transmission projects have increased the capacity in the New York City and Long Island control zones [32]. Additionally, transmission upgrades in Central, Northern and Western New York are planned as part of the New York Energy Highway Blueprint to promote investment in New York’s high-tech economy [33].

Recent upgrades in Ontario have increased the transmission capacity to Toronto from Bruce County. Renewable energy developments have increased the generation capacity of the region from 5.0 GW to 7.3 GW in 2012. There is potential for another 1 GW of renewable energy development in the region [34].

Reasons for transmission and distribution system upgrades are reliability issues, economics, and generation interconnection. Reliability upgrades strengthen the resiliency of the electricity grid to accommodate new generation. Economic upgrades reduce the cost of electricity eliminating transmission constraints for low cost generators. Interconnection upgrades connect remote generation sources to the electrical grid. Reliability and interconnection upgrades are the most common reason for transmission expansion in the NERC region, which includes Ontario and New York (Figure 1.4) [35].
Figure 1.4 – Reasons for transmission upgrades in NERC reliability region.

Renewable energy sources are often located far from the load centres and have intermittent generation profiles. A reliable and resilient transmission system will require upgrades to connect renewable generation. Transmission investments can be reduced by moving the energy consumers to the location of the generation. The Distributed Green Data Centre (DGDC) concept proposes to locate computing loads adjacent to generation facilities and mitigate the need for transmission upgrades.

1.4. The Distributed Green Data Centre Concept

A demand for green computing and a shift towards distributed electricity generation has inspired a novel green data centre concept. The distributed green data centre (DGDC) concept, proposes to collocate small-scale data centres with distributed electricity generation sources. The small-scale performance optimized data centres (PODs) use electricity generated from the renewable energy to provide computing services. Multiple PODs are connected together forming a network of micro-data centres. Computing tasks can be shifted to the location where electricity is being generated or is least expensive.

The Distributed Green Data Centre (DGDC) concept is being researched by a team at Clarkson University in Potsdam, New York. The project is funded by New York State Energy Research and Development Agency (NYSERDA) through NYSERDA PON 1772. The team receives support from project partners Advanced Micro Devices (AMD) and Hewlett-Packard Corporation (HP) [36].
A DGDC is a self-contained computing system capable of autonomously initiating, processing data and shutting down with signals from a central control location. The system includes electrical, computing, and communication equipment that are used to operate the DGDC. Once a DGDC is installed, it is controlled from a central location and minimal direct maintenance is required.

PODs are prefabricated, modular data centres that contain the DGDC computing resources as well as the required electrical and cooling systems. PODs range in size and can be scaled to match the power resources available. PODs cooling and power systems are energy efficient, with a PUE in the range of 1.05 to 1.30 [37]. A key benefit of the POD model is the ability to quickly deploy and install computing resources. The construction time for prefabricated PODs is much lower than traditional brick and mortar data centres. In addition, modular PODs can be relocated to the renewable generation source.

DGDCs collocated with wind energy in New York can facilitate the development of renewable energy in northern and western New York. Data centres in load centres such as New York City and Long Island can be relocated to renewable energy generation as PODs. The DGDC network provides an environmentally sustainable computing option with a low carbon footprint.

The DGDC concept uses both intermittent and dispatchable renewable energy sources. In addition DGDCs can connect to the electrical grid as a primary source or a back-up source. Batteries can store excess electricity and extend the uptime of DGDC. Regardless of the energy sources, some energy storage is required to ensure consistent power quality and allow the POD to shut down properly when power is lost.

Communication and network connectivity are critical for remotely operated DGDCs. Sufficient communication bandwidth to the DGDC network central controller is needed. When power is lost the DGDC workload must be migrated to another location to maintain uptime for the user. The DGDCs network is connected via fiber optics, which are capable of high band width communication. If the electricity at a DGDC site is insufficient to meet demand, then processes will be sent to another location.
A DGDC energy system must have enough bandwidth and energy storage is available to maintain operation and relocate the current processes.

1.5. DGDC Potential Benefits

A DGDC network facilitates the intelligent use of power depending on the local cost of electricity. Market based incentives such as demand response programs can provide signals to DGDC operators to migrate computing and reduce demand on the local grid. A study on a distributed network of data centres, which allocated computer use based on electricity price achieved energy savings in the range of 30%-45% [38]. Hourly electricity prices were used to capture the changes in electricity prices while still staying within the limitations imposed by the routing equipment.

Renewable energy sources located in very remote location far from existing transmission lines are not economically feasible due to the high cost of transmission infrastructure. Renewable energy generators that are sited close to existing infrastructure can also face high interconnection costs if the transmission or distribution grid is not resilient enough to handle the increase in generation capacity. A collocated DGDC can utilize a portion of the generated electricity while still providing electricity to the local grid. This approach could also provide load balancing services in a micro-grid application with renewable generation.

The mobile nature of DGDCs can offer a solution to the “chicken and egg” problem faced between renewable development and transmission upgrades. In order to develop a new renewable energy source, the transmission infrastructure needs to be built first. As a result, the renewable energy projects are often delayed by the planning, permitting and construction of transmission lines. Renewable energy projects take 2-3 years to develop whereas a large scale transmission project can take up to a decade [39]. During the intervening years, renewable projects could be developed with collocated DGDCs to use the generated
electricity. Once the transmission upgrades are completed, the DGDCs are removed and the generated electricity is sold to the grid.

Data centres distributed across a large geographic area provide an additional level of resiliency for ITC services. Localized natural disasters would have a minor impact on the overall performance of a well-designed DGDC network. In addition, redundant copies of critical information can easily be kept in multiple locations.

Grid-tied DGDCs have the option of participating in the local electricity market pricing schemes and renewable energy incentives. A DGDC can minimize the generation peaks from renewable energy while still selling a portion of the generated electricity to the grid. A DGDC with a larger computing and storage resource maximizes the use of low cost energy but increase the capital cost of the system. A method to assess the economic feasibility of a DGDC energy system designs is developed in this thesis.

1.6. Thesis Objective

DGDCs can provide a sustainable source of computing to meet the needs of today’s society. A holistic approach to sustainability respects the need for environmental protection while maintaining economic feasibility and social responsibility. When considering the design of the DGDC all aspects and impacts of the operation must be considered to find a truly sustainable system.

From the broad overview provided above, the objective of this thesis is to;

*Develop a method to validate and compare energy system designs for distributed green data centres while considering the design implications of renewable energy production, electricity market economics and data centre computing demands.*

To meet the above objective a general model is developed to analyze the performance of DGDCs for any location. At each location there is an optimal set of system components to match the renewable energy
availability and the regulatory constraints. The optimal DGDC energy system is defined as the system that provides the most electricity for computing at the lowest lifetime cost, taking into account capital equipment cost, operating expenses and revenue from selling electrical energy.

Revenue from computing services depends on the type of service that is offered. For example, data storage is billed on a $/GB/month, website hosting charges based on upload/download traffic, and high performance computing as $/kWh of electricity consumed. In a DGDC network the revenue at one location is dependent on the price of electricity at all other locations.

Instead of defining a value for computing services, this thesis minimizes the cost of computing services for one location. This is analogous to the approach used by Mohsenian-Rad in [40] on demand-side management in a smart grid application. The study found that a global minimum in power costs can be achieved when each consumer optimizes their individual energy consumption based on load and electricity price. Another study by Mohsenian-Rad and Leon-Garcia [41] optimized a network of independently optimized data centres based on electricity costs, carbon footprint and information latency.

1.7. Thesis Organization

Chapter 2 includes a review of energy system modelling and defines the requirements for a DGDC model. Additional information about inputs and methods are discussed to provide a basis of design for the model. Chapter 3 describes the simulation of a DGDC for one year and Chapter 4, builds on the results to perform a lifetime cash flow analysis. Chapter 5 introduces the DGDC case studies in Kingston, Ontario and Ithaca, New York. The Ontario case study in Chapter 6 shows how the model can assists DGDC designers by comparing investments in battery storage, transmission infrastructure and computing resources. The Ithaca case study in Chapter 7 compares grid-tied and -isolated DGDCs with renewable energy incentives. Chapter 8 verifies the performance of the energy system model and discusses the ramifications of collocated DGDCs.
Chapter 2. DGDC Energy System

2.1. Energy System Modeling

Energy system models are used in many applications from high level national policy planning to designing components for energy systems. The DGDC concept is an integrated system composing of renewable energy, computing demands, electricity economics, and energy policies. The goal of the model is to understand the characteristics of a DGDC energy system and provide options to policymakers and energy system designers.

Lund [42] highlights the important of choice awareness in energy system design. Choice awareness is a concept where decision makers, whether it is a national energy policy or energy system design, are provided with all of the relevant information required to make an informed decision [42]. Without a full picture of all the available alternatives, the designer choices are biased. Energy system models provide choice awareness of design alternatives for decision makers.

Lund provides basic criteria for energy system models [42]. The criteria are applied the DGDC energy system model:

A model should make fair comparative analysis of all possible systems. The DGDC model is designed in such a way that multiple energy system designs or electricity market structures can be compared. The output of the model provides a lifetime cost of computing to compare energy systems.

A model should not focus on the existing institutional set-up. The DGDC system is a unique concept outside of the existing data centre environment. Interaction with the electricity markets can range from a simple fixed contract rate to demand response based on price signals from the electricity market.
The outputs of the model need to provide suitable information for decision makers. The model is designed to optimize the computing resources for a specific geographical location and renewable energy source. In addition to the lifetime cost of computing, other simulation outputs such as transmission utilization and energy storage usage provide designers with insight into DGDC operation.

A model should be allows users to identify and design alternative futures. The DGDC model allows all generation types as well as current and hypothetical electricity market participation programs.

Lund makes a distinction in energy system models based on the type of renewable energy data used in the analysis [42]. Data aggregated into yearly or monthly averages is useful for assessments at a national level with a small share of the total electricity generation market. Aggregated data is easier to compute, document and communicate than hourly generation data. Hourly generation data accurately represents the variable and intermittent nature of renewable energy. This level of accuracy is required for energy systems that contain renewable generation as a main energy source such as a DGDC.

The HOMER Micropower Optimization Model developed by the U.S. National Renewable Energy Laboratory (NREL) fits the criteria of an appropriate model for a DGDC energy system [43]. The HOMER model is used for the design of micro-power energy systems with multiple electrical generation and storage technologies in both grid-tied and -isolated arrangements. HOMER performs a lifetime cash flow analysis of an energy system that allows designers to compare many different system configurations. Financial, environment, and technical outputs are calculated for designers to make informed decisions.

In the initial stage of this research, the HOMER model was tested as a possible modelling program for the DGDC energy system. Ultimately, the model was not feasible due to an incompatibility between the energy loads of a DGDC and the HOMER model inputs. In the HOMER model, the expected electrical load of the energy system is a required input for the simulation. Whereas the DGDC energy loads at a specific location are dependent on the cost of available electricity across the entire DGDC network.
For example, if a DGDC network consisted of two solar powered locations, where one is sunny and one is cloudy, the DGDC in the sunnier location will have the cheapest energy available and will compute more than the cloudy location. This is further complicated for DGDC energy systems that are connected to electrical grid where the price of grid electricity also impacts the amount of computing completed. The HOMER model does not provide a method to define loads based on the current cost of electricity, which is required for a DGDC network application.

Even though the HOMER model was not utilized, guidance was taken from it to develop the DGDC model. The HOMER model is divided between a one year energy system simulation and the optimization of multiple energy systems. HOMER uses hourly data to perform a simulation on the flow of energy through the system components. The HOMER optimization compares energy systems based on the lifetime cost of the system including all of the installation, operation, and end of life costs. These concepts have been adapted to develop a model for a DGDC energy system.

### 2.2. DGDC Systems Model

The DGDC energy system models a single DGDC location without directly considering the implications of the larger DGDC network. Similar to the study in [40] on energy consumption of households in smart grid application, optimizing energy use for an individual DGDC will provide the most efficient DGDC network. Individual DGDC that operate with the lowest lifetime cost provide an overall network with the lowest cost.
The energy system framework consists of four basic components: a generation source, a computing resource, an energy storage device, and connection the electricity grid (Figure 2.1). The power flows between the components (numbers 1 through 6) are tracked during the hourly simulation. This energy system is simplified and does not include many of the other components required for an actual DGDC. The purpose of this simplified model is to determine the general sizing of main DGDC components.

Figure 2.1 – DGDC energy system components and power flows.

Not all components of the DGDC need to be included in each energy system. For example a grid-isolated DGDC would not have an electricity grid component. A DGDC can get electricity from either the renewable energy source or the existing electrical grid or both. Figure 2.2 illustrates the possible configurations of grid-tied and -isolated DGDC energy systems.

Figure 2.2 – Possible DGDC energy system configurations for grid tied and grid isolated systems.
A grid-isolated DGDC will be powered exclusively from the renewable energy source. The relative size of the computing resource compared to the renewable generation size is chosen through optimization of computing, battery and generation requirements. A grid connected DGDC can have three possible configurations when used with a renewable energy source. An oversize renewable energy source will sell excess generated electricity to the electrical grid. An undersized generation source will purchase electricity from the electrical grid for some computing. A DGDC without a renewable generation source will depend exclusively on electrical grid and represents the current state of data centres.

2.3. Computer Energy Loads

Computing demands in data centres are dependent on the applications and processes using the computing resources. Ideally, data centres operate at 100% capacity at all times to maximize the use of the computing resources. In reality, data centres are designed for specific purposes and as a result the data centre experiences times of reduced energy demand.

For example, the Toronto Internet Exchange is a large internet exchange centre redirecting internet traffic for Toronto, Ontario and the surrounding area. The traffic handled by the data centre creates a computational demand and electricity load. The traffic over the course of a week (Figure 2.3) is intermittent with peaks in traffic during the evening and lows early in the morning [44].

Figure 2.3 – Internet traffic at the Toronto Internet Exchange [44].

Another example of an intermittent computing demand is a server hosting data for a large corporation or organization. The number of users that are accessing the information affects demands on a server. The
energy consumption for Botterell Hall on Queen’s University campus (Figure 2.4) mimics server use during a work week [45]. The load within the building peaks daily at noon but with lower energy demands during the weekend.

Figure 2.4 – Electricity demand of Botterell Hall at Queen’s University Campus [45].

In contrast to the intermittent demands of the Toronto Internet Exchange and Botterell Hall, some data centres have a constant power usage profile. The High Performance Computing Virtual Laboratory (HPCVL) in Kingston is a data centre used for a broad spectrum of computing applications, including fluid dynamic modelling, medical imaging and database purposes [46]. Processes completed at HPCVL have job lengths that vary from minutes to months. 5% of processes are completed in less than 5 minutes, 75% take between 1 hour and 1 day, and 20% take months to complete [46]. Computational loads at HPCVL are scheduled to ensure that the energy demands are more consistent over daily and annual timeframes (Figure 2.5).

Figure 2.5 – Daily energy demand (left) and annual energy consumption (right) paof HPCVL.
As shown by these three examples the design of the energy system must consider the expected computational load profiles. An intermittent renewable source of electricity would be unable to provide a reliable source of power but may align well with the variable computing demand profiles.

2.4. Energy Resources

The energy sources for the DGDC computing loads are from one of three sources; either renewable generation, the electrical grid, or the energy storage device. When electricity is generated it can be used either for computing, stored in the battery or it can be sold. It is assumed electrical power can always be bought or sold to the grid but the price of electricity may be variable depending on the contract with the local utility. Stored energy can only be used for computing to reduce the cost of computing or it can be deployed to react to the intermittency in generation.

Intermittent renewable energy source such as solar only generates electricity during the day (Figure 2.6). Averaged over a year no power will be generated by solar energy for 12 hours each day. Additionally if it is cloudy or if the panels are covered with snow, the production will be significantly reduced. In the winter less energy is produced from a bank of solar panels since the days get shorter and the sun is closer to the horizon.

![Image of solar generation output variation]

Figure 2.6 – 8 days (above) and monthly (below) solar generation output variation.
Wind energy generation is also variable, but less cyclic than solar since wind may be encountered both day and night. Wind energy is susceptible to weather systems and production may be constant for multiple days or may not be produced for days. The variability of wind generation is less predictable than the daily cycle of solar energy (Figure 2.7). Over the year there is an increased amount of wind energy production during spring and fall due to unsettled weather.

The yearly variations in solar and wind generation can complement each other if multiple DGDC are networked together. During the summer when wind production is lowest, the solar generation is maximized. In the winter wind energy production increases when solar production is reduced. A DGDC network with a diverse set of renewable energy sources would be able to cope with the variations in renewable energy generation.

DGDCs connected to the electricity grid, have the opportunity to purchase and sell electricity. Depending on local electricity market policies, a grid-tied DGDC has the opportunity to become an active market participant. A fundamental concept of the DGDC is the ability to quickly shift loads to other DGDC to use energy when and where it is available. This capability could be expanded to enable participation in market programs such as demand response or load shedding.

A basic form of DGDC market participation is pricing arbitrage between multiple electricity markets. In New York, the price of electricity is varied based on transmission zone, known as locational based
marginal pricing (LBMP). LBMP is a combination of the marginal price of electricity, marginal cost of losses, and marginal cost of congestion. For example the price of electricity in Long Island is $30.09/MWh whereas the price in the Central Region near Ithaca is $26.90/MWh (Figure 2.8) [47]. If DGDC are located in both locations, the DGDC operator can dispatch the computing load from Long Island to the Central Region.

![Image of LBMP in New York State]

Figure 2.8 – LBMP of electricity in New York State [47].

The grid price of electricity is adjusted constantly in response to changes in demand and generation. Over 5-days in 2012, the grid price of electricity in New York Central transmission zone fluctuated between $6.29/MWh to $81.21/MWh (Figure 2.9). A grid-tied DGDC with energy storage would be able to schedule the computing load and battery cycles to maximize use of low cost electricity.

![Electricity Price Chart]

Figure 2.9 – Price of electricity in the New York Central region over 5 days in 2012.

Electricity price in Figure 2.9 may appear to be random over the course of the day, but in reality the price of electricity can be forecasted. Electricity ISOs forecast days, hours and minutes ahead to ensure
electricity supply and demand is balanced. The price of electricity over the course of a day usually peaks around 5:00pm and is lowest at 4:00am (Figure 2.10 a&b).

![Figure 2.10 a & b – Daily average electricity price in New York (left) and Ontario (right) for 2012.](image)

A DGDC as a market participant responds to high prices by moving computing loads and reducing the overall demand for electricity. Another approach for the ISO to balance supply and demand is to pay customers to reduce their energy consumption with demand response programs. In New York, energy-users bid the amount of load reduction either in a day ahead or a real-time market [48]. In Ontario, participants with predictable energy demand profiles are called upon to reduce their loads during peak periods [49] [50]. The load shifting capabilities of DGDCs allows a grid-tied system to participate in demand response programs.

Each component of a DGDC: the computing, the renewable energy generation, and the electricity grid, present variable amounts of demand and resources. In some cases the renewable energy generation, computing demand and grid electricity prices are correlated. For example, solar energy and the price of electricity are positively correlated, where high solar generation corresponds to higher energy prices (Figure 2.11).
Figure 2.11 – The grid price of electricity compared to the amount of electricity generation from solar panels.

The correlation is not a cause and effect relationship, but rather both the electricity price and generation have similar variations. The price of electricity is typically highest during the day, which corresponds to maximum solar generation. Furthermore, the solar generation is highest during the summer months, when solar irradiance is high. The high summer temperatures cause an increase in the amount of air conditioning required to cool buildings.

The price of electricity is negatively correlated to the amount of wind generation. For wind farms in Ontario the lowest electricity price corresponds the maximum generation (Figure 2.12).

Figure 2.12 – The grid price for electricity compared to the amount of electricity generation from wind turbines.

Wind farms are often larger than solar farms and can contribute a significant portion of electrical grid generation. When wind generation is maximized less electricity from other sources is generated or imported to match demand. If too much wind energy is produced and there is an excess of electricity the local price decreases.

A model with yearly aggregated data or a Monte Carlo simulation with randomly generated values for renewable energy productions, electricity price, and computing demand does not represent system
relationships. The DGDC model will require hourly simulation data from real locations. This will ensure both the variability and correlations between systems components is taken into account.

2.5. Model Assumptions and Design Goals

The model presented in this thesis simulates the operation of a simplified DGDC energy system over the course of a year. The energy system consists of an electricity generation source, an energy storage device, a computing load, and a connection to the electrical grid. Each hour the energy flows between components are simulated, and the real cost of the flows are calculated. The total amount of electricity used for computing and the operating costs are used in a five-year cash flow analysis to determine the net present value of a DGDC.

The model assumes the DGDC interactions with the electrical grid are small and do not affects the electricity market. The price of electricity is not adjusted to reflect the impacts of the DGDC buying and selling of electricity.

The cost of connection to the data transmission network is not included lifetime cash flow analysis. Since all DGDC systems will require a connection to the network, the capital cost of installing the require infrastructure will be similar for any size of computing. This means the cost of data transmission connection has minimal impact on the optimal design of DGDC energy systems.

The conversion and inversion of electricity between AC and DC power is ignored. It is assumed that the electricity from the grid or the generation can be used to charge the battery or power the computing resource without the need to condition to electricity.

The energy model is simulated for an entire year in hourly increments. The model is assumed to be quasi-steady state, where the hour-long time steps are assumed to be steady state. During these time periods, the
generation output, and power flow remain constant between components. This permits the small variations in generation or demand to be ignored in the simulation.

The design goal of the DGDC energy system is to minimize the cost of computing at each location. This represents the real-time operating procedures where computing loads are scheduled at the location with the lowest cost computing. The hourly simulation mimics the goals of a DGDC operator with high and low electricity price and with high and low generation (Table 2.1). The DGDC sells electricity to the grid when the price of electricity is high. When generation is high, the excess generated electricity may be used for computing.

<table>
<thead>
<tr>
<th>Price of Electricity</th>
<th>Low</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td><strong>Buy electricity</strong> for computing and charging the battery</td>
<td><strong>Use generated energy</strong> for computing and charging the battery</td>
</tr>
<tr>
<td>High</td>
<td><strong>Sell electricity</strong> and discharge battery for computing</td>
<td><strong>Sell electricity</strong> and compute with excess generation</td>
</tr>
</tbody>
</table>

Table 2.1 – Operating decisions for a DGDC.

The battery stores electricity when the cost of computing is low and discharge when the cost of computing is high. When generation is high and there is excess electricity, the battery is charged for later use. For example excess solar generation is stored during the daytime and the battery is discharged in the evening (Figure 2.13).

![Figure 2.13 – Battery operation in a grid-isolated solar power DGDC.](image)

In this example, the computing resource is sized to be 30% of generation capability. During the day, solar generation powers the computing and charges the battery. After the sun goes down, the battery begins to
discharge, allowing the computing resource to continue to operate at full power for 17 hours. If the DGDC is grid-tied, the battery can be used to store low cost grid electricity for use during periods of high price electricity.

Traditionally the transmission capacity for renewable generation is sized to meet the maximum power output. An intermittent energy source will produce maximum output at infrequent intervals and the transmission will be underutilized. The capacity factor describes how often a component is used compared the maximum amount the component could be used. A high capacity factor indicates the component is utilized at its maximum capacity.

\[
\text{Capacity Factor} = \frac{\sum_{i=1}^{N} P_i \cdot t_i}{P_{\text{max}} \cdot T_N}
\]

where;
- \( N \) is the number of time steps,
- \( P_i \) is the power level during time step \( i \),
- \( T_i \) is the length of the simulation,
- \( P_{\text{max}} \) is the rated component capacity, and
- \( T_N \) is the length of the simulation.

Solar irradiance received at a solar generation array in Kingston, Ontario indicates peak generation happens infrequently throughout the day (Figure 2.14). Transmission designed to meet the maximum output of the solar farm will have the same capacity factor as the solar generation.

![Normalized solar irradiation data from St. Lawrence College on June 23, 2011](image)

Figure 2.14 – Normalized solar irradiation data from St. Lawrence College on June 23, 2011

If the capacity of the transmission is less than that the maximum production of the solar farm, then the
transmission will have a higher capacity factor. Reducing the transmission capacity means less electricity can be sold to the grid during high generation. Table 2.2 lists the capacity factors for transmission rated at 100%, 75%, 50% and 25% of the solar farm generation.

<table>
<thead>
<tr>
<th>Transmission Capacity [% of generation]</th>
<th>Transmission Capacity Factor</th>
<th>Percent of Electricity Sold to Electrical Grid</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>27 %</td>
<td>100 %</td>
</tr>
<tr>
<td>75</td>
<td>34 %</td>
<td>96 %</td>
</tr>
<tr>
<td>50</td>
<td>43 %</td>
<td>81 %</td>
</tr>
<tr>
<td>25</td>
<td>50 %</td>
<td>47 %</td>
</tr>
</tbody>
</table>

Table 2.2 – Capacity factor and electricity sold for decreasing transmission capacities.

A high transmission capacity factor means the transmission resources is utilized more frequently. The magnitude of the solar generation variability is mitigated for restricted transmission capacities. A grid connected DGDC with a small transmission capacity can use excess generation and increase the capacity factor of the transmission resource.

### 2.6. Modelling Overview

The next two chapters describe the hourly simulation and the economic analysis used for comparing DGDC energy systems. The hourly simulation is conducted for an entire year for each energy system configuration. The outputs of the hourly simulation are used in the economic analysis, including the operating cost and the energy used for computing.

The economic analysis is conducted for the lifetime of the DGDC and takes into account the capital, operating and end of life costs of the system. Multiple energy system configurations are compared, and the best system completes the most computing for the lowest cost.
Chapter 3.  Hourly Simulation Method

3.1.  Simulation Introduction

Operation of the DGDC energy system is modeled using an hourly simulation of energy flows. Power flows within the DGDC are obtained using the hourly production from the renewable energy source and the hourly price of grid electricity. Possible power flows use renewable generation for either computing, storage or sold to the grid. Additionally, electricity may be purchased from the electrical grid and used for either computing or stored in the battery. Linear programming is used to find the minimum cost of supplying electricity for computing.

The amount of energy used for computing each hour is determined using a computing supply and demand curve analysis. The computing supply curve represents the opportunity costs of using electricity for computing instead of selling to the grid or storing in the battery for future use. The supply curve is compared to the computing demand curves, which represents the value of computing to the entire DGDC network. The equilibrium point between these two curves determines the amount of computing performed.

The amount of electricity used for computing, the overall cost of operating the DGDC and the cost of computing is recorded each hour. These values are used in a lifetime cash flow analysis described in Chapter 4.

A symbolic flowchart of the hour-by-hour simulation is provided in Figure 3.1. The hourly simulation contains nested loops. The outer loop repeats for all the hours of the simulation, thereby determining the system costs for the entire simulation year. The inner loop is used to determine the amount of electricity that is used for computing. The rest of this chapter discusses the equations and assumptions that are used in the hourly energy flow simulation.
3.2. Simulation Data

The inputs to the hourly simulation are separated into three categories: energy system capacities, hourly simulation data, and operational variables. Energy system size variables define the maximum capacities of the DGDC components. Hourly renewable energy production and price data for grid electricity define the location specific inputs for the simulation. Operational variables define the operation of the battery and demand for computing resources.

There are seven energy system size variables that define maximum capacities (Table 3.1). The generation and computing resources are limited by the maximum power that can be produced and used, respectively. The transmission capacity is limited by the amount of electricity bought and sold. Storage capacity
indicates how much energy can be stored. The battery is also limited by the maximum charge and discharge rate.

<table>
<thead>
<tr>
<th>Component Capacity</th>
<th>Unit</th>
<th>Symbol</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generation Production</td>
<td>[MW]</td>
<td>PC&lt;sub&gt;gene&lt;/sub&gt;</td>
</tr>
<tr>
<td>Computing Capacity</td>
<td>[MW]</td>
<td>PC&lt;sub&gt;comp&lt;/sub&gt;</td>
</tr>
<tr>
<td>Selling to Grid</td>
<td>[MW]</td>
<td>PC&lt;sub&gt;sell&lt;/sub&gt;</td>
</tr>
<tr>
<td>Buying from Grid</td>
<td>[MW]</td>
<td>PC&lt;sub&gt;buy&lt;/sub&gt;</td>
</tr>
<tr>
<td>Battery Charging</td>
<td>[MW]</td>
<td>PC&lt;sub&gt;charge&lt;/sub&gt;</td>
</tr>
<tr>
<td>Battery Discharging</td>
<td>[MW]</td>
<td>PC&lt;sub&gt;discharge&lt;/sub&gt;</td>
</tr>
<tr>
<td>Battery Storage</td>
<td>[MWh]</td>
<td>PC&lt;sub&gt;batt&lt;/sub&gt;</td>
</tr>
</tbody>
</table>

Table 3.1 – DGDC Energy System Component Capacities

Location specific data for the DGDC include the hourly generation data and the hourly price of electricity. Production data are expressed as a percentage of the maximum generation. Maximum generation is expressed as a value of 1 and a value of 0 means no generation. Equation (3.1) is used to normalize renewable energy production data recorded from an actual generation source.

\[
\text{Normalized Production Value} = \frac{\text{Measured Production [MW]}}{\text{Generator Capacity [MW]}} \quad (3.1)
\]

Hourly generation data is input at an N by 1 column vector, where each row represents the normalized production value during one time step.

\[
\text{Hour}\_\text{Generation} = \begin{bmatrix}
PV_{T=1} \\
PV_{T=2} \\
\vdots \\
PV_{T=N}
\end{bmatrix}
\]

where;

- \(PV\) is the production value during time step \(T\), and
- \(N\) is the number of time steps in the simulation.

The grid price of electricity is a two column vectors, one vector for the price paid and one for the revenue received. Values are reported in $/MWh and account only for the commodity charge of electricity. The rows of the grid price and generation vector correspond to the same time step and must be equal in length for the simulation.
where:

**GridSell** and **GridBuy** are value of electricity sold and bought from the electrical grid, respectively.

**T** is time step, and

**N** is the number of time steps in the simulation.

In addition to grid price and generation vectors, two column vectors are used to describe the shape of the computing demand curve. The battery charging parameter is a six number vector and represents that incentive to charge the battery based on future computing energy costs. These operational parameters are elaborated upon in Section 3.6 and Section 3.8, respectively.

### 3.3. Initial Simulation Conditions

Battery charge/ discharge decisions are based on the battery state of charge and the value of electricity stored. The initial state of charge of the battery is set to zero MWh.

\[ P_{\text{StoredBatt}}(1) = 0 \]

Electricity stored in the battery is assigned a value defining the cost of using the stored electricity. The initial battery value is also set to zero $/\text{MWh}$.\[ C_{\text{batt}}(1) = 0 \]

In addition to the battery conditions, the fixed power flow costs are also defined. Power flow costs represent the costs incurred when power is moved between two components of the DGDC. An obvious example of a power flow cost is the interaction between the generator and the electrical grid. Electricity that is produced by the generator flows to the electrical grid to be sold to the local utility. The “cost” of this flow a payment from the local utility for the electricity.

Two types of power flow costs are used in the simulation, variable costs and fixed costs. Variable costs are defined each hour of the simulation whereas fixed costs are defined once at the beginning of the
simulation. Fixed costs can be used to represent wear on a component or other costs that are incurred during use. Power Flows are uni-directional between two components (Table 3.2). The power flow subscript nomenclature is typical for all flows between components.

<table>
<thead>
<tr>
<th>Power Flow</th>
<th>Energy Source</th>
<th>Energy Sink</th>
<th>Power Flow Nomenclature</th>
<th>Flow Cost Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generated electricity used for computing</td>
<td>Generator</td>
<td>Computer</td>
<td>( P_{\text{gene.comp}} )</td>
<td>Least expensive source of electricity but there is an opportunity cost if electricity can be sold.</td>
</tr>
<tr>
<td>Electricity sold to the grid</td>
<td>Generator</td>
<td>Grid</td>
<td>( P_{\text{gene.grid}} )</td>
<td>Revenue is generated according to the purchasing agreement with the local electricity utility.</td>
</tr>
<tr>
<td>Generated electricity used to charge the battery</td>
<td>Generator</td>
<td>Battery</td>
<td>( P_{\text{gene.batt}} )</td>
<td>Electricity is stored if the future cost of computing is more than the current cost of computing.</td>
</tr>
<tr>
<td>Stored energy used for computing</td>
<td>Battery</td>
<td>Computer</td>
<td>( P_{\text{batt.comp}} )</td>
<td>Battery electricity is used when the stored energy is less expensive than all other sources.</td>
</tr>
<tr>
<td>Grid electricity used for computing</td>
<td>Grid</td>
<td>Computer</td>
<td>( P_{\text{grid.batt}} )</td>
<td>The cost of grid electricity is dependent on the contract with the local electricity utility.</td>
</tr>
<tr>
<td>Grid electricity stored in the battery</td>
<td>Grid</td>
<td>Battery</td>
<td>( P_{\text{grid.comp}} )</td>
<td>Electricity can be purchased from the electricity grid to charge the battery.</td>
</tr>
<tr>
<td>Generated electricity that is constrained</td>
<td>Generator</td>
<td>Dump</td>
<td>( P_{\text{gene.dump}} )</td>
<td>If all other sinks of electricity are constrained, then the electricity is not used or dumped.</td>
</tr>
</tbody>
</table>

Table 3.2 – Power Flows between system components.

The hourly simulation begins after the initial states of the battery and the fixed energy flow costs are defined. Each hour of the simulation follows the same procedure. First the time step conditions are loaded, then a computing supply cost curve is generated and compared to a computing demand curve to determine the amount of power used for computing. Finally the power flows are recorded and the state of the battery is updated for the next time step.
3.4. Time Step Initialization

Each hour begins by loading the grid price of electricity, the generation production, and the incentive to charge the battery. The hourly value of selling to the grid and the cost of purchasing are gleaned from the grid cost vector $\text{Hour\_Grid}(3.2) \& (3.3)$

$$\text{GridSell} = \text{Hour\_Grid} (\text{hour},1)$$
$$\text{GridBuy} = \text{Hour\_Grid} (\text{hour},2)$$

where;
- \text{GridSell} and \text{GridBuy} are the incentives to sell/buy electricity from the grid,
- \text{hour} is the time step, and
- \text{Hour\_Grid} is the two column vector with the grid value of electricity.

The electricity generated during each time step is calculated based on the nameplate capacity of the generation source and the normalized generation production vector (3.4).

$$\text{P\_gene} = \text{PC\_gene} \ast \text{Hour\_Generation}(\text{hour})$$

where;
- \text{P\_gene} is the amount of power generated in the time step \text{hour},
- \text{PC\_gene} is the nameplate capacity of the generator, and
- \text{Hour\_Generation} is the column vector of normalized generation.

The variable power flow costs changes each hour based on the price of electricity, the value of selling electricity, the battery charge level, and the incentive to charge the battery. Equations (3.5) to (3.12) calculate the power flow costs each hour.
\[ C_{\text{gene.comp}} = CF_{\text{gene.comp}} \]  \hspace{1cm} (3.5)
\[ C_{\text{gene.grid}} = CF_{\text{gene.grid}} - \text{GridSell} \]  \hspace{1cm} (3.6)
\[ C_{\text{gene.batt}} = CF_{\text{gene.batt}} + \text{ChargeValue} \]  \hspace{1cm} (3.7)
\[ C_{\text{batt.comp}} = CF_{\text{batt.comp}} + C_{\text{batt}} \]  \hspace{1cm} (3.8)
\[ C_{\text{grid.comp}} = CF_{\text{grid.comp}} + \text{GridBuy} \]  \hspace{1cm} (3.9)
\[ C_{\text{grid.batt}} = CF_{\text{grid.batt}} + \text{GridBuy} + \text{ChargeValue} \]  \hspace{1cm} (3.10)
\[ C_{\text{gene.dump}} = CF_{\text{gene.dump}}; \]  \hspace{1cm} (3.12)

where;

\( C_{xxxx,yyyy} \) is the cost of energy flow from component XXXX to YYYY,
\( CF_{xxxx,yyyy} \) are the fixed energy flow costs,
\( \text{GridSell} \) and \( \text{GridBuy} \) are the value of electricity sold to and bought from the grid,
\( \text{ChargeValue} \) is the incentive to charge the battery, and
\( C_{\text{batt}} \) is the value of electricity stored in the battery.

The incentive to charge the battery, \( \text{ChargeValue} \), is either positive or negative, where a negative value indicates an incentive to charge the battery. The method of calculating the battery incentive is further discussed in Section 3.9.

### 3.5. Cost of Computing Calculation

The cost to operate the DGDC energy system depends on the amount and cost of electricity flowing between components. Power flows are selected to minimizing the overall DGDC cost while respecting constraints imposed on the system. Mixed Integer Linear Programming (MILP) using IBM ILOG CPLEX Optimization Studio [51] was used to find the minimum cost power flows. Revenue is expressed as a negative number and therefore revenue is maximized in the MILP minimization function (3.13).

\[ \text{EnergyCost} = \min \{ f (x) \} \]  \hspace{1cm} (3.13)

While respecting the constrains;

\[ \text{Aeq} \cdot x = \text{Beq} \]
\[ \text{Aineq} \cdot x \leq \text{Bineq} \]
\[ \text{Lb} \leq x \leq \text{Ub} \]
where:

**EnergyCost** is the total cost of all the power flows,

\( f \) is a column vector of power flow costs,

\[
\begin{bmatrix}
  C_{\text{gene.comp}} \\
  C_{\text{gene.grid}} \\
  C_{\text{gene.batt}} \\
  C_{\text{batt.comp}} \\
  C_{\text{grid.comp}} \\
  C_{\text{grid.batt}} \\
  C_{\text{gene.dump}}
\end{bmatrix}
\]

\( x \) is a column vector of the power flows found by CPLEX MILP,

\[
\begin{bmatrix}
  P_{\text{gene.comp}} \\
  P_{\text{gene.grid}} \\
  P_{\text{gene.batt}} \\
  P_{\text{batt.comp}} \\
  P_{\text{grid.comp}} \\
  P_{\text{grid.batt}} \\
  P_{\text{gene.dump}}
\end{bmatrix}
\]

matrix **Aeq** and vector **Beq** describe equality constraints imposed on the system,

matrix **Aineq** and vector **Bineq** describe equality constraints imposed on the system, and

**Lb** and **Ub** are column vectors representing the lower and upper bounds of the power flow vector.

### 3.5.1. Power Flow constraints

Constraints imposed on the system ensure the maximum capacities are not violated and enough electricity is available for computing. The CPLEX minimization function accepts two types of constrains; equalities and inequalities. Equalities follow the form \( X = Y \), whereas an inequalities follow the form \( X \leq Y \).

Two equality constraints are utilized for the minimization. The first ensures that all the electricity generated by the renewable source is either used by the computer, sold to the grid, stored in the battery or dumped (3.14). The second equality ensures that enough power from the generation, battery and grid is available for computing (3.15).
\[ P_{\text{gene}} = P_{\text{gene,comp}} + P_{\text{gene,grid}} + P_{\text{gene,batt}} + P_{\text{gene, dump}} \]  
\[ P_{\text{comp}} = P_{\text{gene,comp}} + P_{\text{batt,comp}} + P_{\text{grid,comp}} \]

where:

- \( P_{\text{gene}} \) is the electricity produced by the generator,
- \( P_{\text{comp}} \) is the electricity used by the computer, and
- \( P_{\text{xxxx, yyyy}} \) are the power flows between component xxxx and yyyy.

Inequality constraints ensure that the amount of power used does not exceed the limits of the battery or the transmission grid. The battery is charged by the generator and the grid (3.16), and discharged to the computer (3.17).

\[ P_{\text{gene,batt}} + P_{\text{grid,batt}} \leq P_{\text{M,charge}} \]  
\[ P_{\text{batt,comp}} \leq P_{\text{M,discharge}} \]

where:

- \( P_{\text{M,charge}} \) and \( P_{\text{M,discharge}} \) are the maximum charging and discharging capacities, and
- \( P_{\text{xxxx, yyyy}} \) are the power flows between components xxxx and yyyy.

The maximum charge (3.18) and discharge (3.19) rates are limited by the lowest of either the battery charge/discharge capacity or the battery charge level.

\[ P_{\text{M,charge}} = \min[PC_{\text{charge}}, PC_{\text{batt}} - P_{\text{StoredBatt}(hour)}] \]  
\[ P_{\text{M,discharge}} = \min[PC_{\text{discharge}}, P_{\text{StoredBatt}(hour)}] \]

where:

- \( P_{\text{M,charge}} \) and \( P_{\text{M,discharge}} \) are the maximum charging and discharging capacities of the battery,
- \( PC_{\text{charge}} \) and \( PC_{\text{discharge}} \) are the charging and discharge capacity of the battery,
- \( PC_{\text{batt}} \) is the total storage capacity of the battery, and
- \( P_{\text{StoredBatt}(hour)} \) is the amount of energy stored in the battery.

Two inequality constraints are used to ensure that the buying and selling of power does not exceed the limits of the transmission system. Grid electricity is used to charge the battery and to power the computing resources (3.20) & (3.21).

\[ P_{\text{gene,grid}} \leq P_{\text{M, selling}} \]  
\[ P_{\text{grid,comp}} + P_{\text{grid, batt}} \leq P_{\text{M, buying}} \]

where:

- \( P_{\text{M, selling}} \) and \( P_{\text{M, buying}} \) are the maximum selling and buying capacities, and
- \( P_{\text{xxxx, yyyy}} \) are the power flows between components xxxx and yyyy.
The flow of energy in/out of the battery and to/from the transmission grid is constrained by a combination of inequality constraints and binary values. These constrains stem from the condition that the battery cannot be charged and discharged simultaneously and electricity cannot be sold to and bought from the electrical grid at the same time. Figure 3.2 illustrates the restrictions placed upon the system.

\[
\begin{align*}
\text{DISCHARGE} & \quad \text{OR} & \quad \text{CHARGE} \\
\text{SELL} & \quad \text{OR} & \quad \text{BUY}
\end{align*}
\]

Figure 3.2 – Battery and transmission grid power flow constraints.

The top row of Figure 3.2 is a choice to either charge or discharge the battery. During each time step either charging the battery from the generator and grid is zero, or discharging to the computer is zero. This is written using logic operators (3.22) and the rearranged (3.23).

\[
\begin{align*}
[P_{\text{gene,batt}} = 0 \land P_{\text{grid,batt}} = 0] & \lor [P_{\text{batt,comp}} = 0] \\
[P_{\text{gene,batt}} = 0 \lor P_{\text{batt,comp}} = 0] & \land [P_{\text{grid,batt}} = 0 \lor P_{\text{batt,comp}} = 0]
\end{align*}
\]

(3.22) \hspace{1cm} (3.23)

In CPLEX MILP an OR statement can be expressed using as combination of two inequality constraints and a binary value. Binary values in CPLEX MILP are assigned a value of either 1 or 0. Combining the binary value [I/O_1] with the two inequalities creates an OR logic statement (3.24) & (3.25).

\[
\begin{align*}
[P_{\text{gene,batt}} = 0 \land P_{\text{grid,batt}} = 0] & \lor [I_1 = 1] \\
[P_{\text{gene,batt}} = 0 \lor P_{\text{batt,comp}} = 0] & \land [I_1 = 1] \land [P_{\text{grid,batt}} = 0 \lor P_{\text{batt,comp}} = 0]
\end{align*}
\]

(3.24) \hspace{1cm} (3.25)
\[ P_{\text{gene.batt}} - PM_{\text{gene.batt}} \cdot [I/O_{-1}] \leq 0 \]  \hspace{1cm} (3.24)
\[ P_{\text{batt.comp}} + PM_{\text{batt.comp}} \cdot [I/O_{-1}] \leq PM_{\text{batt.comp}} \]  \hspace{1cm} (3.25)

where;

- \( P_{xxxx.yyyy} \) are the power flows between components \( xxxx \) and \( yyy \), and
- \( PM_{xxxx.yyyy} \) are the maximum possible power flows between components \( xxxx \) and \( yyy \).

The value of the binary dictates which possible power flows must be zero. In the case where the binary value is \([I/O_{-1}] = 0\), then the generator to battery power flow is zero;

\[ P_{\text{gene.batt}} - PM_{\text{gene.batt}} \cdot [I/O_{-1}] \leq 0 \]
\[ P_{\text{gene.batt}} - PM_{\text{gene.batt}} \cdot 0 \leq 0 \]
\[ P_{\text{gene.batt}} \leq 0 \]

and in the case when the binary value is \([I/O_{-1}] = 1\), then the battery to computer power flow is zero.

\[ P_{\text{gene.batt}} - PM_{\text{gene.batt}} \cdot [I/O_{-1}] \leq 0 \]
\[ P_{\text{gene.batt}} - PM_{\text{gene.batt}} \cdot 1 \leq 0 \]
\[ P_{\text{gene.batt}} \leq PM_{\text{gene.batt}} \]

The binary and inequality constraints are repeated three more times for the remaining OR statements. (3.26) and (3.27) represent the battery being charged by the grid or the battery discharging to the computer.

\[ P_{\text{grid.batt}} - PM_{\text{grid.batt}} \cdot [I/O_{-2}] \leq 0 \]  \hspace{1cm} (3.26)
\[ P_{\text{batt.comp}} + PM_{\text{batt.comp}} \cdot [I/O_{-2}] \leq PM_{\text{batt.comp}} \]  \hspace{1cm} (3.27)

(3.28) and (3.29) represent either selling electricity to the grid or charging the battery from the grid.

\[ P_{\text{gene.grid}} - PM_{\text{gene.grid}} \cdot [I/O_{-3}] \leq 0 \]  \hspace{1cm} (3.28)
\[ P_{\text{grid.batt}} + PM_{\text{grid.batt}} \cdot [I/O_{-3}] \leq PM_{\text{grid.batt}} \]  \hspace{1cm} (3.29)
(3.30) and (3.31) represent either selling generated electricity to the grid or buying electricity for computing.

\[
\begin{align*}
    P_{\text{gene,grid}} - P_{\text{PM,grid}} & \leq 0 \quad (3.30) \\
    P_{\text{grid,comp}} + P_{\text{PM,comp}} & \leq P_{\text{PM,comp}} \quad (3.31)
\end{align*}
\]

The final constraints on the power flows are the upper and lower bounds (Table 3.3). The upper bounds ensure that the component capacities are not exceeded and the lower bounds ensure all power flows are equal or greater than 0.

<table>
<thead>
<tr>
<th>Power Flow</th>
<th>Upper Bound</th>
<th>Lower Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>(P_{\text{gene,comp}})</td>
<td>(\min(\text{P}<em>{\text{comp}}, \text{P}</em>{\text{gene}}))</td>
<td>0</td>
</tr>
<tr>
<td>(P_{\text{gene,grid}})</td>
<td>(\min(\text{P}<em>{\text{PM,selling}}, \text{P}</em>{\text{gene}}))</td>
<td>0</td>
</tr>
<tr>
<td>(P_{\text{gene,batt}})</td>
<td>(\min(\text{P}<em>{\text{PM,charge}}, \text{P}</em>{\text{gene}}))</td>
<td>0</td>
</tr>
<tr>
<td>(P_{\text{batt,comp}})</td>
<td>(\min(\text{P}<em>{\text{PM,discharge}}, \text{P}</em>{\text{comp}}))</td>
<td>0</td>
</tr>
<tr>
<td>(P_{\text{grid,batt}})</td>
<td>(\min(\text{P}<em>{\text{PM,buying}}, \text{P}</em>{\text{charge}}))</td>
<td>0</td>
</tr>
<tr>
<td>(P_{\text{grid,comp}})</td>
<td>(\min(\text{P}<em>{\text{PM,buying}}, \text{P}</em>{\text{comp}}))</td>
<td>0</td>
</tr>
<tr>
<td>(P_{\text{gene,dump}})</td>
<td>(\text{P}_{\text{gene}})</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 3.3 – Upper and lower bounds imposed on the Power Flow possibilities

### 3.5.2. Minimizing Cost of Power Flows

Solving the linear Equation (3.13) with the above constraints finds the lowest cost of providing electricity for computing amount \(\text{P}_{\text{comp}}\). Two example scenarios for a DGDC system are presented in Figure 3.3. The first scenario has no computing demand, \(\text{P}_{\text{comp}} = 0\ kW\), and the second scenario has a high computing demand, \(\text{P}_{\text{comp}} = 75\ kW\). The power flow solution and the system cost for the two scenarios are shown in Table 3.4.
Figure 3.3 – Example DGDC energy system with a high computing and no computing scenario.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>P_{gene.comp}</td>
<td>0.00</td>
<td>50</td>
<td>0.00</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>P_{gene.grid}</td>
<td>-0.10</td>
<td>0</td>
<td>0.00</td>
<td>20</td>
<td>-2.00</td>
</tr>
<tr>
<td>3</td>
<td>P_{gene.batt}</td>
<td>-0.12</td>
<td>0</td>
<td>0.00</td>
<td>20</td>
<td>-2.40</td>
</tr>
<tr>
<td>4</td>
<td>P_{batt.comp}</td>
<td>0.12</td>
<td>20</td>
<td>2.40</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>P_{grid.batt}</td>
<td>0.14</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>P_{grid.comp}</td>
<td>0.14</td>
<td>5</td>
<td>0.70</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>7</td>
<td>P_{gene.dump}</td>
<td>0.00</td>
<td>0</td>
<td>0.00</td>
<td>10</td>
<td>0.00</td>
</tr>
</tbody>
</table>

**TOTAL SYSTEM COST**

Scenario 1

<table>
<thead>
<tr>
<th>Power Flow</th>
<th>Power Flow Cost [$/kWh]</th>
<th>Power Flow [kWh]</th>
<th>Cost [$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>P_{comp}</td>
<td>75kW</td>
<td></td>
<td>$3.10</td>
</tr>
</tbody>
</table>

Scenario 2

<table>
<thead>
<tr>
<th>Power Flow</th>
<th>Power Flow Cost [$/kWh]</th>
<th>Power Flow [kWh]</th>
<th>Cost [$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>P_{comp}</td>
<td>0kW</td>
<td></td>
<td>$-4.40</td>
</tr>
</tbody>
</table>

Table 3.4 – Results from the CPLEX MILP solver example for a single time step.

When 75kW of computing is required, the system uses all of the power from the generator, the maximum battery discharge capacity, as well as 5 kWh is purchased from the electricity grid. In the 0kW computing demand scenario, the maximum charge and maximum selling capacities are reached. The excess power, 10 kWh, is dumped since there is no other used for the generated electricity.
3.5.3. Computing Supply Cost

The total system cost for the lower computing demand scenario (\( P_{\text{comp}} = 0 \text{kW} \)) is $-4.40 which indicates revenue was generated by selling to the grid and charging the battery. When the computing resources demands 75kW, then the total system cost is $3.10. The unit cost of supplying 75kW of computing power for one hour is $0.04/kWh ($3.10/75kWh).

The unit cost analysis ignores the opportunity cost of being unable to sell the power such as in the 0 kW computing scenario. To calculate the true cost, both the total system cost and the revenue that is not generated needs to be included Equation (3.32).

\[
\text{SupplyCost} = \frac{TSC(P_{\text{comp}}) - TSC(0\text{kW})}{P_{\text{comp}}} \tag{3.32}
\]

where:

- **SupplyCost** is the cost of computing in $/kWh,
- \( TSC(P_{\text{comp}}) \) is the total system cost to supply the required amount of computing
- \( TSC(0\text{kW}) \) is the total system cost when no power is supply to the computing
- \( P_{\text{comp}} \) is the amount of power supplied to the computer

Equation (3.32) is applied to the example scenario to show that the true supply cost of computing at 75kW is $0.10/kWh, not the unit cost of $0.04/kWh;

\[
\text{SupplyCost} = \frac{\text{TSC}(75\text{kWh}) - \text{TSC}(0\text{kWh})}{75\text{kWh}} \]

\[
\text{SupplyCost} = \frac{$3.10 - ($-4.40)}{75\text{kWh}} \]

\[
\text{SupplyCost} = $7.50 / 75 \text{kWh} \]

\[
\text{SupplyCost} = $0.10/kWh \]

The supply cost of computing shown above is valid only for 75kWh of computing. The computing supply algorithm is repeated multiple times with the \( P_{\text{comp}} \) constraint varying between 0% and 100% of maximum computing to create a computing supply curve.

3.6. Supply and Demand Analysis

A supply and demand curve analysis determined the amount of electricity used for computing each hour. In general, a supply and demand curve analysis determines the price and quantity of a good that satisfies
both the supplier and the consumer. Supply curves represent the cost of supplying goods to a consumer and demand curves represents the price a consumer is willing to pay. A simple linear example is shown in Figure 3.4. The equilibrium is the point where the supply curve and the demand curve intersect and represent the mutually beneficial price and quantity of good.

![Equilibrium Point](Image)

**Figure 3.4 –** The equilibrium point represents the cost to supply computing at the quantity and price willing to be paid.

In terms of DGDCs, the quantity refers to the amount of electricity used for computing in a time step and the price is the opportunity cost of supplying the electricity used for computing. The supply curve is created using by repeating the analysis in Section 3.5 but including computing amounts between 0% and 100% of maximum computing power (Table 3.5) (Figure 3.5).

<table>
<thead>
<tr>
<th>Computing Supply [kW]</th>
<th>0kW (0%)</th>
<th>15kW (20%)</th>
<th>30kW (40%)</th>
<th>45kW (60%)</th>
<th>60kW (80%)</th>
<th>75kW (100%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Total System Cost [$]</strong></td>
<td>-4.40</td>
<td>-3.90</td>
<td>-2.40</td>
<td>-0.60</td>
<td>1.20</td>
<td>3.10</td>
</tr>
<tr>
<td><strong>Opportunity Cost [$]</strong></td>
<td>0.00</td>
<td>0.50</td>
<td>2.00</td>
<td>3.80</td>
<td>5.60</td>
<td>7.50</td>
</tr>
<tr>
<td><strong>Computing Supply Cost [$/kWh]</strong></td>
<td>0.00</td>
<td>0.03</td>
<td>0.07</td>
<td>0.08</td>
<td>0.09</td>
<td>0.10</td>
</tr>
</tbody>
</table>

Table 3.5 – Computing supply cost data between 0% and 100% of maximum computing capacity.
Figure 3.5 – Computing supply curve for a single time step.

A computing demand curve represents the value of computing as set by the DGDC network operator. Examples of demand curves are shown in (Figure 3.6). The shape requires two parameters, one that sets the maximum amount paid for computing and one that describes the shape of the curve (Equations (3.33a&b)).

![Graph showing computing supply curve](image)

Figure 3.6 – Sample demand curve shapes.

\[
Price = - \frac{MaxPrice}{ComputerCapacity^B} \cdot ComputerPower^B + MaxPrice \tag{3.33a}
\]

\[
Price = MaxPrice \cdot \left(1 - \frac{ComputerPower}{ComputerCapacity}^B \right) \tag{3.33b}
\]

where:

- **Price** is the supply price for the **Computer Power**,
- **MaxPrice** is the maximum amount paid for computing,
- **ComputerCapacity** is the maximum computing capacity, and
- **B** describes the shape of the curve.

The computing demand curve approximates the economic dispatch of the DGDC network. In general, no computing is used when the price is highest (top left) and as the price decreases more computing is demanded by the network operator (bottom right).
Some factors that will cause the demand curve to increase the maximum price paid for computing include:

- Willingness of customers to pay more for computing critical tasks.
- Low availability of renewable energy sources, i.e. nighttime or during cloudy days.
- High percentage of DGDC connected to the electrical grid.
- Requirement for high DGDC network availability.

Factors that lower the maximum price paid for computing and promote the use of low cost electricity include:

- Availability of low cost grid energy e.g areas with constrained transmission.
- High renewable energy production in the DGDC network.
- Reduction in the amount of computer power demanded,
- Non-critical computational processes that can be scheduled to utilize low cost energy.

When the desired computing load is a time-critical process such as streaming a movie or accessing a database, the DGDC network operator will need to use power for computing regardless of the cost. As a result, there will be an upward pressure on the demand curve since computing will need to be completed at a higher cost. For non-time critical loads, such as large computational problems or data analysis, the network operator will schedule these loads during times when there is an abundance of low cost power, lowering the demand curve.

If the computing demand is updated each hour via the DGDC network operator the demand curve would model the realistic operation of the DGDC. Computing loads and server utilization is scheduled to match exactly the amount of power that is available during a time step. The demand curve ensures that power will be used only if the computing supply cost is within the budget of the DGDC network demand.

If computing demands are not known for each hour, a statistical approximation can be used. Instead of the demand curve representing the actual power usage, it represents the frequency that the DGDC is operated at a each price point. The demand curve will represent the likelihood of the DGDC powering on during a
time period. During times of low cost energy all of the computing resources will be utilized. Whereas during time of high cost energy the computer servers will be used less frequently.

Computing supply and demand curves are represented as a 3-column matrix. The first column contains the required computing power, the second contains the supply curve, and the third contains the demand curve. The equilibrium price point and computer power is found using the algorithm shown in the flowchart in Figure 3.7. A sample 3-column matrix is shown with the flowchart as an example. The algorithm indicates that the equilibrium price is $0.033/kWh and the computing amount is 15 kWh.

<table>
<thead>
<tr>
<th>Computing Amount</th>
<th>Supply Cost</th>
<th>Demand Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.000</td>
<td>0.10</td>
</tr>
<tr>
<td>15</td>
<td>0.033</td>
<td>0.08</td>
</tr>
<tr>
<td>30</td>
<td>0.067</td>
<td>0.06</td>
</tr>
<tr>
<td>45</td>
<td>0.084</td>
<td>0.04</td>
</tr>
<tr>
<td>60</td>
<td>0.093</td>
<td>0.02</td>
</tr>
<tr>
<td>75</td>
<td>0.100</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Figure 3.7 – Flow chart representation of the algorithm to find the supply and demand curve equilibrium.

The equilibrium point is found using the discrete points of the supply and demand curve (Figure 3.8). Since the supply and demand curves are not continuous the ideal equilibrium point may be between the discrete price points. As a result the actual power flows are different from the ideal case and the amount of energy used for computing is less than the ideal condition.
Figure 3.8 – The discrete points of the supply and demand curve approximate the ideal price point.

This problem can be minimized by increasing the number of discrete points or resolution of the supply and demand curve. The ideal equilibrium point is less than 30kW but with only six points the demand is found to be 15kW (Figure 3.9a) compared to 25kW (Figure 3.9b) with 16 points.

Figure 3.9 a & b – Comparison of two supply and demand curves with 6 points (left) and 16 points (right).

Increasing the resolution increases the amount of computing since the difference between the actual and modeled equilibrium point is smaller. Increasing the resolution also increases the resources required to compute the simulation since each point requires the model to solve the power flow minimization. An analysis was conducted on the number of discrete points used for the demand and supply curve. A simple DGDC system was simulated over the course of the year. The simulation was run multiple times with computing curve resolutions between 2 and 256 points (Figure 3.10).
3.7. Simulation Results

Once the computing demand is selected the results are recorded, the battery status is updated, and the next time step begins. The power flows between the components, the overall cost of energy, and the equilibrium price are the outputs of the hourly simulation and are used in the net present value analysis (Chapter 4).

The power flows indicate how the individual components of the system are utilized during the simulation. The amount of power that is sold to the grid or used for computing is derived from this data. The costs for all time steps are summed to determine the cost of operating the DGDC for a year.

The battery state of charge is adjusted based on the amount charged or discharged and the efficiency of the battery. Battery efficiency is assumed to be a single value describing the round-trip battery efficiency. The energy available for future time steps accounts for the energy lost in the charging and discharging of a battery. For example, if 10 kWh is stored in a battery that has a round trip efficiency of 90%, only 9 kWh will be available for use and the remaining 1 kW is lost. Equation (3.34) calculates the battery charge for the next time step.
\[
P_{\text{Stored Batt}}(\text{hour} + 1) = P_{\text{Stored Batt}}(\text{hour}) - (P_{\text{batt. comp}} + P_{\text{gene batt}} + P_{\text{grid batt}}) \times \eta_{\text{batt}}
\] (3.34)

where;

- \( P_{\text{Stored Batt}} \) is the amount of power stored in the battery during a time step,
- \( \text{Hour} \) is a time step within the simulation,
- \( P_{\text{xxxx, yyyy}} \) are the power flows between components \( \text{xxxx} \) and \( \text{yyyy} \), and
- \( \eta_{\text{batt}} \) is the battery efficiency.

The stored energy is assigned a value based on the future expected price of electricity. The incentive to charge the battery, Charge Value, is explained in Section 3.8. Equation (3.35) calculates the new battery energy value by averaging the value of the existing energy and the charged energy.

\[
C_{\text{batt}}(\text{hr}+1) = \frac{-\text{Charge Value} \times (P_{\text{gene batt}} + P_{\text{grid batt}}) + C_{\text{batt}}(\text{hr}) \times P_{\text{Stored Batt}}(\text{hr})}{(P_{\text{gene batt}} + P_{\text{grid batt}}) \times \eta_{\text{batt}} + P_{\text{Stored Batt}}(\text{hr})}
\] (3.35)

where;

- \( C_{\text{batt}}(\text{hr}+1) \) is the cost of the battery during time step hour + 1,
- \( \text{Charge Value} \) is the incentive to charge the battery,
- \( P_{\text{xxxx, yyyy}} \) is the power flow between components \( \text{xxxx} \) and \( \text{yyyy} \),
- \( P_{\text{Stored Batt}} \) is the amount of power stored in the battery during a time step, and
- \( \eta_{\text{batt}} \) is the round trip efficiency of the battery.

In the equation above, battery efficiency decreases the amount of electricity that is stored causing the relative cost of the energy stored in the battery increases. The following example shows how the battery inefficiency increases the cost of stored energy.

- Energy in = 1MWh
- Cost of Energy = $20/MWh
- Total Cost = $20

If Battery Efficiency = 90% then

\[
\text{Energy out} = \text{Energy in} \times \text{Battery Efficiency}
\]

Energy out = 0.9MWh

\[
\text{Value of energy} = \frac{\text{Total Cost}}{\text{Energy Out}}
\]

Value of energy = $20/0.9MWh

Value of energy = $22.2/MWh
Since the incentive to charge the battery is based on the future value of the stored electricity, the incentive needs to take into account the change in battery value due to inefficiencies.

### 3.8. Battery Charging Incentive

In a DGDC, the goal of the battery is to reduce the use of high cost energy for computing by charging with low cost energy. The cost of computing will increase when low cost energy charges the battery since there is an added opportunity cost. Figure 3.11 shows how the charging and discharging cycles of a battery compares to a system without a battery.

![Diagram](image)

**Figure 3.11** – The computing cost for a simulation with a battery (solid line) has less deviation than a no-battery simulation (dotted-line)

The charge incentive is determined based on the computing cost in future time steps. An hourly “no battery” simulation is run to determine the cost of computing in a worst-case scenario without the ability to store electricity. The charge incentive is calculated with the “no battery” computing costs for the actual simulation with the battery.

The battery charge incentive mimics the ability for a real DGDC system to predict the future cost of computing. Future time steps are weighted based on the prediction accuracy of the DGDC operator. For example, a grid operator can provide accurate short-range price predictions and would have a high
weighting; whereas, long-term wind generation predictions are less accurate and would have a lower weighting.

An example of a battery forecasting input is shown in Figure 3.12. The example shown has a four hours forecast with 100% weighting, but in the following four hours the certainty drops to 50%. The last four hours has a weighting of only 25%

<table>
<thead>
<tr>
<th>Hours Ahead</th>
<th>Weighting</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>1.00</td>
</tr>
<tr>
<td>8</td>
<td>0.50</td>
</tr>
<tr>
<td>12</td>
<td>0.25</td>
</tr>
</tbody>
</table>

Figure 3.12 – Example battery forecasting weighting parameters.

For each time step the forecasting weighting is applied to determine the charge incentive as shown in Equation (3.36).

\[
\text{ChargeValue}(\text{hour}) = \frac{\sum_{i=1}^{\text{MaxHour}}(\text{NBCC}(\text{hour} + i) \times \text{Weight}(\text{hour} + i))}{\sum_{i=1}^{\text{MaxHours}} \text{Weight}(\text{hour} + i)} \times \eta_{\text{batt}}
\]  

(3.36)

where;

- \text{ChargeValue}(\text{hour}) is the charge incentive for the battery for the time step,
- \text{hour} is the time step,
- \text{MaxHour} is the number of hours ahead the weighting considers,
- \text{NBCC} is the No Battery Computing Cost calculated by simulating the system without a battery,
- \text{Weight} is the weighting assigned to the hour, and
- \eta_{\text{batt}} is the battery efficiency.

The battery efficiency is included in this equation to counteract battery value increase due to inefficiencies. Some stored energy is lost due to battery inefficiency and thus the incentive to charge is decreased because less power will be available.
3.9. **Hourly Simulation Summary**

This chapter describes an hourly simulation of DGDC operation, which models the power flows within the system. Power flows are calculated in order to minimize the cost of supplying electricity for computing. The minimization is completed using the CPLEX MILP solver and constraints ensure that the maximum capacities of the system components are not violated. Computing supply costs are compared against the DGDC network demand to determine the amount of power that is used in each time step. Energy costs and the amount of power used for computing are used in a cash flow analysis described next.
Chapter 4. Energy System Design Optimization

4.1. Design Evaluation Introduction

This chapter presents a lifetime cash flow analysis for DGDC energy system designs. Design of a DGDC energy system requires the optimal sizing of components to provide computing at the lowest possible cost. The system is evaluated over its entire lifetime to assess the cost of providing computing. All potential energy systems are iterated through a cash flow analysis to find the optimal design with the minimum lifetime cost of computing (Figure 4.1).

![Flow chart of the DGDC energy system economic analysis.](image)

The design space defines all the potential energy systems for the optimization. Possible energy systems are run through a yearlong simulation to determine the operational costs. After the simulation, a cash flow analysis for the lifetime of the energy system is completed. The outcome of the cash flow and results from
the year-long simulation are used to determine the most economical energy system design. The remainder of this chapter explains the steps of the net present value analysis.

4.2. Defining the Design space

There are seven variables that define the capacities of the four energy system components. These capacities set the design space of the optimization. Table 4.1 provides descriptions of the seven design space variables.

<table>
<thead>
<tr>
<th>Design Space Variable</th>
<th>Component</th>
<th>Units</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generation</td>
<td>Generator</td>
<td>MW</td>
<td>Name plate capacity or maximum possible generation.</td>
</tr>
<tr>
<td>Computing</td>
<td>Computer</td>
<td>MW</td>
<td>Maximum power used by the computing servers, cooling, and all other power equipment.</td>
</tr>
<tr>
<td>Battery Capacity</td>
<td>Battery</td>
<td>MWh or Hours</td>
<td>Maximum energy that can be stored. Capacity in hours is the time the battery can be discharged at full power.</td>
</tr>
<tr>
<td>Charging</td>
<td>Battery</td>
<td>MW</td>
<td>Maximum power used to charge the battery.</td>
</tr>
<tr>
<td>Discharging</td>
<td>Battery</td>
<td>MW</td>
<td>Maximum battery discharge power.</td>
</tr>
<tr>
<td>Buying</td>
<td>Grid</td>
<td>MW</td>
<td>Maximum amount of electricity that can be bought.</td>
</tr>
<tr>
<td>Selling</td>
<td>Grid</td>
<td>MW</td>
<td>Maximum amount of electricity that can be sold.</td>
</tr>
</tbody>
</table>

Table 4.1 – The component variables used to define the design space.

There is no limit on the upper boundary of component capacities, but the lower bound can be no less than zero. A component capacity of zero indicates the component is not included in the defined energy system. For example, a grid-isolated DGDC would have the buying and selling capacity of zero. Furthermore, if a grid-tied DGDC is able to purchase from the grid but not sell excess electricity, only the selling capacity would be set to zero.
A distribution of the component capacities across the entire design space is selected to find the global minimum. A three variable optimization is shown in Figure 4.2 with an even distribution of component capacities. Up to seven different variables can be used to define the design space.

![Three-dimensional design space diagram](image)

Figure 4.2 – Each dot represents a possible energy system configuration within a three dimensional design space.

The number of scenarios in the optimization is a function of the number of components being optimized and the number of possible component sizes. The design space shown in Figure 4.2 has three components that are being optimized: transmission capacity, charging capacity and battery storage capacity. Transmission capacity and charging capacity both have four possible component sizes \(N_{\text{transmission}} = 4\), \(N_{\text{charging}} = 4\) and the battery capacity has three \(N_{\text{battery}} = 3\). The number of simulation \(N_{\text{simulation}}\) is:

\[
N_{\text{simulation}} = N_{\text{transmission}} \times N_{\text{charging}} \times N_{\text{battery}} \\
N_{\text{simulation}} = 4 \times 4 \times 3 \\
N_{\text{simulation}} = 48
\]

The design space determines the size of the optimization problem. The number of simulations in any design space can be determined using Equation (4.1).

\[
N_{\text{simulation}} = N_{\text{Gene}} \times N_{\text{Comp}} \times N_{\text{Batt}} \times N_{\text{Chg}} \times N_{\text{DChg}} \times N_{\text{Buy}} \times N_{\text{Sell}} \quad (4.1)
\]
The size of the design space dictates the time required to find a solution. Techniques for determining design space to provide useful results are discussed in Section 4.7. Once the parameters for the optimization are selected, the lifetime cost of computing is calculated.

4.3. DGDC Energy System Operation

The operation of the DGDC energy system is simulated over the course of a year. The purpose of the simulation is to determine how the energy system components operate as an energy system. Component capacities affect the operation of the energy system, impacting the DGDCs costs and revenues. The most important values calculated in the simulations are the amount of electricity used for computing and operational costs.

Costs include electricity purchased from the grid, wear and tear on the system components, or other cost associated with how the power is used. Revenue is generated through the selling of electricity to the grid. Both the costs and the revenues are lumped together under the common term operational costs.

A complete explanation of the hourly yearlong simulation is found in Chapter 3. As a summary, the simulation approximates the economic dispatch of the DGDC network operator. A supply and demand curve analysis determines the amount of electricity used for computing each hour based on the cost of energy.

In addition to the operating cost and the computing electricity, information about the operation of the DGDC is recorded during the simulation. During each time step, the power flows between all the components and the equilibrium price are recorded. These power flows provide insight into the DGDC energy system component operation during the year.
The components capacities of an example DGDC are shown in Table 4.2. The DGDC system has solar generation, a battery, and connection to the local electricity grid. Electricity is bought and sold at the hourly variable market price.

<table>
<thead>
<tr>
<th>System Component</th>
<th>Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generation</td>
<td>100 kW</td>
</tr>
<tr>
<td>Computing</td>
<td>100 kW</td>
</tr>
<tr>
<td>Charge/Discharge</td>
<td>50 kW</td>
</tr>
<tr>
<td>Battery Storage</td>
<td>100 kWh</td>
</tr>
<tr>
<td>Buying/Selling</td>
<td>100 kW</td>
</tr>
</tbody>
</table>

Table 4.2 – Component capacities of the sample simulation with solar generation.

An hourly simulation of the DGDC energy system component is calculated and component power use is shown as load duration curves (Figure 4.3). The amount of power used is ordered with the highest values on the left side of the graph. The area under the curve indicates the amount of power used by a component in the simulation.

![Figure 4.3 – Load duration curves for an example DGDC simulation.](image)

This load duration is useful for visualizing the capacity factors of the components. Capacity factors indicate the amount of power used relative to the maximum amount of power that could be used in the year. Capacity factors for the components are shown in Table 4.3.
<table>
<thead>
<tr>
<th>Component</th>
<th>Capacity Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generation</td>
<td>9.6%</td>
</tr>
<tr>
<td>Computing</td>
<td>34.5%</td>
</tr>
<tr>
<td>Buying</td>
<td>34.0%</td>
</tr>
</tbody>
</table>

Table 4.3 – Capacity factors of energy system components.

Battery usage in the simulation is summarized in Figure 4.4. Charging and discharging of the battery is represented as positive and negative values, respectively. Not shown in the graph, but useful to note is the battery held a charge for 26% (2306 hours) of the year.

![Battery Charging (+) and Discharging (-)](image)

Figure 4.4 – Battery charging (+) and discharging (-) of over the course of a year.

Noted earlier, the two most important outputs of the simulation are the yearly operational cost and the total amount of electricity used for computing. These two values are used in the cash flow analysis and for the unit cost of computing. Figure 4.5 shows the cumulative value of these variables over the course of the year.

![Cumulative Curves](image)

Figure 4.5 – Cumulative curves of costs and computing amount over the course of a year.

The flattening of the cost curve in the middle of the graph is due to the increased production of solar energy in the summer. The graph flattens because more revenue is generated from selling to the grid and
less electricity needs to be purchased. The computing curve remains virtually linear; indicating the amount of solar generation has little effect on the computing completed.

4.4. Cash Flow Analysis

A cash flow analysis is used in engineering economics to assist designers in the decision making processes. A cash flow analysis examines all of the cost that are occurred over the lifetime including capital costs, operational costs, replacements cost and end of life costs. Any revenue that is generated is included in determining the overall cost of the system over its lifetime.

Cost and revenues incurred each year are added together to find the net cash flow of the system as shown in Table 4.4. The 0th year includes the initial costs incurred to construct and set-up the DGDC. The net cash flow is summed each year to create cumulative cash flow. The cumulative cash flow indicates a net system value of $1000 in the final year of the system.

<table>
<thead>
<tr>
<th>Year</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital Cost</td>
<td>-$8000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maintenance</td>
<td>-$500</td>
<td>-$500</td>
<td>-$500</td>
<td>-$500</td>
<td>-$500</td>
<td>-$500</td>
</tr>
<tr>
<td>Replacement</td>
<td></td>
<td>-$3000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expenses</td>
<td>-$8000</td>
<td>-$500</td>
<td>-$500</td>
<td>-$500</td>
<td>-$3500</td>
<td>-$500</td>
</tr>
<tr>
<td>Operation Revenue</td>
<td></td>
<td>$2000</td>
<td>$2250</td>
<td>$2500</td>
<td>$2750</td>
<td>$3000</td>
</tr>
<tr>
<td>End of Life</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$2000</td>
</tr>
<tr>
<td>Revenue</td>
<td>$0</td>
<td>$2000</td>
<td>$2250</td>
<td>$2500</td>
<td>$2750</td>
<td>$5000</td>
</tr>
<tr>
<td>Net Cash Flow</td>
<td>-$8000</td>
<td>$1500</td>
<td>$1750</td>
<td>$2000</td>
<td>-$750</td>
<td>$4500</td>
</tr>
<tr>
<td>Cumulative Cash Flow</td>
<td>-$8000</td>
<td>-$6500</td>
<td>-$4750</td>
<td>-$2750</td>
<td>-$3500</td>
<td>$1000</td>
</tr>
</tbody>
</table>

Table 4.4 – Sample cash flow analysis.

Costs incurred over the lifetime include; capital cost, replacement cost, maintenance cost, operational cost, and salvage value. Some typical costs are:
**Capital costs** are incurred during the construction and setting up of the DGDC energy system. The capital for each component is calculated based on the size of the component and the infrastructure that is required.

**Maintenance costs** are yearly costs that are required to maintain the system regardless of how the system is used. For example, the cooling systems for the computing will require cleaning of the filters, the generation will need servicing and inspections or the batteries will need testing. Costs dependent on component use are included as fixed power flow costs in the hourly simulation.

**Replacement costs** are similar to capital cost because they represent a one-time cost for the component. Replacement cost may be less than the capital cost if the required infrastructure is already installed.

**Yearly operation** may incur a cost if power is purchased or provide revenue if power is sold. Operational cost varies greatly based on the design of the energy system and is determined using the hourly simulation.

**Salvage value** is a theoretical value that characterizes the value of the equipment at the end of the cash flow analysis. Equipment with lifetime longer than the system will have a residual value that is not included in the cash flow. To capture this value, a salvage value is calculated. The salvage value of a real system would be the market value of the components once the DGDC is no longer operational.

A method of approximating the salvage value is to prorate based on the number of useful years left in the equipment [52]. For example a piece of equipment that is expected to last 10 year would have half of its value remaining after 5 years. Equation (4.2) shows how the salvage value is calculated.
\[
\text{SalvageValue} = \text{CapCost} \times \frac{\text{Lifetimecomponent} - \text{SimulationLength}}{\text{Lifetimecomponent}}
\]

where;

- \text{SalvageValue} is the value for the remaining life of the component,
- \text{CapCost} is the capital cost of the component,
- \text{SimulationLength} number of years of the lifetime cash flow analysis, and
- \text{Lifetimecomponent} is the expected lifetime of the component.

Cost assumptions used in the economic optimization are scaled to the size of the selected component capacity. The method of scaling, whether it is a linear, exponential, step function or other, is not relevant as long as there is a relationship between the size of the component and the cost.

### 4.5. Net Present Value

The Net Present Value (NPV) calculation is a continuation of the cash flow analysis. The above cash flow does not take into account the time value of money. A company that invests in a DGDC is expected to have a return that is greater than the initial investment else it would be better to invest the capital elsewhere. The DGDC energy systems assumes an expected internal rate of return (IRR) to account for the time value of money. The IRR is the expected rate of growth of an investment of over it lifetime. Cash flows in future years are discounted using Equation (4.3).

\[
\text{DCF}_N = \frac{\text{CF}_N}{(1 + \text{IRR})^n}
\]

where;

- \text{DCF}_N is the discounted cash flow in year \(N\),
- \text{CF}_N is the cash flow in year \(N\),
- \text{IRR} is the Internal Rate of Return, and
- \(n\) is the year of the cash flow.

The cash flow analysis shown in Table 4.4 is illustrated in Figure 4.6. It shows the expenses, revenues, net cash flow, and cumulative cash flow during the lifetime of the system. In the example, the breakeven point, i.e. when the cumulative cash flow is greater than zero, is in the fifth year.
Figure 4.6 – Lifetime revenues, expenses, and cumulative cash flow of a DGDC.

The NPV is calculated for the system above with an IRR of 5%. Table 4.5 shows the discounted cash flow and cumulative cash flow.

<table>
<thead>
<tr>
<th>Year</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Net Cash Flow</td>
<td>-$8000</td>
<td>$1500</td>
<td>$1750</td>
<td>$2000</td>
<td>-$750</td>
<td>$4500</td>
</tr>
<tr>
<td>I.R.R.</td>
<td>5%</td>
<td>5%</td>
<td>5%</td>
<td>5%</td>
<td>5%</td>
<td>5%</td>
</tr>
<tr>
<td>Discounted Cash Flow</td>
<td>-$8000</td>
<td>$1429</td>
<td>$1587</td>
<td>$1728</td>
<td>-$617</td>
<td>$3526</td>
</tr>
<tr>
<td>Cumulative Cash Flow</td>
<td>-$8000</td>
<td>-$6571</td>
<td>-$4984</td>
<td>-$3256</td>
<td>-$3873</td>
<td>-$348</td>
</tr>
</tbody>
</table>

Table 4.5 – Discounted cash flow and cumulative cash flow.

Once the time value of money has been taken into account, the value of the system is -$348 and the breakeven point is longer than 5 years. The difference in the cash flows between discounted and non-discounted is shown in Figure 4.7(a). The cumulative cash flows for the discounted and non-discounted are compared in Figure 4.7(b).

Figure 4.7 (a & b) – Comparison of cash flows (left) and the cumulative cash flows for a discounted cash analysis vs a non-discounted cash flow analysis.
The length of the cash flow analysis can result in drastically different NPV because revenue is generated in the years following the initial investment. Shorter scenarios are less likely recoup the capital cost of the system. Longer scenarios are less accurate because future costs are less predictable. Figure 4.8 shows the above example but over a lifetime of 9 years instead of 5 years. The NPV of a 9 year system is $3808 as opposed to -$348 for the 5 year analysis.

![Figure 4.8](image)

Figure 4.8 – Cash flow analysis with a system lifetime of 9 years results in a NPV that is greater than zero.

In some cases, such as long term purchasing agreements or leases, it may be necessary to examine longer lifetimes. To account for the investment risk of long term projects, then the Internal Rate of Return (IRR) may be variable. As the risk increase for future cash flows, the required IRR also increases (Figure 4.9).

![Figure 4.9](image)

Figure 4.9 – Increasing risk and cash flows uncertainty requires a higher IRR.

To calculate the discounted cash flows for a variable IRR the denominator of Equation (4.3) is altered to include all the rates of return for the previous years, as shown in Equation (4.4).

\[
DCF_N = \frac{CF_N}{[(1 + IRR_1) \times (1 + IRR_2) \times ... \times (1 + IRR_N)]} \tag{4.4}
\]
where:

\( \text{DCF}_N \) is the discounted cash flow in year \( N \),
\( \text{CF}_N \) is the cash flow in year \( N \), and
\( \text{IRR}_x \) is the Internal Rate of Return in year \( x \).

### 4.6. Determine Lifetime Cost of Computing

The final calculation determines the lifetime cost of computing (LCC) for the DGDC energy system. Lifetime cost of computing determines the overall cost to provide one MWh of electricity for computing. The net present value is normalized by the amount of computing performed to compare the ability of an energy system to provide low cost computing (4.5).

\[
\text{Lifetime Cost of Computing} \left[ \frac{\$}{\text{MWh}} \right] = \frac{\text{Net Present Value} [\$]}{\text{Lifetime Computing[MWh]}} \tag{4.5}
\]

The LCC is used to compare any DGDC energy system regardless of the size or arrangement of the system. Rather than comparing the NPV, the optimization evaluates the ability to provide low cost computing. For example, an energy system with storage will have a higher capital cost, but is able to store low cost energy. Over its lifetime the system will use more of the excess generation or low cost electricity for computing. In comparison, a grid connected system will generate revenue from selling generated electricity but will not use as much electricity for computing. These two scenarios illustrate the tradeoff between increasing the NPV and increasing the amount of computing. The lifetime cost of computing ensures that both the economic feasibility and computational performance are used to compare potential systems.

### 4.7. Find Minimum Lifetime Cost of Computing

The Lifetime Cost of Computing is calculated for all energy systems and the system with the lowest LCC is considered to be the optimum. Based on the initial results, more systems can be analyzed to further
refine the optimization. A sample design space optimization is presented below. Table 4.6 shows the design space used for the optimization.

<table>
<thead>
<tr>
<th>Component</th>
<th>Design Space</th>
<th># Simulations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generation</td>
<td>100 kW</td>
<td>1</td>
</tr>
<tr>
<td>Computing</td>
<td>20 kW – 100 kW</td>
<td>5</td>
</tr>
<tr>
<td>Charging/Discharging</td>
<td>0 kW – 100 kW</td>
<td>5</td>
</tr>
<tr>
<td>Battery Capacity</td>
<td>1 hr - 4 hr</td>
<td>4</td>
</tr>
<tr>
<td>Buying/Selling</td>
<td>0 kW – 100 kW</td>
<td>5</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>500</strong></td>
<td></td>
</tr>
</tbody>
</table>

Table 4.6 – Design space for sample DGDC energy system design optimization.

500 energy system configurations are examined to find the optimal system. Part of the simulation results is shown in Figure 4.10. The contour plot shows the cost of computing for 25 DGDC systems with a 40kW Computer and a 2 hr Battery. Each of the 25 line intersections is an energy system with a unique battery charge rate and transmission capacity. The optimal system with the lowest cost of computing has 25kW of transmission capacity and 0kW charging or no battery.

Figure 4.10 – Typical axis labels, units, and values for the contour plots in Figure 4.11.

There are 20 contour plots in Figure 4.11 representing the lifetime cost of computing for all 500 energy system configurations. White markers have been included on the chart to indicate the minimum LCC for each computer power and battery capacity combination.
Figure 4.11 – Results of the optimization showing LCC for 500 energy systems.
The minimum lifetime cost of computing is found to be $486/MWh for a system with the component sizes in Table 4.7. The ideal system has maximum computing capacities, no battery and a grid connection that is rated at 75% of the generation capacity.

<table>
<thead>
<tr>
<th>Component</th>
<th>Optimal Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generation</td>
<td>100 kW</td>
</tr>
<tr>
<td>Computing</td>
<td>100 kW</td>
</tr>
<tr>
<td>Charging/Discharging</td>
<td>0 kW</td>
</tr>
<tr>
<td>Battery Capacity</td>
<td>0 kW</td>
</tr>
<tr>
<td>Buying/Selling</td>
<td>75 kW</td>
</tr>
</tbody>
</table>

Table 4.7 – The optimal energy system design with the lowest lifetime cost of computing.

In addition to the lowest cost of computing, other conclusions about the characteristics of the optimal energy system can be drawn from the graphs. In this example, the best design always requires a certain level of grid-connected electricity since the LCC increases drastically for systems with no transmission capacity. As well, the optimal transmission capacity increases as the computing capacity increases. A possible explanation is that the system relied heavily upon the use of the transmission grid for computing.

All of results indicated that the ideal system was one without a battery to store electricity. The optimization was repeated to refine the previous results. It was assumed that the ideal system would not contain a battery and only scenarios without batteries were computed. The original data and the refined mesh data are shown in Figure 4.12 a & b, respectively.
Figure 4.12 a & b – Initial results for energy systems without energy storage (left) is refined with more energy systems (left).

The white line in Figure 4.12 indicates the lowest cost of computing. The line is graphed in Figure 4.13 showing the cost of computing leveling out for increasing amounts of computing capacity. The increase in computing capacity also requires an increase in transmission capacity.

Figure 4.13 – The cost of computing is level for increasing computing and transmission capacity.

Figure 4.13 illustrates how the results of the simulations can be used to better understand the optimal design. In this case, even though the optimal energy system is one where the computing capacity is maximized, the analysis shows that a system with lower computing and transmission capacity can provide a similar LCC with lower capital costs.
4.8. Economic Modeling Summary

The lifetime cash flow analysis builds on the hourly simulation presented in Chapter 3 to evaluate potential energy systems. Revenue and expenses incurred over the lifetime are summed together in a cash flow analysis to determine the overall benefit of the system. The net present value of the energy system takes into account the time value of money to provide an accurate evaluation of the system costs. Potential energy systems are compared using the Lifetime Cost of Computing, which allows for fair comparison of distinct system. The optimal system is found by selecting the DGDC that can provide the most computing services at the lowest overall lifetime cost.

This chapter, along with Chapter 3, provides a framework for optimizing the design of DGDCs. The model requires many assumptions and inputs that are very specific to individual scenarios and locations. In the following chapters, two potential DGDC locations are analyzed using this framework.
Chapter 5.  DGDC Case Studies

5.1. Ontario & New York Case Studies

In the following chapters, two case studies are conducted using the DGDC energy system model. One case study is located in Kingston, Ontario and the other is in Ithaca, New York. Roof mounted solar generation systems are installed on St. Lawrence College (SLC) in Kingston and on the Tompkins County Public Library (TCPL) in Ithaca. The solar panel arrays are a similar size, but the Ithaca site was installed in 2002, ten years prior to the Kingston site (Table 5.1).

<table>
<thead>
<tr>
<th></th>
<th>Kingston, Ontario</th>
<th>Ithaca, New York</th>
</tr>
</thead>
<tbody>
<tr>
<td>Installed PV Capacity</td>
<td>265 kW</td>
<td>147 kW</td>
</tr>
<tr>
<td>Number of PV Panels</td>
<td>1128</td>
<td>1430</td>
</tr>
<tr>
<td>Operational Date</td>
<td>October 2012</td>
<td>January 2002</td>
</tr>
<tr>
<td>Installation Cost</td>
<td>$3 million</td>
<td>$1 million</td>
</tr>
<tr>
<td>Panel Mounting</td>
<td>Tilted (15°, 20°, 27°)</td>
<td>Flat mounted</td>
</tr>
</tbody>
</table>

Table 5.1 – Kingston and Ithaca case study solar generation facilities.

The St. Lawrence College array in Kingston, Ontario has 1128 solar panels with a rated capacity of 265 kW. 156 of the panels, accounting for 37 kW are mounted on the tilted roof of student residence and the remaining 972 panels (228 kW) are mounted on an instructional building [53]. Figure 5.1 shows an aerial view of St. Lawrence College before the panels were installed with the current location of the solar panels indicated. St. Lawrence College is also home to the Sustainable Energy Applied Research Centre (SEARC) Solar PV Testing Facility, indicated in Figure 5.1a.
The Kingston PV panels are tilt mounted at 15°, 20°, and 27° on instructional and residential buildings (Figure 5.1b&c). Electricity generated by the panels is sold to the grid through an Ontario FIT contract. Under the contract, St Lawrence College receives a guaranteed price of 71.3cents/kWh for 20 years [56]. Current FIT incentives for solar systems is 31.6cents/kWh [60].

The solar panels in Ithaca, New York were installed on Tompkins County Public Library as part of a building renovation project in 2002 [57]. 1430 panels were flat mounted on the roof of the library covering 1600m² (Figure 5.2) [54].

The project was partially sponsored by NYSERDA as part of the Department of Energy’s Million Solar Roof initiative. The remaining panel cost was covered by Tompkins County. Even though the panels were
not expected to generate a profit over their lifetime, the project was justified because of environmental, social, and educational benefits [61].

The climates in Kingston and Ithaca are very similar and both have similar temperature profiles (Figure 5.3). On average, Kingston has a slightly colder winter and fewer sunny days than Ithaca. Skies in Ithaca are clear or mostly clear 29% of the time compared to Kingston’s 19% [62].

Solar irradiance data for Kingston and Ithaca is provided by Natural Resources Canada [27] and NREL [29], respectively. Figure 5.4 a&b displays the monthly average solar irradiance for a flat plate collector, facing south and titled to the latitude. Ithaca’s solar insolation is slightly lower but the data for Kingston is reported as a larger range and both locations are assumed to have the same solar energy potential.

The similarities in climate and energy potential make the two sites good candidates for case studies. The major differences between the New York and Ontario locations are the energy policies and renewable
energy incentives between. The electricity policies and regulations are set by one or more of the governing bodies that operate and oversee the Ontario and New York electricity market (Table 5.2).

<table>
<thead>
<tr>
<th>Organization</th>
<th>Ontario</th>
<th>New York</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reliability Commission</td>
<td>Provincial governing agencies</td>
<td>Federal Energy Reliability Commission (FERC)</td>
</tr>
<tr>
<td>Federal Regulator</td>
<td>North American Electric Reliability Corporation (NERC)</td>
<td></td>
</tr>
<tr>
<td>Reliability Region</td>
<td>Northeast Power Coordination Council (NPCC)</td>
<td></td>
</tr>
<tr>
<td>Market Regulator</td>
<td>Ontario Energy Board (OEB)</td>
<td>New York State Public Service Commission</td>
</tr>
<tr>
<td>System Operator and Balancing Authority</td>
<td>Ontario Independent Electric System Operator (IESO)</td>
<td>New York ISO (NYISO)</td>
</tr>
<tr>
<td>Transmission Operator</td>
<td>Hydro One</td>
<td>National Grid</td>
</tr>
<tr>
<td>Electricity Production</td>
<td>Ontario Power Authority (OPA)</td>
<td>New York Power Authority (NYPa)</td>
</tr>
</tbody>
</table>

Table 5.2 – Governing bodies for the New York and Ontario Electricity supply.

### 5.2. Cast Study Cost Assumptions

A multi-year cash flow analysis calculates the Net Present Value (NPV) of DGDC energy systems to access the financial feasibility. The NPV takes accounts for all the system costs and revenues over a five year period. Any costs that are incurred in future years are discounted to reflect the time value of money. A five year economic analysis balances the long life of the DGDC energy system with the uncertainty of future costs.

#### 5.2.1. Internal Rate of Return

DGDC system costs and revenues are discounted by an Internal Rate of Return (IRR) to capture the time value of money. The IRR for the case studies is equal to the interest rate of a risk free investment. This rate is approximated using the federal bond rates for the United States and Canada. The U.S. Department
of Treasury [65] and the Bank of Canada [66] provide a yield curve daily, which is used to approximate the risk free rate of return. The yield curve, shown in Figure 5.5, is the expected interest rate for investments with maturity terms between 1 and 30 years.

![Yield Curve Graph](image)

Figure 5.5 – The average yield curves for Canada and the United States between January 2012 and October 2012.

5.2.2. Transmission Cost

The cost of connecting to the local electrical grid depends on the location of the DGDC and the existing electrical infrastructure. The local distribution network may require upgrades to handle the additional load, there may be environmental barriers, land zoning requirements, or the location may be very remote. Upgrades to the local grid may not be funded by the local utility which can greatly increase the cost of connection for the DGDC.

For these case studies, an average cost of transmission is required to compare many sizes and compositions of DGDC energy systems. Five solar developers in New York and Ontario were contacted to determine average connection costs as shown in Figure 5.6. Cost estimation for developers in New York are slightly higher than Ontario but are comparable for small solar capacities.
The estimates from the solar developers are modeled as a linear function with a non-zero intercept (5.1). The slope of the line represents the cost per kW of capacity for transmission and the intercept is equal to interconnection fee charged by the local utility.

\[
\text{CostGrid} = 118 \$/\text{kW} \times C_{\text{BuySell}} + 2500
\]

where;

- \text{CostGrid} is the interconnection costs, and
- \text{C}_{\text{BuySell}} is the connection capacity to the electrical grid in [kW].

### 5.2.3. Generation Cost

A study from Lawrence Berkeley National Laboratory reviewed the installed cost of over 200 000 solar installation projects (Table 5.3) [67]. The median capital cost for systems installed in 2012 with generation >100kW is used for both case studies.

<table>
<thead>
<tr>
<th>PV System Size</th>
<th>Installed Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>\leq 10kW</td>
<td>$5.30/W</td>
</tr>
<tr>
<td>10-100kW</td>
<td>$4.90/W</td>
</tr>
<tr>
<td>&gt;100kW</td>
<td>$4.60/W</td>
</tr>
</tbody>
</table>

Table 5.3 – Median cost of installed solar generation facilities in 2012 [67].

A review of eleven papers published in 2008 indicated that O&M costs for solar resources can range between $10-25/kW-Yr [68]. For these case studies, the O&M cost is assumed to be $10/kW-Yr. (Table 5.4).
<table>
<thead>
<tr>
<th>HP POD Model</th>
<th>Power Capacity</th>
<th>Capital Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>HP POD 20c</td>
<td>292 kW</td>
<td>$4.0 million</td>
</tr>
<tr>
<td>HP POD 40c</td>
<td>600 kW</td>
<td>$5.4 million</td>
</tr>
<tr>
<td>HP EcoPOD</td>
<td>1350 kW</td>
<td>$8.0 million</td>
</tr>
</tbody>
</table>

Table 5.5 – Installed costs for HP POD modular data centres [69].

The HP POD provides a basis of cost assumptions for modular computing systems of various sizes. The marginal cost for the data centres indicates a larger POD will benefit from scales of economy. An exponential curve is fitted to the HP POD cost data in Figure 5.7.

Figure 5.7 – Computer cost assumption of HP POD modular data centres.

The curve approximates the economies of scale that are present for the construction of a DGDC. Equation 5.2 describes the cost for computing resources.
where;

\[ \text{Cost}_{\text{comp}} = 302200 \times P_{\text{comp}}^{0.45} \]

Cost\text{\_comp} is the capital cost of the computing, and

\( P_{\text{comp}} \) is the power capacity of the computing resources and related systems.

An accurate cost estimate for DGDC computing resources is dependent on the intended use and reliability requirements. The cost assumptions based on the HP PODs may not be accurate for computing resources smaller than 250kW.

5.2.5. Battery Cost

Energy storage in both case studies is assumed to be lead acid batteries. Lead acid batteries have characteristics that are similar to the needs of a DGDC energy system (Table 5.6). In addition, lead acid batteries are well researched and widely used.

<table>
<thead>
<tr>
<th>Battery Type</th>
<th>Lead Acid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power Rating</td>
<td>0-20 MW</td>
</tr>
<tr>
<td>Discharge Time</td>
<td>Seconds-hours</td>
</tr>
<tr>
<td>Storage Duration</td>
<td>Minute to days</td>
</tr>
</tbody>
</table>

Table 5.6 – Lead acid battery characteristics [70].

A review from Beaudin et al. [71] provides a range of costs and lifetime cycles of lead acid batteries. The average values from recent papers are used for both case studies (Table 5.7).

<table>
<thead>
<tr>
<th>Capital Cost</th>
<th>$450/kWh</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lifetime Cycles</td>
<td>1125 cycles</td>
</tr>
<tr>
<td>Storage Replacement Cost</td>
<td>$0.40/kWh</td>
</tr>
</tbody>
</table>

Table 5.7 – The pertinent battery characteristics for the case studies [71].

The storage replacement cost accounts for the wear of using the battery based on the amount of energy that is stored. The assumption made is that every year investments will be required to replace a percentage of the batteries equal to the amount of use. The cost is derived from the $/kWh battery capital cost and the number of cycles in the lifetime of the battery as shown in Equation (5.3).
\[
\text{Storage Replacement Cost} = \frac{\text{Battery Cost}}{\text{LifetimeCycles}} 
\]

where;

- **Storage Replacement Cost** is the cost/kWh of use for the battery [$/kWh],
- **Battery Cost** is per kWh cost of replacing the battery [$/kWh], and
- **LifetimeCycles** is the number of cycles before a battery requires replacement.

### 5.2.6. Electricity Demands Charge

The cost of electricity purchased from a local utility is composed of two costs: demand and commodity. The commodity charge is proportional to the amount of electricity that is used in a billing period. The demand charge is proportional to the maximum electricity used at any point within the billing period. Demand in the DGDC model is assumed to be the larger of either the selling or buying capacity. The yearly demand charge is shown in Equation (5.4).

\[
\text{DemandCost} = (C_{\text{Fixed}} + C_{\text{kW}} \times P_{\text{grid}}) \times 12\text{months} 
\]

where;

- **DemandCost** is the yearly cash flow cost [$],
- **C_{\text{Fixed}}** is a fixed demand charge [$],
- **C_{\text{kW}}** is the variable demand charge [$/kW], and
- **P_{\text{grid}}** is the maximum buying and selling capacity of the DGDC [$].

In Ontario the demand charge, or delivery charge, is regulated by the Ontario Energy Board (OEB). Each year the delivery rates are applied for by the local utility and approved by the OEB. The 2012 Kingston Hydro Corporation’s demand rates for small, medium, and large commercial (Table 5.8) are published in Kingston Hydro Corporation Tariff of Rates and Charges [72]. The Kingston case study uses the demand rate for medium commercial between 50kW and 4999kW.

<table>
<thead>
<tr>
<th>General Service Classification</th>
<th>Fixed Rate</th>
<th>Variable Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Less than 50kW</td>
<td>$33</td>
<td>$0.0228/kW</td>
</tr>
<tr>
<td>50kW to 4999kW</td>
<td>$271</td>
<td>$5.0574/kW</td>
</tr>
<tr>
<td>Greater than 5000kW</td>
<td>$5000</td>
<td>$6.0798/kW</td>
</tr>
</tbody>
</table>

Table 5.8 – Monthly demand rate for non-residential consumers in Kingston [72].

In New York, the delivery and demand charge is regulated by the New York Public Service Commission. Demand charges are paid to the New York State Electric and Gas (NYSEG). Fixed and variable rates are
tiered based on the Service Classification and load factor (Table 5.9) [73]. Service Class 2, intended for non-residential customers between 5kW and 500kW, is used as the service classification of a DGDC.

<table>
<thead>
<tr>
<th>Service Classification No 2</th>
<th>...with high load factor (68%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed Rate</td>
<td>Variable Rate</td>
</tr>
<tr>
<td>$18.34</td>
<td>$8.31/kW</td>
</tr>
<tr>
<td>$18.34</td>
<td>$5.73/kW</td>
</tr>
</tbody>
</table>

Table 5.9 – Monthly demand rates for Service Classification No 2 consumers in Ithaca [73].

5.3. Simulation Parameters

The yearly energy simulation makes a series of assumptions to represent the operation of the DGDC energy system. The battery charging and discharging assumes knowledge of future computing cost. Future computing costs are weighted, as shown in Table 5.10, to approximate the uncertainty of forecasting electricity prices, computing demand and renewable energy generation. See Section 3.8 for more information on battery charging incentive. Computing costs in near future are heavily weighted, and forecasts further ahead are weighted less.

<table>
<thead>
<tr>
<th>Hours Ahead</th>
<th>Weighting</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>1.00</td>
</tr>
<tr>
<td>8</td>
<td>0.50</td>
</tr>
<tr>
<td>12</td>
<td>0.25</td>
</tr>
</tbody>
</table>

Table 5.10 – Battery charging incentive weighting of future computing costs.

The efficiency of the battery is assumed to be 90% and is used to determine the amount of energy lost in storage.

The number of points used for the supply and demand curve analysis is set to 16 points chosen based on the analysis in Section 3.6. A 16 point resolution offered a good compromise between accuracy and computational workload. Based on the analysis, the modelled computing amount is within 20% of the best case and each energy system simulation takes less than 5 minutes (Figure 3.10). Increasing the resolution lengthens the simulation times and has diminishing gains in model accuracy.
5.4. Hourly Generation Data

5.4.1. Kingston St Lawrence College Solar Array

The St. Lawrence College panels began producing power in October 2012. Hourly production data has been recorded since then and is available from the Deck monitoring system [74]. Reliable data is available since November 23, 2012. The energy generation of the SLC panels for all of 2012 is estimated using solar irradiation data recorded by the Sustainable Energy Applied Research Centre (SEARC) at St. Lawrence College. A model provided by Sandia National Laboratories is used estimate the electricity production using the SEARC solar irradiation data [75].

The modeled data is compared to the metered energy production of the St. Lawrence College solar panels as seen in Figure 5.8. In general, the Sandia model of the solar irradiation data indicates higher energy production than what is actually produced. The Sandia model does not take into account external factors such as snow coverage, or panel malfunctions. For the purpose of the case study, this data is considered sufficient since it accurately demonstrates the variable nature of solar energy.

![Figure 5.8 – Comparison of metered data from DECK Monitoring and Sandia modeled data from SEARC.](image)

The modelled production from the St. Lawrence College site is typical of what can be expected for solar panels over the course of a year (Figure 5.9).
5.4.2. Ithaca Tompkins County Public Library Solar Panels

The solar panels used for the Ithaca case study are located on the roof of Tompkins County Public Library. SunPower Performance Monitoring has recorded solar generation since 2002 [76]. Due to degradation and panel malfunction the performance of the panels has been decreasing since the installation of the panels in 2002 (Figure 5.10).

Figure 5.10 – Monthly maximum generation showing panel degradation since installation.

In addition to the solar degradation of the panels, the panels are partially shaded by a hotel and a parking garage to the south of the library. A 3-D model of TCPL, the Cayuga Street Parking Structure and the Holiday Inn was used to analyze the amount of shading at three locations on the solar array (Figure 5.11).

Figure 5.11 – Model of TCPL with Cayuga Street Parking Garage and the Holiday Inn [58].
A sun shading chart in Appendix A shows the time of the year and the time of day when the parking garage and hotel are shading the solar panels. Most of the shading occurs in winter between September and March, between the hours of 2pm and 4pm. The effect of shading is noticeable in the winter afternoons when generation drops off very quickly causing the curve to be asymmetric (Figure 5.12a). In the summer, the curve is symmetrical in the morning and afternoon (Figure 5.12b).

![Winter Generation](image1)

![Summer Generation](image2)

**Figure 5.12 a&b – Solar generation at TCPL in the winter (top) and the summer (bottom).**

The impact on yearly production is minimal because the solar irradiation is significantly lower in the winter. Maximum generation in the summer (100kW) is significantly higher than winter maximum generation (40kW). Figure 5.13 is the normalized production data from 2012 and is typical of solar generation facilities.

![Normalized Production](image3)

**Figure 5.13 – Ithaca solar panel production in 2012 as a percentage of the maximum generation.**
5.5. Case Studies Introduction

Chapters Six and Chapter Seven apply the DGDC energy system model to each of the case study locations. In the first case study in Kingston, Ontario the energy model is used to optimize the design of energy system components. The DGDC is connected to the electricity grid with an Ontario Feed in Tariff (FIT) program and three grid electricity pricing structures. Finally a grid isolated system is examined to determine the optimal computing and battery capacity.

The second case study in Ithaca, New York addresses design consideration such as transmission costs assumptions and solar renewable energy incentives. A grid-tied and a grid-isolated system are compared on the ability to provide low-cost computing over 5 years. These case studies demonstrate how the model can assist in design decisions for DGDC energy systems. Cost assumptions are generalized for a wide range of scenarios to understand the effects of energy policies on DGDC design.
Chapter 6.  Kingston, Ontario Case Study

6.1.  Ontario Electricity Economics

The first case study focuses on electricity market economic policies in Ontario. For purchasers of electricity there are three pricing options available; time-of-use, hourly variable rate, and fixed contract pricing. Each pricing scheme is used to simulate the operation of the DGDC. Generated electricity sold to the electrical grid is compensated through the Ontario Feed-In-Tariff (FIT). Generators are provided a flat rate for all electricity produced. The rate set through the FIT program is much higher than the wholesale cost of electricity.

6.1.1.  Time-of-Use Rates

Time-of-use has three tiers of prices depending on the time of day, season, and day of week (Table 6.1). The highest pricing tier corresponds to the peak electricity demands when generation is most expensive. Time-of-use mimics the hourly price variations evident in electricity generation. In the winter the peak prices occur during the morning and evening when building heating and lighting loads are highest. In the summer, peak demand occurs during mid-day when cooling loads are highest.

<table>
<thead>
<tr>
<th>Time of Day</th>
<th>Summer</th>
<th>Winter</th>
<th>Weekend and Holidays</th>
</tr>
</thead>
<tbody>
<tr>
<td>Night 7pm – 7am</td>
<td>Off-peak</td>
<td>Off-peak</td>
<td>Off-peak</td>
</tr>
<tr>
<td>Morning 7am – 11am</td>
<td>Mid-peak</td>
<td>On-peak</td>
<td>Off-peak</td>
</tr>
<tr>
<td>Afternoon 11am-5pm</td>
<td>On-peak</td>
<td>Mid-peak</td>
<td>Off-peak</td>
</tr>
<tr>
<td>Evening 5pm-7pm</td>
<td>Mid-peak</td>
<td>On-peak</td>
<td>Off-peak</td>
</tr>
</tbody>
</table>

Table 6.1 – Time of use daily and season price tier schedule [77].

Time-of-use electricity prices set by the Ontario Energy Board (OEB) are adjusted bi-annually in May and November. The rates for 2012 are a combination of three prices (Table 6.2) [78]. The electricity rates are translated into a data series for each hour of the year.
### Table 6.2 – Time of use electricity prices as set by the Ontario Energy Board [78].

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Off-peak</td>
<td>6.2</td>
<td>6.5</td>
<td>6.3</td>
</tr>
<tr>
<td>Mid-peak</td>
<td>9.2</td>
<td>10</td>
<td>9.9</td>
</tr>
<tr>
<td>On-peak</td>
<td>10.8</td>
<td>11.7</td>
<td>11.8</td>
</tr>
</tbody>
</table>

6.1.2. **Fixed Contract Pricing**

Fixed rate contracts provide energy users with a consistent and predictable cost of electricity. Customers in Ontario can use the Regulated Rate Plan (RRP) with prices set by the OEB or sign a fixed rate contract with an electricity retailer.

Users who opt to go with an electricity retailer are also required to pay the Ontario Global Adjustment charge [77]. The global adjustment charge is used to cover the cost difference between market price and the price paid to generators as well as to support conservation and demand response programs [79]. The RRP has the global adjustment cost integrated into the cost.

Table 6.3 shows the cost comparisons between the OEB regulated rate and electricity retailers in November of 2013. The electricity retailer contract price is based on a 2-year fixed contract from Superior Energy which offers fixed price contracts in Kingston. Direct Energy in Toronto, Ontario offers customers 100% guaranteed green power at a rate of 5.99 cents/kWh.

<table>
<thead>
<tr>
<th>Regulated Rate Price [78]</th>
<th>Electricity Retailer</th>
</tr>
</thead>
</table>
| 8.3 cents/kWh             | Electricity Retailers Contract [80] | 4.2 cents/kWh  
|                           | Global Adjustment [79] | 6.2 cents/kWh  
|                           | Total                | 10.4 cents/kWh |

Table 6.3 – Comparison of the regulated rate plan and a fixed contract from an electricity retailer.

The electricity retailer rate is higher than the Regulated rate plan which represents the risk assumed by the retailer for a long-term contract. The regulated rate plan is adjusted bi-annually to reflect the estimated cost of electricity. The prices in Table 6.4 are used for the fixed rate price in the Kingston case study.
<table>
<thead>
<tr>
<th>Effective Date</th>
<th>Price (¢ per kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nov 1, 2011</td>
<td>8.3</td>
</tr>
<tr>
<td>May 1, 2012</td>
<td>8.8</td>
</tr>
<tr>
<td>Nov 1, 2012</td>
<td>8.7</td>
</tr>
</tbody>
</table>

Table 6.4 – Ontario regulated rate plan prices for 2012 [78].

6.1.3. Hourly Ontario Electricity Price

The Hourly Ontario Electricity Price (HOEP) is a real-time cost of providing electricity in Ontario. The IESO website provides the real-time cost of electricity as well as a cost projection for future hours (Figure 6.1).

![Price chart](chart.png)

Figure 6.1 – HOEP and the projected hourly cost of electricity from IESO website [81].

The HOEP is added to the global adjustment charge, which is updated monthly (Table 6.5). In 2012, the maximum global adjustment charge was 6.2 cents/kWh in March.
<table>
<thead>
<tr>
<th>Month</th>
<th>Global Adjustment Rate [$/MWh]</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>42.46</td>
</tr>
<tr>
<td>February</td>
<td>50.62</td>
</tr>
<tr>
<td>March</td>
<td>62.34</td>
</tr>
<tr>
<td>April</td>
<td>60.72</td>
</tr>
<tr>
<td>May</td>
<td>56.50</td>
</tr>
<tr>
<td>June</td>
<td>52.55</td>
</tr>
<tr>
<td>July</td>
<td>33.59</td>
</tr>
<tr>
<td>August</td>
<td>41.78</td>
</tr>
<tr>
<td>September</td>
<td>47.62</td>
</tr>
<tr>
<td>October</td>
<td>53.81</td>
</tr>
<tr>
<td>November</td>
<td>54.26</td>
</tr>
<tr>
<td>December</td>
<td>40.64</td>
</tr>
</tbody>
</table>

Table 6.5 – Global adjustment charges in 2012.

The HOEP and Global adjustment are added together to determine the price of electricity for the simulation. Figure 6.2 shows the distribution of hourly prices over 2012. The price has an average value of 12.2 cents/kWh, a minimum of -4.7 cents/kWh and a maximum value of 51.4 cents/kWh.

![Figure 6.2 – The Hourly Ontario Electricity Price in 2012.](image)

6.1.4. Demand Curve

For the Ontario case studies, the demand curve is constant throughout the entire simulation. The curve is set so half of the computing resources are utilized if the price is equal to the average of the RRP (8.6 cents/kWh). The B factor of the demand curve (Equation 3.33) is B=1 to represent a linear relationship between cost and utilization (Figure 6.3).
6.1.5. **Ontario Feed-in Tariff**

The most important factor of this simulation is the rate of payment for selling electricity to the electrical grid. The Ontario Feed-in Tariff is set by the Ontario Power Authority [82]. This case study uses the Ontario FIT price from the schedule posted on August 13, 2010 [83]. For roof-top panels between 250 and 500kW received 63.5 cents/kWh in 2012. The Feed-in Tariff drives the performance of the DGDC energy system since virtually all generated power will be sold to the electrical grid.

### 6.2. Electricity Pricing Comparison

The initial design space examines 320 possible energy systems for each of the three electricity pricing mechanisms. The capacities are evenly spaced to between 0% and 120% of generating capacity (Table 6.6). The battery capacities are set to provide one to four hours of energy storage for the selected charging/discharging capacities.

<table>
<thead>
<tr>
<th>Component</th>
<th>Capacities</th>
<th># Simulations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generation</td>
<td>100%</td>
<td>1</td>
</tr>
<tr>
<td>Computing</td>
<td>40% - 120%</td>
<td>5</td>
</tr>
<tr>
<td>Charge/Discharge</td>
<td>0% - 120%</td>
<td>4</td>
</tr>
<tr>
<td>Battery Capacity</td>
<td>1hr - 4hr @ Discharge Capacity</td>
<td>4</td>
</tr>
<tr>
<td>Selling/Buying Capacity</td>
<td>0% - 120%</td>
<td>4</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>320</strong></td>
<td></td>
</tr>
</tbody>
</table>

Table 6.6 – Initial case study component capacities expressed as a percentage of generation capacity.
The full results of the scenarios using Time-of-Use, Fixed contract and HOEP are included in Appendix B. A summary of the systems with lowest cost of computing is shown in Table 6.7. The results indicate the Time-of-Use pricing mechanism can provide the lowest cost of computing.

<table>
<thead>
<tr>
<th>Pricing Scheme</th>
<th>Lowest Cost of Computing</th>
<th>Computer Capacity</th>
<th>Transmission Capacity</th>
<th>Battery Discharge Rate</th>
<th>Battery Discharge Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time of Use</td>
<td>$1,642</td>
<td>120%</td>
<td>120%</td>
<td>40%</td>
<td>2 hours</td>
</tr>
<tr>
<td>Fixed Contract</td>
<td>$1,988</td>
<td>120%</td>
<td>80%</td>
<td>40%</td>
<td>1 hour</td>
</tr>
<tr>
<td>HOEP</td>
<td>$2,720</td>
<td>20%</td>
<td>0%</td>
<td>120%</td>
<td>4 hours</td>
</tr>
</tbody>
</table>

Table 6.7 – Lowest Cost of Computing for three Kingston electricity pricing schemes.

For fixed contract and time-of-use billing, the computing capacity is maximized and large transmission capacity is required. For the Hourly Ontario Electricity Price, a small computer and large battery is utilized in a grid-isolated system. These energy system designs are typical of the lowest cost energy system in each pricing scheme scenario.

The two distinct energy system arrangements demonstrate different ways of minimizing the cost of computing. In the HOEP pricing scheme the small grid isolated computing system minimizes the capital cost of the system. In the other pricing schemes, a large grid tied system maximizes the amount of computing that is completed. A comparison of the grid prices of electricity in Figure 6.4 shows that the cost of computing is strongly related to the cost of grid based electricity. The higher the cost of electricity causes a higher the cost of computing, which indicates that a large portion of the electricity for computing is from the electrical grid.
Due to the reliance on the electrical grid, the selection of an appropriate demand curve is critical. A demand curve lower than the energy price will result in minimal amounts of energy purchased from the electrical grid, as is observed with the HOEP scenario. In contrast, for electricity prices below the demand curve, the DGDC relies on the grid as a source of energy. Selection of the demand curve is explored further in the Ithaca case study in the next chapter.

In Kingston, Ontario, the FIT program strongly influences the performance of the energy system. A cumulative power flow diagram (Figure 6.5) show power flows within the system during the year. The computing and buying line are identical, as is the generation and selling lines. This is because all of the generated electricity is sold directly to grid to receive the FIT incentive. Since no power comes from the solar panels for computer, the grid supplies all electricity for computing.
6.3. Grid-Connected DGDC

The grid-connected computing system is further examined to find the limits for computing and transmission capacity. Figure 6.6 from the fixed-contract pricing scheme shows the results for a one hour and four hour battery with a large computing resource. Both figures are nearly identical indicating there is little difference in computing cost between a one and a four-hour battery. Furthermore the cost of computing remains nearly constant for all charging capacities (horizontal axis). This indicates the battery storage hours and charging capacities have little effect on cost of computing.

Figure 6.6 – DGDCs have similar costs for different battery charging and storage capacity.

For the rest of this grid connect case study, it is assumed that no battery is used. Instead it focuses on optimizing transmission and computer capacity. The three pricing scenarios are re-simulated with computing capacity sized between 100% and 300% of the solar generation size Figure 6.7.

Figure 6.7 – Cost of computing for DGDC systems with very large computing and transmission capacities.

For all three scenarios the cost of computing is lowest when the computing capacity is greatest. In response to a maximized computing capacity, the transmission capacity increases to supply the computing load. This trend is verified for computing capacities 15 times larger than the generation (Figure 6.8).
Figure 6.8 – Lowest cost of computing continues to decrease as the computer capacity increases.

The computer capacity tends to be maximized for three reasons: the demand curve selection, computing capacity economies of scale, and unrealistic transmission cost assumptions. The demand curve selection, based on the fixed contract price, ensures the computing resource will be utilized 50% of the time. Doubling the computing capacity doubles the amount of computing completed, but the capital cost does not double due to economies of scale. Therefore the lifetime cost of computing will continue to decreases as the computing capacity is maximized. This is compounded by the transmission cost assumption, which does not take into account the cost of upgrades to the utilities distribution network.

The optimal computing size for a grid tied scenario with a fixed contract pricing scheme is likely in the range of 200% to 400% of the renewable energy resource. The optimal transmission capacity is around 200% of the renewable energy capacity based on diminishing reduction in cost of computing for increasing computing sizes (Figure 6.9).
In summary, a grid connected DGDC in Kingston would require a very large computing resource. The transmission capacity would be as large as the computing resource. Batteries would not be required since all generated electricity is sold to the grid and there is no incentive to store electricity.

### 6.4. FIT Incentives

The Ontario case study examined the effect of various electricity pricing schemes on DGDC energy system design. The two outcomes from this analysis are:

1. The relationship between the grid price of electricity and the assumed computing demand curve drastically impacts the optimal design of the DGDC. This conclusion is further expanded in the grid-tied Ithaca case study.

2. The FIT incentive effectively makes a grid-connect DGDC a stand-alone solar panel selling directly to the grid and a stand-alone data centre buying electricity directly from the grid. Therefore, the DGDC concept is not practical for an Ontario grid-tied application and further analysis focuses on grid isolated DGDCs.

Since the inception of the Ontario FIT program in 2009, the incentive for solar panels has been revised 4 times from $713/MWh down to $316/MWh [83] (Table 6.8).
Applying these reduced incentives to the Ontario grid-tied case study would not have a significant impact of the overall performance of the DGDC. The computing demand curve used for the Ontario case study (Figure 6.3) sets the maximum price that DGDC is willing to pay for computing at $172/MWh. Therefore, the DGDC will continue to sell all generated electricity directly to the grid if the FIT incentive is greater than the demand for computing ($172/MWh).

### 6.5. Grid Isolated DGDC

The probable application of an Ontario DGDC is in an off-grid environment. Example of locations include urban areas where the distribution network are constrained or in very remote locations without transmission infrastructure. Based on the results from the initial simulations, the optimal off-grid DGDC has a small computing resource and a large battery to store excess generation. The design space is refined for a grid isolated application with computing capacities of less than 25% of the generation and batteries capable of storing up to 9hr (Table 6.9).

<table>
<thead>
<tr>
<th>Component</th>
<th>Capacity</th>
<th># Simulations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generation</td>
<td>100kW</td>
<td>1</td>
</tr>
<tr>
<td>Computer</td>
<td>5 - 25 kW</td>
<td>5</td>
</tr>
<tr>
<td>Battery Capacity</td>
<td>4 – 9hr</td>
<td>6</td>
</tr>
<tr>
<td>Charge/Discharge Rate</td>
<td>60 – 110 kW</td>
<td>6</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td><strong>180</strong></td>
</tr>
</tbody>
</table>

Table 6.9 – The design space for the grid disconnected DGDC energy system.
Each grid point of the five graphs in Figure 6.10 shows a DGDC with a unique battery and computer capacity. The 20% capacity computing graph has the lowest average cost of computing of all the computing capacities. The cost of computing for the small 5% capacity computing is significantly higher than computing capacities over 15%. Computing resources less than 15% of the generation are not large enough to effectively use the power generated by the renewable generator without significant investment in battery capacity.

Figure 6.10 – Simulation results for optimization of a grid isolated DGDC system.

The 20% computing resource is plotted with additional battery capacities up to 12 hours (Figure 6.11). A refined colour bar shows how the battery capacity and charging/discharging capacity impact the cost of computing. A red line is drawn along where the cost of computing is at a minimum. This red line is plotted on a graph of the battery capacities (Figure 6.12). This line corresponds to a battery capacity of approximately 0.6 MWh. The optimizing of a DGDC is dependent on the total storage capacity of the battery and the charging/discharging capacity of the battery does not play a significant role.
The minimum computing cost occurs when the battery capacity is 0.54MWh (Figure 6.13). A larger battery capacity increases the capital cost but does not significantly increase the amount of computing. A smaller battery capacity requires the battery to dump excess generated electricity.

In Kingston, the optimal grid disconnected system with a 100kW solar resource has a 20kW computing resource and a 0.54MWh battery capable of storing 27 hours of computing. During the first five years of operation the energy system utilizes 92% of the electricity generated by the solar panels. A summary of the yearly power flows is provided in Figure 6.14, which indicates that 9 MWh of the generated electricity is dumped or lost due to battery inefficiencies. The 109 MWh of computing is divided between powering, cooling and supporting the computing resources.
To minimize the total lifetime cost of computing, a large battery is necessary to store generated energy for computing. A system with a smaller battery would have a lower capital cost and operating cost, but would not complete as much computing. In this off-grid scenario, the battery enables a computing uptime of 62%. Since the computing resource is more expensive than a battery is necessary to increase the battery size to maximize the uptime of the computing resource.

6.6. **Kingston Case Study Summary**

The Kingston case study demonstrates the role of policy in the determining the feasibility of a DGDC system. The Ontario FIT program provides excellent incentives for developing solar energy resources but only provides incentive to solar resources connected directly to the electricity grid. In order the use generated electricity for computing, the demand for computing must be greater than FIT incentive; otherwise it will be more beneficial to sell the energy directly to the grid. This analysis shows that virtually all electricity would be sold to the grid and a grid-tied DGDC located in Ontario is not feasible.

In general, the computing demand curve has a strong influence on the design of a grid-tied DGDC. If the computing demand is high, then the size of the computing resource is increased and energy is purchased from the electrical grid. If the computing demand is low, then the computing resource is only used when there is an excess of solar generation or low price of grid electricity. The design of the optimal grid-tied
DGDC energy system is strongly related to the relationship between the computing demand curve and the grid price of electricity.

Practical physical and economic limits are required for large computing capacities. The current cost assumption for transmission does not account for the limits of existing transmission system to accommodate large computing resources. These limits could be applied to the cost assumption as a large increase in cost when the transmission reaches a specific capacity. Another approach is to restrict the design space within which the model searches for an optimal energy system. Either approach highlights the importance of ensuring the results of the optimization are physically and economically possible.

Grid isolated DGDC energy systems tend to utilize a computing resource that is much smaller than the solar panel capacity. Electricity is stored in a large battery for use when there is no generation. The battery increases the uptime of the computer and reduces the lifetime cost per kWh of computing. The cost of computing is strongly related to the total battery capacity, and not to the charging or discharging limits of the battery.
Chapter 7. Ithaca, New York Case Study

7.1. Grid Isolated Optimization

The second case study examines a solar powered energy system in Ithaca, New York. First a grid isolated system is optimized to determine the optimal computing capacity. The optimal grid-isolated DGDC is then connected to the electrical grid and the cost of computing is compared between an on- and off-grid DGDC.

The initial design space was chosen based on the Kingston, Ontario case study as it was assumed that performance would be similar between the two locations. The design space includes a computing resource 10-50% of generation and a battery capable of storing between 1-10 hours of generation. The results (Figure 7.1) indicate a computing capacity of 20% of the generation can provide the lowest cost of computing.

![Figure 7.1 – Lowest cost of computing for a grid-isolated DGDC in Ithaca.](image)

The battery capacity for the 20% computing capacity is re-simulated with 2 MWh (20 hours) of energy storage (Figure 7.2). The system with the lowest cost of computing has a battery capacity of 1000 kWh. Increasing the battery capacity greater than 400kWh (Line A) does not significantly lower the amount of electricity dumped each year (red line). A larger battery results in less dumped energy but there are lower gains for increasing the battery capacity past 400kWh.
Figure 7.2 – Lifetime cost and electricity dumped for a 20kW grid-isolated DGDC.

The best grid-isolated DGDC with a 100kW solar farm in Ithaca has a computing capacity of 20kW and a 400kWh battery. A 400kWh battery is chosen because it performs similar to the optimal 1000 kWh battery but with a lower capital cost. Each year the DGDC uses 103 MWh of the 113 MWh of generated electricity. The uptime of the 20kW computing system is 57.5%. A five year lifetime cash flow analysis indicates the net present cost of the system is $941 000 and the average cost of computing is $1831/MWh. This energy system is used for comparison with grid-tied DGDCs. The next section examines this 20kW DGDC when it is connected to the New York electricity grid.

### 7.2. New York Electricity Pricing

The New York State Public Service Commission regulates electricity prices and the New York State Electric Gas Corporation (NYSEG) sets the electricity rates used in the Ithaca case study. Electricity rates are composed of a fixed monthly delivery charge and a commodity charge. The amount charged for delivery depends on the characteristics of the DGDC as shown in Section 5.2.6.

Customers in the Service Class 2 are eligible for either a monthly fixed or an hourly variable electricity rate. Both rates are composed of the commodity charge as well tariffs, surcharges, and adjustments shown in Appendix C. NYSEG produces a statement for each charge every month and historical statements are available since 2006 [73].
The variable hourly rate is posted in real time for each geographic transmission zone within the NYISO [84]. Ithaca, New York is part of the Central Transmission zone, the hourly price and the fixed monthly price for this region over the course of 2012 is shown in Figure 7.3.

![Variable Hourly Price vs Monthly Fixed Price](image_url)

Figure 7.3 – Hourly variable (red) and fixed monthly (blue) price of electricity for Ithaca, New York.

The NYSEG provides the archived fixed price for supply service since 2009 [85]. The fixed monthly rate also includes a merchant function charge [73]. The total monthly charge in 2012, Table 7.1 is a combination of the monthly supply charge, the merchant function charge and the charges found in Appendix C.

<table>
<thead>
<tr>
<th>Month</th>
<th>Monthly Fixed Price</th>
<th>Monthly Charges (Appendix C)</th>
<th>Merchant Function Charges</th>
<th>Total Cost [cents/kWh]</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>4.63</td>
<td>0.07</td>
<td>0.30</td>
<td>5.00</td>
</tr>
<tr>
<td>February</td>
<td>3.99</td>
<td>0.28</td>
<td>0.30</td>
<td>4.57</td>
</tr>
<tr>
<td>March</td>
<td>3.97</td>
<td>0.51</td>
<td>0.30</td>
<td>4.78</td>
</tr>
<tr>
<td>April</td>
<td>4.67</td>
<td>0.97</td>
<td>0.30</td>
<td>5.94</td>
</tr>
<tr>
<td>May</td>
<td>3.10</td>
<td>0.85</td>
<td>0.30</td>
<td>4.25</td>
</tr>
<tr>
<td>June</td>
<td>2.96</td>
<td>0.63</td>
<td>0.30</td>
<td>3.89</td>
</tr>
<tr>
<td>July</td>
<td>2.83</td>
<td>0.64</td>
<td>0.30</td>
<td>3.77</td>
</tr>
<tr>
<td>August</td>
<td>3.87</td>
<td>0.53</td>
<td>0.30</td>
<td>4.70</td>
</tr>
<tr>
<td>September</td>
<td>4.58</td>
<td>0.54</td>
<td>0.34</td>
<td>5.46</td>
</tr>
<tr>
<td>October</td>
<td>5.39</td>
<td>0.61</td>
<td>0.35</td>
<td>6.35</td>
</tr>
<tr>
<td>November</td>
<td>4.56</td>
<td>0.63</td>
<td>0.36</td>
<td>5.55</td>
</tr>
<tr>
<td>December</td>
<td>5.21</td>
<td>0.54</td>
<td>0.36</td>
<td>6.11</td>
</tr>
</tbody>
</table>

Table 7.1 – NYSEG Supply Service fixed monthly rate in Ithaca.
As shown in the Ontario case study, the amount of electricity purchased from the grid is dependent of the computing demand. A system with a high demand will purchase more grid electricity and will have a lower lifetime cost of computing. To compare an grid-tied and grid-isolated system, the computing demand curve is selected to ensure the amount of electricity bought and sold is equal. This means that the both systems are compared with equal amounts of net energy.

For this case study, the computing demand curve is based on the fixed monthly cost of electricity as set by NYSEG. The computing demand is scaled between 85% and 140% of the fixed price in order to balance the amount of electricity bought and sold (Figure 7.4). The energy bought and sold is balanced when the fixed contract rate is scaled to 117% (red mark). Electricity will not be purchased if the cost of electricity is greater than 117% of the monthly fixed contract rate.

![Figure 7.4 – Computing demand based on the NSYSEG Supply Service is scaled to balance the electricity bought and sold. The red mark is the chosen scaling value.](image)

Each month the computing demand curve changes for the new fixed price of electricity. The computing demand curves for all 12 months are shown in Figure 7.5. The B factor of the demand curve (Equation 3.33) is $B=1$ to represent a linear relationship between cost and utilization.
The grid-tied design space is restricted to a 20kW computing resource connected to a 100kW solar system and the electrical grid. The cost of electricity purchased from the electrical grid is based on the NYSEG hourly variable rate. This case study assumes the solar panels are connected in a net metering program where excess generated electricity offsets the cost of purchasing from the electrical grid. Therefore it is assumed the revenue from selling electricity is equal to the cost of electricity.

The results (APPENDIX D) indicate a grid connected 20kW computing resource and 100kW solar generator will optimally have a transmission capacity of 10kW and a 200kWh battery. The system is able to sell 30% of the 113MWh of generated electricity over the course of the year. Compared to the grid-isolated system (Table 7.2) the cost of computing over the lifetime of the system is $10/MWh less.

<table>
<thead>
<tr>
<th></th>
<th>Grid-Isolated</th>
<th>Grid-Tied</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lifetime Cost of Computing</td>
<td>1831 $/MWh</td>
<td>1821 $/MWh</td>
</tr>
<tr>
<td>Net Present Cost</td>
<td>$947 000</td>
<td>$926 000</td>
</tr>
<tr>
<td>Uptime</td>
<td>65%</td>
<td>97%</td>
</tr>
<tr>
<td>Electricity for Computing</td>
<td>103 MWh</td>
<td>102 MWh</td>
</tr>
<tr>
<td>Electricity Sold</td>
<td>0 MWh</td>
<td>27 MWh</td>
</tr>
</tbody>
</table>

Table 7.2 – Performance comparison of on- and off-grid 20kW computing and 100kW of solar.

The full results of the lifetime cash flow analysis for the grid isolated and the grid-tied system are included in Appendix E. Table 7.3 summarizes the difference in capital and operating costs for the two systems.
Due to the larger battery required for the grid-isolated system the capital cost and the operating cost are higher. The grid-tied system has a cost for transmission but is able to generate revenue from selling electricity. The cost of transmission interconnection can provide a significant barrier for the development of a renewable energy generation. The next section builds on this case study by adjusting the capital cost assumptions for transmission infrastructure.

### 7.3. Cost of Grid Connection

Estimating the cost of transmission for all potential DGDC locations is not practical due to the nature of transmission interconnection. Each specific location has factors and barriers that will impact the cost of connecting a solar resource to the electrical grid. The grid-tied DGDC lifetime cash flow analysis is recalculated with higher transmission interconnection costs.

The goal of this section is to determine the cost of transmission that makes a grid isolated economically superior. The previous simulation used a transmission cost function based on an average from solar generation developers. Four more simulations are computed with transmission cost functions that are higher than the original assumption (Figure 7.6).
Figure 7.6 – High transmission cost functions and empirical connect costs from developers.

The fixed cost of connecting increases from $2500 up to $10000 for the higher transmission cost assumptions. The marginal cost per MW of transmission capacity also increases from $118/MW up to $207/MW. The lifetime cost of computing for each scenario is compared in Figure 7.7 to determine the cost of transmission that makes the lifetime cost of computing equal to a grid isolated system.

\[
\text{Lifetime Cost of Computing} = \frac{\text{Cost of Transmission}}{455 \text{ MWh}} - 1812/\text{MWh} \tag{7.1}
\]

A grid-tied system will have a lifetime cost of computing equal to grid-isolated system when the capital cost of transmission connection is $8291. It is more economical to have a grid-isolated system with a large battery if the cost of transmission above this value.
7.4. New York Solar Generation Incentives

The final part of this case study examines renewable energy incentives in Ithaca, New York. In New York one incentive for solar power is the New York State Energy Research and Development Agency (NYSERDA) Solar PV Program Financial Incentives PON 2112. The program provides incentives to offset capital costs for residential systems under 25kW and commercial systems under 200kW. The incentive may not exceed 40% of the installed cost or $140,000 for non-residential systems [86]. The value of incentive is separated into two tiers: $1.00/W for installed capacity below 50kW and $0.60/W for capacity above 50kW.

This solar incentive is directed towards homeowners and business that wish to install a roof-top solar system. The solar panels are connected to the building electrical loads behind the meter. Any excess generation higher than the building demand is credited to the consumer’s bill each month. If the generation exceeds demand in a month and there is excess generation, the consumer receives credits which are carried forward indefinitely [25].

The size of the solar generation cannot exceed 110% of the building consumption over a one year period. Two methods are used to calculate of the DGDC electricity consumption; one based on the power used by the computer, and one based on the electricity purchased from the electrical grid. The hourly simulation calculates the electricity used by the DGDC for computing and the amount purchased.

The effective solar panel capacity is the electricity used divided by the actual generation. The maximum eligible solar panel size is equal to 110% of the effective generation and is used for calculating the amount of funding from the New York PV Incentive. The lifetime cost of computing for a system without an incentive is $1821/MWh, which is significantly higher than grid connected systems receiving solar incentives (Table 7.4).
### Table 7.4 – PON 2112 Solar PV incentive calculated based on total computing vs grid purchases.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Computing Electricity</td>
<td>100.1</td>
<td>86%</td>
<td>86</td>
<td>95</td>
<td>76 806</td>
<td>1667</td>
</tr>
<tr>
<td>Electricity Purchased</td>
<td>29.9</td>
<td>26%</td>
<td>26</td>
<td>28</td>
<td>28 280</td>
<td>1764</td>
</tr>
</tbody>
</table>

Further investigation is required to determine if the PON 2112 incentive can actually be applied to a DGDC energy system. Regardless, this shows that capital cost incentives can be applied using this model and highlights the importance of the hourly simulation results in estimating incentive funding. In the next section a Renewable Energy Credits (REC) incentive is applied to the DGDC concept.

### 7.5. Renewable Energy Credits

Renewable Energy Credits (RECs) are not used in New York but this section examines a hypothetical scenario where a New York based DGDC energy system could benefit from RECs in another state. The scenario involves two DGDC with a high-speed network connection: one in New York, and one in another state with a REC program. The DGDC in the REC state draws all of its power from the electricity grid, whereas the New York location has solar generation.

When the sun is shining in New York and electricity is being generated, computing processes move from servers in the REC state to servers in New York powered by solar power. As a result, there is a reduction in demand at grid tied system in the REC state. This is equated to producing electricity in REC state in the form of demand response. Since the computing demand is being met with renewable energy in New York this demand response would qualify for REC funding.

RECs are earned for production of electricity from renewable generation sources and one REC is equivalent to 1 MWh of generated renewable energy. Not all RECs are equal and prices are differentiated
based on type of generation, location produced, and other factors. Once the generator earns a REC, the REC can be sold to satisfy renewable energy targets or quotas.

There are many markets where RECs can be traded and each have rules to determine if a REC qualifies. The market price varies between less than $1 for voluntary markets to over $500 for Solar RECs (SERC) [87]. This case study looks at three levels of REC pricing for different markets (Table 7.5).

<table>
<thead>
<tr>
<th>REC Market Type</th>
<th>REC Approximate Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voluntary REC</td>
<td>$1/MWh</td>
</tr>
<tr>
<td>Compliance REC</td>
<td>$50/MWh</td>
</tr>
<tr>
<td>Solar REC</td>
<td>$100/MWh</td>
</tr>
</tbody>
</table>

Table 7.5 – Market price of REC for the New York case study.

The scenario assumes only electricity generated by the solar panels and used by the computer is eligible for RECs. Only electricity that is generated onsite can qualify which excludes electricity bought from the New York grid or energy lost due to battery storage.

In the case of a grid-isolated system, all of the electricity used for computing qualifies for RECs. For a grid-tied system the hourly simulation determines the amount of electricity eligible for RECs. All electricity flowing from the generation to the computing qualifies, but only a portion of the battery to computing electricity qualifies. The percentage of generated electricity used to charge the battery determines the percentage of eligible stored electricity.

The three levels of REC values are applied to the grid-connected and grid-isolated DGDCs (Table 7.6). Since all the computing for a grid-isolated system qualifies the reduction in lifetime cost of computing is equal to the value of the REC. Only a portion of the grid connect computing qualifies and has less of an effect on the lifetime cost of computing.
When the REC incentive is low the grid-tied system is better than the grid-isolated. For higher REC values, the grid-isolated system has the lower cost of computing. The grid-connected and grid-isolated systems have equal lifetime computing costs when the REC incentive is $38/MWh (Figure 7.8).

Figure 7.8 – Grid-tied and grid-isolated Lifetime Cost of Computing with REC Incentives

### 7.6. Ithaca Case Study Summary

In Ithaca, a grid-isolated DGDC relies exclusively on the solar energy available on site. To increase the up-time of the computing resource a battery is required to store the electricity. A grid-connected energy system does not need as large a battery, but there is an additional cost to connect the local transmission and distribution network.

Based on the original transmission cost assumptions a grid connected system is more profitable than a grid isolated system. The cost assumption used for transmission is dependent on grid characteristics at the point of connection. A grid-isolated system is more profitable when the cost of transmission connection is doubled from $4000 to $8000. This makes the economic model a useful tool that can be used by designers to choose between a grid-isolated and grid-connected system.
Another aspect of a grid connected DGDC is the eligibility for financial incentives such as the NYSERDA Solar PV Program. The hourly simulation is used to estimate the performance and estimate the funding eligibility. The hourly model is also used for a hypothetical Renewable Energy Credit program for a DGDC network. In this scenario, solar generation in New York offsets electricity demand in another state with a REC program. A grid-isolated solar DGDC is more profitable than a grid-tied system when the REC is valued more the $38/MWh.

Other renewable energy incentives and carbon reduction programs can be applied to the DGDC simulation. For example, a carbon tax, would apply an additional cost to the price of grid electricity in order to account for the carbon footprint of the generation source. Since electricity is not purchased from the grid equally throughout the day/year, it would not be appropriate to use a yearly average of the carbon intensity. Instead a real-time hourly value for grid carbon intensity would be required. For example, the Ontario electricity grid relies on fossil fuel peaking plants during demand peaks such as hot summer days when a solar DGDC would not need to purchase electricity.

This case study shows that the DGDC model can be used for comparing both on- and off-grid DGDC energy systems. The model is able to compare renewable energy incentives and examine hypothetical energy policies. The transmission cost functions and renewable energy incentives scenarios show how cost assumptions can impact the optimal design of the system.

7.7. Case Study Comparison

The Ithaca case studies build on the work completed in the Kingston case study. The Kingston case study focuses on the design and the sizing of the energy system components whereas the Ithaca case study looks at the external factors. In this section the optimal grid-isolated DGDC from both locations are compared as well as the Ithaca grid-tied and grid-isolated DGDC energy systems.
The Kingston and Ithaca grid-isolated DGDC both had optimal computing capacities of 20 kW. The Kingston systems had an optimal battery capacity of 540 kWh and utilized 92% of the generation. The Kingston case study used an initial battery cost assumption of $900/kWh which was revised to $450/kWh for the Ithaca case study. This resulted in a larger optimal battery capacity of 1000 kWh for the Ithaca DGDC. Even with the larger battery in the Ithaca case study, the percentage of energy used for computing remained the same (Table 7.7). A difference in generation daily profiles between locations may require a larger battery to complete the same computing. As well an increase to the battery capacity past an optimal point has a diminishing impact on performance.

<table>
<thead>
<tr>
<th></th>
<th>Kingston</th>
<th>Ithaca</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Computer Size</strong></td>
<td>20 kW</td>
<td>20 kW</td>
</tr>
<tr>
<td><strong>Battery Capacity</strong></td>
<td>27 hours</td>
<td>50 hours</td>
</tr>
<tr>
<td><strong>Generation</strong></td>
<td>118.6 MWh</td>
<td>116.3 MWh</td>
</tr>
<tr>
<td><strong>Computing</strong></td>
<td>109.0 MWh</td>
<td>106.9 MWh</td>
</tr>
<tr>
<td><strong>Computing/Generation</strong></td>
<td>92%</td>
<td>92%</td>
</tr>
</tbody>
</table>

Table 7.7 – Comparison of grid-isolated DGDCs with lowest the LCC.

In the Ontario grid-tied scenario, the FIT incentive ensures that all generated electricity is sold to the grid which makes the DGDC concept impractical. In the Ontario case study, the cost of computing continued to decrease as the computing capacity increased. This is similar to the current state of data centre designs where the size is maximized to take advantage of economies of scale.

Comparing the cumulative power of the Ithaca grid-tied and grid-isolated systems indicates the computing completed by the grid-tied system is more consistent over the year (Figure 7.9). A significant portion of the grid-isolated computing is completed during the summer months as it is completely reliant on the solar generation. The grid-tied DGDC relies on purchasing electricity in the winter and then transitions to using the solar generation in the summer.
The computing resources for the grid-isolated DGDC are either full on or completely off for the majority of the year, whereas, the grid-tied DGDC is operated almost all hours of the year. The computing amount for the grid-tied DGDC is varied over the year as cost of computing changes each hour (Figure 7.10).

Over the course of the year, the computer utilization of both system is equal, but the uptime on the grid-tied DGDC is 97% (Table 7.8).

The grid-isolated DGDC with a large battery is a readily available computing source in the summer when the solar generation is maximized. In the winter, the reliability of the grid-isolated is reduced as there is insufficient generation to keep the batteries charged over a long period. A grid-isolated solar DGDC
would only be feasible in a network of DGDCs powered by other renewable generation types or connected to the electricity grid.

A grid-tied DGDC is a preferable arrangement for a small DGDC network that requires a baseline level of reliability. With a connection to the electrical grid, the DGDC can ensure that there is always a source of computing for the network. Instead of relying on the large battery to store renewable generation, a grid-tied DGDC “stores” electricity on the grid to be purchased at a later date.
Chapter 8. Conclusion and Recommendations

8.1. DGDC Design Evaluation

This thesis presents an energy system simulation and comparison framework for optimizing the design of Distributed Green Data Centres (DGDC). The framework consists of two parts: a year-long hourly simulation and a lifetime cash flow analysis. First the operation and performance of the DGDC is simulated using hourly renewable energy generation profiles and hourly electricity prices. Next a 5-year cash flow analysis is calculated using the output of the hourly simulation and component cost assumptions. The energy system designs are compared based on the total lifetime cost of computing in $/MWh of computing power.

The methodology is used for case studies in Kingston, Ontario and in Ithaca, New York. These case studies demonstrate the ability of the model to optimize DGDC energy systems for specific locations with unique solar energy resources and electricity market policies. The Ithaca case study further compares the cost performance of grid-connected and grid-isolated DGDCs. Additional scenarios with revised transmission interconnection cost assumptions and renewable energy incentives are completed.

In this chapter, the DGDC simulation is reviewed to show how the operation of the DGDC is accurately modelled. Second, the potential benefits of DGDC applications are highlighted and the ramifications of DGDCs are discussed with results from this model. Finally, future work paths for this DGDC model are presented.

8.2. The DGDC Simulation

The most computational intensive component is the year-long hourly simulation of the DGDC operation. The hourly simulation mimics how an actual DGDC would react in the real world with variable power availability and electricity prices. Data from real solar panels (Ithaca case study) or from solar irradiance
measurements (Kingston case study) can be used as generation data. Hourly time steps ensure variations in the electricity price are considered when choosing how much power is used for computing.

In each time-step, the power used for computing is determined based on the cost of supplying the power. During times of expensive grid power, less computing is completed and power comes directly from the renewable generation or the battery. Results from the Ithaca case study show the computer being used during the day when solar energy is being produced and in the evening when stored electricity is available (Figure 8.1). At night, when no more energy is available, energy is purchased if the price is low (hours 1 to 7) or the computing loads are migrated (hour 31). In addition to determining the power used for computing, the model also decides when to charge the battery. The charging algorithm assumes knowledge of future computing cost and charges the battery if the future cost will be high. The battery is then discharged when the stored electricity is cheapest of all available sources.

![Figure 8.1](image)

Figure 8.1 – (A) Price of electricity, (B) DGDC component power flows, and (C) battery state of charge for an Ithaca DGDC on March 25-26, 2012.

The computing demand curve determines the amount of computing based on the cost of supplying power. In the Figure 8.2, the cost of electricity used for computing is compared to the grid price of electricity. In the Ithaca, the average price of the grid based electricity is 37.87$/ MWh whereas in the optimal DGDC
design, the average cost of computing is 23.06$/MWh. Over the course of a year, the power used for computing is on average 1.9cents/kWh less than grid electricity.

![Graph showing electricity and computing cost over years](image)

Figure 8.2 – The cost of computing is less than the cost of grid electricity for the Ithaca DGDC.

A battery with a grid-tied DGDC enables stored electricity to be used when the grid electricity price is high. The Ithaca case study determined a battery is useful for minimizing the lifetime cost of computing. The higher capital cost of a battery is justified over the lifetime of the DGDC since increasing the computing completed reduces the lifetime cost of computing.

### 8.3. DGDC Benefits and Ramifications

A grid connected DGDC energy system can provide positive benefits to the local electricity grid. Typically when a renewable energy resource is connected to the electrical grid, the transmission/distribution infrastructure needs capacity for the maximum output of the renewable energy resource. Since the maximum generation is achieved only a fraction of the time, the transmission capacity is under-utilized. Without the DGDC the Ithaca solar resource would use transmission resource at 13 % of the full transmission capacity (Figure 8.3).

![Graph showing transmission utilization over years](image)

Figure 8.3 – Transmission capacity factor for the Ithaca solar resource is 13%.
When a DGDC energy system is connected to the solar resource, the generation peaks are used by the computing resource or stored in the battery. As result a lower transmission capacity is required to connect the resource to the grid. The transmission capacity of the Ithaca grid-tied DGDC is 10% of the maximum generation, and is able to sell 24% of the generated electricity. The capacity factor for the reduced transmission resource is 61% with both buying (30%) and selling (31%) electricity (Figure 8.4).

Figure 8.4 – Transmission capacity factor for a grid connected DGDC is 61%.

In some cases, new solar facilities may not be practical due to high cost infrastructure upgrades. A DGDC co-located reduces the magnitude of transmission infrastructure while still connecting the solar generation to the grid. If upgrades are completed at a later date, the mobile DGDC can be relocated and the solar resource can fully connect to the electrical grid. Co-located DGDCs can encourage renewable energy development prior to transmission line approval and construction.

As opposed to using transmission infrastructure to reach the consumers, a DGDC brings the market price to the generation facility. This enables the DGDC to be an active participant in the electrical market such as selling when prices are high and buying when prices are low. With variable electricity price, a DGDC in Ithaca purchases more (66%) electricity when the price is below the median price and sell more (65%) when above (Figure 8.5).
Figure 8.5 – DGDC buying and selling patterns based on grid electricity price.

A DGDC system can reduce the amount of electricity purchased with battery storage and computing load migration enabling it to react to changes in the electricity prices. A DGDC is able capitalize on price incentives from energy market programs such as Demand Response or RECs. The DGDC network operators would migrate critical processes/applications to other DGDCs locations when electricity prices increase or demand response incentives are available.

The implementation of a DGDC network introduces the concept of a variable computing cost. The network can migrate computing loads to the lowest cost electricity instead of being reliant on the price at a single location. The DCDC operator can schedule computing processes to maximize the use of low cost electricity from the grid or energy generated by renewable energy.

Critical processes which require high priority, such video streaming or website hosting, would require a high cost computing to ensure availability. Batch processing or data backup, with lower priority, can be scheduled to use lower cost electricity when available. At the Ithaca DGDC, the average supply price for 95% availability is 40$/MWh whereas low cost computing (0-5$/MWh) is available for 17% of the computing in a year (Figure 8.6).
Figure 8.6 – Ithaca DGDC yearly computing supply curve. The percentage of computing available with higher power costs.

When solar generation output is highest, the cost of computing in Ithaca decreases as shown in Figure 8.7. Low cost and low priority batch processes can use excess electricity during intermittent peaks in renewable generation. Instead of needing to curtail generation during production peaks, the DGDC uses the excess electricity on-site while still providing a constant source of renewable generation to the electrical grid.

Figure 8.7 – Cost of computing in Ithaca decreases with high generation output.

The most likely implementation of a DGDC computing network would be for niche computing applications that can be responsive and adaptable to available energy resources. Computing applications using DGDCs must have processes that are either time-independent or location-independent. An example of a time-independent process would be computer modelling of complex problems such as fluid dynamics of gene sequencing. These types of processes are expected to take a long time to complete and getting a result in a timely manner is not critical, as a result they can utilize low cost computing when it is available such as during the day when the sun is shining.
Location independent processes can utilize DGDC computing resources in any location where ever it is available. These processes would be replicated over multiple DGDC and the process would be shifted to new location as the resource availability changes between locations. Applications would be able to shift their loads to utilize the data at the site where the lowest cost electricity is available. Services such as website hosting or video stream could have multiple copies saved across multiple locations which would also serve as a data back-up service to ensure long-term data storage.

8.4. Future Work

This model optimizes the high level design of a simplified DGDC. All of the four energy system components are represented as a “black box” with a maximum power capacity. It is assumed the components can produce or receive maximum energy at any time. These components are much more complex and the actual power availability would depend on other factors not included in this model. In addition, this model bases the optimization on the electricity price and generation output from 2012. If the simulation was conducted for other years, the optimization may produce an alternative optimal system to meet the supply and demand for the data.

The lifetime cash flow analysis indicates the high cost of the system may prohibit the development of the DGDC concept. The intent of this economic analysis was not to produce an accurate cost estimate for DGDC energy system, but rather to provide a means to compare and optimize energy systems designs. To recover the high cost of installation, a solar powered DGDC would likely need to be grid-tied to maximize the use of the computing resource.

Three future areas of work relating to this thesis are additional case studies, improvements to the simulation model, and incorporating computing demands from the DGDC network.

More case studies could be competed using alternative source of generation. Small scale solar generation does not generate electricity at night and has reduced production during the winter. Other generation
sources such as wind or hydro may have a higher generation capacity factors and less variability in output. A large scale wind farm may provide scales of economy for computing infrastructure and may reduce congestion on high voltage transmission lines.

The simulation model and lifetime cash flow analysis could be refined to reduce the computational time for each energy system. For example, a computational intense part of the simulation is finding the computing equilibrium point each hour of the year. The current algorithm creates a supply curve by resolving the power flows for all possible computing amounts and then searches for the equilibrium point. A leaner algorithm could generate successive supply curves with fewer points, and intelligently refining the computing amounts to search for the equilibrium point.

The model allows for a variable computing demand curve each hour. The demand curve represents the relative price consumers are will to pay for computing across the entire DGDC network. For example, the demand for hosting for corporate data would be higher during working hours than on weekends, whereas the HPCVL in Kingston requires a constant source of electricity at all times. Since a single DGDC location has a percentage of downtown or reduced computing output multiple DGDC locations are required to meet the demands of consumers. The computing demand curve provides the same price signals to all DGDC location to ensure the lowest cost computing available at any location is utilized first. Further work with the demand curve could incorporate the characteristics of the DGDC network supply and demand.
References


[57] QPK Design Architects Engineers Site & Planning, "Tompkins County Library 2020".


APPENDIX A. – Ithaca Sun Shading Chart

Sun shading on the TCPL solar array due to the Cayuga Street Parking Structure and the Holiday Inn. The sun chart template for Ithaca, NY is provided by the University of Oregon Solar Radiation Monitoring Laboratory [88].
APPENDIX B. – Kingston Case Study Results

Kingston simulation with Time of Use energy costs

![Diagram showing battery discharge amount and computing maximum power capacity with different charge rates and time durations.](image)
Kingston simulation with Fixed Contract energy costs

Computing Maximum Power Capacity

<table>
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<tr>
<th>Battery Discharge Amount</th>
<th>1 hour</th>
<th>2 hour</th>
<th>3 hour</th>
<th>4 hour</th>
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<td>20%</td>
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<tr>
<td>120%</td>
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</table>
Kingston simulation with HOEP energy costs

Battery Discharge Amount

1 hour 2 hour 3 hour 4 hour

Computing Maximum Power Capacity
20% 40% 60% 80% 100% 120%

Transmission

Charge Rate
APPENDIX C. – Ithaca additional tariffs, surcharges, and charges

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<th>Transition Charge</th>
<th>System Benefit Charge</th>
<th>Renewable Portfolio Charge</th>
<th>Temp. State Assessment Surcharge</th>
<th>RDM Adjustment</th>
<th>TOTAL Charges</th>
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<td>0.10</td>
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<td>0.20</td>
<td>0.03</td>
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<td>Gen Cap [MW]</td>
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<td>Buy Cap [MW]</td>
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<td>Batt3</td>
<td>Batt4</td>
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<td>NPV [$]</td>
<td>Dump [MWh]</td>
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Example Data:
- Gen Cap: 4, 0.5, 8, 0.2, 12
- Comp Cap: 1, 1, 9, 0.3, 1, 1
- Charge Cap: 0.05, 1.5, 0.05, 0.1
- Discharge Cap: 0.05, 1, 1, 0.1
- Batt Size: 2, 5, 5, 12, 42, 3
- Sell Cap: 1, 0.5, 1, 0.5, 0.5, 0.5
- Buy Cap: 0.5, 1, 1, 0.5, 0.5, 0.5

Simulation Results:
- NPV: \$8952.1, \$930.8, \$26.2, \$54.4

Input Data Files:
- inputdata/computer/ITHACA_month_1Ad3.xlsx
- inputdata/generation/TCPL_2012_1.xlsx
- inputdata/grid/Ithaca_hour.xlsx
## APPENDIX E. – Grid-isolated vs Grid-connected

### Grid Connect DGDC Energy System

<table>
<thead>
<tr>
<th>Initial Cost</th>
<th>Year 1</th>
<th>Year 2</th>
<th>Year 3</th>
<th>Year 4</th>
<th>Year 5</th>
<th>End of Life</th>
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<tr>
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<td></td>
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<td>Generation</td>
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<td><strong>TOTAL</strong></td>
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<td>$ 0</td>
<td>$ 0</td>
<td>$ 0</td>
<td>$ 0</td>
<td>$ 0</td>
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</table>

| **Salvage Value** |        |        |        |        |        |             |
| Generation       |        |        |        |        |        | -$ 383 333  |
| Computer         |        |        |        |        |        | -$ 581 739  |
| Battery          |        |        |        |        |        | -$ 90 000   |
| **TOTAL**        |        |        |        |        |        | -$1 055 072 |

| **Operation & Maintenance** |        |        |        |        |        |             |
| Generation        | $ 1 000 | $ 1 000 | $ 1 000 | $ 1 000 | $ 1 000 |             |
| Computer          | $ 29 087 | $ 29 087 | $ 29 087 | $ 29 087 | $ 29 087 |             |
| Battery           | $ 15 987 | $ 15 987 | $ 15 987 | $ 15 987 | $ 15 987 |             |
| Transmission      | $ 92    | $ 92    | $ 92    | $ 92    | $ 92    |             |
| **TOTAL**         | $ 0     | $ 46 166 | $ 46 166 | $ 46 166 | $ 46 166 | $ 0         |

| **Annual Charges** |        |        |        |        |        |             |
| Electricity Demand Charge | $ 1 217 | $ 1 217 | $ 1 217 | $ 1 217 | $ 1 217 |             |
| System Operational Costs | -$ 393  | -$ 393  | -$ 393  | -$ 393  | -$ 393  |             |
| **TOTAL**           | $ 0     | $ 824   | $ 824   | $ 824   | $ 824   | $ 0         |

| **NET CASH FLOW** | $1 717 157 | $46 990 | $46 990 | $46 990 | $46 990 | $46 990 | -$1 055 072 |

| **Discounted Net Cash Flow** | $1 717 157 | $46 907 | $46 777 | $46 596 | $46 327 | $45 969 | -$1 024 196 |

| **Discounted Cumulative Cash Flow** | $1 717 157 | $1 764 065 | $1 810 842 | $1 857 438 | $1 903 765 | $1 949 734 | $925 539 |

| **NET PRESENT COST** | $ 925 539 |         |         |         |         |         |             |
# Grid Isolated DGDC Energy System

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<th>Year 3</th>
<th>Year 4</th>
<th>Year 5</th>
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<td><strong>TOTAL</strong></td>
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