A Decision-Guided Energy Framework for Optimal Power, Heating, and Cooling Capacity Investment

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Abstract: We propose a Decision-Guided Energy Investment (DGEI) Framework to optimize power, heating, and cooling capacity. The DGEI framework is designed to support energy managers to (1) use the analytical and graphical methodology to determine the best investment option that satisfies the designed evaluation parameters, such as return on investment (ROI) and greenhouse gas (GHG) emissions; (2) develop a DGEI optimization model to solve energy investment problems that the operating expenses are minimal in each considered investment option; (3) implement the DGEI optimization model using the IBM Optimization Programming Language (OPL) with historical and projected energy demand data, i.e., electricity, heating, and cooling, to solve energy investment optimization problems; and (4) conduct an experimental case study for a university campus microgrid and utilize the DGEI optimization model and its OPL implementations, as well as the analytical and graphical methodology to make an investment decision and to measure trade-offs among cost savings, investment costs, maintenance expenditures, replacement charges, operating expenses, GHG emissions, and ROI for all the considered options.

1 INTRODUCTION

Sustainable enterprise development has been considered a significant and competitive strategy of corporate growth in manufacturing and service organizations. A significant part of sustainable development involves new technologies for local electricity, heating, and cooling generation. Making optimal decisions on planning and investment of these technologies to support commercial and industrial facilities is an involved problem because of complex operational dependencies of these technologies. This is exactly the focus of this paper.

Currently, the existing approaches to support the optimization of energy plants can be divided into two categories: (1) optimal operation of an energy system and (2) a better plant-process design (Broccard et al., 2010). The former category is related to the optimized scheduling of an electric power plant. Some researchers, such as Bojic and Stojanovic (Bojić and Stojanović, 1998), proposed an optimization procedure based on a MILP solver (SAS Institute, 2012) to provide an operation diagram which allows users to find an optimum composition of energy consumption that minimizes the operating expenses of an energy system (Brodsky and Wang, 2008); (Brodsky et al., 2009); (Brodsky et al., 2011). The latter approach includes the analysis of simulations carried out to determine the most suitable matching between a plant and its loads that could increase the plant power output. Some researchers, e.g., Savola et al., (Savola and Keppo, 1997) did extensive research to propose an off-design simulation and mathematical modelling of the operation at part loads and a Mixed-Integer Non-Linear Programming (MINLP) optimization model for increasing power production (Savola and Fogelholm, 2007); (Tuula Savola et al., 2007).

However, neither of the above approaches considers optimizing the complex interactions between the existing components and the newly added energy equipment that would result in a higher operating cost, such as the charges on electricity and gas consumptions, as well as significant environmental impacts, i.e., greenhouse gas (GHG) emissions, e.g., carbon dioxide (CO_2) and mono-nitrogen oxide (NO_x). Without considering such interactions for every time interval over an investment time horizon, it would be impossible to make optimal recommendations on

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energy planning and investment.

Thus this paper focuses on addressing the above shortcomings. More specifically, the contributions of this paper are as follows. First, we propose a Decision-Guided Energy Investment (DGEI) Framework shown in Figure 1. Given electricity, heating, and cooling generation processes, utility contracts, historical and projected demand, facility expansions, and Quality of Service (QoS) requirements, the DGEI framework is designed to recommend optimal settings of decision control variables. These decision control variables include the amount of electricity, heating, and cooling that is generated by the supply of water and gas, which is inputted to each deployed component in every time interval. The goal of the DGEI framework is to learn optimal values of those decision control variables in order to minimize the total operating cost within the required quality of service and within the bound for GHG emissions, as well as to take into account all components' interactions. Second, to support the DGEI framework, we develop a DGEI optimization model, i.e., a MILP formulation construct, to solve the adjusted cost minimization problem. Furthermore, we implement the DGEI optimization model by using the IBM Optimization Programming Language (OPL) (Hentenryck, 1999); (The IBM Corporation, 2012). Third, we propose an analytical and graphical methodology to determine the best available investment option based upon the evaluation parameters shown in Figure 1. The parameters include investment costs, maintenance expenditures, replacement charges, operating expenses, cost savings, return on investment (ROI), and GHG emissions. Finally, we use the methodology and the DGEI framework to conduct an experimental case study on the microgrid at the Fairfax campus of George Mason University (GMU). This study has been conducted and used by the GMU Facilities Management Department (FMD) to make actual investment decisions.

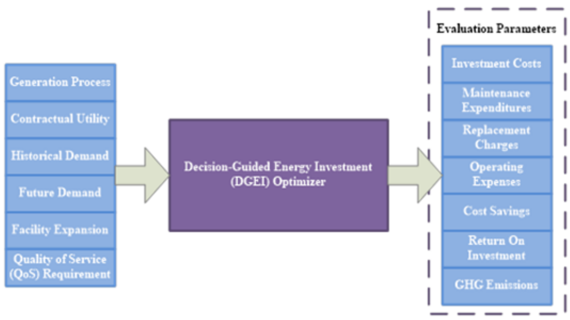

Figure 1: Decision-Guided Energy Investment (DGEI) Framework.

The rest of the paper is organized as follows. Using the GMU Fairfax campus microgrid as an example, we describe its energy investment problem in Section 2. We explain our DGEI framework and optimization model in Section 3 and demonstrate the OPL implementation in Section 4. In Section 5, we present the analytical and graphical methodology to determine an optimal investment option. In Section 6, we conduct the experimental analysis on the GMU energy investment case and illustrate the relationships among the investment costs, ROI, and GHG emissions of the various options in tabular and graphical formats. We also explain and draw the conclusion for the investment options from the graphs and tables in detail on the GMU energy investment problem. In Section 7, we conclude and briefly outline the future work.

2 PROBLEM DESCRIPTION OF REAL CASE STUDY

Consider the real case study at GMU, in which the GMU Facilities Management Department (FMD) is planning to extend and or expand the existing energy equipment in order to meet the current and future demand of electricity, heating, and cooling across the expanding Fairfax campus in Virginia. Presently, the GMU existing energy facilities at the Fairfax campus operate a centralized heating and cooling plant (CHCP) system and utilize the electricity purchased from the Dominion Virginia Power Company (DVPC) to satisfy all the energy demand. Over the past 10 years, the campus has experienced a significant growth on a square-foot basis in terms of land use. Since the campus continues its expansion at a rapid rate, the existing CHCP system and the electricity consumption have reached a saturated point where the current capacity and facilities will not be able to satisfy the future energy demand, i.e., electricity, heating, and cooling. For these reasons, a study has been conducted to determine the best available investment option, e.g., a new cogeneration (CoGen) plant, with regards to a possible methodology to meet the current and future electricity, heating, and cooling demand, while also addressing the optimal operations of the newly added facility with the existing energy equipment.

The diagram in Figure 2 depicts the GMU energy generation process which supplies heating, cooling, and electricity to the entire Fairfax campus. The GMU energy facilities have a CHCP system to supply the hot and cold water (see the red and blue resources) which are distributed across the facilities to the campus buildings to meet the heating and cooling demand (see the upper two sub-processes on the right), i.e., heating and air-conditioning to the buildings. To supply the heating and cooling to the campus buildings, the CHCP system needs the inputs, i.e., natural gas (see the yellow resource on the left), water (see the light blue resource on the left), and electric power (see the green resource on the left). These resources come from the gas supply, i.e., Washington Gas Light Company (WGLC), the water supply, i.e., Fairfax County Water Authority (FCWA), and the electricity supply, i.e., Dominion Virginia Power Company (DVPC), correspondingly. In addition, the facilities also need to satisfy the electricity demand across the entire campus, where the electricity demand is beyond the demand from the CHCP consumption. Any excessive electric power supply can also be resold to the DVPC (see the electricity resell on the right). Furthermore, the facilities also commit a curtailment demand (see the curtailment demand on the right) to the energy curtailment program through EnergyConnect (EC), Inc. Both the electricity resell and the curtailment commitment can bring certain revenues and savings to offset the overall operational costs on a monthly basis and the capital expenditures in the long run. The facilities also generate greenhouse gas (GHG) emissions, such as carbon dioxide (CO_2) (see the black resource at the bottom right).

Given the expansion of the GMU Fairfax campus, in addition to the increasing electricity demand, the heating and cooling demand is also expected to increase. The CHCP system will not have enough capacity to meet the future need. The GMU plan is to employ a procurement strategy, i.e., the deployment of the best available investment option, which will satisfy projected demand and minimize investment costs, maintenance expenditures, replacement charges, operating expenses, and GHG emissions, as well as maximize cost savings and return on investment (ROI) at the same time. The FMD managers are now considering some viable options. One of the considerable options is to integrate a new cogeneration (CoGen) plant (see the lower sub-process in the middle), i.e., the Combined Heating and Power (CHP) Plant (Biezma and San Cristobal, 2006); (Broccard, et al., 2010), into the existing facilities shown in Figure 2. The new CoGen plant has turbines to generate electricity to complement the electricity demand, uses the generated heat as a by-product to complement the heating demand, and collaborates with the ammonia process technology (American Electric Power Inc., 2012) to supply the cooling demand. Now, the challenging question is how to analytically determine the best investment option that satisfies all the energy demand, i.e., electricity, heating, and cooling, at the lowest operating costs.

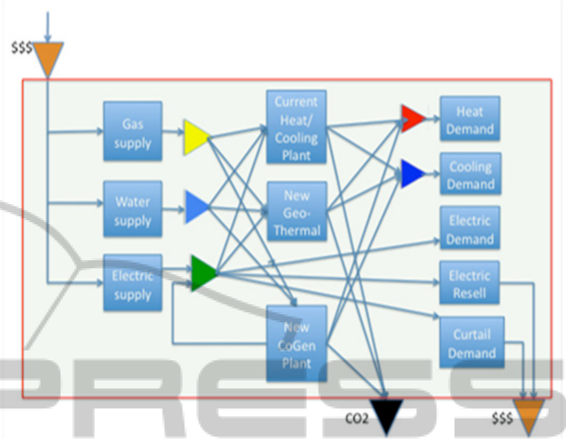

Figure 2: Prospective Heating, Cooling, and Electric Power Facilities at the GMU Fairfax campus.

3 DECISION-GUIDED ENERGY INVESTMENT (DGEI) FRAMEWORK AND OPTIMIZATION MODEL

To answer the above question, we propose the DGEI framework depicted in Figure 1. This framework is composed of six energy-investment libraries, i.e., Energy Generation Process (EGP), Energy Contractual Utility (ECU), Energy Historical Demand (EHD), Energy Future Demand (EFD), Energy Facility Expansion (EFE), Quality of Service (QoS) requirements, and a DGEI optimizer. The EGP is an extensible library that enables domain experts to construct an energy generation process to supply electricity, heating, and cooling. The ECU is a library that contains energy contractual terms for calculating bill utilities, e.g., an electricity bill, a water bill, and a gas bill. The EHD and EFD are the libraries that store historical and projected energy demand respectively. The EFE library archives the facility expansion of an organization in terms of square-footage increase. The QoS library stores the QoS requirements that the energy facilities of an organization need to meet, e.g., the maximal power interruptions allowed per monthly pay period in an organization. The DGEI optimizer supports energy managers to utilize all the libraries, i.e., EGP, ECU, EHD, EFD, EFE, and QoS, as inputs to the decision optimization process, which minimizes operating expenses and maximize cost savings. This decision optimization process not only optimizes the interactions between the existing and the considerable energy facility options but also minimizes the environmental impacts on the surroundings, i.e., minimizing the GHG emissions. In addition to the GHG emissions, energy managers also utilize (1) return on investment (ROI), i.e., the gain return efficiency among different investments, (2) the investment costs, i.e., an amount spent to acquire a long-term asset, and (3) equipment expenses, i.e., maintenance expenditures plus replacement charges, to evaluate all the available investments and then to determine the best option.

To solve an energy investment optimization problem in terms of minimizing the operating cost and the GHG emissions is to formulate a DGEI optimization model. This model optimally learns decision control variables, which require several input data sets, i.e., the historical and projected electricity, heating, and cooling demand over a time horizon, the electric and gas contractual utility, the operational parameters and capacity constraints of the existing and the new electric power plants, as well as the energy aggregation of the supply and demand, e.g., electricity, gas, heating, and cooling, to minimize the entire operating expenses. Using the GMU energy investment optimization problem over the 10-year time horizon as an example, we explain the above terminologies used in this case study in the following subsections.

3.1 Electricity, Heating, and Cooling Demand over a Time Horizon

The electricity, heating, and cooling demand over a time horizon is the input, including the usage of the historical and projected quantities, which are provided from the GMU Facilities Management Department, to the DGEI optimization model that requires the domain users to define all (i.e., past plus future), past, and future power intervals over the 10-year time horizon.

- AllPowerIntervals is a set of all powerIntervals, where each powerInterval is a tuple which includes several attributes, i.e., pInterval, payPeriod, year, month, day, hour, and weekDay. We use negative and zero integers to represent the past time horizon and positive integers to denote the future time horizon. For example, pInterval is an hourly time interval of the energy demand, where $-8759 \leq$ pInterval ≤ 78840. payPeriod is a monthly pay period of the energy demand, where $-11 \leq$ payPeriod ≤ 108. Other attributes' intervals include $2011 \leq$ year ≤ 2020, $1 \leq$ month ≤ 12, $1 \leq$ day ≤ 31, $0 \leq$ hour ≤ 23, and $0 \leq$ weekDay ≤ 6.
- PastPowerIntervals is a set of past powerIntervals of tuples, where $-8759 \leq$ pInterval ≤ 0, $-11 \leq$ payPeriod ≤ 0, year = 2011, $1 \leq$ month ≤ 12, $1 \leq$ day ≤ 31, $0 \leq$ hour ≤ 23, and $0 \leq$ weekDay ≤ 6.
- FuturePowerIntervals is a set of future powerIntervals of tuples, where $1 \leq$ pInterval ≤ 78840, $1 \leq$ payPeriod ≤ 108, $2012 \leq$ year ≤ 2020, $1 \leq$ month ≤ 12, $1 \leq$ day ≤ 31, $0 \leq$ hour ≤ 23, and $0 \leq$ weekDay ≤ 6.

After declaring the power intervals, the quantities of electricity, heating, and cooling demand can be stored in their arrays over their power intervals. These three quantities of demand are provided by the GMU Facilities Management Department.

- demandKw[AllPowerIntervals] ≥ 0 is an array of electricity demand over the AllPowerIntervals. This array stores both the historical and the projected demand over the PastPowerIntervals and the FuturePowerIntervals respectively.
- demandHeat[FuturePowerIntervals] ≥ 0 is an array of projected heating demand over the FuturePowerIntervals.
- demandCool[FuturePowerIntervals] ≥ 0 is an array of projected cooling demand over the FuturePowerIntervals.

3.2 Electric and Gas Contractual Utility

To determine the total operating cost, we need to compute the consumption expenses of electricity and gas supply according to their utility contracts.

The consumption expenses of electricity include both the peak demand charge and the total power consumption charge that are explained in detail as follows.

3.2.1 Peak Demand Charge

For the electricity supply, utilityKw[AllPowerIntervals] ≥ 0 is an array of electricity supplied from the DVPC over the AllPowerIntervals.

historicUtilityKw[i] is an array of past electricity demand from the GMU, i.e., `historicUtilityKw[i] = demandKw[i]`, which satisfies the constraint, i.e., `utilityKw[i] == historicUtilityKw[i]`, where i ∈ PastPowerIntervals. This constraint is to assure that the electricity consumed by the GMU in the past year, i.e., 2011, is equivalent to the supply from the DVPC.

payPeriodSupplyDemand[p] is the peak demand usage per future pay period (p). This peak demand usage meets the below contractual constraints (*C1* and *C2*) and is determined based upon the highest of either (*C1*) or (*C2*):

C1: The highest average kilowatt measured in any hourly time interval of the current billing month during the on-peak hours of either between 10 a.m. and 10 p.m. from Monday to Friday for the billing months of June through September or between 7 a.m. and 10 p.m. from Monday to Friday for all other billing months.

C2: 90% of the highest kilowatt of demand at the same location as determined under (*C1*) above during the billing months of June through September of the preceding eleven billing months.

The logic constraints of both *C1* and *C2* can be expressed as follows:

```
if (i.payPeriod == p ∧ i.weekDay ≥ 1 ∧ i.weekDay ≤ 5 ∧ ((i.month ≥ 6 ∧ i.month ≤ 9 ∧ i.hour ≥ 10 ∧ i.hour ≤ 22) ∨ (i.month ≤ 5 ∧ i.month ≥ 10 ∧ i.hour ≥ 7 ∧ i.hour ≤ 22)))
    payPeriodSupplyDemand[p] ≥ utilitykW[i]
else if (i.month ≥ 6 ∧ i.month ≤ 9 ∧ i.payPeriod ≥ p − 11 ∧ i.payPeriod ≤ p ∧ i.weekPay ≥ 1∧ i.weekDay ≤ 5 ∧ i.hour ≥ 10 ∧ i.hour ≤ 22)
    payPeriodSupplyDemand[p] ≥ 0.9 * utilitykW[i];
```

, where i ∈ AllPowerIntervals, p ∈ FuturePayPeriods, and 1 ≤ FuturePayPeriods ≤ 108. Using these logic constraints, we can determine the optimal peak demand usage per future pay period, which consumes more than the expected electricity supply per powerInterval from the DVPC.

generationDemandCharge[p], i.e., `generationDemandCharge[p] = 8.124 * payPeriodSupplyDemand[p];`, is the Electricity Supply (ES) service charge, i.e., the peak demand charge, where p ∈ FuturePayPeriods, and 8.124 is the dollar charge per kW.

3.2.2 Total Power Consumption Charge

payPeriodKwh[p] is the total power consumption per future pay period, i.e., `payPeriodKwh[p] = ∑utilitykW[i];`, where i ∈ AllPowerIntervals, p ∈ FuturePayPeriods, and i.payPeriod = p.

payPeriodKwhCharge[p] is the total kWh charge per future pay period, i.e., payPeriodKwhCharge[p] ≥ 0, which satisfies the below contractual constraints:

```
if (payPeriodKwh[p] ≤ 24000)
    payPeriodKwhCharge[p] = 0.01174 * payPeriodKwh[p]
else if (payPeriodKwh[p] ≤ 210000)
    payPeriodKwhCharge[p] = 0.01174 * 24000 + 0.00606 * (payPeriodKwh[p] − 24000)
else
    payPeriodKwhCharge[p] = 0.01174 * 24000 + 0.00606 * 186000 + 0.00244 * (payPeriodKwh[p] − 210000);
```

, where p ∈ FuturePayPeriods, 0.01174 is the dollar charge of the first 24000 kWh consumed, 0.00606 is the dollar charge of the next 186000 kWh consumed, and 0.00244 is the dollar charge of the additional kWh consumed. Note that if payPeriodSupplyDemand[p] is 1000 kW or more, 210 kWh for each peak demand usage over 1000 kW is added to the total power consumption to calculate payPeriodKwhCharge[p].

3.2.3 Total Electricity Cost

The total electricity cost per future pay period is the sum of payPeriodKwhCharge[p] and generationDemandCharge[p], i.e., `electricCostPerFuturePayPeriod = (payPeriodKwhCharge[p] + generationDemandCharge[p]);`, where p ∈ FuturePayPeriods.

Table 1: Descriptions for the Constant Values in the DGEI Optimization Model of the GMU Energy Investment Problem.

Constant	Description
0.9	Percentage of the highest kW of demand during the billing months of June through September of the preceding 11 billing months
8.124	Amount ($) of Electricity Supply (ES) demand charged per kW
24000	First ES kWh
0.01174	Amount ($) of the first 24000 ES kWh charged per kWh
186000	Next ES kWh
0.00606	Amount ($) of the next 186000 ES kWh charged per kWh
210000	Sum of the first ES kWh and the next ES kWh
0.00244	Amount ($) of the additional ES kWh charged per kWh
210	kWh for each ES kW of demand over 1000 kW

The total electricity cost of all the

FuturePayPeriods is the aggregations of all the total electricity costs per future pay period, i.e., `electricCost = ∑(payPeriodKwhCharge[p] + generationDemandCharge[p]);`, where $p \in$ FuturePayPeriods.

Table 1 summarizes the descriptions of all the constant values from the electric utility contract used in the DGEI optimization model for the GMU energy investment problem.

3.2.4 Total Gas Consumption Charge

Regarding the gas supply, utilityGas[FuturePowerIntervals] ≥ 0 is an array of gas supplied from the WGLC over the FuturePowerIntervals. The total gas cost of all the FuturePowerIntervals is the aggregations of all the total gas utility per future power interval, i.e., `gasCost = (∑(utilityGas[i]/btuPerDth)) * gasPricePerDth;`, where $i \in$ FuturePowerIntervals, btuPerDth = 1000000 BTU, which is the amount of energy per decatherm, and gasPricePerDth = \$6.5, which is the gas charge per decatherm.

3.2.5 Total Operating Cost

The total operating cost is the sum of the total electricity cost of all the future pay periods and the total gas cost of all the future power intervals, i.e., `totalCost = electricCost + gasCost;`.

3.3 Operational Parameters and Capacity Constraints of the CHCP and the Cogen Plant

In addition to the supply and demand of gas and electricity, the operational parameters and the capacity constraints of the CHCP and the CoGen plant are also considered.

3.3.1 The CHCP Plant

For the CHCP plant, gasIntoCHCP[FuturePowerIntervals] ≥ 0 is an array of natural gas input to the CHCP over the FuturePowerIntervals to generate the heat supply. kwIntoCHCP[FuturePowerIntervals] ≥ 0 is an array of power input to the CHCP over the FuturePowerIntervals to generate the cool supply. heatOutCHCP[FuturePowerIntervals] ≥ 0 is an array of heat output from the CHCP over the FuturePowerIntervals to satisfy the partial heating demand. coolOutCHCP[FuturePowerIntervals] ≥ 0 is an array of cool output from the CHCP over the FuturePowerIntervals to satisfy the partial cooling demand. The CHCP constraints include:

- `heatOutCHCP[i] * gasPerHeatUnit ≤ gasIntoCHCP[i];`, i.e., the amount of gas consumed to generate the heat cannot be more than that of the gas input;
- `coolOutCHCP[i] * kwhPerCoolUnit ≤ kwIntoCHCP[i];`, i.e., the amount of electric power consumed to generate the cool cannot be more than that of the power input;
- `heatOutCHCP[i] ≤ chcpMaxHeatPerHr;`, i.e., the amount of heat generated cannot be more than the maximal heat output of the CHCP; and
- `coolOutCHCP[i] ≤ chcpMaxCoolPerHr;`, i.e., the amount of cool generated cannot be more than the maximal cool output of the CHCP, where $i \in$ FuturePowerIntervals, gasPerHeatUnit = (1 / 0.78), and kwhPerCoolUnit = (1 / 0.94).

3.3.2 The CoGen Plant

For the CoGen plant, gasIntoCogen[FuturePowerIntervals] ≥ 0 is an array of gas input to the CoGen plant over the FuturePowerIntervals to generate the power supply. kwOutCogen[FuturePowerIntervals] ≥ 0 is an array of power output from the CoGen plant over the FuturePowerIntervals to satisfy the partial electricity demand. heatOutCogen[FuturePowerIntervals] ≥ 0 is an array of heat output from the CoGen plant over the FuturePowerIntervals to satisfy the partial heating demand. coolOutCogen[FuturePowerIntervals] ≥ 0 is an array of cool output from the CoGen plant over the FuturePowerIntervals to satisfy the partial cooling demand. The constraints of the CoGen plant include:

- `kwOutCogen[i] * cogenGasPerKwh ≤ gasIntoCogen[i];`, i.e., the amount of gas consumed to generate the power cannot be more than that of the gas input;
- `kwOutCogen[i] ≤ cogenMaxKw;`, i.e., the amount of power generated cannot be more than the maximal electricity output of the CoGen plant;
- `heatOutCogen[i] ≤ cogenHeatPerKwh * kwOutCogen[i];`, i.e., the amount of heat generated cannot be more than the maximal heat supply that is restricted by the power output of the CoGen plant;
- `heatOutCogen[i] ≤ cogenMaxHeatPerHr * (kwOutCogen[i]/cogenMaxKw);`, i.e., the amount of heat generated cannot be more than the maximal heat output of the CoGen plant;
- `coolOutCogen[i] ≤ (cogenMaxHeatPerHr * (kwOutCogen[i]/cogenMaxKw) -`

`heatOutCogen[i]) * cogenHeatToCoolRatio;`, i.e., the amount of cool generated cannot be more than the maximal cool supply that is restricted by the power and heat output of the CoGen plant; and

- `coolOutCogen[i] ≤ cogenMaxCoolPerHr;`, i.e., the amount of cool generated cannot be more than the maximal cool output of the CoGen plant,

where i ∈ FuturePowerIntervals, cogenMaxKw = 7200 kW is the maximal power output, cogenHeatPerKwh = 10300 kWh is the amount of heat generated per kWh, cogenHeatToCoolRatio = cogenMaxCoolPerHr/cogenMaxHeatPerHr is the ratio of converting heat to cool supply, cogenMaxHeatPerHr = 40000000 BTU is the maximal heat supply of the CoGen plant per hour, cogenMaxCoolPerHr = 2400 Tons is the maximal cool supply of the CoGen plant per hour, cogenGasPerKwh = gasBTUPerGallon/kWhPerGallon/cogenGasToKwh Efficiency is the amount of natural gas consumed per kWh, for gasBTUPerGallon = 114000 BTU is the amount of energy generated per gallon of gas, kwhPerGallon = 33.41 is the amount of kWh generated per gallon of gas, and cogenGasToKwhEfficiency = 0.33 is the efficiency of the CoGen plant to generate power from natural gas.

3.4 Energy Aggregations of Supply and Demand

The aggregations of energy supply and demand within the entire energy system include:

- `kwIntoCHCP[i] + demandKw[i] ≤ utilityKw[i] + kwOutCogen[i];`, i.e., the amount of power input to the CHCP and the power demand from the GMU cannot exceed the amount of power supply provided from the DVPC and the power output generated from the CoGen plant, where i ∈ FuturePowerIntervals.
- `demandReduction[i] ≤ (utilityKw[i] + kwOutCogen[i]) - (kwIntoCHCP[i] + demandKw[i]);`, i.e., the power supply reduction cannot exceed the difference between the total power supply (utilityKw[i] + kwOutCogen[i]) and the total power demand (kwIntoCHCP[i] + demandKw[i]), where demandReduction[FuturePowerIntervals] ≥ 0 is an array of extra power supply that can be cut from the power inputs over the FuturePowerIntervals, and i ∈ FuturePowerIntervals.
- `∑demandReduction[i] ≤ maxKwReductionPerPayPeriod;`, i.e., the total power reductions over the future power intervals cannot exceed the allowable maximal power interruptions per future pay period, where i ∈ FuturePowerIntervals, p ∈ FuturePayPeriods, and i.payPeriod = p.
- `utilityGas[i] ≥ gasIntoCogen[i] + gasIntoCHCP[i];`, i.e., the gas input to the CoGen plant and to the CHCP cannot exceed the gas supply provided from the WGLC, where i ∈ FuturePowerIntervals.
- `heatOutCogen[i] + heatOutCHCP[i] ≥ demandHeat[i];`, i.e., the heat demand from GMU cannot exceed the heat supply generated from the CoGen plant and the CHCP, where i ∈ FuturePowerIntervals.
- `coolOutCogen[i] + coolOutCHCP[i] ≥ demandCool[i];`, i.e., the cool demand from GMU cannot exceed the cool supply generated from the CoGen plant and the CHCP, where i ∈ FuturePowerIntervals.

3.5 DGEI Optimization Model

After declaring all the input data sets and the above constraints, which the input data sets need to satisfy, the DGEI optimization model for the GMU energy investment problem can be formulated as follows in Figure 3.

$$
\begin{array}{l}
\mathit{Minimize\ totalCost} \\
\\
\mathit{Subject\ To} \\
\quad \forall i \in \mathit{PastPowerIntervals}, \mathit{utilityKw}[i] == \mathit{historicUtilityKw}[i] \\
\quad \forall i \in \mathit{AllPowerIntervals}, \\
\quad \mathit{payPeriodSupplyDemand}[p] \geq \\
\quad \begin{cases}
\mathit{utilityKw}[i]\ \mathit{if}\ (i.\mathit{payPeriod} = p \wedge i.\mathit{weekDay} \geq 1 \wedge i.\mathit{weekDay} \leq 5 \wedge \\
\quad ((i.\mathit{month} \geq 6 \wedge i.\mathit{month} \leq 9 \wedge i.\mathit{hour} \geq 10 \wedge i.\mathit{hour} \leq 22) \vee \\
\quad (i.\mathit{month} \leq 5 \wedge i.\mathit{month} \geq 10 \wedge i.\mathit{hour} \geq 7 \wedge i.\mathit{hour} \leq 22))) \\
0.9 * \mathit{utilityKw}[i]\ \mathit{if}\ (i.\mathit{month} \geq 6 \wedge i.\mathit{month} \leq 9 \wedge i.\mathit{payPeriod} \geq p - 11 \wedge i.\mathit{payPeriod} \leq p \wedge \\
\quad i.\mathit{weekDay} \geq 1 \wedge i.\mathit{weekDay} \leq 5 \wedge i.\mathit{hour} \geq 10 \wedge i.\mathit{hour} \leq 22)
\end{cases} \\
\quad \mathit{where}\ p = 1, \ldots, 108 \\
\quad \forall i \in \mathit{FuturePowerIntervals}, \mathit{heatOutCHCP}[i] * \mathit{gasPerHeatUnit} \leq \mathit{gasIntoCHCP}[i] \\
\quad \forall i \in \mathit{FuturePowerIntervals}, \mathit{coolOutCHCP}[i] * \mathit{kwhPerCoolUnit} \leq \mathit{kwIntoCHCP}[i] \\
\quad \forall i \in \mathit{FuturePowerIntervals}, \mathit{heatOutCHCP}[i] \leq \mathit{chcpMaxHeatPerHr} \\
\quad \forall i \in \mathit{FuturePowerIntervals}, \mathit{coolOutCHCP}[i] \leq \mathit{chcpMaxCoolPerHr} \\
\quad \forall i \in \mathit{FuturePowerIntervals}, \mathit{kwOutCogen}[i] \leq \mathit{cogenGasPerkWh} \leq \mathit{gasIntoCogen}[i] \\
\quad \forall i \in \mathit{FuturePowerIntervals}, \mathit{kwOutCogen}[i] \leq \mathit{cogenMaxKw} \\
\quad \forall i \in \mathit{FuturePowerIntervals}, \mathit{heatOutCogen}[i] \leq \mathit{cogenHeatPerKwh} * \mathit{kwOutCogen} \\
\quad \forall i \in \mathit{FuturePowerIntervals}, \mathit{heatOutCogen}[i] \leq \mathit{cogenMaxHeatPerHr} * (\mathit{kwOutCogen}[i]/\mathit{cogenMaxKw}) \\
\quad \forall i \in \mathit{FuturePowerIntervals}, \mathit{coolOutCogen}[i] \leq (\mathit{cogenMaxHeatPerHr} * (\mathit{kwOutCogen}[i]/\mathit{cogenMaxKw}) - \\
\quad \mathit{heatOutCogen}[i]) * \mathit{cogenHeatToCoolRatio} \\
\quad \forall i \in \mathit{FuturePowerIntervals}, \mathit{coolOutCogen}[i] \leq \mathit{cogenMaxCoolPerHr} \\
\quad \forall i \in \mathit{FuturePowerIntervals}, \mathit{kwIntoCHCP}[i] + \mathit{demandKw}[i] \leq \mathit{utilityKw}[i] + \mathit{kwOutCogen}[i] \\
\quad \forall i \in \mathit{FuturePowerIntervals}, \mathit{demandReduction}[i] \leq (\mathit{utilityKw}[i] + \mathit{kwOutCogen}[i]) - (\mathit{kwIntoCHCP}[i] + \\
\quad \mathit{demandKw}[i]) \\
\quad \forall p \in \mathit{FuturePayPeriods}, \sum_{i \in \mathit{FuturePowerIntervals} \wedge i.\mathit{payPeriod} = p} \mathit{demandReduction}[i] \leq \mathit{maxKwReductionPerPayPeriod} \\
\quad \forall i \in \mathit{FuturePowerIntervals}, \mathit{utilityGas}[i] \geq \mathit{gasIntoCogen}[i] + \mathit{gasIntoCHCP}[i] \\
\quad \forall i \in \mathit{FuturePowerIntervals}, \mathit{heatOutCogen}[i] + \mathit{heatOutCHCP}[i] \geq \mathit{demandHeat}[i] \\
\quad \forall i \in \mathit{FuturePowerIntervals}, \mathit{coolOutCogen}[i] + \mathit{coolOutCHCP} \geq \mathit{demandCool}[i] \\
\qquad \mathit{coolOutCHCP}[i] \geq 0, \mathit{coolOutCogen}[i] \geq 0, \mathit{demandReduction}[i] \geq 0, \mathit{gasIntoCHCP}[i] \geq 0, \mathit{gasIntoCogen}[i] \\
\qquad \geq 0, \mathit{heatOutCHCP}[i] \geq 0, \mathit{heatOutCogen}[i] \geq 0, \mathit{kwOutCogen}[i] \geq 0, \mathit{kwIntoCHCP}[i] \\
\qquad \geq 0, \mathit{payPeriodSupplyDemand}[p] \geq 0, \mathit{utilityGas}[i] \geq 0, \mathit{utilityKw}[i] \geq 0, \mathit{where}\ i \\
\qquad \in \mathit{FuturePowerIntervals}.
\end{array}
$$

Figure 3: The DGEI Optimization Model for the GMU Energy Investment Problem.

4 OPL IMPLEMENTATION FOR DGEI OPTIMIZATION MODEL

The DGEI optimization model has been implemented by using the OPL language. Using the GMU historical data of power usage in the past year, i.e., 2011, and its projected electricity, cooling, and heating demand over a future time horizon from 2012 to 2020, we use the OPL language to implement and demonstrate the DGEI optimization model to solve the GMU energy investment problem and minimize the operating cost.

The intuition of using the OPL language is that its optimization formulation looks like the DGEI optimization model. When comparing the DGEI optimization model in Figure. 3 with the OPL formulation from Figure 4.1 to Figure 4.9, we realize that both models are very similar to each other. Only some notations and syntaxes are different that is shown in Table 2. For example, instead of using the summation sign (∑) in the DGEI optimization model, the OPL language uses the keyword, "sum", to perform the aggregation. Rather than using the if-then statement in the mathematics, the OPL uses the specific construct with the implication operatior (=>).

Table 2: Differences between DGEI Optimization model and OPL formulation model.

DGEI Optimization Model	OPL Formulation Model
Notation: Summation Sign ∑ Example: ∑(demandKw[i] – kW[i]) ≤ 2 * annualBound	Syntax: sum Example: sum(i in PowerIntervals : i.pInterval >= 1) (demandKw[i] - kW[i]) <= annualBound * 2
Notation: If-then Statement Example: if (payPeriodKwh[p] ≤ 24000) payPeriodKwhCharge[p] = 0.01174 * payPeriodKwh[p]	Syntax: => Example: (payPeriodKwh[p] <= 24000) => (payPeriodKwhCharge[p] == 0.01174 * payPeriodKwh[p])
Notation: Where clause Example: peakDemandBound[p] ≤ payPeriodSupplyDemand[p], where p ∈ PayPeriods	Syntax: forall Example: forall (p in PayPeriods) peakDemandBound[p] <= payPeriodSupplyDemand[p]

More specifically, the OPL implementation construct is described as follows. In Figure 4.1, from the line number 9 to 12, the value 12, i.e., the total 12 months of 2011, is assigned to the variable nbPastPayPeriods, the value 108, i.e., the total 108 months from 2012 to 2020, is assigned to the variable nbPayPeriods, and the value 0 is assigned to the maximal power interruptions, i.e., maxKwReductionPerPeriod. The FuturePayPeriods is ranged from 1 to 108. From the line number 15 to 23, we declare a tuple of a power interval that has the attributes, including pInterval, payPeriod, year, month, day, hour, and weekDay. The line number 25 to 27 declares and initializes AllPowerIntervals that include both PastPowerIntervals and FuturePowerIntervals. The line number 30 to 32 declares and initializes the demandKw[AllPowerIntervals], the demandHeat[FuturePowerIntervals], and the demandCool[FuturePowerIntervals] arrays.

```
1  /****************************************
2   * OPL 12.4 Cogeneration Plant Analysis    *
3   * Author: Alex Brodsky and Chun-Kit Ngan  *
4   * Creation Date: July 24, 2012 at 8:28PM  *
5   * Updated Date: August 12, 2012 at 03:15PM*
6   *****************************************/
7
8   //General Input Data
9   int nbPayPeriods = ...;
10  int nbPastPayPeriods = ...;
11  float maxKwReductionPerPayPeriod = ...;
12  range FuturePayPeriods = 1 .. nbPayPeriods ;
13  float intervalSize = 1.0;
14
15  tuple powerInterval{
16    int pInterval;
17    int payPeriod;
18    int year;
19    int month;
20    int day;
21    int hour;
22    int weekDay;
23  }
24
25  {powerInterval} AllPowerIntervals = ...;
26  {powerInterval} PastPowerIntervals = {i | i in AllPowerIntervals : i.pInterval <= 0};
27  {powerInterval} FuturePowerIntervals = {i | i in AllPowerIntervals : i.pInterval >= 1};
28
29  //Demand Input Data
30  float demandKw[AllPowerIntervals] = ...;
31  float demandHeat[FuturePowerIntervals] = ...;
32  float demandCool[FuturePowerIntervals] = ...;
33
```

Figure 4.1: General and Demand Input Data.

```
34  //Electric Cost
35  dvar float+ utilityKw[AllPowerIntervals];
36  dvar float+ payPeriodSupplyDemand[FuturePayPeriods];
37  float historicUtilityKw[i in PastPowerIntervals] = demandKw[i];
38  dvar float+ demandReduction[FuturePowerIntervals];
39
40  dexpr float payPeriodKwh[p in FuturePayPeriods] =
41        sum(i in AllPowerIntervals : i.payPeriod == p) utilityKw[i];
42  pwlFunction kwhCost = piecewise {0.01174-> 24000; 0.00606 -> 210000; 0.00244};
43  dexpr float payPeriodKwhCharge[p in FuturePayPeriods] = kwhCost(payPeriodKwh[p]);
44  dexpr float generationDemandCharge[p in FuturePayPeriods] = 8.124 * payPeriodSupplyDemand[p];
45  dexpr float electricCost = sum(p in FuturePayPeriods)
46                            (payPeriodKwhCharge[p] + generationDemandCharge[p]);
47
```

Figure 4.2: Total Electricity Cost.

Figure 4.2 declares the decision control variables, i.e., utilityKw[AllPowerIntervals], payPeriodSupplyDemand[FuturePayPeriods], and payPeriodKwh[FuturePayPeriods], to compute payPeriodKwhCharge[FuturePayPeriods] and generationDemandCharge[FuturePayPeriods] that are summed together to determine the total electricity cost over all the future pay periods while satisfying the electric contractual constraints.

Figure 4.3 declares the constants, i.e., gasPricePerDth and btuPerDth, and utilityGas[FuturePowerIntervals] to calculate the total gas cost over all the future power intervals.

```
//Gas Cost
float gasPricePerDth = 6.5;
float btuPerDth = 1000000.0;
dvar float+ utilityGas[FuturePowerIntervals];
dexpr float gasCost = (sum(i in FuturePowerIntervals)
                          (utilityGas[i]/ btuPerDth)) * gasPricePerDth;

```

Figure 4.3: Total Gas Cost.

Figure 4.4 declares the objective function to minimize the total operating cost, i.e., the total electricity cost plus the total gas cost.

```
//Objective Function
dexpr float totalCost = electricCost + gasCost;
minimize totalCost;

```

Figure 4.4: Total Operating Cost.

Figure 4.5 declares the constants, i.e., gasPerHeatUnit, kwhPerCoolUnit, chcpMaxHeatPerHr, and chcpMaxCoolPerHr, and the arrays, i.e., gasIntoCHCP[FuturePowerIntervals], kwIntoCHCP[FuturePowerIntervals], heatOutCHCP[FuturePowerIntervals], and coolOutCHCP[FuturePowerIntervals], used in the CHCP capacity constraints.

```
//Central Heating and Cooling Plant
float gasPerHeatUnit = (1 / 0.78); //GasBTU / heatBTU
float kwhPerCoolUnit = (1 / 0.94); //ton / kWH
float chcpMaxHeatPerHr = 108000000.0;  //Total Existing Capacity Btu/hr
float chcpMaxCoolPerHr = 11880;    //Total Existing Capacity Ton/hr

dvar float+ gasIntoCHCP[FuturePowerIntervals];
dvar float+ kwIntoCHCP[FuturePowerIntervals];
dvar float+ heatOutCHCP[FuturePowerIntervals];
dvar float+ coolOutCHCP[FuturePowerIntervals];

```

Figure 4.5: Operational Parameters and Data Structures of the CHCP Plant.

Figure 4.6 declares the constants from the line number 71 to 79, and the arrays, i.e., gasIntoCogen[FuturePowerIntervals], heatOutCogen[FuturePowerIntervals], coolOutCHCP[FuturePowerIntervals], and kwOutCHCP[FuturePowerIntervals], which are used in the capacity constraints of the CoGen plant.

```
70 //New Cogeneration Plant
71 float cogenMaxHeatPerHr = 40000000.0;  //Btu/hr
72 float cogenMaxCoolPerHr = 2400.0;      //ton/hr
73 float cogenMaxKw = 7200.0;                //kW
74 float cogenGasToKwhEfficiency = 0.33;
75 float gasBTUPerGallon = 114000.0;
76 float kWhPerGallon = 33.41;
77 float cogenGasPerKwh = gasBTUPerGallon/kWhPerGallon/cogenGasToKwhEfficiency; //BTU/kWh
78 float cogenHeatPerKwh = 10300.0;       //Btu/kWh = Net Heat Rate
79 float cogenHeatToCoolRatio = cogenMaxCoolPerHr / cogenMaxHeatPerHr;
80
81 dvar float+ gasIntoCogen[FuturePowerIntervals];
82 dvar float+ heatOutCogen[FuturePowerIntervals];
83 dvar float+ coolOutCogen[FuturePowerIntervals];
84 dvar float+ kwOutCogen[FuturePowerIntervals];
85
```

Figure 4.6: Operational Parameters and Data Structures of the CoGen Plant.

Figure 4.7 defines all the capacity constraints for the CHCP and the CoGen plant.

```
subject to{
//Central Heating and Cooling Plant Constraints
   forall (i in FuturePowerIntervals){
       heatOutCHCP[i] * gasPerHeatUnit <= gasIntoCHCP[i];
       coolOutCHCP[i] * kwhPerCoolUnit <= kwIntoCHCP[i] * intervalSize;
       heatOutCHCP[i] <= chcpMaxHeatPerHr * intervalSize;
       coolOutCHCP[i] <= chcpMaxCoolPerHr * intervalSize;
   }

//New Cogeneration Plant Constraints
   forall (i in FuturePowerIntervals){
       kwOutCogen[i] * intervalSize * cogenGasPerKwh <= gasIntoCogen[i];
       kwOutCogen[i] * intervalSize <= cogenMaxKw;
       heatOutCogen[i] <= cogenHeatPerKwh * kwOutCogen[i] * intervalSize;
       heatOutCogen[i] <= cogenMaxHeatPerHr * intervalSize * (kwOutCogen[i]/cogenMaxKw);
       coolOutCogen[i] <= (cogenMaxHeatPerHr * intervalSize * (kwOutCogen[i]/cogenMaxKw)
                             - heatOutCogen[i]) * cogenHeatToCoolRatio;
       coolOutCogen[i] <= cogenMaxCoolPerHr * intervalSize;
   }

```

Figure 4.7: Capacity Constraints of the CHCP and the CoGen Plant.

Figure 4.8 defines the contractual constraints for the electricity bill.

```
//Electric Contractual Utility Constraints
   forall(i in PastPowerIntervals) utilityKw[i] == historicUtilityKw[i];

   forall(p in FuturePayPeriods)
      forall(i in AllPowerIntervals : i.payPeriod == p && i.weekDay >= 1 && i.weekDay <= 5
      && ((i.month >= 6 && i.month <= 9 && i.hour >= 10 && i.hour <= 22) ||
          (i.month <= 5 && i.month >= 10 && i.hour >= 7 && i.hour <= 22)))
             (payPeriodSupplyDemand[p] >= utilityKw[i]);

   forall(p in FuturePayPeriods)
      forall(i in AllPowerIntervals : i.month >= 6 && i.month <= 9 &&
      i.payPeriod >= p - 11 && i.payPeriod <= p &&
      i.weekDay >= 1 && i.weekDay <= 5 && i.hour >= 10 && i.hour <= 22)
             payPeriodSupplyDemand[p] >= 0.9 * utilityKw[i];


```

Figure 4.8: Contractual Electricity Utility Constraints.

Figure 4.9 defines the constraints for the energy aggregations of electric power, gas, heat, and cool.

```
//Electric Power Aggregation
  forall (i in FuturePowerIntervals){
      (kwIntoCHCP[i] + demandKw[i]) <= (utilityKw[i] + kwOutCogen[i]);
      demandReduction[i] <= (utilityKw[i] + kwOutCogen[i]) - (kwIntoCHCP[i] + demandKw[i]);
  }

  forall (p in FuturePayPeriods) {
      (sum(i in FuturePowerIntervals: i.payPeriod == p)
          demandReduction[i]) <= maxKwReductionPerPayPeriod;
  }

//Gas Aggregation
  forall (i in FuturePowerIntervals)
      utilityGas[i] >= gasIntoCogen[i] + gasIntoCHCP[i];

//Heat Aggregation
  forall (i in FuturePowerIntervals)
      heatOutCogen[i] + heatOutCHCP[i] >= demandHeat[i];

//Cool Aggregation
  forall (i in FuturePowerIntervals)
      coolOutCogen[i] + coolOutCHCP[i] >= demandCool[i];
}
```

Figure 4.9: Energy Aggregations of Supply and Demand.

5 ANALYTICAL METHODOLOGY ON EVALUATION AMONG ENERGY INVESTMENT OPTIONS

For domain experts being able to formulate and implement the above DGEI optimization model to determine the best investment option, we propose an analytical methodology that guides the domain experts to achieve this goal. The methodology includes six steps.

STEP 1: Collect historical energy demand, such as electricity, heating, and cooling, from each building unit, and forecast those demands in terms of growth on a square-foot basis over the future time horizon.

STEP 2: Identify all the possible energy investment options, such as the expansion of current facilities and the procurement of cogeneration plants.

STEP 3: Formulate, implement, and execute the DGEI optimization model that integrates historical and projected energy demand, electric and gas contractual utility, operational parameters and capacity constraints of energy equipment, as well as energy aggregations of supply and demand in each considered option under the assumption of optimal interactions among available resources.

STEP 4: Compute the annualized evaluation parameters for each option based upon the results from the optimization process in STEP 3.

The parameters include the investment cost (I_i), equipment cost (E_i), i.e., maintenance expenditure (M_i) plus replacement charge (R_i), operating expense (C_i), i.e., the charges on electricity and gas consumptions, cost saving (S_i), i.e., $C_0 – C_i$, where i $\geq$ 0 denotes an investment option and C_0 is the operating cost of a base investment option that the other available options compare with, and return on investment (ROI_i), i.e., S_i / (I_i – I_0), as well as the GHG emissions ($MTCDE_i$), i.e., G_i * 0.053 MTCDE/Million-Btu + P_i * 0.513 MTCDE/Million-Wh, shown in Table 3, against the various investment options, where 0.053 and 0.513 are the factors, which are calculated from the historical data.

Note that the base investment option is the option that the current capacity of the existing facilities is expanded without procuring any new energy equipment.

Using the ROI and GHG emissions, domain users and experts can plot the analytical graphs to illustrate the relationships among the ROI, GHG emissions, and investment expenses, which enable the domain experts to determine the best investment option among all of the options being considered.

Table 3: Evaluation Parameters of ROI and GHG Emissions for Determining the Best Investment Option.

Parameter	Symbol
Investment Cost	I_i
Maintenance Expenditure	M_i
Replacement Charge	R_i
Equipment Cost	E_i
Operating Expense	C_i
Cost Saving	S_i
Return on Investment	ROI_i
Average Annual Gas Consumption MBTU	G_i
Average Annual Electric Power Consumption MWh	P_i
GHG Emission	$MTCDE_i$

STEP 5: Remove any option that is dominated by the other options in terms of the evaluation parameters.

STEP 6: Construct a trade-off graph to evaluate the options that are not dominated among others and then make a final decision.

Note that although STEP 1, 2, 4, 5, and 6 are typical processes of evaluations, STEP 3 is not typical at all as the problem that we solve is a non-trivial optimization problem.

6 ANALYTICAL METHODOLOGY ON EXPERIMENTAL CASE STUDY

After the process from STEP 1 to STEP 3 in the experimental case study at GMU, the four investment options, including ① the expansion of the existing CHCP only, ② the addition of a CoGen plant to the existing CHCP, ③ the half capacity of the Option ① with the half planned capacity of the CoGen plant, and ④ the full capacity of the Option ① with the full planned capacity of the CoGen plant, have been chosen to be evaluated to meet the electricity, heating, and cooling demand of the Fairfax campus over the next 9 years from 2012 to 2020.

In STEP 4, using the evaluation parameters, i.e., ROI and GHG emissions, discussed in Section 5 and the OPL to solve the GMU energy investment problem in Section 4, we obtained Table 4 and Figure 5 that can be used to determine the best investment option.

Table 4: Evaluation Parameters of ROI and GHG Emissions for Determining the GMU Energy Investment Options.

Investment Option	Investment Cost ($M)	Annual Maintenance Cost ($)
1 Expanded CHCP	$34.293	$343,200
1 CoGen Plant + 1 Current CHCP	$65.328	$655,600
½ CoGen Plant + ½ Expanded CHCP	$46.995	$499,400
1 CoGen Plant + 1 Expanded CHCP	$99.621	$998,800

Investment Option	Annualized Replacement Cost ($M)	Annualized Equipment Cost ($M)
1 Expanded CHCP	$3.429	$3.772
1 CoGen Plant + 1 Current CHCP	$3.850	$4.506
½ CoGen Plant + ½ Expanded CHCP	$4.699	$5.199
1 CoGen Plant + 1 Expanded CHCP	$7.279	$8.278

Table 4: Evaluation Parameters of ROI and GHG Emissions for Determining the GMU Energy Investment Options. (Cont.)

Investment Option	Annualized Average Operational Cost ($M)	Annualized Saving over the Expanded CHCP ($M)
1 Expanded CHCP	$6.244	$0.000
1 CoGen Plant + 1 Current CHCP	$5.494	$0.016
½ CoGen Plant + ½ Expanded CHCP	$5.557	-$0.740
1 CoGen Plant + 1 Expanded CHCP	$5.492	-$3.754

Investment Option	ROI (%)	Average Annual Gas Consumption (MBTU)
1 Expanded CHCP	0.000%	510,500.00
1 CoGen Plant + 1 Current CHCP	0.052%	523,622.22
½ CoGen Plant + ½ Expanded CHCP	-5.827%	520,888.89
1 CoGen Plant + 1 Expanded CHCP	-5.747%	523,600.00

Investment Option	Average Annual Electric Power Consumption (MWh)	GHG Emission (MTCDE)
1 Expanded CHCP	141,433.33	99611.799
1 CoGen Plant + 1 Current CHCP	141,333.33	100255.977
½ CoGen Plant + ½ Expanded CHCP	141,344.44	100116.811
1 CoGen Plant + 1 Expanded CHCP	141,333.33	100254.799

In STEP 5, the Option ③ and ④ are the dominated cases that can be removed from our consideration list because of the negative ROI.

In STEP 6, according to the Table 4 and Figure 5, we can conclude that the Option ① should be chosen because of the three observations. First, the GHG emissions and the equipment cost of the Option ① are the lowest. Second, even though the

ROI of the Option ②, i.e., 0.052%, is marginally better than that of the Option ①, the GHG emissions of the Option ② is the highest among all the options being considered. Third, it is not economical at all for GMU to invest $31 million dollars, i.e., the Option ② investment cost minus the Option ① investment cost, more to earn only 0.052% ROI in the next 9-year timeframe. Thus, the Option 1 is the best long-term option for GMU.

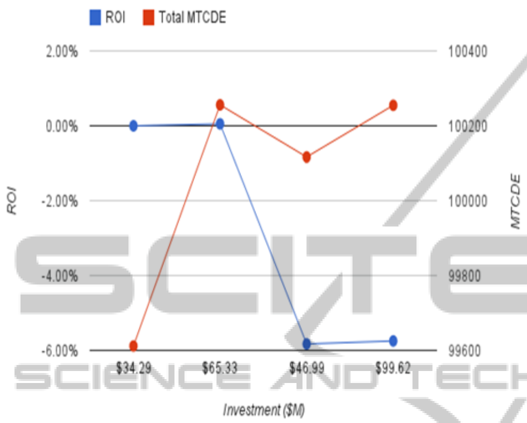

Figure 5: ROI (%) and GHG Emissions (MTCDE) vs. Investment Cost ($M) across the Four Investment Options.

7 CONCLUSIONS AND FUTURE WORK

In this paper, we propose a Decision-Guided Energy Investment (DGEI) Framework to optimize power, heating, and cooling capacity. The DGEI framework is designed to support energy managers to (1) use the analytical and graphical methodology to determine the best investment option that satisfies the designed evaluation parameters, such as ROI and GHG emissions; (2) develop a DGEI optimization model to solve energy investment problems that the operating expenses are minimal in each considered investment option; (3) implement the DGEI optimization model using the IBM OPL language with historical and projected energy demand data, i.e., electricity, heating, and cooling, to solve energy investment optimization problems; and (4) conduct an experimental case study on the Fairfax campus microgrid at George Mason University (GMU) and utilize the DGEI optimization model and its OPL implementations, as well as the graphical and analytical methodology to make the investment decision and trade-offs among the cost savings, investment costs, maintenance expenditures, replacement charges, operating expenses, GHG emissions, and return on investment (ROI) for all the considered options.

Technically, the core challenge is the development of the DGEI optimization model that is very accurate in terms of the contractual terms and engineering constraints, and yet efficient and scalable, which is done by the careful modelling of mainly continuous decision variables and using constructs that avoid introduction of combinatorics, e.g., explicit or implicit binary variables, into the model. However, the DGEI optimization problem that we formulate is implemented by using the OPL language. This OPL construct is then sent to the IBM CPLEX solver which is the branch-and-bound-based algorithm with the exponential time complexity, i.e., $O(k2^N)$, where k is the number of decision control variables, and N is the size of the learning data set. Thus the future research focus will develop a new algorithm that will be able to solve the energy investment problems at a lower time complexity.

Concerning the real case study at George Mason University and its CHCP system, it is clear that GMU must develop and research other available options beyond those discussed in the analysis of this paper in order to meet the future needs of the Fairfax campus demand. Thus, the DGEI framework further developed will aid the GMU energy decision makers to determine the optimal solutions that will satisfy the GMU short- and long-term power, heating, and cooling demand. Note that our framework is applicable to solve any energy investment problem in different domains of industry. Therefore, the future work includes the advanced development of the DGEI libraries and optimization models that enable domain users and experts to integrate more clean and efficient energy equipment, such as geothermal electric power facilities, into the existing plants optimally in order to support the continuous development of enterprises and organizations.

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APPENDIX: ABBREVIATION

Abbreviation	Full Name
CHCP	Centralized Heating and Cooling Plant
CO_2	Carbon Dioxide
CoGen	Cogeneration
DGEI	Decision-Guided Energy Investment
DVPC	Dominion Virginia Power Company
EC	EnergyConnect
ECU	Energy Contractual Utility
EFD	Energy Future Demand
EFE	Energy Facility Expansion
EGP	Energy Generation Process
EHD	Energy Historical Demand
ES	Electricity Supply
FCWA	Fairfax County Water Authority
FMD	Facilities Management Department
GHG	Greenhouse Gas
GMU	George Mason University
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Non-Linear Programming
NO_x	Mono-Nitrogen Oxide
OPL	Optimization Programming Language
QoS	Quality of Service
ROI	Return On Investment
WGLC	Washington Gas Light Company