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OPTIMAL PLANNING AND OPERATION OF A MULTI-ENERGY SYSTEM

LI ZHENGMAO

School of Electrical & Electronic Engineering

A thesis submitted to the Nanyang Technological University
in partial fulfillment of the requirement for the degree of
Doctor of Philosophy

20191027

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

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Authorship Attribution Statement

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*(B) This thesis contains material from 6 papers published/ under review in the following peer-reviewed journals/ from papers accepted at conferences in which I am listed as an author.

Chapter 3 is published as **Li Z**, Xu Y. Optimal coordinated energy dispatch of a multi-energy microgrid in grid-connected and islanded modes. Applied Energy, **210**: 974-986 (2018). [https://doi.org /10.1016/j.apenergy.2017.08.197](https://doi.org/10.1016/j.apenergy.2017.08.197).

The contributions of the co-authors are as follows:

- Prof. Xu provided the initial project direction and discussed the idea with me.
- I prepared the manuscript drafts. Then it was revised by Prof. Xu.
- I collected all the data and did the simulation, then discussed the effectiveness of this paper with Prof. Xu.
- When the paper was in revision, Prof. Xu gave me suggestions and helped to revise the response letter.

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The contributions of the co-authors are as follows:

- Prof Xu suggested the research topic as well as the general idea.
- I wrote the drafts of the manuscript and then discussed it with Prof. Xu about the value of this work.

- I performed all the simulations, collected the operation data, and conducted a literature review.
- Prof. Xu gave a lot of suggestions on the paper writing and which journal that should be submitted to.
- Prof. Xu provided plenty of comments on how to revise the paper after the first-round revision.

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- Prof Xu provided the research directions and some suggestions for this research.
- I wrote the drafts of the manuscript and then discussed it with Prof. Xu and Dr. S Mazzonei about the value as well as the practical applications of this work.
- I conducted all the simulations, collected the planning and operation data, as well as finished the paper.
- Prof. Xu and Dr. Fang gave a lot of advice on the paper writing and also on which journal that should be submitted to.
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- Prof Xu gave me a lot of advice on this topic and provided the research direction.

- I prepared the drafts of the manuscript and then discussed it with Prof. Xu and Dr. Wu about the practical applications of this work.
- I performed all the simulations, learned the advanced algorithms, as well as sought help from other members who had experience in this topic.
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- Prof Xu and Dr. Fang gave me a lot of advice on this topic.
- I prepared the drafts of the manuscript and then discussed it with Prof. Xu and Dr. Fang about the value of this work.
- I performed all the simulations, conducted the multi-objective optimization, as well as finished the paper.
- Prof. Xu and Dr. Fang checked on the paper writing, and also gave a lot of advice on how to improve this paper.
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- Prof Xu and Dr. Fang gave me a lot of advice on this topic, as well as helped me to improve the idea.
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- I performed all the simulations and finished the coding of the robust optimization part assisted by Dr. Zheng.
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22.Oct. 2019

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Summary

Given the permanent pursue of higher energy utilization efficiency, lower energy supplying cost and carbon emissions, the multi-energy systems, which aim to integrate diverse energy carriers, such as electricity, heat, cooling, gas, *etc.*, are becoming emerging diagrams. The multi-energy systems are usually in forms of the land-based ones, such as multi-energy microgrids (MEMGs), smart buildings, or mobile ones like multi-energy ships (MEPs), *etc.* In those systems, the multiple energies can be simultaneously generated by highly efficient co- or tri-generation units, such as the combined cooling heat and power (CCHP) plants. Coordinated with the heterogeneous energy storage (mainly the electric energy storage and thermal storage) and renewable energy-based generators, they contribute to improving the holistic energy utilization efficiency, reducing the emission, maintaining the system reliability, and so on. Recently, the multi-energy systems in different forms have received significant attention both in the academia and industry. How to optimally deploy all the units based on their characteristics, handle the system diverse uncertainties via effective methods, and optimally dispatch the multiple energy resources are some key research topics.

In the MEMG scope, firstly, to enhance the dispatch flexibility of the multiple energy resources in the day-ahead energy market, a system-wide optimal coordinated energy dispatch method for the MEMG in both the grid-connected and islanded modes is proposed. The studied MEMG consists of the multiple energy carriers covering dispatchable generation units (fuel cells, electric boilers, CCHP plants, and electric chillers), non-dispatchable generation units (wind turbine and photovoltaic cell), and energy storage devise (battery storage, heat storage tanks and ice storage tanks). The dispatch problems are formulated as the mixed-integer linear programming (MILP) models for both operating modes, which can be efficiently solved by commercial solvers. Then comprehensive case studies are performed to examine the effectiveness with comparisons with other methods are done. The simulation results have shown that the proposed method has much higher energy efficiency.

Then, to handle the diverse uncertainties such as from renewable energy sources (RES), power loads and electricity transaction prices between the

microgrid and utility grid, a temporally coordinated operation method for MEMG under diverse uncertainties is proposed. The method aims to coordinate multiple energies in different timescales considering distinct properties of thermal and power energy: the CCHP plants, power-to-thermal conversion (PtC) units, and thermal storage (TS) are dispatched hourly in the day-ahead operation stage; in the intra-day online operation stage, the electric energy storage (EES) is dispatched to supplement the day-ahead operation decisions every 5 minutes after the uncertainties are realized. Based on constraints linearization and uncertain scenario generation and reduction, the problem is converted to a deterministic two-stage MILP equivalent model that can be solved efficiently. Finally, the proposed method is verified on an IEEE 33 bus distribution network based MEMG. Compared with the existing methods, the simulation results indicate that the proposed method can better coordinate multiple energies with low operating costs and high robustness.

For the MEMGs, expect for their optimal operation, the proper placement of its inner units is also critical for the enhancement of the system energy efficiency and network reliability. In this sense, a two-stage coordinated method for optimally placing heterogeneous distributed generators (DtGs) in a MEMG project considering the uncertainties from RES. Apart from optimizing the traditional DtG size and location, the method considers the optimal DtG type and investment year simultaneously by maximizing the project's net present value (NPV), which consists of the investment and operation costs. The whole problem is modeled as a two-stage coordinated stochastic optimization (SO) model, where the long-term DtG investment is determined at the first stage and operation decisions are determined at the second stage. The proposed method is verified on a test MEMG system. The simulation results show that its NPV is positive, which means the method is effective and should be implemented. Compared with conventional DtG placement approaches, the proposed method is more robust against the RES uncertainties and can better coordinate the heterogeneous energies with higher dispatch flexibility and economic profits.

For the same purpose as the optimal DtG placement, the optimal deployment of heterogeneous energy storage (HES), which mainly consists of EES and TS, is essential as well. In this regard, a method for HES deployment in a residential multi-energy microgrid (RMEMG), considering diverse uncertainties and multi-

energy demand-side management (DSM) is presented. Apart from the HES size, location planning, its optimal investment phase is also determined by maximizing the system equivalent daily profit (EDP). To handle the system uncertainties from RES, power demands, outdoor temperature, and residential hot water needs, the scenario-based multi-stage adaptive SO approach is utilized. Then through the constraint linearization and stochastic scenario sampling, the original nonlinear deployment model is converted to a MILP one and tested on an IEEE 33-bus distribution network based RMEMG. The effectiveness of the proposed method is verified by comparing it with the existing practices. The comparison results indicate that the proposed HES deployment method can effectively increase the system EDP and more immune to system uncertainties. Further, it can be practically applied for the emerging RMEMGs, such as smart buildings, intelligent homes, *etc.*, which get long-term DSM contracts.

In addition to the land-based MEMGs, the MEP system, which is a form of the mobile multi-energy system, is another researching focus given there is an increasing number of ships from the shipping industry all over the world. A MES can be regarded as a mobile microgrid, and how to reduce the ship operating costs and gas emissions are the priority for the ship operation. Consequently, the optimal operation of a MES microgrid is studied. Apart from the conventional diesel generators (DGs), EES, and photovoltaic cells (PVs), the CCHP unit is introduced. Besides, to flexibilize the CCHP operation and enhance the multi-energy interaction, the thermal storage and PtC unit are also included. Then, a multi-objective coordinated energy dispatch and voyage scheduling method for the MES microgrid is presented to simultaneously reduce the cost and emissions. After the constraint linearization, the coordination method is formulated as a MILP problem. Further, the multi-objective MILP problem is solved by the augmented ε -constraint method (AUGMECON) with Cplex solver. Finally, the proposed method is verified on a testing MES microgrid, and by comparing it with traditional benchmarks, its advantages are demonstrated.

Further, currently, the AC/DC system configuration is effective to reduce the holistic energy utilization efficiency by reducing the energy conversion cost. Then in the MES microgrid, a novel hybrid AC/DC ship system is studied. In order to address the uncertainties from RES, onboard power loads and outdoor

temperature, a robust coordination operation approach for the MES is proposed to coordinate all the units in different timescales by a two-stage robust optimization (RO) method. This method aims to minimize the ship operating cost under the worst case of uncertainties so that all the operational constraints can be fully satisfied. Then after the constraint linearization, the coordination model is formulated as a MILP problem and solved by the efficient Cplex solver. Finally, the proposed method is verified and compared with the existing ship operation benchmarks. The simulation results show that our method is effective in reducing the ship's operating cost and robust against the uncertainties.

All the current research indicates that the multi-energy systems would be a trend for the future energy system with its high energy utilization efficiency. With the increasing number of land-based or mobile multi-energy systems, rising penetration of RES and widespread installation of smart meters, the proposed methods can be directly applied for the emerging multi-energy systems for the cost-saving and emission reduction.

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Abstract

The multi-energy systems, both in the land-based or mobile forms, aim to integrate diverse energy carriers, such as gas, electricity, heat, cooling, *etc.* They are becoming promising diagrams for future energy systems in which, multiple energies can be simultaneously coordinated by heterogeneous units such as energy storage and distributed generators. Recently, the multi-energy systems in different forms have received significant attention both in the academia and industry.

This thesis studies the optimal planning and operation of a multi-energy system. First, the system dispatch flexibility is enhanced by the introduction of heterogeneous units. Further, the system's diverse uncertainties are handled for more reliable and robust planning and operation. Finally, optimal coordination of all the units is investigated to improving the energy utilization efficiency, reducing the emission and cost, maintaining the system reliability, *etc.*

The proposed methods could be directly utilized for the real multi-energy system.

Keywords: multi-energy systems, heterogeneous distributed generators, heterogeneous energy storage, diverse uncertainties, energy utilization efficiency.

List of Acronyms

AUGMECON	Augmented ε -Constraint Method
C&CG	column-and-constraint generation
CCHP	Combined Cooling Heat and Power
CG	Dispatchable Generation Units
DG	Diesel Generator
DM	Decision-Maker
DSM	Demand-Side Management
DtG	Distributed Generators
EB	Electric Boiler
EC	Electric Chiller
EES	Electric Energy Storage
ES	Energy Storage
FC	Fuel Cell
FHL	Following Heat Load
FPL	Following Power Load
GT	Gas Turbine
HES	Heterogeneous Energy Storage
HRU	Heat recovery unit
HST	Heat Storage Tank
IST	Ice Storage Tank
KKT	Karush–Kuhn–Tucker
LO	Lexicographic Optimization
MEMG	Multi-Energy Microgrid
MES	Multi-Energy Ship
MEP	Multi-Energy Photovoltaic
MG	Microgrid
MILP	Mixed-Integer Linear Programming
MPPT	Maximum Power Point Tracking
MT	Micro-Turbine
NPV	Net Present Value
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
PBDR	Price-Based Demand Response
PSO	Particle Swarm Optimization
PtC	Power-To-Thermal Conversion
PVs	Photovoltaic Cell
RES	Renewable Energy Sources
RMEMG	Residential Multi-Energy Microgrid
RO	Robust Optimization
SEMG	Single-Energy Microgrid
SO	Stochastic Optimization
SOC	State of Charge
TS	Thermal Storage
TST	Thermal Storage Tank
WT	Wind Turbine

Nomenclature

The main notations used in this thesis are presented below separately for each chapter. It should be noted that some of the notations are used in different chapters, however, for the sake of consistency they are repeated in each chapter when they are being used. Besides, to present the same meaning, different chapters may use different symbols.

Chapter 3

Sets and Indices

j	Index (set) of CG, running from 1 to N_{CG}
k	Index (set) of the blocks, running from 1 to N_L
t	Index (set) of optimization periods, running from 1 to N
ξ	Set of decision variables

Variables

B_k^t	Binary state of block k
Cap_{ES}	Capacity of ES
C_{EX}^t / C_{PH}^t	Power exchange/energy deviation cost
$C_{F,FC}^t / C_{F,MT}^t$	Fuel cost of FC/MT
C_F^t / C_{OM}^t	Fuel/maintenance cost
C_H^t / C_C^t	Revenue of supplying heat/cooling in grid-connected microgrid
C_{HO}^t / C_{SHC}^t	Revenue of supplying heat/ cooling in grid-connected/ islanded microgrid
C_{SH}^t / C_{SC}^t	Revenue of supplying heat/cooling in islanded microgrid
C_{ST}^t / C_{SD}^t	Start-up/shut-down cost
$C_{U,FC}^t / C_{U,PG}^t$	Unit power generation cost of FC/MT for only power generation
$C_{U,S}^t / C_{U,W}^t$	Unit power generation cost of MT in summer/winter
$E_{ES}^0 / E_{ES}^{NA^t}$	Starting/ending energy of ES
E_{ES}^t	Energy stored in ES
$F(\xi)$	Objective function
F_G / F_S	Net operation cost of grid-connected /islanded microgrid
$H(\xi) / G(\xi)$	Equality/ inequality constraints
P_B^t / P_S^t	Purchasing/selling power of microgrid
P_{BSC}^t / P_{BSD}^t	Discharging/charging power of BS
$P_{CG,j}^t$	Power of controllable unit j
P_{EB}^t / P_{EC}^t	Power inputs of EB/EC
P_{ESC}^t / P_{ESD}^t	Charging/discharging power of EES
P_{HSTC}^t / P_{HSTD}^t	Discharging/charging power of HST
P_{ISTC}^t / P_{ISTD}^t	Discharging/charging power of IST
P_L^t	Power loads
P_{MT}^t / P_{FC}^t	Power outputs of MT/FC
P_{WT}^t / P_{PV}^t	Power outputs of WT/PV
Q_{EB}^t / Q_{EC}^t	Heat/cooling outputs of EB/EC
Q_{GB}^t	Heat/cooling outputs of GB
P_{GAS}^t	Natural gas inputs for GB
Q_{MTH}^t / Q_{MTC}^t	Heat/cooling output of MT
$Q_{TE}^t / Q_{IE}^t / P_{DE}^t$	Heat/cooling/power surplus

$Q_{TS}^t/Q_{IS}^t/P_{DS}^t$	Heat/cooling/power shortage
U_j^t	Binary status of unit j , $U_j^t=1$ is on, 0 is off
γ_B^t/γ_S^t	Binary state variables with $\gamma_B^t=1/\gamma_S^t=1$, microgrid purchases/sells power
$\gamma_{ESC}^t/\gamma_{ESD}^t$	Binary state variables with $\gamma_{ESC}^t=1/\gamma_{ESD}^t=1$, ES is charging/discharging
$\gamma_{TE}^t/\gamma_{IE}^t/\gamma_{DE}^t$	Binary indicators of the heat/cooling/power surplus, 1 means that there is an energy surplus
$\gamma_{TS}^t/\gamma_{IS}^t/\gamma_{DS}^t$	Binary indicators of heat/cooling/power shortage, 1 means that there is an energy shortage
η_{MT}^t/η_{FC}^t	Electrical efficiency of MT/FC
Parameters	
Cap_{ES}	Capacity of ES
COP_{EB}/COP_{EC}	Coefficient of performance for EB and EC
c_G/L_{NG}	Unit price/lower heating value of natural gas
c_H/c_C	The unit price of supplying heat/cooling to customers
$c_{TE}/c_{IE}/c_{DE}$	Unit cost for heat/cooling/power surplus
$c_{TS}/c_{IS}/c_{DS}$	Unit cost for heat/cooling/power shortage
$C_{ST,j}^U/C_{SD,j}^D$	Unit start-up/shut-down cost of unit j
$E_{ES}^0/E_{ES}^{N\Delta t}$	Starting/ending energy of ES
$K_{EC}^{om}/K_{EB}^{om}/K_{MT}^{om}$	The unit maintenance cost of EC/EB/MT
K_{FC}^{om}/K_{ES}^{om}	The unit maintenance cost of FC/ES
K_{WT}^{om}/K_{PV}^{om}	The unit maintenance cost of WT/PV
P_1/P_{N+1}	Minimum/maximum power outputs of N_L blocks
P_k	The starting point of the k th block
$P_{ESC}^{max}/P_{ESD}^{max}$	Maximum charge/discharge power of ES
$P_{CG,j}^{min}/P_{CG,j}^{max}$	Minimum/maximum power of unit j
$R_{CG,j}^{up}/R_{CG,j}^{down}$	Maximum ramp up/down rate of unit j
α_k/β_k	Slope/intercept of a linear function in block k
Δt	Unit dispatch interval, 1h
η_{GB}	The gas-to-thermal efficiency of the GB
τ_{EES}/τ_{TS}	The decay rate of electrical energy storage/thermal storage
η_{EES}/η_{EESD}	The charging/discharging efficiency of the electrical energy storage
COP_H/COP_C	Coefficient of performance of heat recovery unit/absorption chiller
η_{TS}/η_{TSD}	The charging/discharging efficiency of the thermal storage
$\xi_{ES}^{min}/\xi_{ES}^{max}$	Minimum/maximum state of charge of energy storage
η_H/η_C	The conversion efficiency of heat recovery unit/absorption chiller

Chapter 4

Sets and Indices

t/i	Index of dispatch periods/buses
b/k	Index of branches/linear pieces
N_T	Set of dispatch periods
$N_M/N_W/N_P$	Set of buses that install CCHP plants/ WTs/PVs
$N_E/N_B/N_H$	Set of buses that install PtCs/ BSs/TSTs
$Br(i)$	Set of the branches that connect to bus i

$Br(i,l)$ Set of the branch between bus i and l

Constants and Parameters

η_H	The efficiency of heat recovery unit/absorption chiller
η_{TSTD}/η_{TSTD}	Charging/discharging efficiency of TSTs
T_{TST}/T_{BS}	The decay rate of TSTs/BSs
η_{BSD}/η_{BSD}	Charging/discharging efficiency of TSTs
θ/ψ	Scale parameters for Beta Distribution
N_F	The normalized factor for Beta Distribution
μ/σ	Mean/standard deviation for Normal Distribution
Δt	Unit dispatch interval
γ_G/γ_{HR}	Unit gas/thermal energy selling price
$\gamma_{WT}/\gamma_{PV}/\gamma_{MT}$	The unit maintenance cost of WTs/ PVs /MTs
$\gamma_{PT}/\gamma_{BS}/\gamma_{TST}$	The unit maintenance cost of PTCs/BSs /TSTs
γ_B/γ_S	Purchasing/selling price
C_{CG}^U/C_{CG}^D	CGs' unit start-up/shut-down cost
$P_{CG}^{max,i}/P_{CG}^{min,i}$	Maximal/minimal CG's power outputs
$R_{CG}^{up,i}/R_{CG}^{down,i}$	CG's ramp up/down rates
$P_{ESC}^{max,i}/P_{ESC}^{max,i}$	ES's maximal charging/discharging power
$\xi_{ESC}^{min,i}/\xi_{ESC}^{max,i}$	ES's maximal/minimal state of charge (SOC)
Cap_{ES}^i	ES's capacity
R^b/X^b	Resistance/reactance of branch b
α_k/β_k	Slope/intercept of a linear function in the k th piece
P_k	The starting point of the k th block
η_{PC}	The efficiency of PtC units
ΔV_{BUS}^{max}	Maximal voltage deviation

Variables

$f/\bar{f}$	Original nonlinear function /approximated linearized function
P_{MT}^i/H_{MT}^i	Power or thermal outputs of MTs
$\eta_{MT}^{t,i}$	Electrical efficiency of MTs (CCHP plant)
P_{PT}^i/H_{PT}^i	Power or thermal energy outputs of PTCs
E_{TST}^i/E_{BS}^i	Energy stored in TSTs/BSs
P_{TSTD}^i/P_{TSTD}^i	Absorbing/releasing power of TSTs
P_{BSD}^i/P_{BSD}^i	Charging/discharging power of BSs
P_{RES}^i	Power outputs of RES
P_L^i/H_L^i	System power/thermal loads
F_G	Net operating cost
$C_{FD}/C_{OM}/C_{EX}$	Fuel/maintenance/power transaction cost
$C_{ST}/C_{SD}/C_{HR}$	Start-up/shut-down cost/thermal energy selling revenue
P_{BUY}^i/P_{SELL}^i	Purchasing/selling power
$U_{CG}^{t,i}$	Binary status of controllable generators (CG)
P_{CG}^i	CG's power outputs
P_{ESO}^i/P_{ESD}^i	ES's charging and discharging power
$\varepsilon_{ESO}^{t,i}/\varepsilon_{ESD}^{t,i}$	ES's charging/discharging state
E_{ES}^i	Energy stored in ESs;
$P_{PF}^b/Q_{PF}^{t,b}$	Active/reactive power that flows on branch b
$P_L^t/Q_L^{t,i}$	Active/reactive power loads at bus i
V_{BUS}^i	The voltage at bus i
$P_{PF}^{t,0,b}/Q_{PF}^{t,0,b}$	Active/reactive power that flows on the lateral branch of branch b
B_k^t	Binary state of piece k
P_k	The power output of the MT in the k th piece

Chapter 5

Superscript

Λ	Set for {p, q, d, t, i}
b	Index of branches, be Br(i, i+1)
$d/t/i$	Index of days/dispatch periods/buses
$p/q/c/s$	Index of years/DtG types/seasons /scenarios

Constants and Parameters

a^q, b^q	Cost coefficients for DGs
C_{DtG}^U / C_{DtG}^D	Unit DtG start-up/shut-down cost
dr	Discount rate
N_D / N_T	Number of days in a season/dispatch periods in a day
N_P	Project lifetime
N_Q	Total number of DtG types
N_B	Total number of buses in the MEMG
N_{CB} / N_{NB}	Total number of candidate/non-candidate buses
N_{CQ} / N_{VQ}	Total number of DtGs with discrete unit/ continuous capacity
P_{REAL}^{DtG}	Available active power of RES
$P_L / H_H / H_C$	Power/heat/cooling loads of the MEMG
$R_{DtG, DOWN} / R_{DtG, UP}$	Maximal ramping down/up limits
R^b / X^b	Branch resistance /reactance
$S_{DtG, ALL}$	Maximal DtG investment capacity for the MEMGs
$S_{DtG, MIN} / S_{DtG, MAX}$	Minimal/maximal DtG investment capacity for each bus
S_{UN}^{DtG}	The unit capacity of DtGs in discrete size
V_0	Substation voltage
$\gamma_{DtG, MIN} / \gamma_{DtG, MAX}$	Minimal/maximal DtG output ratio to its capacity
Δt	Unit dispatch interval
ΔV_{BUS}^{max}	Maximal bus voltage deviation
$\varepsilon_{DtG, SAL}$	The salvage factor, which is the ratio of DtG salvage value to its initial investment cost
η_{MT} / η_{DG}	Electrical efficiency of MTs/DGs
η_{EB} / η_{EC}	Coefficient of performance of EBs/ECs
η_{MH} / η_{MC}	Power to heat/cooling ratios of MTs
$K_{MT} / K_B / K_{DG}$	Emission conversion factor of MTs/ grid/DGs
X_B / X_S	Electricity purchasing/selling prices between the MEMGs and utility grid
X_{CO2}	Unit CO ₂ penalty price.
$X_{DtG, INV}$	Unit DtG investment cost
$X_{DtG, F} / X_{DtG, V}$	The fixed/variable unit maintenance cost of DtGs
X_{NG} / X_{DG}	Price for the natural gas/diesel
$X_{PS} / X_{HS} / X_{CS}$	The power/heat/cooling retail price to the local customers
X_{RES}	The unit RES curtailment cost
X_{SUB}	Unit subsidy price for RES

Variables

C_{CT}	RES curtailment cost
C_{FO} / C_{TC}	Cost from fuel consumption/power transaction
C_{INV}	The investment cost for DtGs
C_{MC} / C_{EM}	Cost from DtG maintenance/gas emission
C_{REV} / C_{SUB}	Revenue from the local customers/RES subsidy

C_{ST}/C_{SD}	Start-up/shut-down cost
C_{SAL}^{NP}	DtG salvage value
H_{EB}/H_{EC}	Heat/cooling outputs for EBs/ECs
N_{DtG}	Number of DtGs in discrete size
P_{WT}/P_{PV}	Power outputs of WTs /PVs
P_{BX}/P_{SX}	Purchasing/selling power from/to the utility grid
P_{DtG}/P_{DG}	Power outputs of DtGs/DGs
P_{EB}/P_{EC}	Power inputs for EBs/ECs
P_F	Diesel inputs for DGs
P_G	Gas inputs for MTs
$P_{MT}/H_{CMT}/H_{HMT}$	Power/cooling/heat outputs of MTs
P_{PF}/Q_{PF}	Active /reactive power flow
$P_{PF}^{p,d,t,0,b}/Q_{PF}^{p,d,t,0,b}$	Parallel power flow of branch b;
S_{DtG}	DtG capacity
U_{DtG}/U_{DG}	Binary variable to indicate whether a DtG/DG is on: 0 is off, 1 is on
U_{DtGI}	Binary variable to indicate whether a DtG is installed: 1 is installed, 0 is not
V_{BUS}	Bus voltage

Chapter 6

Superscript

$\wedge$	Set for {p, d, t, i}
$p/t/d/i$	Index of years/dispatch periods/days/buses
b	Index of branches, $b \in Br$ (i, i+1)
j	Index for the price levels

Constants and Parameters

a_{BH}	Correction factor for envelopes like walls, doors, etc.
A_{CL}	Air volume that infiltrates into the room
C_{AV}	Equivalent specific heat of the room
C_{WR}/C_{Air}	Specific heat capacity of water/air
dr	Discount rate
l_{LE}	Gap length of the door or window crack
K_{HT}	Heat transfer coefficient of the room
L_{PL}/L_{QL}	Active/reactive PBDR levels
$N_P/N_B/N_T/N_D$	Number of years/buses/dispatch periods/days a year
P_{REAL}^{DG}	Available energy resource of RES
$P_{DL}/H_{HL}/H_{CL}$	Power/heat/cooling demands
P_{WT}/P_{PV}	The power output of wind turbines/photovoltaic cells
$P_{Pr}^{DL}/Q_{DL,Pr}$	Active/reactive power demands before the DSM
R/X	Branch impedance
$S_{ES,MIN}/S_{ES,MAX}$	Minimal/maximal HES capacity for each bus/group
S_{BH}	Area of the building envelope
$S_{ES, ALL}$	Maximal energy capacity for the HES system
T_{IW}	The temperature of inlet water for water tanks
$T_{IN}^{set}/T_{SW}^{set}$	Temperature set-point for room/hot water
$V_0/\Delta V_{BUS}^{max}$	Substation voltage/maximal voltage deviation
V_{RB}/V_{HW}	The volume of the room/hot water needed

β_{cx}/β_{jx}	Correction factor due to solar irradiation/wind blow
$\gamma_{DG, MIN}/\gamma_{DG, MAX}$	The minimal and maximal DG output ratio
γ_{it}	The ratio of intrusion loss to basic thermal transfer loss
Δt	Unit dispatch interval
$\Delta T_V/\Delta T_W$	Maximal temperature deviation for room/ hot water
ϵ_{SAL}^{ES}	The ratio of HES salvage value to its investment cost
η_{BC}/η_{BD}	Charging/discharging efficiency of battery storage
η_{MT}	Electrical efficiency of CCHP plants
η_{TC}/η_{TD}	Charging/ discharging efficiency of thermal storage
κ_{MT}/κ_B	Emission penalty price of CCHP plants/utility grid
ρ_{WR}/ρ_{Air}	Water/air density
τ_T/τ_B	The decay rate of thermal/battery storage
χ_B/χ_S	Power purchasing/selling price between MEMG and utility grid
$\chi_{DG, M}/\chi_{ES, M}$	The unit maintenance cost of generators/storage
$\chi_{ES, INV}$	Unit investment cost of energy storage
χ_{NG}	Nature gas price
$\chi_{PS}/\chi_{HS}/\chi_{CS}$	Power/heat/cooling retail prices to the local customers
$\chi_{PS}/\chi_{HS}/\chi_{CS}$	Power/heat /cooling retail prices to the local customers
χ_{SUB}	The unit subsidy price for RES

Variables

a	Binary indicator for the state of price or load levels
C_{FO}/C_{TC}	Fuel/power transaction cost
C_{INV}/C_{SAL}	Investment cost/salvage value.
C_{MO}/C_{EM}	Maintenance/gas emission cost
C_{REV}/C_{SUB}	Revenue from local customers/RES subsidy
C_{ST}/C_{SD}	Start-up/shut-down cost
E_T/E_B	Energy stored in the thermal/battery storage
H_{BH}/H_{AH}	Basic/additional thermal transfer loss
H_{CN}/H_{CR}	Infiltration/intrusion thermal loss
H_{EB}/H_{EC}	Heat/cooling output of electric boilers/chillers.
H_{MH}/H_{MC}	Heat/cooling output of CCHP plants
H_{TC}/H_{TD}	Charging /discharging power of thermal storage
H_{TL}/H_{NET}	Total space thermal demands/net thermal
P_{MT}	The power output of CCHP plants
P_{BC}/P_{BD}	Charging/ discharging power of battery storage
P_{BX}/P_{SX}	Purchasing/selling power between MEMG and utility
P_{DG}/P_{ES}	Generalized power output for generators/storage
P_{EB}/P_{EC}	Power input for electric boilers/chillers.
P_{PF}/Q_{PF}	Active/reactive power flow
P_{RL}/Q_{RL}	Active/reactive power loads after demand response
$P_{PF}^{p,d,t,0,b}/Q_{PF}^{p,d,t,0,b}$	Parallel active/ reactive power of branch b
$R_{DG,DN}/R_{DG,UP}$	Maximal ramping down/up limits
S_{ES}	The capacity of the energy storage
T_{IN}/T_{OT}	Indoor/outdoor temperature
T_{SW}	The temperature of the water inside the water tank
U_{DG}	Binary state to indicate the on-off status of generators
U_{ES}	Binary state to denote investment decisions for HES

U_{ESC}/U_{ESD}	Binary charging/discharging states of HES
V_{BUS}	Bus voltage

Chapter 7

Superscript

j	Index for the DGs
t	Index of the dispatch periods

Constants and Parameters

$a_{DG}^f, b_{DG}^f, c_{DG}^f$	DG fuel cost coefficients, k\$/(MW) ² , k\$/(MW), k\$
$a_{DG}^g, b_{DG}^g, c_{DG}^g$	DG gas emission coefficients, ton/(MW) ² , ton/(MW), ton
α_{PL}/β_{PL}	Proportional/exponential coefficient for the relationship between the propulsion loads and speed
A_{PV}	The total area of PV modules, m ²
G_{PV}^t/G_{PV}^{std}	The actual/standard solar irradiance, W/m ²
N_{DG}/N_T	Total number of DGs/periods
$P_{EESD}^{max}/P_{TSD}^{max}$	Maximal discharging/releasing power for the EES/TS, MW
$P_{ESC}^{max}/P_{ESD}^{max}$	Maximal charging/discharging power for ES, MW
$P_{DG,j}^{min}/P_{DG,j}^{max}$	Minimal/maximal outputs for DGs, MW
$P_{GT}^{min}/P_{GT}^{max}$	Minimal/maximal power limits for GT, MW
$P_{PtC}^{min}/P_{PtC}^{max}$	Minimal/maximal power limits for PtC unit, MW
P_{GT}^R/E_{ES}^{rate}	Rated capacity of GT, MW/energy storage, MWh
$R_{DG,j}^{min}/R_{DG,j}^{max}$	Ramp down/up limits for DGs, MW/h
T_c/T_{C_ref}	The ambient/reference temperature, °C
$T_{DG,j}^U/T_{DG,j}^D$	Minimal off/on time for DGs, h
T_W	The reference temperature of the thermal pipeline, °C
U_v^t	Binary indicator for cruising or berthing periods with 1 as cruising, 0 as berthing
v_s^{rate}/D_s^{rate}	Rated cruising speed, kn /distance, nm
α_1, α_2	The heat loss coefficients for MEP system, W/(°C·m ²), W/(°C ² ·m ²)
β_C	The PV temperature coefficient, 1/°C
γ_{PF}/γ_{TP}	The PV packing factor/transmittance
Δt	Unit dispatch period, h
η_{ESC}/η_{ESD}	Charging/discharging efficiency of ES
η_{GT}^t	Electric efficiency of GT
η_{MPPT}	The efficiency of PV power tracking equipment
η_{PVP}/η_{PVT}	The actual power/thermal efficiency
$\eta_{PVP-ref}$	The reference PV power efficiency
K_{GT}	The unit gas emission factor of GT, ton/MW
$\xi_{DG,j}^m/\xi_{GT}^m$	Unit maintenance cost for DGs/GTs, k\$/MW
ξ_{ES}^m/ξ_{PTC}^m	Unit maintenance cost for ESs/PtC unit, k\$/MW
ξ_{PV}^m	Unit maintenance cost for the MEP system, k\$/MW
ξ_{NG}	Natural gas price, k\$/MW
T_{ES}	The decay rate of ES
χ_{GT}	The ratio of GT's thermal to its power outputs
$\chi_D^{min}/\chi_D^{max}$	Minimal/maximal distance ratios
$\chi_{ES}^{min}/\chi_{ES}^{max}$	Minimal/maximal state of charge of ES
$\chi_v^{min}/\chi_v^{max}$	Minimal/maximal speed ratios

χ_{PtC}	Power to the thermal conversion efficiency of PtC unit
$\chi_P^{RE} / \chi_Q^{RE}$	System power /thermal reserve ratio
Variables	
$COST/EMI$	Ship operating cost, k\$/gas emissions, ton
$C_{FU}^t / C_{OM}^t / C_{ST}^t$	Fuel, k\$/h/maintenance, k\$/h /start-up cost, k\$
E_{ES}^t	Current stored energy in ES, MWh
F_{DG}^t / G_{DG}^t	DG fuel cost, k\$ /gas emissions, ton
F_{GT}^t / G_{GT}^t	GT fuel cost, k\$/gas emissions, ton
G_{EM}^t	Gas emissions, ton/h
$P_{DG,j}^t / P_{GT}^t$	The power outputs of DGs/GT, MW
P_{EESC}^t / P_{EESD}^t	Charging/discharging power of EES, MW
P_{ESC}^t / P_{ESD}^t	Charging/discharging power of ES, MW
P_{PL}^t	Ship propulsion loads, MW
P_{PtC}^t / Q_{PtC}^t	Power inputs /thermal outputs of PtC units, MW
P_{PVP}^t / P_{PVT}^t	The power/thermal outputs of MEP system, MW
P_{SL}^t / Q_{SL}^t	Service power/thermal loads, MW
P_{TSC}^t / P_{TSD}^t	Absorbing/releasing power of TS, MW
Q_{GT}^t	GT thermal output, MW
$T_{CG,i}^{on,t} / T_{CG,j}^{off,t}$	Previous on/off time for DGs at the current period, h
$U_{DG,j}^t$	On-off state variable for DGs, with 1 meaning the DG is on, 0 is off
U_{GT}^t	On-off state variable for GTs, with 1 meaning the GT is on, 0 is off
v_s^t / D_s^t	Actual cruising speed, kn /distance, nm
Y_{ESO}^t / Y_{ESD}^t	Binary indicator for charging/discharging of ES, with 1 meaning the DG is charging/ discharging, 0 is not.

Chapter 8

Sets and indices

t	Index for the dispatch interval
j	Index for the DGs
N_T	Set of dispatch intervals
N_J	Set of DGs
N_B	Set of dispatch intervals when the ship is at berth

Parameters

$\chi_v^{\min} / \chi_v^{\max}$	Minimal/maximal speed ratio
$\chi_D^{\min} / \chi_D^{\max}$	Minimal/maximal distance ratio
$v_s^{\text{rate}} / D_s^{\text{rate}}$	Rated ship speed/cruising distance
Δt	Unit dispatch period
α_{PL} / β_{PL}	Parameters between the ship propulsion loads and speed
R_T	The thermal resistance of the building shells
$CAIR$	Heat capacity of the air
$\theta_{IN}^{\min} / \theta_{IN}^{\max}$	Minimal/maximal indoor temperature
$k_{GAS}^f / k_{DG}^{f,j}$	Unit fuel cost for CCHP unit/DGs
$k_{GT}^m / k_{DG}^{m,j} / k_{PT}^m$	Unit maintenance cost for CCHP unit/DGs/PtC unit
$k_{AD}^m / k_{BS}^m / k_{TS}^m$	Unit maintenance cost for BS/TS/power transfer between AC and DC side
$k_{DG}^{u,j}$	The unit start-up cost of the DGs
KCl	Unit power purchasing cost from the land
$k_{GT}^e / k_{DG}^{e,j}$	Unit emission cost for CCHP unit/DGs

$P_{DG}^{min,j} / P_{DG}^{max,j}$	Minimal/maximal power outputs of DGs
$R_{DG}^{min,j} / R_{DG}^{max,j}$	Power ramp down/up limits of DGs
$T_{DG}^{on,t,j} / T_{DG}^{off,t,j}$	The on/off time of DGs before the current period
$T_{DG}^{u,j} / T_{DG}^{d,j}$	The minimal up-/down- time for the DGs
$P_{GT}^{min} / P_{GT}^{max}$	Minimal/maximal power outputs of CCHP unit
$P_{PT}^{min} / P_{PT}^{max}$	Minimal/maximal power outputs of PtC unit
η_{TE} / η_{PC}	The thermal efficiency of the CCHP unit/PtC unit
η_{AD} / η_{DA}	The efficiency of the converter from AC to DC/ DC to AC
$P_{BC}^{max} / P_{BD}^{max}$	Maximal charging/ discharging power of BS
T_{BS} / T_{TS}	The decay rate of BS/TS
$P_{TC}^{max} / P_{TD}^{max}$	Maximal charging/ discharging power of TS
η_{BC} / η_{BD}	Charging/discharging efficiency of BS
η_{TC} / η_{TD}	Charging/discharging efficiency of TS
$E_{BS}^{rate} / E_{TS}^{rate}$	The energy capacity of BS/TS
$\chi_{BS}^{min} / \chi_{BS}^{max}$	Minimal/maximal state of charge of BS
$\chi_{TS}^{min} / \chi_{TS}^{max}$	Minimal/maximal state of charge of TS
P_{CI}^{max}	Maximal purchasing power from the land
$P_{AD}^{max} / P_{DA}^{max}$	Maximal power transfer from AC to DC/DC to AC
Variables	
$\dot{V}_s / D_s^t$	Ship cruising speed/distance
$P_{PL}^t / P_{EL}^t / P_{TL}^t$	Ship propulsion/service power/thermal loads
$\theta_{IN}^t / \theta_{OUT}^t$	Indoor/outdoor temperature
P_{TG}^t	Total thermal generation
C_{FU}^t / C_{OM}^t	Fuel/maintenance cost
$C_{ST}^t / C_{CI}^t / C_{GE}^t$	Start-up/power purchasing/gas emission cost
$P_{GT}^t / P_{DG}^{t,j}$	Power outputs of CCHP unit/DGs
P_{BC}^t / P_{BD}^t	Charging/discharging power of BS
P_{TC}^t / P_{TD}^t	Charging/discharging power of thermal storage
P_{AD}^t / P_{DA}^t	Power transfer from AC to DC/ DC to AC
P_{PT}^t	Power consumption of PTC unit
P_{CI}^t	Purchasing power from the land
$U_{DG}^{t,j}$	Binary state for DGs, with 0 denotes the DGs are off
P_{GO}^t / P_{PT}^t	Thermal outputs of CCHP unit/PTC unit
E_{BS}^t / E_{TS}^t	Energy stored in BS/TS
P_{EP}^t / P_{TP}^t	Power and thermal outputs of the PV system

1.) Introduction

1.1 Motivation

Along with the development of renewable DtGs, communication, and energy storage technologies, *etc.*, the current energy supply systems and associated information or communication infrastructures and so on, are undergoing a radical transformation, which has significantly increased the couplings and interactions of multiple energies from the national or community scale down to building level [1]. To achieve the objectives of the cost/emission reduction, energy savings, and coordinated scheduling of various energy types, countries all over the world are making great efforts to develop comprehensive energy supply networks for integrating multiple energy sources [3]-[4]. Under this circumstance, the multi-energy system both land-based and mobile, whereby power, heat, gas, cooling, *etc.*, optimally interact with one another by a cluster of distributed generations, heterogeneous energy storage, is an emerging paradigm. It is essential for increasing the overall economic, technical and environmental performance, relative to “classical” energy systems, whose sectors are treated “separately” [1], [5]. For example, Nanyang Technological University, Singapore, is building an offshore MEMG that integrates multiple RES such as solar, wind and natural gas, as well as energy storage devices [6]. Denmark has launched an ambitious collaboration project with China on MEMGs that will increase the proportion of green energy in power system; China, on the other hand, is studying how the individual components such as heat pumps and fuel cells (FCs) can be controlled so that the conversion to heat or cooling is as smooth as possible, and so that the wind energy is utilized as efficiently as possible [7]-[8].

In multi-energy systems, the power and thermal energy (heat/cooling) are more closely related both in generation and consumption. Thermal energy (heat and cooling) is hard to transmit as there would be huge heat transfer loss but the easy to store, as the envelope of the building, the pipelines have the intrinsic nature of heat isolation. Nonetheless, the power has the opposite property, that is, it is easy to transmit but hare to store. In this regard, they are complementary in terms of reservation and transmission. Moreover, the ever-growing demands of district power heat/cooling and the production of RES make it is more and

more inevitable to achieve the optimal integration and interaction of all types of energy. Nowadays, the multi-energy systems have received significant research attention especially for the coordination of the power and thermal energies under diverse uncertainties [9]. As a new diagram with different structure and units, how to optimize the energy flows in the multi-energy systems, to realize the economical, reliable multi-energy coordination contribute huge research significance.

1.2 Objectives

The research objectives throughout this thesis are to provide methods for the economic and reliable operation of the different multi-energy systems, in order to reduce the overall planning and operating cost, increase the penetration level of renewable energies, as well as fulfill the reliable system operation. The specific research objectives of this thesis lie in the following aspects:

1) For the land-based multi-energy systems, *i.e.*, MEMGs and RMEMGs, *etc.*:

First and foremost, this thesis aims to provide an optimal system-wide coordinated dispatch method for MEMGs in both the grid-connected and islanded modes. In this regard, the different pricing schemes and energy properties are made full use of to reduce the system operating cost as well as enhance the holistic energy utilization efficiency.

Second, by taking advantage of different energy properties, the diverse uncertainties from RES, multi-energy demands, transaction prices are handled through the two-stage SO method. Thus, the system reliability is guaranteed with minimal operating costs.

Finally, in addition to the operation, the optimal planning for all the inner units in the multi-energy systems, such as the heterogeneous DtGs and ES are also investigated to further reduce the project net present costs. Then, the investor for multi-energy systems could get references for deploying all the units with economic and reliable options.

2) For the mobile multi-energy systems, *i.e.*, the MEP microgrids, *etc.*:

On the one hand, this thesis aims to provide a multi-objective coordinated energy dispatch and voyage scheduling method for the MEP-integrated MEP microgrid. Then the gas emissions and operating costs are reduced at the same

time.

On the other hand, given the emerging hybrid AC/DC system structure, the robust coordinated energy dispatch and voyage scheduling methods are proposed for more reliable and economic ship operations.

Furthermore, this thesis aims at providing beneficial references for the current multi-energy systems of different forms with coordinated thermal and power supply, long-term demand-side management (DSM) contracts and increasing RES penetration levels.

1.3 Major Contributions of the Thesis

The major contributions of this thesis can be summarized as follows:

a) A system-wide optimal coordinated energy dispatch method is proposed for the MEMG in both the grid-connected and islanded mode. The system dispatch flexibility is highly enhanced with the introduction of TS and PtC units.

b) The temporally coordinated system dispatch model is presented for a more economical, reliable and robust system operation under diverse uncertainties from RES, power demands and transaction prices.

c) A two-stage stochastic placement method for heterogeneous DtGs in the MEMG under RES uncertainties is proposed. Apart from the DtG size and location planning, the type and investment year optimization is also considered for a more comprehensive and flexible DtG placement. Finally, the optimal project cost or profit can be obtained.

d) A new stochastic HES deployment model in the grid-connected RMEMGs is proposed. Except for the traditional size and location planning, the investment phase selection is also considered for a more comprehensive and flexible HES deployment. This is because there is an annual load growth. Besides, the DSM for multiple energies is incorporated, given its advantage in flexibilizing system operation and reducing energy bills. Finally, for the thermal system, the DSM in terms of specific thermal modeling for the local residential buildings is built with thermal dynamics and thermal inertia combined.

e) A MES microgrid that combines the CCHP unit, TS, PtC unit and multi-energy photovoltaic (MEP) system is studied. Then the augmented ε -constraint method (AUGMECON)-based multi-objective coordinated voyage scheduling and energy dispatch method for MES microgrid is proposed to simultaneously

optimize the ship operating cost and gas emissions.

f) A hybrid AC/DC MES microgrid with flexible voyage and thermal loads is proposed. The cold ironing technique is introduced to support the ship when it is at berth. Then a coordinated operation method for voyage scheduling and energy dispatch is presented, which deals with the uncertainties from solar power and thermal energy as well as multi-energy service loads through a two-stage RO approach.

g) Linearization methods are used to convert all the above models to the MILP problem considering the specific property of the multi-energy system model, which can then be solved efficiently by commercial solvers such as Cplex or Gurobi.

1.4 Organization of the Thesis

This thesis stands on the point of the multi-energy systems and aims to optimal plan and operate all the related units based on the multi-energy characteristics. The rest of this thesis is organized as follows. Chapter 2 lists the literature survey. Chapter 3 presents the system-wide optimally coordinated energy dispatch for the MEMGs in grid-connected and islanded modes. Chapter 4 introduces the temporally coordinated optimal operation of a MEMG Under diverse uncertainties; Chapters 5 and 6 present the optimal deployment of heterogeneous DtGs and HES in the MEMGs under diverse uncertainties, respectively. Chapter 7 covers the multi-objective coordinated energy dispatch and voyage scheduling for a MES microgrid. Chapter 8 deals with the robust coordination of hybrid AC/DC ship operation. Chapter 9 is the conclusion of this thesis as well as the introduction of future work. Chapter 10 gives the appendix.

2.) Literature Survey

In the literature, a number of research efforts have been put on the planning and operation of the current energy systems, but when it comes to the operation flexibility enhancement, optimal coordination of multiple energies, diverse uncertainties handling, *etc.*, some issues in the land-based or mobile multi-energy systems still remain open.

Firstly, **in the operation flexibility enhancement of the land-based multi-energy systems**, when supplying the multiple energies, most of the research works focus on the operation of individual CCHP plants, which can generally fall into two operation strategies, *i.e.*, following power load (FPL) and following heat load (FHL) [10]-[17]. Ref. [10] works on the FPL/FHL switching strategies to enhance the integrated performance of energy consumption, operation cost and CO₂ emissions of the CCHP plants. In [11] and [12], operation strategies for the CCHP plants are designed in terms of IF-THEN conditions and corresponding evaluation criteria. With a ground source heat pump, ref. [13] configures a CCHP-organic Rankine cycle system and analyzes its performance in the cost savings, gas emission reduction, and system efficiency improvement. In [14], the matrix modeling approach is introduced to optimize the input and output power of the CCHP plant as well as its capacity. Smith *et al* [15] propose a hybrid strategy to minimize the excess power and thermal energy produced by CCHP plants. In [16] an improved operational strategy for CCHP plants based on the following-power-load strategy is introduced to minimize the energy consumption for a building. Li *et al* [17] model a CCHP plant to investigate its benefits in reducing the operating cost, CO₂ emissions, and energy consumption, then based on the conventional strategies, five operational strategies are employed for the dispatching.

Though so much work has been done on the optimal operation of the individual CCHP plants, yet the coordinated operation of the CCHP plant with other DtGs at a system level was not considered in the above works. In this regard, the multi-energy coordination performance at the system level should be further explored.

To supply multiple energies at the system (*e.g.*, microgrid) level, traditional research works are mostly on the single-energy grid-connected microgrid [18]-

[19], which do not integrate multiple energy resources. The coordination of the CCHP plants with other DtGs in supplying multiple energies is mainly based on the grid-connected microgrids [20]-[21]. Ref [22] investigated the coordination of CCHP plant and photovoltaic prosumers to minimize the operation cost in a grid-connected microgrid. In [23], the RO method was employed to coordinate the CCHP plant with DGs of uncertain output to handle their intermittency. Ref [24] proposed an integrated multi-objective dispatch model for the microgrid to minimize its net operation cost and gas emissions. In [25], an optimization model for the operation and design of microgrid satisfying power and heat demands was established considering the uncertainty of renewable energies. In our recent research work [26], dynamic dispatch of grid-connected MEMGs considering the opportunity profit from the electrical energy storage was studied. When it comes to the multi-energy dispatch of the islanded microgrids, few research works have been done. Yet, most of the islanded microgrids research still focuses on the single energy dispatch, *i.e.*, power dispatch [19],[27]-[29]. In practice, multi-energy management of the islanded microgrids is quite necessary especially for remote areas like the Semakau Island microgrid in Singapore [6]. Without the grid as the backup, operation objectives for islanded microgrids can be rather different from the grid-connected ones. Ref [30] is one of the few studies, which proposed a multi-objective optimization model for the minimization of the fuel cost and gas emission.

All the above works dispatch the individual CCHP plant via FPL/FHL or hybrid of the two strategies, while at the system level, the CCHP plant typically operates under the FHL strategy in grid-connected microgrids since the power imbalance can be compensated by the utility grid. For islanded microgrids, the FPL strategy for the CCHP plant is preferred in that power system requires a precise power balance all the time, while the imbalance of heat/cooling for short periods is acceptable [20]. However, under all the above strategies, power, heat/cooling outputs of CCHP plant are highly coupled and dependent on one another, which makes the operation of microgrid not flexible enough, and potentials of CCHP plant in cost reduction and energy efficiency enhancement are not fulfilled.

In practice, the TS (heat storage tanks or ice storage tanks) and PtC units (electric boiler or electric chiller) can be introduced to enhance the dispatch

flexibility and coordination degree of multiple energies [31].

Secondly, **for handling diverse uncertainties in the operation of land-based multi-energy systems while maintaining the system reliability and economy**, in the above literature [30]-[31], the multi-energy coordination is based on the deterministic day-ahead operation, but the uncertainties of the RES, power loads and transaction prices are ignored, which is not practical for application. Then, to handle uncertainties from RES outputs and power loads, Guan *et al* [32] employ the SO method to minimize the power and natural gas cost at the building level. In [33] and [34], the RO based scheduling methods for the CCHP plants are proposed to handle the system uncertainties. The research work in [35] conducts a two-stage operation to smooth out the RES fluctuations and follow the load variations; at the first stage, the deterministic operation is employed to set the reference for the second stage rolling process. However, in the above existing works, different properties of power and thermal energy are not fully considered and coordinated at the system level. Further, the refs [10]-[35] ignore the power network's constraints, so the operation decisions may lead to security violations in some cases.

To guarantee the system operating security, the online optimization of the energy networks, like the real-time power flow is essential. In this regard, ref. [36] presents an overview of the recent studies on real-time power flow of the power system under wind energy penetration and provides an essential review of the major advancements in this area. Excellent works have been done in the real-time power flow area and provide insightful references for the secure system operation. On top of this, other energies can be further integrated for coordinated and comprehensive system operation.

Besides, apart from off-line dispatch methods which are based on classic algorithms, real-time optimal power flow methods have also been proposed in the literature [36]. The study in [37] develops a real-time active-reactive optimal power flow method to simultaneously optimize the wind active power curtailment and reactive power dispatch as well as discrete reference values of slack bus voltage. Besides, a novel reconciliation algorithm is proposed to converge the real-time mixed-integer nonlinear programming problem. Authors in [38] propose a two-phase, *i.e.*, prediction phase and realization phase, solution approach to solve the large-scale complex real-time power flow optimization

problem under the penetration of renewable energies. Ref. [39] proposes a novel sensitivity-based approach for simulating local controllers in the distribution network. This approach improves the computational performance of the power flow model and is of practical value for real-time applications. While such real-time optimal power flow techniques are promising, they have not been applied in MEMG dispatch problems.

Thirdly, **for the optimal planning of all the inner units such as heterogenous DtGs and ES in multi-energy systems.** The system planning can be regarded as the extension of its operation. This is because, in the system operation, the type, size, location, etc., of all the inner units are assumed as predefined. With those fixed decisions, the only thing that decision-makers do is to obtain dispatch decisions. However, for the system planning expect for the dispatch decisions in the operation, the investment decisions should also be obtained. In this sense, the planning problem is more complicated than the operation one. In the literature, the planning scheme can be mainly categorized into the deployment of the DtGs and HES. **For the optimal deployment of DtGs,** its placement in the energy network is critical for the system techno-economic performance [40]-[41]. Specifically, DtG placement refers to deciding their type, location, size, investment year, generation mix, etc. In the literature, the DtG placement has been optimized for the purpose of power loss minimization [42], reliability enhancement [43], system voltage stability improvement [44] and cost-benefit balancing [45], etc. Ref. [46] proposes a coordinated short-term scheduling and long-term expansion planning method for DtGs in a microgrid (MG) for minimization of annual cost and pollution from the combustion processes. Ref. [47] firstly decides the locations for the DtGs by identifying the loss sensitivity index of each bus, then determines their size based on the cost-benefit analysis. Ref. [48] presents an optimization model that determines the optimal DtG size and generation mix for an isolated MG. All of the above studies in [42]-[48] assume that there is perfect generation information for the power outputs of wind turbines (WTs) and PVs. However, the RES outputs are stochastic in nature and their uncertainties should be tackled for a robust system planning solution, so as to avoid violation of the operational limits if the significant uncertainties occur.

To handle the uncertainties in the DtG placement, Ref. [49] employs the RO

method to maximize the system long-term cost under the RES uncertainties. Ref. [50] presents a model for DtG placement in a MG with uncertain physical information and the model is then solved by the RO method. Ref. [51] describes a DtG placement method for minimizing the cost for supplying a remote telecommunication station exclusively by the RES, and the RO method is also used. Ref. [52] compare the stochastic and RO methods in the optimal DtG placement scheme under the objective of minimizing system annualized cost. The simulation results show that the RO method tends to be conservative over a long planning period than the stochastic method and highly depends on the predefined uncertainty budgets.

It is worth noting that the DtG placement in [42]-[52] only focuses on the single-energy microgrids (SEMGs), *i.e.*, the MG with only the electricity. However, with the fast development of the MEMGs [1], multiple energy carriers such as the power and thermal energy are interacted and coordinated by the heterogeneous DtGs. Thus, the above traditional separate planning methods would not be enough for the long-term planning of interdependent energy systems. Further, “synergies” among the heterogeneous energies in the MEMGs would introduce an additional energy supply degree of freedom, in this regard, the system cost/profit would be potentially reduced/increased.

In the related literature, ref. [53] presents a reliability-constrained optimization approach to determine the size of CCHP plants. The RES uncertainties are handled by the SO method in the operation. Ref. [54]-[55] obtain the best DtG alternatives and control strategies by considering the uncertainties in a long-term timeframe based on the decision theory. Nonetheless, for the DtG placement research in [54]-[55], the distribution network power flow model is not considered, hence the planning decisions may not be viable for practical application. In Ref. [56], a DtG planning method for a residential MEMG with the RES, BS and demand response scheme is proposed. The stochastic model takes the RES intrinsic fluctuation behaviors into account. Ref. [57] propose a multi-objective optimization model and an evidential reasoning approach to solve the DtG sizing problem. In this model, the interval variables are introduced to tackle the RES uncertainties. However, in the above research work [56]-[57], the DtG placement only considers the power-related DtGs, while the placement of other energy-type of DtGs such as the CCHP units is not studied sufficiently,

that is, their placement is pre-defined. Consequently, “synergies” among heterogeneous energies have not been optimally achieved in their studies.

Moreover, most of the above works focus only on determining the size and location of DtGs [42]-[52], [53]-[57], but a more comprehensive study on simultaneously deciding the DtG type as well as investment year under the multi-energy coordination scheme has not been studied sufficiently yet. The DtG type and investment year optimization are also critical for MEMGs for the following reasons:

1) Prior to the project, choosing the right types of DtGs is important because different types of DtGs have different economic and technical properties. The DtG type optimization would bring a new degree of freedom for the DtG placement and potentially reduce/increase the system cost/profit.

2) For the investment year optimization, Ref. [42]-[52], [53]-[57] haven't taken the annual load growth [54] into account, and they only consider the one-time DtG investment at the beginning of the project. However, with the practical ever-growing loads, their DtG placement decisions would probably be far from enough. Besides, the investment year optimization will bring more flexibility for the DG placement and hence further reduce the system cost. In the literature, few studies have considered the investment year optimization: Ref. [58] proposes a tri-level expansion planning framework for an isolated MG under uncertainty, and Ref. [59] presents a stochastic multi-objective approach for optimal dynamic planning of interconnected MGs under uncertainty. Though the investment year is considered, the studies in [58]-[59] are still limited in the SEMG research scope. To sum up, for the DtG placement, it is necessary to consider different DtG investment phases and multiple DtG types in the MEMGs.

On the other aspect, **for the optimal planning of ES**, currently, it focuses mainly on the EES. Ref. [60] formulates an optimal placement model for the EES in a power network to shift loads and minimize the generation cost. In [61], a cost-effective method for EES sizing in the distribution system is proposed. This method decides the optimal EES capacity with regard to its operating cost under different RES penetration levels. Ref. [62] presents a model for integrating EES in a microgrid at the minimum cost, to analyze its potential advantages with different conceivable regulatory services. Ref. [63] determines the optimal EES size in the RES-integrated power system to get the minimal system operating

cost. However, in the above research, the EES only facilitates RES integration without considering the system-wide operation. Hence, their deployment solutions may not be optimal from the system perspective. Therefore, ref. [64] studies the EES deployment in a microgrid based on cost-benefit analysis. The time series and neural network techniques are used to forecast the wind speed and solar radiations, respectively. In [65], to determine the optimal EES size and location, the probabilistic load model is adopted to incorporate more load scenarios. The above research has utilized the deterministic optimization method by simply assuming that there is perfect information about the RES generation and end-user energy consumption. Nonetheless, the RES and energy consumption are intrinsically uncertain, which makes the solutions from the deterministic method unreliable.

In the literature, to deal with system uncertainties in the deployment of ES, various approaches are employed. In [66], the optimal EES deployment is obtained by the deterministic optimization tool with the uncertainties addressed by the model predictive control method. Ref. [67] studies the optimal EES sizing problem to minimize the annual cost by a bi-level programming method. The uncertainties are managed by the system reserve. Though the uncertainties are considered, both works still use the deterministic models, which fail to provide a reliable or robust deployment plan. Regarding this, the stochastic and robust optimization approaches have been employed. Authors in [68] propose a stochastic optimization method for EES sizing in a wind-diesel-based isolated grid. In [69], the optimal EES sizing problem in microgrids with highly penetrated wind energy is solved by the unit-commitment-based RO method. Authors in [70] investigate an efficient cost-reliability optimization method to obtain the optimal EES location and size in a microgrid considering the DSM for electricity. To handle the uncertainties from WTs, the stochastic optimization method is utilized. Ref. [71] introduces the SO approach for EES deployment in remote systems, to reduce the system operating cost. Authors in [72] propose a joint robust capacity optimization method for EES and DtG to save the operating cost under the fluctuating RES outputs. For the long-term planning research, the worst-case-oriented RO method tends to be too conservative compared with the stochastic one, and highly depends on the predefined uncertainty budgets.

Most of the existing research work focuses only on the deployment of EES in

the power system. However, in the multi-energy systems, especially for RMEMGs, such as smart buildings, intelligent homes, *etc.* [73], which require plenty of thermal demands. In this regard, to effectively enhance the holistic energy efficiency and operation flexibility, the EES deployment is shifted to HES deployment in the RMEMGs, with the uncertainties from only the power system to multi-energy systems, such as the outdoor temperature or thermal demands [74]. However, in the literature, very limited research work has been done in this area. Ref. [75] plans the HES size aiming to minimize the project cost and gas emissions by a two-stage solution method. The first stage uses the genetic algorithm to solve the planning problem and the second stage applies the MILP solvers to get the operating solution. In [76], both the system structure and HES capacity configuration are studied in a planning framework of the smart microgrid. Then, a MILP based planning model was proposed to minimize the total operating cost. The study in [77] proposes a novel optimal design model for a microgrid that involves HES. To reduce the computational burden, the model uses the typical design days to represent the yearly horizon. Though the above research investigates the HES deployment, the network constraints and the effects of multi-energy uncertainty sources are totally ignored. In this regard, the system reliability cannot be guaranteed, and their solutions are not practical for the real application.

Besides, as the DSM is a promising and effective solution to support the system operation as well as save energy bills for residents, currently, there is a widespread installation of the smart meters in residential buildings with a long-term DSM contract [73]. Compared with the electricity, thermal energy (heat or cooling) gets higher inertia, as residents can be comfortable within a tolerable temperature range [78]. In this sense, though the DSM for electricity is widely studied in areas such as power grid transmission planning [79], RO [80], low-carbon sustainability [81], *etc.*, its coordination with the thermal energy is rarely studied especially for the HES deployment of RMEMGs.

Furthermore, most of the existing deployment works, either for EES or HES, only considers the one-off installation at the beginning of the project as they ignore the increasing load growth. Thus, their deployment decisions would be probably far from enough, given the annual load growth in reality [82]. In this regard, the multi-phase deployment, in which the HES can be invested at

different years of the project, is critical for the more comprehensive and flexible planning research.

On the operation of the mobile energy system, that is, mainly on the ship operation, at present, the worldwide concern about air quality and fuel consumption has led to stricter regulations in the shipping industry [83]. Consequently, the increasing attention both in academia and industry has been paid for a more efficient and clean onboard energy system [84]. Refs. [85] and [86] propose an optimal planning and dispatch model for a drilling vessel. Based on the model, it mainly decides the optimal capacity and dispatch strategy for EES. Ref. [87] presents a method for finding the optimal EES dispatch and analyzing the economy of the ship system with PVs via the interval optimization method. Ref. [88] obtains the size and dispatch of EES in a cruising ship with PVs installed based on the adaptive multi-clustering algorithm. Ref. [89] proposes an approach for determining the optimal size and dispatch of PVs, DGs, and EES. The aim is to minimize ship investment cost, fuel cost, and gas emissions. Ref. [90] solves the sizing problem of a merchant marine vessel and determines the appropriate configuration of PVs and ESS in an optimal and reliable manner.

The above research works only consider the ship energy dispatch and when the ship cruising, it follows the presumed fixed cruising speed and distance. Nonetheless, the ship voyage can also be scheduled simultaneously for an efficient energy dispatch [91]. This is because, under the obligation of punctual arrival, the ship cruising speed can be varied in a secure range. As the shipping speed is driven by the propulsion loads, the ship energy dispatch will also be affected. Regarding the voyage scheduling, a few works have been done in the literature. In [92] a joint voyage and power dispatch method of a cruising ship with only DGs are analyzed. It aims to minimize the operating cost by limiting the emissions and guaranteeing the operational constraints. Based on [92], Ref. [93] proposes an optimal power management method to reduce the fuel cost of a cruising ship with newly introduced EES under the predefined emission limits. Ref. [94] obtains the minimal ship operating cost by effectively scheduling the power sources and adjusting the propulsion loads by varying the ship's speed under the pollution constraints. Ref. [95] present an optimal power and voyage management method to obtain the minimal fuel cost under the gas emission

limits. The particle swarm optimization (PSO) method is utilized to obtain the results. Though the voyage scheduling is considered in their works, reducing the gas emissions should be a continuous effort, and merely confining the emission below a value does not suffice to address the air pollution problem. Besides, as the reduction of gas emissions and operating cost can be conflicting goals, multi-objective optimization methods such as non-dominated sorting genetic algorithm II (NSGA-II) can be utilized as [96]-[97]. In both studies, the optimal energy dispatch is obtained to reduce the cost and emissions at the same time.

Furthermore, the above ship operation research only investigates the dispatch of power energy. However currently, with the forecasted revenue of cruise tourism rising sharply from 23.3 G\$ (2007) to 57 G\$ (2027) worldwide [12], there is an increasing trend to design the cruise ships larger and larger for the growing business. The cruising ship is basically a MES (mobile) microgrid, where the multiple energies are to be served simultaneously. Thus, it is essential to study the coordination of heterogeneous energies to reduce the operating cost and gas emissions in the cruising ships.

For the handling of the diverse uncertainties in the MEP with the emerging AC-DC configuration, it can be seen that in [85]-[97], all the above ship power systems assume a pure AC configuration, while in reality, the onboard power loads, such as data centers, electronic devices, lighting appliances, etc., and energy storage are all of the DC types. Therefore, there are a huge number of AC-DC/DC-AC converters in the ship systems, which may result in low system efficiencies and high system costs.

In addition, given the stricter regulations from Marine Pollution Protocol, the shipping industry is pushing for zero-emission renewable energies [86]. However, their uncertainties will compromise the MES's operating performance. In the literature, to solve the operational problems under uncertainties, the SO and RO methods have been widely adopted. For the SO, it requires generating an enormous number of scenarios to deal with the probabilistic constraints. However, it is generally hard to accurately characterize the probabilistic distributions of the uncertain variables, and the corresponding computing burden is excessively high. On the other hand, the RO seeks to identify the worst case in a pre-defined uncertainty set to immune against any uncertainty

realization. It is gaining increasing research interest. The RO only relies on uncertainty sets with the low computational burden to achieve the full robustness. Currently, the RO has been widely used in power and logistics systems, but little work is done for the AC/DC multi-energy ship systems.

Last but not least, as **for the optimization methods of the planning and operation problems**, mostly the evolutionary algorithms like the Genetic Algorithm or PSO [9]-[12], [18]-[20], [32], [46], [55], [75], [95], [96], *etc.*, are employed given the nonlinear nature of the problems. However, these algorithms are computationally demanding especially when the problem size is high. Further, they often suffer from issues such as inconsistent solutions and difficulty to rigorously converge. Since the new competitive environment in the power system requires more accurate and efficient tools to support decisions for the resource dispatch, a more efficient solution process and solution quality are needed.

Based on the current research status, it can be seen that:

- 1: Multi-energy coordination is essential for cost-savings, emission reduction, energy efficiency improvement, *etc.* However, most of the current research works deal with the energy flow in the single energy system.
- 2: Enhancing the operating flexibility could provide another degree of freedom for the multi-energy supply. However, the operation mode of current research works on multi-energy systems is of rather limited flexibility.
- 3: Handling system uncertainties brought by renewable energies, multi-energy loads, outdoor temperature, *etc.*, would guarantee a more reliable and practical operation scheme. However, most of the research work on the multi-energy system operation is deterministic, and further, among the stochastic research works, only the uncertainties from the power systems are considered.
- 4: For the mobile multi-energy system, the voyage scheduling and energy dispatch can be optimized concurrently to save the cost and reduce the emissions, however, current research works only investigate the energy power dispatch problem.

To sum up, it is essential to obtain the optimal planning and operation decisions for the multi-energy systems in different forms under diverse uncertainties for system reliability, cost-savings, and emission-reduction.

3.) Optimal Coordinated Energy Dispatch of Multi-Energy Microgrids in Grid-Connected and Islanded Modes

3.1 Introduction

For land-based multi-energy systems, currently, the MEMGs are the research focus. At the power distribution level, the MEMG in which gas, electricity, heat, cooling and so on can interact with each other, have high energy efficiency in both the grid-connection and islanded mode [97]. The MEMGs make significant contributions in supporting ancillary service to the system, reducing operation cost/gas emissions, improving power quality and enhancing local reliability and so forth [98]. Besides, microgrids can behave like a single flexible entity for the utility grid to dispatch and control.

When supplying the multiple energies in the grid-connected mode, as there is a reliable power supply from the utility grid, the FHL mode is used for the CCHP plant to satisfy the system heat/cooling demands. On the contrary, given the thermal inertia, the FPL mode is mostly utilized for the system multi-energy generation in the islanded microgrid without extra power support [10]. Those fixed modes impair the multi-energy dispatch flexibility. Further, in the literature, more research is done on the grid-connected microgrids, however, the microgrid in islanded mode is equally essential.

In this chapter, a comprehensive MEMG that includes the CCHP plant, EES (battery storage), PtC units (electric chillers and electric boilers), TS (heat storage tank and ice storage tank), WTs, PVs, and the FCs is studied. The heat/cooling storage tanks are utilized to decouple the inflexible operation strategies of the CCHP plants, then its heat/cooling and power outputs can participate in the day-ahead energy market. The conversion units, *i.e.*, electric boilers (EB) and electric chillers (EC), which transfer power to heat/cooling, can further enhance the coordination of different energies. Then to obtain the higher dispatch flexibility and energy utilization efficiency, the system-wide optimal coordinated dispatching models under both the grid-connected and islanded modes are proposed. The objectives of both models are to minimize the net operation costs subject to the operational limits. Besides, the nonlinear models are linearized to the MILP ones for high solution efficiency. Finally, typical scenarios and comparisons with the traditional dispatch models are used to fully

verify the effectiveness of proposed dispatch models.

3.2 Typical Structure of the Multi-Energy Microgrids

Though there is a huge difference between the utility grid and microgrid in the types of generation units, yet they are quite similar to each other in the planning and operation. Thus, the investigation on the operation of microgrids is essential for the research of the grid dispatch and control. Figure 3-1 shows the typical structure of a MEMG which contains RES-based generators (WTs and PVs), EES, CCHP plants, FCs and heat/cooling storage tanks.

The voltage for the main distribution grid is 10kV and for the microgrid, it is 0.38kV, the microgrid communicates with the main grid via the transmission line.

Figure 3-1. The Typical Structure of a MEMG

It can be seen from Figure 3-1 that there are different energy flows from the energy generation side to the energy consumption side, *i.e.*, gas, electricity, heat, and cooling. The fuel for the CCHP plants and the FCs is natural gas; The CCHP plant is the core unit of supplying multiple energies and along with other DtGs and storage devices, it could supply the energy demand for the MEMG; There is a switch between the utility grid and microgrid: when the switch is on, the microgrid operates in the grid-connected mode, while off, it operates in the islanded mode [1], [99]-[101]; The utility grid can supply powerful and reliable voltage and frequency support for the microgrids when it operates in the grid-connected mode; An energy management system is installed whose basic function is to help dispatch all the DtGs and record their input and output status.

All the operational data needed can be collected/provided by the inner smart meters. The performance for the microgrid energy management concludes two folds, *i.e.*, the technical performance and economic performance. The technical performance is mainly the level of the system voltage and/or power; the economic performance refers to the system's net operating cost or profit.

3.2.1 Distributed Generation Units (DtGs)

The components modeling of the MEMGs mainly focuses on their ON/OFF statuses and generation outputs. The detailed modelings are given below.

Note that the MTs (or CCHP plants), EBs, FCs, and ECs, *etc.*, are all in the small sizes, flexible control fast start-up/shut-down rates. Thus, they can be regarded as dispatchable generation units (CG). The WTs and PVs whose power outputs are uncertain/volatile are categorized as the non-dispatchable generation units [9], [26].

3.2.1.1 Combined cooling, heat and power (CCHP) plants

Among all the DtGs, the CCHP plants generate power and thermal (heat or cooling) energy at the same time by a prime mover with a heat recovery system, they play a key role in solving the problem of low energy efficiency of separation production systems [1].

Typically, the CCHP plants consist of three parts: a micro-turbine (MT), an absorption chiller and a heat recovery unit. The MT consumes natural gas to generate power, and at the same time, the waste heat can be utilized by the heat recovery unit or absorption chiller to produce heat or cooling energy [26], [103]. In this regard, the energy utilization efficiency can be greatly improved.

In this chapter, Capstone's MT C65, which has a high international market share, is used as the reference for the CCHP plant modeling (there are different types of MTs). The relation between its power outputs and electrical efficiency can be modeled as [38]

$$\eta_{MT}^t = 0.076 \left(P_{MT}^t / 65 \right)^3 - 0.310 \left(P_{MT}^t / 65 \right)^2 + 0.415 \left(P_{MT}^t / 65 \right) + 0.107 \quad (3-1)$$

The corresponding heat and cooling outputs are

$$Q_{MTH}^t = \eta_H COP_H P_{MT}^t (1 - \eta_{MT}^t - \eta_L) / \eta_{MT}^t \quad (3-2)$$

$$Q_{MTC}^t = \eta_C COP_C P_{MT}^t (1 - \eta_{MT}^t - \eta_L) / \eta_{MT}^t \quad (3-3)$$

Both the heat and cooling energy come from the waste heat. Thus, they share similar properties. If the waste heat is not recovered, the MT operates only for the power generation [10], [14]-[15].

It should be noted that for simplicity, the electrical efficiency of the CCHP plants can be also a constant [26].

3.2.1.2 Fuel cells (FCs)

The FCs could convert the energy stored in O_2 and H_2 into the pollution-free electrical energy by an electrochemical process. Due to their high electrical efficiency, the waste heat from the FCs is not recovered [26], [104]-[106].

Usually, the proton-exchange membrane fuel cell IFC PC-29 powered by natural gas is utilized, the electrical efficiency can be given by Eqs.(3-4).

$$\eta_{FC}^t = -0.0023P_{FC}^t + 0.674 \quad (3-4)$$

The same as CCHP plants, the electrical efficiency of the FCs can be also a constant [26], [106]-[107].

3.2.2 Heterogeneous Energy Storage (HES)

Energy storage can decouple the energy generation from its consumption and reduce the imbalance between energy supply and demand [25], [29]. For the practical application in MEMGs, the HES system mainly consists of the EES, and TS (heat storage or cooling storage).

3.2.2.1 Electrical energy storage (EES)

Currently, the EES including the power-type like supercapacitors and the energy-type like the electrochemical batteries is intensively investigated. The power-type energy storage is mostly utilized to alleviate the effects of fluctuating outputs of renewable energy generators on the power system operation; the energy-type ES is mainly used for peak shaving in the energy management field [9], [34].

For the day-ahead (or any other long time) dispatch scheme, the energy-type storage is applied [26], [60].

The power and energy relationship of the EES is as Eqs.(3-5)

$$E_{EES}^t = (1 - \tau_{EES}) E_{EES}^{t-1} + (P_{EESC}^t \eta_{EESC} + P_{EESD}^t / \eta_{EESD}) \Delta t \quad (3-5)$$

3.2.2.2 Thermal storage (TS)

Under FHL/FPL strategies, the power and heat or cooling outputs of the CCHP plants are highly limited by each other, which restricts the operation of the CCHP plant in the multi-energy dispatch [26]. To decouple those inflexible operation strategies, the TS which mainly includes the heat storage tank (HST) and ice storage tank (IST) are deployed. The operating principles for the TS are like the EES. Nowadays, HST and IST have already been widely employed in different nations such as Denmark and China [7].

The power and energy relationship of TS is as follows

$$E_{TS}^t = (1 - \tau_{TS}) E_{TS}^{t-1} + (P_{TSC}^t \eta_{TSC} + P_{TSD}^t / \eta_{TSD}) \Delta t \quad (3-6)$$

3.2.3 Power-to-Thermal Conversion (PtC) Units

The PtC units mainly include the EBs (for winter) and ECs (for summer). They help to transfer the energy from one type to other types and are essential for the interaction and coordination of multiple energies.

The models for the EBs and ECs are given below [23], [107].

$$Q_{EB}^t = P_{EB}^t COP_{EB} \quad (3-7)$$

$$Q_{EC}^t = P_{EC}^t COP_{EC} \quad (3-8)$$

The PtC units use the same pipelines with the CCHP plants, which enables the system to dispatch them under the unified system model.

3.2.4 Gas Boilers (GBs)

The GBs could burn natural gas to generate heat. It is mostly used in the conventional or separate generation microgrids [25]. If their heat is put through the absorption chiller, cooling energy could be obtained. The model for the GBs is rather simple as below [108].

$$Q_{GB}^t = \eta_{GB} P_{GAS}^t \quad (3-9)$$

3.3 The System-Wide MEMG Dispatch Model

In this study, the MEMG consists of a WT, a PV, BS, a CCHP plant, a FC, an EB, a HST, an EC and an IST (the overall structure can be seen in Figure 3-1). Besides, it can be operated in both modes with regards to the switch status [26]-[28].

3.3.1 Optimally Coordinated Dispatch

The system-wide coordinated dispatch models are proposed respectively according to the different microgrid operation modes. To reflect the practical operation condition of CCHP plants and FCs, their nonlinear energy efficiency is employed in the dispatch model and the specific type of EES used is the BS.

Grid-connected mode

In the grid-connected MEMGs, the power imbalance can be compensated by the utility grid. The objective is to minimize the system net operation cost:

$$\textbf{Objective function: } \min F_G = \sum_{t=1}^N (C_F^t + C_{EX}^t + C_{OM}^t + C_{ST}^t + C_{SD}^t - C_{HC}^t) \Delta t \quad (3-10)$$

$$\textbf{Fuel cost: } C_F^t = C_{F,FC}^t + C_{F,MT}^t = [c_G (P_{MT}^t / \eta_{MT}^t + P_{FC}^t / \eta_{FC}^t)] / L_{NG} \quad (3-11)$$

$$\textbf{Maintenance cost: } C_{OM}^t = \left[\begin{aligned} &P_{EC}^t \cdot K_{EC}^{om} + P_{WT}^t \cdot K_{WT}^{om} + P_{PV}^t \cdot K_{PV}^{om} + P_{EB}^t \cdot K_{EB}^{om} \\ &+ P_{MT}^t \cdot K_{MT}^{om} + P_{FC}^t \cdot K_{FC}^{om} + (P_{ESC}^t + P_{ESD}^t) \cdot K_{ES}^{om} \end{aligned} \right] \quad (3-12)$$

$$\textbf{Start-up cost: } C_{ST}^t = \sum_{j=1}^{N_{CG}} \max(0, U_j^t - U_j^{t-1}) C_{ST,j}^U \quad (3-13)$$

$$\textbf{Shut-down cost: } C_{SD}^t = \sum_{j=1}^{N_{CG}} \max(0, U_j^{t-1} - U_j^t) C_{SD,j}^D \quad (3-14)$$

$$\textbf{Power exchange cost: } C_{EX}^t = C_{BU}^t - C_{SE}^t = c_B^t P_B^t - c_S^t P_S^t \quad (3-15)$$

$$\textbf{Revenue for supplying heat/cooling: } C_{HC}^t = C_H^t + C_C^t = c_H^t Q_H^t + c_C^t Q_C^t \quad (3-16)$$

Constraints

The operation constraints are [29], [73],[80]:

Energy balance:

$$\textbf{Power balance: } P_{WT}^t + P_{PV}^t + P_{MT}^t + P_{FC}^t + P_{BSD}^t - P_{BSC}^t + P_B^t - P_S^t = P_L^t + P_{EB}^t + P_{EC}^t \quad (3-17)$$

$$\textbf{Heat balance: } Q_{EC}^t + Q_{MTC}^t - P_{ISTC}^t + P_{ISTD}^t = Q_C^t \quad (3-18)$$

$$\textbf{Cooling balance: } Q_{EB}^t + Q_{MTH}^t - P_{HSTC}^t + P_{HSTD}^t = Q_H^t \quad (3-19)$$

For dispatchable units:

$$\textbf{Power outputs limits: } U_j^t \cdot P_{CG,j}^{\min} \leq P_{CG,j}^t \leq U_j^t \cdot P_{CG,j}^{\max} \quad (3-20)$$

$$\textbf{Ramp up or down limits: } R_{CG,j}^{\text{down}} \Delta t \leq P_{CG,j}^t - P_{CG,j}^{t-1} \leq R_{CG,j}^{\text{up}} \Delta t \quad (3-21)$$

Power transaction:

$$\textbf{Exchanging power limits: } 0 \leq P_B^t \leq \gamma_B^t P_B^{\max}, 0 \leq P_S^t \leq \gamma_S^t P_S^{\max} \quad (3-22)$$

$$\textbf{State limits: } \gamma_B^t + \gamma_S^t \leq 1 \quad (3-23)$$

Energy storage:

$$\text{Charging power limits: } 0 \leq P_{ESC}^t \leq \gamma_{ESC}^t P_{ESC}^{\max} \quad (3-24)$$

$$\text{Discharging power limits: } 0 \leq P_{ESD}^t \leq \gamma_{ESD}^t P_{ESD}^{\max} \quad (3-25)$$

$$\text{Energy limits: } \zeta_{ES}^{\min} Cap_{ES} \leq E_{ES}^t \leq \zeta_{ES}^{\max} Cap_{ES} \quad (3-26)$$

$$\text{Starting and ending energy limits: } E_{ES}^0 = E_{ES}^{N\Delta t} \quad (3-27)$$

$$\text{State limits: } \gamma_{ESC}^t + \gamma_{ESD}^t \leq 1 \quad (3-28)$$

Note that CG is a generalized abbreviation that includes MT, EB, EC or FC and ES is a generalized abbreviation for the BS, HST, and IST.

Islanded mode

Without the utility grid as the backup, the energy generation and consumption must be balanced within the islanded microgrids [101]. Thus, the demand response should be involved. Compared with the grid-connected microgrids, the multi-energy demand response cost, *i.e.*, cost from (electrical/thermal) load shedding and/or (electrical /thermal) generation dumping should be considered in the system net operation cost [97].

$$\text{Objective function: } \min F_s = \sum_{t=1}^N (C_F^t + C_{OM}^t + C_{ST}^t + C_{SD}^t - C_{SHC}^t + C_{PH}^t) \Delta t \quad (3-29)$$

$$\text{Energy demand response cost: } C_{PH}^t = \begin{bmatrix} c_{TS} Q_{TS}^t + c_{TE} Q_{TE}^t + c_{IS} Q_{IS}^t + \\ c_{IE} Q_{IE}^t + c_{DS} P_{DS}^t + c_{DE} P_{DE}^t \end{bmatrix} \quad (3-30)$$

Revenue for supplying heat/cooling to customers:

$$C_{SHC}^t = C_{SH}^t + C_{SC}^t = \begin{bmatrix} c_H^t (Q_H^t - Q_{TS}^t) + \\ c_C^t (Q_C^t - Q_{IS}^t) \end{bmatrix} \quad (3-31)$$

The cost items with the same symbols are the same as the grid-connected microgrid.

Constraints:

The operation constraints for the islanded microgrid are:

Energy balance:

$$\text{Power balance: } \begin{bmatrix} P_{WT}^t + P_{PV}^t + P_{MT}^t + P_{FC}^t + P_{BSD}^t - P_{BSC}^t = \\ P_L^t - P_{DS}^t + P_{DE}^t + P_{EB}^t + P_{EC}^t \end{bmatrix} \quad (3-32)$$

$$\text{Cooling balance: } Q_{EC}^t + Q_{MTC}^t - P_{ISTC}^t + P_{ISTD}^t = Q_C^t - Q_{IS}^t + Q_{IE}^t \quad (3-33)$$

$$\text{Heat balance: } Q_{EB}^t + Q_{MTH}^t - P_{TSTC}^t + P_{TSTD}^t = Q_H^t - Q_{TS}^t + Q_{TE}^t \quad (3-34)$$

Energy demand response

$$\text{Energy demand response limits: } \begin{cases} 0 \leq P_{DS}^t \leq \gamma_{DS}^t P_L^t, 0 \leq P_{DE}^t \leq \gamma_{DE}^t P_L^t \\ 0 \leq Q_{TS}^t \leq \gamma_{TS}^t Q_H^t, 0 \leq Q_{TE}^t \leq \gamma_{TE}^t Q_H^t \\ 0 \leq Q_{IS}^t \leq \gamma_{IS}^t Q_C^t, 0 \leq Q_{IE}^t \leq \gamma_{IE}^t Q_C^t \end{cases} \quad (3-35)$$

$$\text{State limits: } \gamma_{DS}^t + \gamma_{DE}^t \leq 1, \gamma_{TS}^t + \gamma_{TE}^t \leq 1, \gamma_{IS}^t + \gamma_{IE}^t \leq 1 \quad (3-36)$$

Other constraints are in line with the grid-connected microgrid.

In the system operation model, there are some nonlinear items such as Eqs. (3-2), (3-3), (3-11), (3-13) and (3-14). To speed up the solution process, those nonlinear items are linearized in Chapter 10 (with the specific equations indicated).

3.3.2 Solution Method for the Dispatch Models

After the linearization, the proposed models can be expressed as a general linear programming problem with the standard form as:

$$\begin{cases} \text{objective. Min}_{\xi} F(\xi) \\ \text{s.t.} & H(\xi) = 0 \\ & G(\xi) \geq 0 \end{cases} \quad (3-37)$$

The decision variables ξ consist of binary and continuous variables. All the objective and constraint expressions are linear, so the proposed dispatch models are typical MILP problems.

Then commercial solvers Cplex which have high performance in solving MILP problems can be employed to solve the problems via the platform General Algebraic Modelling System (GAMS) [62].

3.4 Case Studies

3.4.1 Data Input

In this section, the proposed dispatch models are validated in a MEMG testbed. The hourly power outputs of WTs and PVs for the typical winter and summer days can be obtained by forecasting [9], [109]-[110]. It is assumed that no heat loads in summer and no cooling loads in winter [26]. The power outputs of WTs, PVs and system load profiles are shown in Figure 3-2. The data are obtained from [9], [19], [111], with minor changes.

For case studies, simulation is conducted for a 24h dispatch horizon with unit dispatch interval as 1h. The real-time power pricing is shown in Figure 3-3 [19]. For supplying the heat and cooling energy, the fixed pricing scheme is adopted

[23]. The parameters for case studies are listed in Table 3-1 and Table 3-2. All the units are assumed to be off before the dispatch [3].

Figure 3-2. Forecasting loads, PV and WT power outputs.

Figure 3-3. The real-time price structure.

Table 3-1. PARAMETERS OF ENERGY STORAGE (¥/kWh) [3]-[5]

Type	η_c/η_d	Decay	P_{ESC}^{max}	P_{ESD}^{max}	ξ_{min}	ξ_{max}	$K_{ES}^{om}/(\text{¥/kWh})$	E_{ES}^0	Cap_{ES}
BS	0.9	0.001	37.5	37.5	0.2	0.8	0.0073	30	150
HST	0.87	0.01	45	45	0	0.9	0.0012	0	160
IST	0.85	0.01	40	40	0	0.9	0.0014	0	120

Table 3-2 VALUES OF THE PARAMETERS [26], [111]

Parameters	Value	Parameters	Value	Parameters	Value
η_H, η_C	85%	P_{MT}^{min}	15kW	K_{EC}^{om}	0.0104¥/kWh
η_L	15%	P_{MT}^{max}	65kW	K_{WT}^{om}	0.0145¥/kWh
COP_H	1.20	P_{EB}^{min}	0kW	K_{PV}^{om}	0.0133¥/kWh
COP_C	2.00	P_{EB}^{max}	50kW	K_{EB}^{om}	0.0089¥/kWh
COP_{EB}	0.85	P_{FC}^{min}	5kW	K_{MT}^{om}	0.0990¥/kWh
COP_{EC}	3.5	P_{FC}^{max}	40kW	K_{FC}^{om}	0.0841¥/kWh
$C_{ST,MT}^U$	1.94¥	P_{EC}^{min}	0kW	C_{IS}	0.12¥/kWh
$C_{ST,EB}^U$	1.23¥	P_{EC}^{max}	40kW	C_{IE}	0.10¥/kWh
$C_{ST,FC}^U$	2.21¥	P_B^{max}	60kW	C_{DS}	1.50¥/kWh
$C_{ST,EC}^U$	1.32¥	P_S^{max}	60kW	C_{DE}	0.90¥/kWh
$C_{SD,MT}^D$	1.82¥	C_{TS}	0.20¥/kWh	R_{MT}^{up}	10kW/min
$C_{SD,EB}^D$	1.14¥	C_{TE}	0.15¥/kWh	R_{MT}^{down}	5kW/min
$C_{SD,FC}^D$	2.05¥	C_H	0.30¥/kWh	R_{FC}^{up}	2kW/min
$C_{SD,EC}^D$	1.15¥	C_C	0.20¥/kWh	R_{FC}^{down}	2kW/min
R_{EB}^{down}	2kW/min	R_{EC}^{up}	4kW/min	C_G	2.70¥/m ³
R_{EB}^{up}	3kW/min	R_{EC}^{down}	3kW/min	L_{NG}	9.78kWh/m ³

Two cases based on the conventional models for supplying multiple energies in microgrids are compared in this report.

Case 1: *Separate generation*: heat and cooling loads are met by the GBs with heat efficiency of 85% and absorption chiller, power loads are all satisfied by power generation units [23], [25].

Case 2: *Typical tri-generation*: the CCHP plant operates under the FHL strategy in the grid-connected microgrids and under FPL strategy in the islanded microgrids with GB working as a supplement [25]-[27].

Case 3: *The system-wide coordinated generation* proposed.

The detailed combination of the units in the three cases is summarized in Table 3-3.

Table 3-3 COMBINATION OF ALL THE UNITS IN THREE CASES										
NO.	Common Units				Summer			Winter		
	PV/WT	FC	BS	CCHP	GB	EC	IST	GB	EB	HST
Case 1	√	√	√	√	√			√		
Case 2	√	√	√	√	√			√		
Case 3	√	√	√	√		√	√		√	√

The mathematical models are implemented in the GAMS via the Cplex solver. The program is run on an Intel(R) Xeon(R) E5-1630 3.70GHz personal computer with 16G memory.

3.4.2 Remarks

For the waste heat is not recovered in **Case 1**, the MT works only for power generation; In **Case 2** and **Case 3**, the MT generates power and cooling in summer and power and heat in winter. To better illustrate the simulation results for the grid-connected microgrids, the unit cost of FC for power generation can be calculated as:

$$C_{U,FC}^t = C_{F,FC}^t / P_{FC}^t + K_{FC}^{om} \quad (3-38)$$

Similarly, for the power generation, the unit cost of MT in the only power generation mode is:

$$C_{U,PG}^t = C_{F,MT}^t / P_{MT}^t + K_{MT}^{om} \quad (3-39)$$

The unit cost of MTs (CCHP plants) operating in summer and winter is as follows:

$$C_{U,W}^t = (C_{F,MT}^t - C_{H,m}^t) / P_{MT}^t + K_{MT}^{om} \quad (3-40)$$

$$C_{U,S}^t = (C_{F,MT}^t - C_{C,m}^t) / P_{MT}^t + K_{MT}^{om} \quad (3-41)$$

Fig.4-5 presents the unit cost curves of FC and MT in different conditions.

Figure 3-4. Unit power generation cost of FC and MT in different modes

For the nonlinear electrical efficiencies, the unit cost of FC is increasing, but the unit cost of MT in different conditions is decreasing. Since the coefficient of performance of the absorption chiller is higher than that of the heat recovery unit, therefore the unit cost of MT (CCHP plant) operating in winter is greater than that in summer, but with the recovery of waste heat, they are both lower than the unit cost of MT in only power generation condition. In addition, Figure 3-4 shows that within FC's maximum capacity, the unit cost is always lower than that of MT.

3.4.3 Simulation Results

1: Grid-connected Mode

Figure 3-5 and Figure 3-6 show the simulation results of the grid-connected MEMG in all 3 cases. The net operation cost is listed in Table 3-4.

In those figures, P_N denotes the total power loads minus the summation of WTs and PVs power outputs; P_E denotes the subtraction of purchasing power with selling power; BS is the discharging power minus the charging power. HST and IST denote the releasing heat/cooling energy minus the absorbing, respectively.

It is indicated in Figure 3-5 and Figure 3-6 that all the units in the three cases are scheduled based on their unit cost as well as operational constraints. Since the unit power generation cost of FC is lower than MT (Figure 3-4), FC outputs in priority to MT when there is power shortage; Except for satisfying the internal power loads, FC and MT will output extra power when their unit cost is less than the selling prices in order to obtain more power exchange revenue. Besides, the charging or discharging decisions of BS is made with respect to real-time pricing to shift loads and lower the net operation cost.

In **Case 1**, the heat and cooling loads are met by GB (Figure 3-5 (b), Figure 3-6(b)), the power loads are supplied by the FC, MT, BS and power exchange (Figure 3-5(a), Figure 3-6(a)) based on their individual cost functions. The simulation results show that the heat and power are scheduled without any interaction, and the net operation cost is highest since the efficiency of GB is low, and heat generated by MT is all wasted (Figure 3-5. (a), Figure 3-6. (a), period 14, Table 3-4).

Table 3-4 NET OPERATION COST OF GRID-CONNECTED MICROGRID (¥)

Cost/ Revenue Item	Summer			Winter		
	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3
Fuel cost	822.7	808.2	685.6	1342	1564.3	1507.5
Maintenance cost	77.4	103.6	94.5	88.9	195	175.5
Start-up and shut-down cost	9.4	16.1	6.11	9.4	9.8	7.4
Power exchange cost	537.3	350.5	377.6	629.9	177.6	187.8
Heat or cooling revenue	528.4	528.4	528.4	960.1	960.1	960.1
Net operation cost	918.6	750.1	635.7	1110.3	986.6	918.3

In **Case 2**, the MT supplies heat/cooling in priority under FHL strategy and GB works as a supplement (Fig. 4-6 (d), Fig. 4-7 (d)). The fixed power outputs of MT coordinate with the FC, BS and the power exchange to satisfy the total power loads (Fig. 4-6 (c), Fig. 4-7 (c)). For the waste heat is fully utilized, the

net operation cost is thus lower than **Case 1**. However, under the FHL strategy, MT's power outputs are highly limited by its cooling/heat outputs. Hence MT cannot join in the energy market flexible (Table 3-4).

By marked contrast, the system-wide optimal coordinated dispatch of power, heat, and cooling is realized in **Case 3**. When the purchasing prices are lower than the unit cost of MT operating in summer or in winter, power participates in the heat/cooling dispatch, *i.e.*, EB/EC outputs in priority to the MT to transfer power to heat/cooling (Figure 3-5(e),(f), period 1-9, 17-18, 23-24 and Figure 3-6(e),(f) period 1-7, 22-24). When the purchasing prices are higher than the unit cost of the MT operating in summer or winter, HST/IST stores the surplus heat/cooling to decouple inflexible strategies of CCHP plant, then more power can be generated by MT to supply the power loads or sold to grid for revenue (Figure 3-5(e), (f), period 11-14 and Figure 3-6(e), (f), period 12-17). When the purchasing prices fall in between the above two price intervals, heat/cooling participate in the power dispatch, *i.e.*, HST or IST releases heat/cooling in order to decrease the MT power outputs (Figure 3-5(e), (f), period 17-19 and Figure 3-6(e),(f), period 20-21,24). Further, from Fig. 4-5, with the increasing power outputs of MT, the unit cost is decreasing. Thus, in this way, the HST/IST helps MT to fully utilize this advantage to further reduce the net operation cost. Hence, the operation cost of **Case 3** is the lowest (Table 3-4).

In summary, the proposed models can effectively achieve the system-wide coordination for the grid-connected microgrid and lower its net operation cost.

In terms of the solution speed, all the solutions are obtained within 3.39s with minimal solver time is 1.24s, which is computationally efficient.

2: Islanded Mode

The simulation results of the islanded microgrid are shown in Figure 3-7 and Figure 3-8. The net operation cost is listed in Table 3-5 Net Operation Cost of Islanded Microgrid (¥). Similarly, P_D , Q_T , and Q_I denote the subtraction of power, heat and cooling shortage with their respective surplus.

It is shown in Figure 3-7 and Figure 3-8 that since there is no power support from the grid, demand response will be invoked with the multi-energy demand response cost. As shown in Table 3-2, the unit power demand response cost is much higher than the unit cost of DtGs, then all the DtGs and ES are scheduled to reduce power demand response cost.

Figure 3-7. Power and heat balance condition of the 3 cases in summer.

Case 1 (a), (b), Case 2 (c), (d), Case 3 (e), (f).

In **Case 1**, the heat/cooling loads are all met by the GB (Figure 3-7(b), Figure 3-8(b)), the power loads are supplied by the FC, MT, and BS (Figure 3-7 (a), Figure 3-8 (a)). The demand response is invoked only when there is still energy shortage after the maximum power outputs of all the units (Figure 3-7 (a) period 14, 16-17, Figure 3-8 (a) period 1,7,16-20). Since it cost more for GB to supply heat/cooling and the waste heat generated by MT is wasted (Figure 3-7 (a), Figure 3-8 (a), period 14), the operation cost is highest (Table 3-5).

In **Case 2**, under FPL strategy, the MT supplies the power loads in priority, if

there is still heat/cooling shortage, GB will start to work as a supplement (Figure 3-7 (d), Figure 3-8 (d)). If there is a power imbalance, FC starts to output power and coordinates with BS and demand response if necessary, to satisfy the total power loads (Figure 3-7 (b), Figure 3-8 (b)). However, under the FPL strategy, heat/cooling outputs of MT are limited by its power outputs, which hinders its effect in the heat/cooling dispatch. Besides, the power outputs of MT are not generated regarding its operation cost but only the inflexible strategy. Thus, the net operation cost of **Case 2** is high.

Figure 3-8. Power and heat balance conditions of the 3 cases in winter.

Case 1 (a), (b), Case 2 (c), (d), Case 3 (e), (f).

Table 3-5 Net Operation Cost of Islanded Microgrid (¥)

Cost/ Revenue Item	Summer			Winter		
	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3
Fuel	1713.8	1482.4	1254.6	2494.6	1796.1	1671.5
Maintenance	208.4	197.8	165.9	231.3	218.4	206.7
Startup and shutdown	15	6.4	7.4	7.2	9.8	7.4
Energy demand response	50.3	9	126.4	0.1	41.1	34
Heat or cooling revenue	528.4	528.4	520.1	960.1	960.1	910.7
Net operation cost	1459.2	1167.2	1034.2	1773.1	1105.4	1008.9

By contrast, **Case 3** realizes the system-wide coordination between power, heat/cooling, *i.e.*, the power generation units join in the heat/cooling dispatch with the support of the EC/EB, the MT generates the power and heat/cooling coordinately with the assistance of the HST/IST just as the grid-connected microgrid does (Figure 3-7 (e), (f), Figure 3-8 (e), (f)). Thus, the overall dispatch is more flexible and efficient. Besides, the demand response also joins in the overall dispatch according to the energy demand response cost, which further enhances the dispatch flexibility. The net operation cost of **Case 3** is still the lowest (Table 3-5).

Furthermore, the maximal solution time for all the islanded cases are 4.51s, which again shows the high solution efficiency. In addition, the solution time is enough for the day-ahead dispatch scheme.

3.5 Conclusions and Future Work

This chapter proposes comprehensive system-wide optimal coordinated dispatch models for a multi-energy microgrid in both the grid-connected and islanded mode. In the proposed models, the HST/IST could decouple the inflexible operation strategies of the CCHP plant and make it join in the power and heat/cooling dispatch with higher freedom. Besides, the EB/EC can significantly enhance the interactions between the dispatch of power and heat/cooling. The comprehensive case studies based on the separate generation model, tri-generation model and optimal coordinated dispatch model proposed in this report fully demonstrate that the proposed models can reduce the net operation cost, achieve more efficient and flexible operation of the multi-energy microgrid. It is concluded that the system-wide optimal coordinated dispatch models can provide beneficial references to the optimal design, planning, and operation of multi-energy supplying networks in different modes and have great potential in further reducing the net operation cost.

However, as this work is limited to the deterministic optimization, that is, the

forecasting value of multi-energy loads, energy generation of the renewable energies, etc., are all assumed accurate enough, the dispatch decisions are not practical for the real-world application. Further, energy flow limits should also be involved in for reliable operation.

4.) Temporally Coordinated Optimal Operation of a Multi-Energy Microgrid Under Diverse Uncertainties

4.1 Introduction

Chapter 3 studies the system-wide optimal dispatch of all the units in the MEMGs with the assumption of the accurate forecasting of RES, multi-energy demands, power transaction prices, *etc.* Though the simulation results show that the proposed method could enhance the system multi-energy dispatch flexibility and save the total energy supplying cost, there are still some issues that should be addressed. First, the different energy properties are not considered sufficiently: compared with electric power, thermal energy is of slow response speed due to the thermal inertia. Besides, slow transmission speed and a large transfer rate of thermal energy will cause a high time delay and great thermal losses [78]. Second, as DtGs can be categorized into the dispatchable and non-dispatchable ones, the former can achieve a reliable and cost-effective dispatch like the CCHP plants and PtC units; the latter, specifically RES-based units, *e.g.*, WTs and PVs, are inherently uncertain and intermittent [112]. To fully utilize the different properties of DtGs would further increase operating efficiency. Third, given the random human and market behaviors [5], power loads and electricity transaction prices are highly stochastic; together with the non-dispatchable units, the diverse uncertainties will pose considerable technical and economic challenges to the MEMG operation [6]. In this regard, the deterministic dispatch method in Chapter 3 won't guarantee a reliable system dispatch solution.

From the above, how to coordinate different energies and address diverse uncertainties in the MEMGs to achieve optimal and robust operation is a promising research topic.

In this chapter, a temporally coordinated stochastic operation method for a grid-connected MEMG which consists of WTs, CCHP plants, PVs, PtC units, thermal storage tanks (TST), and BS is proposed. To accommodate different properties of the energy carriers, thermal-related units including CCHP plants, PtC units, and TS are dispatched to manage the slow variations in a longer timescale at the day-ahead operation stage. The power-related units BS act in a shorter time scale at the intra-day online operation stage and respond to the

fast variations of uncertain resources. The two timescales are coordinated via the SO model, where the day-ahead operation makes initial decisions irrespective of uncertainties, and online operation replies on a recourse action to compensate day-ahead decisions after the system uncertainties are revealed.

4.2 Multi-Energy Microgrid Modelling

4.2.1 Structure of the Studied MEMG

The typical structure of the studied MEMG is like Chapter 3 in Figure 3-1. The difference lies in twofold:

- 1) To guarantee the energy supply reliability, the MEMG is distribution-network-based. This is because the power flow constraints are included.
- 2) There are no FCs involved as if the FC is put into use, the suitable temperature requirement should be 1000°C or higher, besides, the fuel source for the FC is hydrogen, which also gets a high requirement for transmission and storage due to the safety issues. [106].

Then in the distributed-network-based MEMG, the thermal (heat or cooling) loads are supplied by the CCHP plants, PtC units, and TS; the power loads are supplied by the CCHP plants, BS, WTs and PVs [26]. Besides, the MEMG is connected to the main grid for power transactions [31], [33].

4.2.2 Components Modelling

Like Chapter 3, this study focuses on the system operation and component modeling mainly focuses on the external characteristics.

- 1) **The CCHP plants:** Different from Chapter 3, the Capstone's MTs C200, which also has a high international market share, is employed as the core unit of the CCHP plants [113]. The relation between the power outputs and electrical efficiency is:

$$\eta_{MT}^{t,i} = 2.499 \times 10^{-6} (P_{MT}^{t,i})^3 - 1.544 \times 10^{-3} (P_{MT}^{t,i})^2 + 0.2910 P_{MT}^{t,i} + 9.092 \quad (4-1)$$

The corresponding thermal outputs can be expressed as:

$$H_{MT}^{t,i} = \eta_H \left[1.222 \times 10^{-4} (P_{MT}^{t,i})^3 + 2.062 \times 10^{-4} (P_{MT}^{t,i})^2 + 0.621 P_{MT}^{t,i} - 370.4 \right] \quad (4-2)$$

Note that multiple C200 MTs can be integrated as a single larger unit named a MultiPac when the power loads are larger than the maximal power outputs of a single unit, the loads are shared evenly among all the C200 MTs [35].

- 2) **PtC units:** different from Chapter 3 with the specific models for EBs and

ECs, the PtC units is denoted with a generalized model as:

$$H_{PT}^{t,i} = P_{PT}^{t,i} \eta_{PT} \quad (4-3)$$

3) **Heterogeneous energy storage (HES)**: the models for TS and EES (BS is used) are the same as Chapter 3.

4.3 Proposed Operation Method

4.3.1 Timescale Decomposition

Given the large thermal inertia [78], the thermal energy changing rate is rather low. Besides, thermal loads are usually much steadier than power loads, so the short-term thermal load forecasting (*i.e.*, hourly-ahead) can be considered accurate enough. In this chapter, the operating states of the CCHP plants, PtC units, and TS are planned in a relatively long timescale, which is set as 1 hour. Their operation decisions are made in the day-ahead time window (first stage). Then, to counteract the adverse effects from the diverse uncertainties, during the intra-day online operation phase (second stage), fast-responding devices, *i.e.*, BS, are dispatched to complement the day-ahead operation decisions after the uncertainty is realized. As the BS can respond faster, it acts in a shorter timescale (5 minutes), which can be used in the online operation.

This timescale separation acknowledges the distinct properties of different energy carriers and units' response speeds. Note that other timescale lengths (*i.e.*, half-hour, 15mins, *etc.*) can also be considered if necessary, which does not affect the effectiveness of the proposed method [97].

4.3.2 Temporally Coordinated Operation Framework

To address the uncertainties and make full use of different energy carriers, a temporally-coordinated operation framework is developed in Figure 4-1 the day-ahead operation (long timescale) aims to dispatch the status of the CCHP plants, TS and PtC units every hour based on the forecasting of power loads, transaction prices and RES outputs; within each hour, the intra-day online operation (short timescale) dispatches BS every 5 minutes in response to the faster variations of the uncertain sources.

Figure 4-1. Temporally coordinated Stochastic Operation Framework

For implementation, at the day-ahead decision cycle, the CCHP plants, TS, and PtC units are dispatched a day ahead for the next day's 24 hours based on the hourly predictions. Then, the intra-day online operation compensates the day-ahead decisions for the negative effects of fast and stochastic variations. At each online dispatch interval, the random variations of the next 5-min's power loads, transaction prices and RES outputs are predicted and used as the inputs to optimize the BS's states. Since the BS's charging and discharging power speed is very fast (within seconds-minutes), the 5-min dispatch interval is feasible. However, other dispatch intervals, e.g., half an hour, can also be considered without affecting the effectiveness of the proposed method.

It is worth noting that many forecasting techniques have been developed in the literature, showing that the shorter lead time forecasting tends to be more accurate than the longer lead time one, hence the uncertainties can be better grasped in the online short-term operation time-window [114].

4.4 Mathematical Formulation

4.4.1 Multi-energy Microgrid Coordination Model

The operation of the networked-based MEMGs aims to minimize the system's net operating cost while satisfying the network operational limits in the presence of diverse uncertainties. The mathematical models for the two stages are as follows:

$$\textbf{Objective Function: } \min F_G = C_{FC} + C_{OM} + C_{EX} + C_{ST} + C_{SD} - C_{HR} \quad (4-4)$$

where

$$\textbf{Fuel cost: } C_{FC} = \sum_{t \in N_T} \sum_{i \in N_M} (\gamma_G P_{MT}^{t,i} / \eta_{MT}^{t,i}) \Delta t \quad (4-5)$$

$$\textbf{Power transaction cost: } C_{EX} = \sum_{t \in N_T} (\gamma_B P_{BUY}^{t,1} - \gamma_S P_{SELL}^{t,1}) \Delta t \quad (4-6)$$

$$\text{Maintenance cost: } C_{OM} = \sum_{t \in N_T} \sum_{i \in N_W} \left[\gamma_{WT} P_{WT}^{t,i} + \sum_{i \in N_P} \gamma_{PV} P_{PV}^{t,i} + \sum_{i \in N_M} \gamma_{MT} P_{MT}^{t,i} + \sum_{i \in N_E} \gamma_{PT} P_{PT}^{t,i} \right. \\ \left. + \sum_{i \in N_B} \gamma_{BS} (P_{BSC}^{t,i} + P_{BSD}^{t,i}) + \sum_{i \in N_H} \gamma_{TST} (P_{TSTC}^{t,i} + P_{TSTD}^{t,i}) \right] \Delta t \quad (4-7)$$

$$\text{Stat-up cost: } C_{ST} = \sum_{t \in N_T} \sum_{i \in (N_M \cup N_E)} \max(0, U_{CG}^{t,i} - U_{CG}^{t-1,i}) C_{CG}^U \quad (4-8)$$

$$\text{Shut-down cost: } C_{SD} = \sum_{t \in N_T} \sum_{i \in (N_M \cup N_E)} \max(0, U_{CG}^{t-1,i} - U_{CG}^{t,i}) C_{CG}^D \quad (4-9)$$

$$\text{Heat selling revenue: } C_{HR} = \sum_{t \in N_T} \sum_{i \in N_M} \gamma_{HR} H_L^{t,i} \Delta t \quad (4-10)$$

Constraints:

For CCHP plants and PtC units:

As mentioned above, CCHP plants and PtC units are dispatchable (denoted by subscript CG), they are subject to their power outputs (13) and ramp up/down limits (14).

$$U_{CG}^{t,i} \cdot P_{CG}^{min,i} \leq P_{CG}^{t,i} \leq U_{CG}^{t,i} \cdot P_{CG}^{max,i} \quad (4-11)$$

$$R_{CG}^{down,i} \Delta t \leq P_{CG}^{t,i} - P_{CG}^{t-1,i} \leq R_{CG}^{up,i} \Delta t \quad (4-12)$$

For heterogeneous energy storage:

Both the TST and BS belong to the ES. Their operation models can be formulated as Eqs.(4-13) -(4-17), where the subscript ES represents either TST or BS. The charging and discharging power of the ES is constrained by the corresponding minimal and maximal power as Eqs.(4-13)-(4-14); Eq.(4-15) denotes that energy stored in the ES should be within the available capacity; Eq.(4-16) denotes that for the ES at each dispatching cycle, the starting energy is the same as the ending, in order to keep the same dispatch flexibility at different dispatching cycles; Eq.(4-17) means that in each dispatch interval, the summation of the binary charging and discharging states of energy storage should be less than or equal to 1, in this way, the charging and discharging states cannot happen simultaneously [32].

$$0 \leq P_{ESC}^{t,i} \leq \varepsilon_{ESC}^{t,i} P_{ESC}^{max,i} \quad (4-13)$$

$$0 \leq P_{ESD}^{t,i} \leq \varepsilon_{ESD}^{t,i} P_{ESD}^{max,i} \quad (4-14)$$

$$\varepsilon_{ES}^{min,i} Cap_{ES}^i \leq E_{ES}^{t,i} \leq \varepsilon_{ES}^{max,i} Cap_{ES}^i \quad (4-15)$$

$$E_{ES}^{0,i} = E_{ES}^{N_T \Delta t, i} \quad (4-16)$$

$$\varepsilon_{ESC}^{t,i} + \varepsilon_{ESD}^{t,i} \leq 1 \quad (4-17)$$

Linearized distribution load flow:

The power distribution network's power flow in the multi-energy microgrid can be modeled as linearized Dist-Flow [15] as Eqs.(4-18)-(4-20) with the assumption that all the DtGs are of the unity power factor as ref.[80]. Besides, the cost from power loss is relatively low, for simplicity, we ignore it without loss of the solution accuracy as ref. [80] and [64].

$$\text{Active power: } \begin{bmatrix} P_{PF}^{t,b+1} = P_{PF}^{t,b} - P_{PF}^{t,0,b+1} - P_L^{t,i} + P_{WT}^{t,i} \\ + P_{PV}^{t,i} + P_{BSD}^{t,i} - P_{BSC}^{t,i} + P_{MT}^{t,i} - P_{PT}^{t,i} \end{bmatrix}, b \in Br(i), \forall i, t \quad (4-18)$$

$$\text{Reactive power: } Q_{PF}^{t,b+1} = Q_{PF}^{t,b} - Q_{PF}^{t,0,b+1} - Q_L^{t,i}, b \in Br(i), \forall i, t \quad (4-19)$$

$$\text{Voltage: } V_{BUS}^{t,i+1} = V_{BUS}^{t,i} - (R^b P_{PF}^{t,b} + X^b Q_{PF}^{t,b}) / V_0, b \in Br(i, i+1), \forall i, t \quad (4-20)$$

Voltage limits, i.e., the voltage should be maintained in a secure range.

$$1 - \Delta V_{BUS}^{\max} \leq V_{BUS}^{t,i} \leq 1 + \Delta V_{BUS}^{\max} \quad (4-21)$$

To illustrate the Eqs.(4-18)-(4-20) in a more intuitive way, a simple power network model is shown in Figure 4-2.

Figure 4-2. Schematic Diagram of a Radial Distribution Network.

In Figure 4-2, p and q correspond to P_{PF} and Q_{PF} in Eqs. (4-18)-(4-19). P and Q denote the net active and reactive loads, which are equal to the subtraction of the loads with the generation. The details can be referred to [97].

Thermal energy balance, i.e., the thermal energy generation should be equal to consumption.

$$H_L^{t,i} = H_{MT}^{t,i} + H_{PT}^{t,i} + P_{TSTD}^{t,i} - P_{TSTC}^{t,i} \quad (4-22)$$

There are some nonlinear items such as Eqs. (4-2),(4-5) ,(4-8) and (4-9). The linearization process can be referred to as the appendix in Chapter 10 (with the specific equations indicated).

4.5 Solution Method

Due to the diverse uncertain sources, the mathematical model of Eqs.(4-4)-(4-21) is a stochastic programming problem. This section will convert the model into a tractable deterministic equivalent model based on scenario generation and reduction techniques.

4.5.1 Uncertainty Modelling

For the RES units like WTs and PVs, their stochastic variations or forecasting errors usually follow the Beta distribution [116]:

$$f_{P_{RES}^{t,j}} = \left(P_{RES}^{t,j}\right)^{\theta-1} \cdot \left(1-P_{RES}^{t,j}\right)^{\psi-1} \cdot N_F \quad (4-23)$$

Since power loads and transaction prices are mainly affected by human behaviors, the Normal distribution is employed to represent their forecasting errors [112]:

$$f_{P_L^{t,j}} = 1/\left(\sqrt{2\pi}\sigma\right) \cdot \exp\left[-\left(P_L^{t,j} - \mu\right)^2 / \left(2\sigma^2\right)\right] \quad (4-24)$$

4.5.2 Stochastic Programming Model

The stochastic optimization method constitutes an effective tool for making decisions under uncertainties and reveals the fact when the uncertainties become known as time evolves. The coordination model of Eqs.(4-4)-(4-21) is formulated into a two-stage SO model as:

$$\min_{z \in F_A} \left\{ F(z) + E[G(z, \omega)] \right\} \quad (4-25)$$

where $F(z)$ is the day-ahead operation objective, z is the day-ahead decision vector; $E[G(z, \omega)]$ is the expectation of the intra-day online operation problem; $G(z, \omega)$ is the intra-day online operation objective, which is equal to $\min_y \in \Omega(z, \omega) L(y)$, where y is the online decision vector, ω is the random vector.

4.5.2 Deterministic Equivalence

Assuming that ω has a finite number of possible realizations, called scenarios, denoted as $\omega_1, \omega_2, \dots, \omega_n$ with respective possibilities of $\chi_1, \chi_2, \dots, \chi_n$, then the expectation term in Eq.(4-25) can be written as:

$$E[G(z, \omega)] = \sum_{n \in N_S} \chi_n G(z, \omega_n) \quad (4-26)$$

where N_S is the number of scenarios; n is the scenario index.

In this way, the original SO model can be reformulated into the deterministic

equivalence as:

$$\min_{z, y_1, y_2, \dots, y_n} F(z) + \sum_{n \in N_s} \chi_n L(y_n) \quad (4-27)$$

$$\begin{aligned} s.t. \quad & z \in F_A \\ & y_n \in \Omega(z, \omega_n), \forall n \end{aligned} \quad (4-28)$$

From the deterministic equivalence, a “*here-and-now*” decision z is made in the day-ahead operation before the realization of uncertainties; after a realization of the uncertain scenario ω in the intra-day online operation, a “*wait-and-see*” decision y is made to compensate the difference between the prediction and reality in the day-ahead operation, y is also named as the ‘recourse actions’.

Based on the objective function in Eq.(4-27), the two stages are coordinated since day-ahead decisions are obtained with effects from the online operation stage; when optimizing the online operation decisions, day-ahead decisions are passed down as state variables.

Specifically, for day-ahead operation, $F(z)$ and z correspond to the operating cost and power outputs of day-ahead operation units, respectively; set F_A corresponds to the constraints of Eqs.(4-11) -(4-21) for each hour. For intra-day online operation, $L(y_n)$ corresponds to the summation of the operating cost of WTs, PVs, BS, and power transaction cost; y corresponds to battery’s power outputs in every 5-min interval; ω corresponds to the stochastic variations of the RES outputs, power loads and transaction prices; $\Omega(z, \omega)$ corresponds to constraints of Eqs.(4-13)-(4-21) for each 5-min interval.

4.5.3 Scenario Generation and Reduction

Based on the possibility distributions of diverse uncertain sources in Eqs.(4-23) -(4-24), The Latin hypercube sampling method is used to generate a near-random sample of parameter values. It partitions each input distribution into several intervals of equal possibility and selects one sample from each interval. Compared with the Monte Carlo method, Latin hypercube can spread the sample points more evenly across all possible values.

Then, to alleviate the computational burden from a large number of scenarios. The simultaneous backward reduction method [116] is implemented to choose a much smaller but rather representative set of scenarios for the practical applications.

After the scenario reduction, the problem is converted to a small-scale deterministic MILP equivalent model. Commercial solvers like Cplex or Gurobi can be utilized to efficiently solve the model.

4.6 Simulation Results

4.6.1 Test System

The proposed method is tested on the grid-tied MEMG shown in Figure 4-3, which is structured on the IEEE 33-bus radial distribution system [2]. A winter case is tested. Since long-distance thermal transmission will lead to high time delay and great thermal loss [78], [22], in this study, the thermal energy is supplied locally within a geographical region (denoted as heat supply region 1-3) and no heat network is modeled. The substation voltage V_0 is 1.0 p.u. with the voltage limits ΔV_{BUS}^{max} set as $\pm 5\%$ of the nominal level (12.66kV) [116]. The ramp-up and -down rates for the CCHP plants are set as 30 kW/min and 15 kW/min [26], while those rates for EBs are 24 kW/min and 20 kW/min [118].

Figure 4-3 33-Bus Radial Distribution System Based Multi-Energy Microgrid

The location and size of all the units are given in Table 4-1

Within each heat supply region, the CCHP plants, PtC units, and TS are assumed to be installed on the same bus. The heat ratio of each region to the base heat capacity (3MW) is set as 30%, 37%, and 33%. The total capacity of all DtGs (WTs, PVs, and CCHP plants) is 6.6 MW, which is sufficient for the microgrid to support itself under islanding conditions [80], [97]. In addition, the

capacity of the point of connection linking the microgrid and main grid is set as 1.5 times of microgrid's peak power loads [64]. Stochastic variations for RES generation, power loads and transaction prices are set as 25%, 7.5% and 15% deviation to their forecasted values, respectively.

Table 4-1 The capacity of CCHP plants, WT, PVs, PtCs, and TSTs [80], [97],[118]

Bus	Rated Power (kW)/ Rated Energy(kWh)					
	WT	PV	PtC unit	MT	TST	BS
4	200	100	600	1000	500/1500	250/800
6	250	150	-	-	-	250/800
11	300	100	500	1000	600/1800	150/480
13	200	100	-	-	-	200/640
16	350	200	-	-	-	100/320
19	300	250	-	-	-	150/480
23	350	250	-	-	-	200/640
28	-	-	400	1000	600/1800	-
31	350	150	-	-	-	100/320

Based on the average data in Tianjin, China, 2018 winter (Dec.-Feb.), Figure 4-4 shows a day-ahead prediction of 24-hour output rates for RES generation and loads. The day-ahead prediction for transaction prices is shown in Figure 4-5, which is from [117]. For the heat energy supplied to the customers, the fixed pricing scheme is considered [26], [117].

Figure 4-4 Day-ahead Forecasted Rates for RES Outputs and Loads

Figure 4-5 Day-ahead Forecasted Transaction Prices

It should be indicated that any other real-world data can also be applied, and they won't influence the effectiveness of the proposed method. The simulations are run on an Intel(R) Xeon(R) E5-1630 3.70GHz 64-bit PC of 16G RAM. Commercial MILP solver Cplex is used for solving the mathematical model on the GAMS platform (Version 25.1.1).

4.6.2 Day-Ahead Operation Results & Discussion

In the day-ahead operation, 2000 random scenarios are initially generated based on day-ahead predictions. Then, they are reduced to 10 representative ones with corresponding possibilities. The total scenario generation and reduction time are 1.29 hours, however, both processes can be done off-line. The heat dispatch *i.e.*, the day-ahead operation decisions for each heat supply region, is shown in Figure 4-6 to Figure 4-8, respectively. The total expected operation cost is \$2118.69.

Figure 4-6 Heat Dispatch of Thermal Group 1

Figure 4-7 Heat Dispatch of Thermal Group 2

Figure 4-8. Heat Dispatch of Thermal Group 3

It can be seen that through the CCHP plants, PtC units and TSTs, the multiple energies are coordinated and CCHP operation is more flexible: when the transaction prices are lower than the CCHP unit power generation cost, power-to-thermal conversion units output in priority to CCHP plants to transfer power to heat (Figure 4-6 1h-8h, 22h-24h, Figure 4-7 1h-6h, 23h-24h and Figure 4-8 1h-7h, 22h-24h); when the transaction prices are higher than CCHP plants' unit power generation cost, thermal storage tanks store the surplus heat from CCHP plants (Figure 4-6 12h-16h, 19h-21h, Figure 4-7 12h-16h, 18h-21h and Figure 4-8 8h-9h, 13h-16h, 19h-21h), in this way, more power can be generated to supply power loads or sold to grid for revenue; when the prices fall in between

the above two price intervals, thermal storage tanks releases heat to decrease energy outputs of CCHP plants (Figure 4-6 18h, Figure 4-6 17h, and Figure 4-8 17h, 18h). Thus, the proposed method achieves flexible coordination of different energies.

Besides, the heat dispatch in the 3 different regions are similar but not the same, this is because the heat supply regions are located at different buses, the power flow constraints can influence the heat supply via the CCHP plants and PtC units. In this regard, the heat and power energy are also well coordinated to satisfy the network security constraints.

The number of the state and decision variables of the day-ahead dispatch model is 33816 and 37392, respectively. Using the Cplex solver, the solution is obtained after 94 iterations, which only takes 3.1 minutes. Therefore, it is very computationally efficient for practical day-ahead implementation.

4.6.3 Intra-day Online Operation Results& Discussion

For the online operation stage, the RES outputs, power loads and transaction prices are predicted in a 5-min interval in the 3-hour ahead rolling horizon [8] (note that other time horizons like 6 hours or 12 hours can also be used based on different forecasting lead times [116]). Then, the operating decisions are optimized for the whole 3-hour time horizon, but only the first 5-min operating decision is practically adopted, and the remaining are discarded. The whole process is rolling every 5 minutes.

Specifically, given the day-ahead operating decisions, the intra-day online operation is to optimize the operating states of BS with the simplified objective of (4-4) as:

$$\underset{P_{BSC}, P_{BSD}, P, V, Q}{MIN} F_S = C_{OM} + C_{EX} + (C_{FC} + C_{ST} + C_{SD} - C_{HR}) \quad (4-29)$$

Since the day-ahead decisions are fixed, the fuel cost, start-up/shut-down cost, and thermal revenue, *i.e.*, $(C_{FC} + C_{ST} + C_{SD} - C_{HR})$ are also fixed. Then the online operation is to minimize the maintenance cost of BS and real-time electricity transaction costs, *i.e.*, $(C_{OM} + C_{EX})$ under constraints (4-13)-(4-21).

The specified 5-min predictions of the load rates, RES generation rates and transaction prices are given in Figure 4-9 to Figure 4-10.

Figure 4-9. Online Values of WT, PV and Power Loads

Figure 4-10. Online Transaction Prices

With the online data, the simulation results for the power dispatch is shown in Figure 4-11.

Figure 4-11. 24-hour Online Power Dispatch

In Figure 4-11, the CCHP/PtC means the summation of their power outputs/consumption in three regions. Since they are the day-ahead decisions, their values remain constant in the intra-day online operation within each hour. Along with the main grid, BSs respond to the fast variations from RES generation, power loads and transaction prices under operational constraints in the online operation. For a detailed analysis, the power dispatch of 7h-9h and 13h-15h are replotted in Figure 4-12 (a)-(b).

In Figure 4-12 (a), it can be seen that due to the low prices at 7h-8h (5-min interval 73-96), CCHP power outputs are kept at a low level, microgrid purchases power from the main grid to charge BS and generate heat via PtC units; when the price is higher at 9h (5-min interval 97-108), CCHP plants generate more power for selling to the main grid for more transaction revenue. Meanwhile, the extra heat is used to charge thermal storage tanks. Besides, we can see that the energy stored in BS at 7h-8h which is of low prices is then discharged at 9h with a higher price, at the same time, the microgrid purchases power at 7h-8h and sell it to the main grid at 9h. In this way, battery storages cooperate with the grid to make full use of price differences to reduce the operating cost.

Similar analysis can be done for 13h-15h (5-min interval 145-180) in Figure 4-12 (b): since the transaction prices of those hours are high, no power is converted to heat via power-to-thermal conversion units, while the CCHP power outputs remain at a high level to satisfy the system heat and power loads (see also in Figure 4-6 to Figure 4-8); microgrid sells power to the main grid all the time with high prices; BS can still take the advantage of price difference to charge/discharge to reduce the operating cost.

The net operating cost is \$2411.46 with the intra-day online operation implemented. For the intraday-online dispatch stage of the model, the number of states and decision variables for each dispatch cycle (3 hours) are 4716 and 4896, respectively. The solution time is only 4.5s, which is fully compatible with the online use requirement. It is also important to indicate that all the operational constraints are satisfied and there are no voltage violations and branch overflow at both operating stages.

4.6.4 Performance Check & Comparison

To fully demonstrate the advantage of our method, three test groups (each has 1000 random scenarios) are further generated to check the performance of the proposed method and compared with three traditional operational methods in the literature.

Method #1: Single-stage deterministic operation [31]-[32]. All the controllable resources are dispatched at the same stage (day-ahead stage) and no uncertainties are considered.

Method #2: Single-stage stochastic operation [23]-[24]. The uncertainties for RES generation, power loads and transaction prices are considered, but all the units are dispatched at one stage as reference.

Method #3: Two-stage deterministic optimization. The first-stage operation is the same as **Method #1**, i.e. no uncertainties are considered. The second-stage operation is the same as our proposed method, i.e., the BS and transaction power are utilized to follow the online power and price fluctuations.

Method #4: The proposed temporally coordinated stochastic operation.

The three test groups have different levels of uncertainty as shown in Table 4-2, where the percentage value means the deviation percentage to their respective forecasted values.

Table 4-2 Three Uncertainty Levels

Uncertainty	Level 1	Level 2	Level 3
RES Generation	25%	35%	45%
Power Loads	7.5%	10%	12.5%
Transaction Prices	15%	20%	25%

These random scenarios are substituted into the optimization results of the four methods. For the 1000 scenarios in each group, the average operation cost and average voltage violation rates are compared in Table 4-3.

Table 4-3 Results of Different Uncertainty Levels

Item	Method #1	Method #2	Method #3	Method #4
Uncertainty level 1 (Lower Uncertainty)				
Average cost (\$)	2183.46	2149.65	2468.20	2440.22
Average voltage violation (%)	30.40	16.50	0	0
Uncertainty level 2 (Medium Uncertainty)				
Average Cost (\$)	2218.89	2188.97	2483.19	2450.78
Average voltage violation (%)	74.70	49.80	0	0
Uncertainty level 3 (High Uncertainty)				
Average Cost (\$)	2341.64	2282.66	2556.04	2508.65
Voltage violation (%)	97.20	77.90	0	0

According to Table 4-3, it can be found that in terms of the average costs, the stochastic methods are lower than the corresponding deterministic methods,

i.e., cost of **Method #2** is lower than **Method # 1**, **Method #4** is lower than **Method # 3**. This is because stochastic scenarios are addressed in their day-ahead operation, so the operation decision is immunized to the uncertainties [31]. This justifies the effectiveness of the stochastic optimization method.

In terms of voltage violation, the single-stage methods have considerable violation rates while the two-stage methods have no violation at all, which justifies the effectiveness of the recourse effect of the two-stage operation method. Comparing the single-stage methods, the stochastic method has a much lower voltage violation rate since the uncertainties are considered. For the same reason, comparing the two-stage methods, while both can ensure the voltage security, the proposed method (**Method #4**) has a lower operating cost.

Moreover, when uncertainty level increases, the average costs of all the methods will increase and the voltage violation rate for single stage methods will increase accordingly. This clearly implies that uncertainty has a negative impact on the grid operating performance and should be well addressed in the two-stage coordinated SO framework.

The number of the state and decision variables, as well as the computing time for the four methods, are listed as Table 4-4.

Table 4-4 The Computation Parameters for Different Methods

Item	First Stage			Second Stage		
	State Variables	Decision Variables	Computation Time	State Variables	Decision Variables	Computation Time
Method#1	5520	8016	1.3 min	-	-	-
Method#2	26688	8880	1.8 min	-	-	-
Method#3	5520	8016	1.3 min	3528	144	1.7s
Method#4	33816	37392	3.1 min	4716	4896	4.5s

It can be seen from Table 4-4 that the proposed method has the most state and decision variables due to the coordination modeling of two operating stages and the uncertain variables. However, since the whole model is linearized into a MILP problem, its computation speed is still highly fast which is fully compatible with online use.

In summary, the comparison results verify the general superiority of the proposed method in terms of achieving reasonable operating costs with satisfying security constraints under uncertainty. Especially, with increased uncertainty, the superiority of our method becomes more manifest.

4.7 Conclusion and Future Work

Based on different properties of multiple energies, a temporally coordinated operation method is proposed for a grid-tied MEMG under diverse uncertainties. Simulation results on the IEEE 33-bus distribution network illustrate that the proposed method can achieve multi-energy coordination with higher flexibility while satisfying system security constraints. Compared with three traditional methods, the proposed method is generally superior in terms of achieving reasonable operating costs with the guarantee of system security. Besides, with the increasing uncertainty level, the superiority of our method become more prominent. For the real application, the proposed method can be embedded in the microgrid energy management system to provide reference power output setpoints to DtGs, ES, *etc.*, to minimize the total operating cost.

In this study, since the thermal energy is locally supplied within a small area, the heat and gas networks are not considered, the future work can consider large-area multi-energy supply with the thermal and gas network integrated. Besides, although this thesis does not meet any numerical solution difficulties, in the future, more efficient and effective algorithms to enhance the convergence and feasibility can be used. Finally, in this chapter, the capacity, location as well as the type of all the units are predefined. To further reduce the system cost, the optimal system planning can be conducted.

5.) Optimal Placement of Heterogeneous Distributed Generators in a Grid-Connected Multi-Energy Microgrid Under Uncertainties

5.1 Introduction

In Chapters 3 and 4, the system-wide optimal coordinated dispatch model is proposed to minimize the total operating cost and improve energy utilization efficiency. Besides, the diverse uncertainties from RESs, power transaction prices, multi-energy demands are also tackled by the two-stage SO method for a reliable dispatch plan. Those studies are all from the system operation perspective, in which the planning aspects of the system, such as the size, location as well as the type of all the units are assumed as fixed. However, in fact, the optimal planning of all the units under diverse uncertainties in the multi-energy systems are essential for the cost-saving, reliability-enhancement and emission reduction as well [118].

As all the units can be mainly classified into the DtGs and ES. In this Chapter, the optimal planning of the DtGs is studied first. In this regard, a two-stage optimal placement method for heterogeneous DtGs in the MEMG under RES uncertainties is proposed. Compared with the conventional operation research, the DtG planning problem is investigated in the multi-energy coordination scheme. The heterogeneous DtGs in this study include the WTs, DGs, CCHP plants, PVs, EBs, and ECs. Apart from the DtG size and location planning, this study considers their type and investment year optimization for a more comprehensive and flexible DtG placement, to optimally minimize or maximize the project cost or profit. Besides, to handle the RES uncertainties and avoid any conservative solutions, the proposed DtG placement model is formulated as a multi-stage SO problem. Finally, the model is converted into a MILP problem via linearization processing with comprehensive case studies are done to verify its effectiveness and advantages.

5.1.1 Multi-Energy Conversion Modelling

The structure of the grid-connected MEMG is similar to Figure 3-1 but the DG is applied instead of the FCs. The input energy is transferred into the output side by a multi-energy conversion block. For the multi-energy supply, the system thermal (heat or cooling) loads are provided by the EBs, CCHP plants and ECs; the system power loads are supplied by the DGs, CCHP plants, WTs, PVs as

well as the transaction power from the utility grid.

The system uncertainty comes from the non-dispatchable DtGs and should be handled to maintain the system operation reliability and economy [97], [116]. In addition, the DtGs can also be classified according to their energy carriers, in this way, the CCHP plant is the tri-generation unit while others can only generate a single type of energy.

The mathematical model of a multi-energy conversion block [119] is given in Eq.(5-1).

$$\underbrace{\begin{bmatrix} P_{DG} \\ P_{MT} \\ H_{HMT} + H_{EB} \\ H_{CMT} + H_{EC} \end{bmatrix}}_{\text{Output}} = \underbrace{\begin{bmatrix} \eta_{DE} & 0 & 0 & 0 \\ 0 & \eta_{MT} & 0 & 0 \\ 0 & \eta_{MH} & \eta_{EB} & 0 \\ 0 & \eta_{MC} & 0 & \eta_{EC} \end{bmatrix}}_{\text{Multi-energy Conversion Matrix}} \times \underbrace{\begin{bmatrix} P_F \\ P_G \\ P_{EB} \\ P_{EC} \end{bmatrix}}_{\text{Input}} \quad (5-1)$$

5.2 Mathematical Modelling for DtG Placement

The DtG placement in the MEMGs aims to find the most economic DtG planning scheme under the system reliability constraints. Consequently, the uncertainties from RES-based generators should be handled for a robust DtG placement solution. In this section, the specific mathematic modeling for the DtG placement under the uncertainties is presented.

5.2.1 Two-Stage DtG Placement Framework

The framework for the proposed two-stage coordinated method for the DtG placement in a grid-connected MEMG under RES uncertainty is shown as Figure 3-1, where the planning decisions are divided into the first- and second-stage decisions:

1) **The first- or investment-stage decisions**, which refer to the investment plan, namely the type, location, size and installation phase of heterogeneous DGs. In this thesis, 4 years are taken as a unit investment phase. The DtG capacity to be installed at the beginning year of a phase (*i.e.*, the 1st, 5th, 9th, *etc.*, year) is set as the separate decision variable sets. During each phase, the capacity is kept the same for the whole phase.

2) **The second- or operation-stage decisions**, which refer to the optimal operating dispatch of all the DtGs after they are installed.

Figure 5-1. Proposed Two-stage DtG Placement Structure.

The mathematical models of the above two-stage planning framework will be detailed in the next section.

5.2.2 Two-Stage Mathematical Modelling

In this study, the objective function is the project NPV which should be maximized [120]. The two-stage DtG placement problem in Figure 5-1 can be modeled as:

$$\text{Objective function: } NPV_s = \underset{z \in CF_z, x \in CG_x}{\text{Max}} \left[\underbrace{-F(z)}_{\text{Investment Stage}} + \underbrace{G(x)}_{\text{Operation Stage}} \right] \quad (5-2)$$

where in Eq.(5-2), NPVs denotes the NPV of the project. z is the decision variables of the planning stage, i.e., DtG type, size, location, and investment phase. CF_z denotes the constraints for the DtG placement, which are shown in Eqs.(5-4)-(5-12). $F(z)$ is the objective of the investment stage, and its mathematical model is shown in Eq.(5-3). x denotes the decision variable at the operation stage. CG_x and $G(x)$ are the constraints and objective of the operation stage.

Constraints for the investment stage:

$$F(z) = \sum_{p \in N_p} \frac{C_{INV}^p - C_{SAL}^{N_p}}{(1+dr)^{p-1}} \quad (5-3)$$

$$C_{INV}^p = \sum_{q \in N_Q} \sum_{i \in N_{CB}} \left[\chi_{DtG, INV} \cdot (S_{DtG}^{p,q,i} - S_{DtG}^{p-1,q,i}) \right] \quad (5-4)$$

$$C_{SAL}^{N_p} = \varepsilon_{DtG, SAL}^{p,q} C_{INV}^p \quad \forall p, q \quad (5-5)$$

$$S_{DtG}^{p,q,i} = N_{DtG}^{p,q,i} \cdot S_{DtG, UN}^q + S_{DtG}^{p-1,q,i} \quad \forall p; q \in N_{CQ}; i \in N_{CB} \quad (5-6)$$

$$S_{DtG}^{p,q,i} \geq S_{DtG}^{p-1,q,i} \quad \forall p; q \in N_{VQ}; i \in N_{CB} \quad (5-7)$$

$$S_{DtG}^{p,q,i} \geq 0 \quad \forall p, q; i \in N_{CB} \quad (5-8)$$

$$S_{DtG}^{p,q,i} = S_{DtG}^{p-1,q,i} \quad \forall q; i \in N_{CB}; p \neq 1^{st} \text{ year of each phase} \quad (5-9)$$

$$U_{DtG}^{p,q,i} \cdot S_{DtG,MIN}^q \leq S_{DtG}^{p,q,i} \leq U_{DtG}^{p,q,i} \cdot S_{DtG,MAX}^q \quad \forall p,q; i \in N_{CB} \quad (5-10)$$

$$\sum_{i \in N_{CB}} S_{DtG}^{p,q,i} \leq S_{DtG,ALL}^q \quad \forall p,q \quad (5-11)$$

$$\sum_{i \in N_{NB}} U_{DtG}^{p,q,i} = 0 \quad \forall p,q \quad (5-12)$$

where Eq.(5-3) is the mathematical model for the NPV from the investment stage. Eqs.(5-4) shows the DtG investment cost. Eq. (5-5) is the salvage value, which means that the owner of the project can get some cash back by selling the used DGs at the end of the project [24]. Eq.(5-6) denotes the capacity limits of DtGs that have a discrete unit size, such as the WTs, DGs and CCHP plants. Eq.(5-7) denotes the capacity limits for the DtGs such as PVs, EBs, and ECs, which are available in all variable sizes. Eq.(5-8) means that all the capacity should be larger than or equal to 0, and Eq.(5-9) denotes that only the DtG capacity to be installed at the beginning year of a phase are set as separate decision variables. Eq.(5-10) denotes the DtG capacity limits for each node and Eq.(5-11) denotes the total DtG capacity limits of the MEMG. Eq.(5-12) denotes that the DtGs cannot be installed at the non-candidate buses.

Constraints for the operation stage:

$$G(x) = \sum_{p \in N_p} \left[\begin{array}{c} C_{REV}^p + C_{SUB}^p - C_{FC}^p - C_{TC}^p \\ -C_{CT}^p - C_{MC}^p - C_{EM}^p - C_{SD}^p - C_{ST}^p \end{array} \right] / (1+dr)^p \quad (5-13)$$

$$C_{REV}^p = \sum_{q \in N_Q} \sum_{d \in N_D} \sum_{t \in N_T} \sum_{i \in N_B} (\chi_{PS} P_L^\Lambda + \chi_{HS} H_H^\Lambda + \chi_{CS} H_C^\Lambda) \quad \forall p \quad (5-14)$$

$$C_{SUB}^p = \sum_{q \in N_Q} \sum_{d \in N_D} \sum_{t \in N_T} \sum_{i \in N_{CB}} \chi_{SUB} \cdot (P_{WT}^\Lambda + P_{PV}^\Lambda) \quad \forall p \quad (5-15)$$

$$C_{FC}^p = \sum_{q \in N_Q} \sum_{d \in N_D} \sum_{t \in N_T} \sum_{i \in N_{CB}} \left[\frac{\chi_{NG} P_{MT}^\Lambda / \eta_{MT} +}{\chi_{DG} (a^q U_{DG}^\Lambda + b^q P_{DG}^\Lambda)} \right] \quad \forall p \quad (5-16)$$

$$C_{TC}^p = \sum_{q \in N_Q} \sum_{d \in N_D} \sum_{t \in N_T} (\chi_B P_{BX}^{p,q,d,t,1} - \chi_S P_{SX}^{p,q,d,t,1}) \quad \forall p \quad (5-17)$$

$$C_{MC}^p = \sum_{q \in N_Q} \sum_{i \in N_{CB}} \left(\chi_{DG,F} S_{DtG}^{p,q,i} + \sum_{d \in N_D} \sum_{t \in N_T} \chi_{DtG,V} P_{DtG}^\Lambda \right) \quad \forall p \quad (5-18)$$

$$C_{EM}^p = \sum_{q \in N_Q} \sum_{d \in N_D} \sum_{t \in N_T} \sum_{i \in N_{CB}} \chi_{CO2} \left[\frac{(\kappa_{MT} P_{MT}^\Lambda) + (\kappa_B P_{BX}^\Lambda) +}{\kappa_{DG} (a^q U_{DG}^\Lambda + b^q P_{DG}^\Lambda)} \right] \quad \forall p \quad (5-19)$$

$$C_{ST}^p = \sum_{q \in N_Q} \sum_{d \in N_D} \sum_{t \in N_T} \sum_{i \in N_{CB}} \max(0, U_{DtG}^\Lambda - U_{DtG}^{p,q,d,t-1,i}) C_{DtG}^U \quad \forall p \quad (5-20)$$

$$C_{SD}^p = \sum_{q \in N_Q} \sum_{d \in N_D} \sum_{t \in N_T} \sum_{i \in N_{CB}} \max(0, U_{DtG}^{p,q,d,t-1,i} - U_{DtG}^\Lambda) C_{DtG}^D \quad \forall p \quad (5-21)$$

$$C_{CT}^p = \sum_{q \in N_Q} \sum_{d \in N_D} \sum_{t \in N_T} \sum_{i \in N_{CB}} \chi_{RES} (P_{DtG,REAL}^\Lambda - P_{DtG}^\Lambda) \quad \forall p \quad (5-22)$$

$$\gamma_{DtG,MIN} S_{DtG}^{p,q,i} \cdot U_{DtG}^\Lambda \leq P_{DtG}^\Lambda \leq \gamma_{DtG,MAX} S_{DtG}^{p,q,i} \cdot U_{DtG}^\Lambda \quad \forall p, q, d, t, i \in N_{CB} \quad (5-23)$$

$$P_{DtG}^\Lambda \leq P_{DtG,REAL}^\Lambda \quad \forall p, q, d, t, i \in N_{CB} \quad (5-24)$$

$$R_{DtG,DOWN}^q \Delta t \leq P_{DtG}^\Lambda - P_{DtG}^{p,q,d,t-1,i} \leq R_{DtG,UP}^q \Delta t \quad \forall p, q, d, t, i \in N_{CB} \quad (5-25)$$

$$H_H^{p,d,t,i} = H_{HMT}^\Lambda + H_{EB}^\Lambda \quad \forall p, q, d, t, i \quad (5-26)$$

$$H_C^{p,d,t,i} = H_{CMT}^\Lambda + H_{EC}^\Lambda \quad \forall p, q, d, t, i \quad (5-27)$$

$$P_{PF}^{p,d,t,b+1} = P_{PF}^{p,d,t,b} - P_{PF}^{p,d,t,0,b+1} - P_L^{p,d,t,b} + P_{DG}^{p,d,t,b} \quad \forall p, q, d, t, i \quad (5-28)$$

$$Q_{PF}^{p,d,t,b+1} = Q_{PF}^{p,d,t,b} - Q_{PF}^{p,d,t,0,b+1} - Q_L^{p,d,t,b} \quad \forall p, q, d, t, i \quad (5-29)$$

$$V_{BUS}^{p,d,t,i+1} = V_{BUS}^{p,d,t,i} - (R^b P_{PF}^{p,d,t,b} + X^b Q_{PF}^{p,d,t,b}) / V_0 \quad \forall p, q, d, t, i \quad (5-30)$$

$$1 - \Delta V_{BUS}^{\max} \leq V_{BUS}^{p,d,t,i} \leq 1 + \Delta V_{BUS}^{\max} \quad \forall p, q, d, t, i \quad (5-31)$$

where Eq.(5-13) denotes the NPV from the operation stage. Eq.(5-14) is the revenue from selling power, heat and cooling energy to the local customers. Eq.(5-15) is the subsidy for the utilization of RES. Eq.(5-16) means that the system fuel cost comes from the DGs and CCHP plants. Eq.(5-17) is power transaction revenue with the utility grid (the first bus is directly connected to the utility grid). Eq.(5-18) denotes the DtG maintenance cost. Eq.(5-19) is the emission cost from CCHP plants, utility grid, and DEs. Eqs.(5-20) and (5-21) denote the start-up and shut-down cost of the dispatchable DtGs. Eq.(5-22) is the cost of RES power curtailment if needed. Eq.(5-23) means that the DtG power output is limited by the installed capacity times the generation efficiency. Eq.(5-24) denotes that for non-dispatchable DtGs, their power outputs are limited by the available power generation capacity. Note that in Eqs. (5-22) and (5-24), the DtG in the subscript refers merely to RES-based generators. As the RES-based generators are sub-set of the DtGs, to avoid any confusion from the different abbreviations or variables, no new abbreviations are set solely for them. Eq.(5-25) shows the ramp-up/-down limits for the CCHP plants, DGs, ECs, and EBs. Eqs.(5-26)-(5-27) mean that the heat and cooling generation should be

equal to the consumption. Eqs.(5-28)-(5-30) model the power flow of the distribution network, which is based on the linearized Dist-Flow equations [116]. Eq.(5-31) constrains the bus voltage magnitude.

It should be noted that there are a number of nonlinear items in Eqs.(5-20)-(5-21),(5-23). To reduce the computation burdens and improve solution quality, those nonlinear items are linearized in the Appendix (Chapter 10, all the equations are specified in this chapter), in this regard, the MILP solvers like the Cplex can be used to solve the problem efficiently and with high quality.

5.3 Solution Method

The dimension of the DtG placement problem can be very high, due to many DtG types, system buses, planning years, dispatch periods and operating days in each year. Besides, uncertainties from RES-based generators should be handled in the MEMG operation. This section reduces the problem dimension first and then proposes the SO method for tackling the uncertainties.

5.3.1 Typical Seasonal Day Selection

In the two-stage DtG placement framework, there are 365 dispatch days in a year that makes the problem size excessively high. To reduce the computation burden, a set of typical seasonal days is selected to represent the whole year [9]. Then, the two-stage planning model can be converted as:

$$NPV_s = \underset{z \in CF_z, x \in CG_x}{Max} \left[\underbrace{-F(z)}_{\text{Investment Stage}} + \underbrace{\sum_{c \in N_c} N_D^c \cdot G(x|c)}_{\text{Operation Stage}} \right] \quad (5-32)$$

$$s.t. \quad (5-3)-(5-31) \quad (5-33)$$

where N_D^c is the number of days in season c ; N_C is the number of seasons; $G(x|c)$ is the objective of the operation stage in season c .

Note that all the 365 dispatch days can still be fully modeled if the computational burden is not a concern.

5.3.2 Stochastic Optimization Model Under Typical Days

To handle the RES uncertainties, the operation stage is solved by a two-stage SO method. At its first stage, dispatch decisions for all the heterogeneous DtGs before the realization of RES uncertainties are determined. They are called the

“*here-and-now*” decisions. At the second stage when the real-time RES outputs are revealed, the power exchange between MEMG and utility grid compensates the first-stage decisions to maintain the energy balance. The transaction power is the “*wait-and-see*” decision.

a) **Stochastic model:** in this study, the SO model can be denoted as:

$$\begin{aligned}
 \text{Min } G(x|c) &= \text{Min}_w \{S(w|c) + E[Q(w|c, \omega)]\} \\
 \text{s.t. } w &\in CS_w \mid Z \\
 Q(w|c, \omega) &= \text{Min}_y L(y|c) \\
 y &\in CL(w, \omega)
 \end{aligned} \tag{5-34}$$

where $S(w|c)$ is the objective of DtG operation in Eqs.(5-13)-(5-22); w denotes the decision variables for the DtG dispatch; CS_w is constraints for w in Eqs.(5-23)-(5-27); ω is stochastic variation of the RES outputs; $Q(w|c, \omega)$ is the optimal value of transaction cost under the uncertainty; y is the decision variable which denotes the transaction power; $L(y|c)$ is the mathematical formulation for transaction cost in Eq.(5-17); $CL(w, \omega)$ means the constraints for y in Eqs.(5-28)-(5-31); $E[Q(w|c, \omega)]$ denotes the expectation of transaction cost.

b) **Deterministic Equivalent:** assuming that ω has a finite number of possible realizations which are called the scenarios and denoted as $\omega_1, \dots, \omega_n$ with respective possibilities of $\chi_1, \dots, \chi_n$, then the model in Eq.(5-34) can be converted into a deterministic one as follows:

$$\begin{aligned}
 \text{Min}_x G(x|c) &= \text{Min}_{w, y_1, y_2, \dots, y_n} \left[S(w|c) + \sum_{n \in N_s} \chi_n L(y_n|c) \right] \\
 \text{s.t. } w &\in CS_w \mid Z \\
 y_n &\in CL(w, \omega_n), \forall n
 \end{aligned} \tag{5-35}$$

where n is the index of the forecasted scenarios; N_s is the total number of scenarios. All the scenarios can be obtained by the scenario generation and reduction techniques, which are commonly utilized in the literature as [116].

In Eq.(5-35), the objective and constraints are all linear, thus our proposed two-stage DtG placement model can be efficiently solved by some existing solvers such as the Cplex.

5.4 Test System Setup and Case Study

For the proposed DtG placement method, its effectiveness is justified on a test MEMG system. Besides, since there are already some traditional DtG

placement methods in the literature, the superiority of our proposed method should be further verified in comparison with them. In this section, the corresponding case studies are done in the following sub-sections.

5.4.1 Test System Setup

The proposed DtG placement method is tested on a grid-connected MEMG as shown in Fig.4, which is structured on the IEEE 33 bus radial distribution system [54]-[55].

Figure 5-2. The 33-Bus Radial Distribution System Based Multi-Energy Microgrid.

In this study, the data from a MG system in Tianjin, China is utilized to model this MEMG. Practically, in Tianjin, thermal energies are mainly supplied locally for a region of residential buildings or communities (denoted as the thermal group 1-3 in Figure 5-2), as the long-distance thermal transmission will result in high time delay and great thermal loss. Given this fact, the heat network is not modeled. The project lifetime is 12 years with 4 years as one investment phase, i.e., the new DtG installation only happens at the beginning of the 1st, 5th and 9th year. The discount rate is 6% [9] and load growth rates for power and thermal energy are set as 6.7% and 5%, respectively [54], [116]. The salvage factors for three phases are set as 0.05, 0.15 and 0.25, respectively. Other technical details for the heterogeneous DtGs are listed in Table 5-1

Table 5-1, which summarizes the synthesized figures from available literature, reports and commercial catalogs [22], [121], [122]. Other technical details regarding the MEMG can be seen in Figure 5-2.

The dispatch horizon for the operation-stage is set as 1 day and the dispatch interval is 1 hour [71].

Tianjin has four distinct seasons as the spring (91days), summer (91days), autumn (91 days) and winter (92 days) [123]. Based on the data of the year 2017 (Jan.-Dec.), Figure 5-3 shows the total forecasted RES generation and multi-energy demands of four typical seasonal days in the year 2018. The energy tariffs are shown in Table 5-2 [9], [117] and the prices for the power transaction, natural gas and diesel are extracted from Tianjin Development and Reform Commission [124]. For the thermal and power energy supplied to the customers, the fixed pricing scheme is applied.

Table 5-1 Parameters for different DtGs

Type	Unit size (kW)	Investment cost (\$/kW)	Maintenance cost (\$/kWh)	System size limits (kW)	Bus size limits (kW)	Power to heat ratio	Power to cooling ratio	Electric Efficiency (%)
Micro-turbine (or CCHP plants)								
ICE250	250	1452	0.0159	3000	1000	1.48	1.78	28
Cap200	200	1795	0.0121	3000	1000	1.57	1.89	30
Cap-65	65	2134	0.0078	3000	1000	1.8	2.16	32
Diesel Generators								
DG-A	80	1521	0.16	3500	800	a	b	-
DG-B	120	1121	0.24	3500	800	0.0161	0.252	-
Wind turbines								
WT-A	80	2134	0.24	1800	320	-	-	-
WT-B	120	2012	0.32	1800	320	-	-	-
Photovoltaic cells								
PV-A	-	2039	0.32	1500	200	-	-	-
PV-B	-	1792	0.45	1500	200	-	-	-
Electric Boilers								
EB-A	-	231	0.2	2000	700	3	-	-
EB-B	-	195	0.23	2000	700	2.75	-	-
EB-C	-	158	0.25	2000	700	2.5	-	-
Electric Chillers								
EC-A	-	489	0.2	1800	600	-	4	-
EC-B	-	395	0.25	1800	600	-	3.5	-

Figure 5-3. Typical Daily RES Generation and Multi-energy Loads

The load ratio of each group to the total thermal loads is set as 35%, 30%, and 35%, respectively. The capacity of the substation linking the MEMG and utility grid is set as 1.5 times of its peak power loads [97]. The forecasting errors for the RES generation are set as 25%-deviation to their prediction values [116].

5.4.2 Methods Comparison

To fully demonstrate the advantages of the proposed method, three DtG placement methods that are commonly employed in the literature, are compared as follows:

Table 5-2 Energy tariffs and CO₂ conversion factors [9], [22], [121]-[123]

Type	Price(\$/kWh)	Time period
Local power	0.17	All-day
Local thermal	0.022	All-day
Power transaction	0.0768	0:00-6:00,22:00-24:00
	0.1429	6:00-8:00,11:00-17:00
	0.1785	8:00-11:00,17:00-22:00
Natural gas	0.0569	All day
Diesel	1.0 (\$/L)	All-day
Unit RES curtailment	0.005	All-day
CO ₂ emission	0.0312 (\$/kg)	All day
Emission Conversion Factors	Value	Unit
CCHP plants	0.184	kg/kWh
Utility grid	0.889	kg/kWh
DEs	2.6	kg/L

Method #1: Separately DtG placement in SEMGs [9]: in this method, under the RES uncertainties, the GBs are utilized instead of the CCHP plants, EBs, and ECs for the thermal loads. The WTs, DGs and transaction power are coordinated to satisfy the system power loads. The parameters for GBs are shown in Table 5-3.

Table 5-3 Parameters for gas boilers [9]

Type Parameters	GB-A		GB-B		GB-C	
	Heat	Cooling	Heat	Cooling	Heat	Cooling
Efficiency	0.75	0.89	0.8	0.95	0.82	0.98
Maintenance (\$/kW)	0.29		0.33		0.36	
Investment (\$/kW)	35		42		52	
Emission factors (kg/kWh)	0.226					
System/bus size limits(kW)	8000/1000					

Method #2: Single-type single-investment-phase DtG placement: from the above simulation results, only the Cap-65, DG-B, WT-B, EB-A, EC-A, and PV-B are considered and installed at the beginning of the 1st project year [42]-[49]. Other placement aspects remain the same as the proposed method.

Method #3: Deterministic DtG placement: the uncertainties from RES generation are not considered and other placement aspects remain the same.

5.4.3 Assumptions for Case Study

In the case study, to verify the effectiveness of the proposed DtG placement method, some assumptions are made below. Though those assumptions make different methods simple, they are reasonable and effective in reducing the problem dimensions.

1) All the DtGs are assumed to have the same lifetime as the project. In fact, different DtGs should have different lifetime, however, considering DtG lifetime in detail would make the model much more complicated without adding novel scientific contributions. As this thesis aims to focus more on the DtG planning and multi-energy coordination in the MEMGs. The above assumption is made. Besides, the system performance considering different DtG lifetime is listed as the future work.

2) The pre-defined candidate buses, the number of the thermal groups, some simulation data such as the salvage factors, *etc.*, can also be regarded as parameter assumptions. However, as the proposed model aims to provide a general DtG placement method, any other real-world reasonable data or configuration for the DtGs or system structure can also be applied, which won't influence its effectiveness.

3) It is assumed that the initial sizes for all DtGs are 0. In practice, it can be other real-world values that won't affect the effectiveness of the proposed method.

The simulation is conducted on an Intel(R) Xeon(R) E5-1630 3.70GHz 64-bit PC with 16G RAM. The Cplex solver is used to solve the model via the GAMS.

5.4.4 Simulation Results and Discussions

For the DtG placement method, the simulation results of the project NPV are used to verify its effectiveness. If the NPV is positive, it means that the project should be invested as it gains value, or it should be definitely rejected [125]. Compared with other methods, the NPV difference denotes the indicator for the superiority of the proposed method. In this section, the NPV of the proposed method and traditional methods are compared and analyzed.

5.4.5 Investment-Stage Simulation Results & Discussions

In the simulation, 2000 random scenarios are initially generated and then reduced to 10 representative ones with corresponding possibilities using the

simultaneous backward method [116]. The total scenario generation and reduction time are 1.08 hours for each typical day, however, both processes can be done off-line. The scenarios and possibilities are shown below.

(i) The corresponding possibilities for the 10 scenarios
Figure 5-4. The scenarios and corresponding possibilities.

The optimization results for the investment-stage are listed in Table 5-4. Note

that in Table 5-4, first, the grey blocks denote that there are investment decisions at this phase and its subtraction with the DtG size at the last phase is the newly installed DtG capacity at the new phase. For example, at Phase-1 (year 1-4), there is a 90.7kW installation of EB-A at bus 9, at Phase-2 (year 5-8), the newly installed EB-A is $(128.1-90.7)=37.4\text{kW}$, and at Phase-3 (year 9-12), an additional capacity of $(129.6-128.1)=1.5\text{kW}$ of the EB-A is installed. Second, if no DtG installed at a certain phase, the phase index is omitted, e.g., for EB-B at bus 12, the installation of EB only occurs at Phase-3 (year 9-12). Finally, if no more DtG installation at later phases, the phases are combined, e.g., the WT-A at bus 6, where there is the only new installation at the first phase.

Table 5-4 The DtG placement results (kW)

Year/Bus	3	6	9	12	18	22	25	27	30	33
Cap-65										
1-4	65	195	65	130	0	0	130	65	0	65
5-8	65	195	65	195	0	65	130	65	65	65
9-12	65	195	65	195	65	65	130	65	65	130
EB-A										
1-4	123.2	96	90.7	0	146.8	41.5	167.8	92.9	0	0
5-8	123.2	96	128.1	0	146.8	88.5	214.8	92.9	0	0
9-12	138.5	96	129.6	0	146.8	120.4	216.2	92.9	0	0
EB-B										
9-12	0	0	0.0	57.1	0	66.7	74.1	0	0	0
EC-A										
1-4	200.2	0	68.4	0	105.8	0	141.3	0	0	48.25
EC-B										
1-4	0	0	25.0	0	0	50.7	74.3	0	0	0
5-8	0	0	50.3	0	0	103.8	115.2	0	0	0
9-12	0	0	90.9	0	0	143.0	115.2	0	0	0
PV-B										
1-12	137.6	137.6	136.2	122.2	118.9	137.7	181.6	181.6	177.8	169
WT-A										
1-12	80	0	0	0	0	80	80	0	80	0
WT-B										
1-12	0	240	120	0	240	0	240	0	120	0

From the investment-stage simulation results, it can be seen that:

1) The investment-related parameters, mainly the unit investment cost and the operation-related parameters such as the energy efficiencies and energy conversion ratios, *etc.*, would exert different effects on the DtG placement. For the CCHP plants, though the type Cap-65 has the highest unit investment cost, the high energy efficiency and energy conversion ratio result in much lower operation cost (*i.e.*, fuel cost) in the long run, thus, it is installed rather than other two types. For EB, the unit investment cost of EB-A is higher than EB-B, but the operation efficiency of EB-B and EB-C is lower, which leads to the investment

of EB-A at earlier stages and larger capacity (there is no investment of EB-C at all). Similar results are obtained for the EC investment. For the WTs and PVs, as their operation performance (mainly maintenance cost) are similar, the investment cost plays a leading role in their placement.

2) The unit size will affect the placement of DtGs in discrete sizes. Except for higher efficiency, Cap-65 has a smaller unit size, which means that it is more flexible for deployment, thus, the Cap-65 type of MT is chosen. As for WTs, though WT-B is the majority, the smaller unit size of WT-A is more economical than a unit of WT-B, when not so large capacity is needed.

3) Though the unit investment cost for DGs is lower than the CCHP plants, there is still none DGs installed, this is because the CCHP plants can provide multiple energies with higher efficiency and lower cost than the DGs. The results verify the effectiveness and practicability of the placement of co- or tri-generation units in the MEMGs.

4) The investment phase optimization plays a role in the placement of some DtGs such as the Cap-65, EB-A, EC-B, *etc.* The reasons lie in two aspects: on the one hand, with the increasing multi-energy loads, their capacities which are invested at the earlier phases are not enough; on the other hand, the DGs which are invested at later phases tend to get more salvage value. The specific case study will be done in the later section

5) For the RES-based generators, *i.e.*, WTs and PVs, there is an only one-time investment at Phase-1 and their installed capacity is larger than the maximal RES available active power which results in no RES curtailment at all. This is because the RES outputs are the energy generation with relatively low investment and operation costs, and they tend to be utilized as much as possible.

5.4.6 Operation-Stage Simulation Results & Discussions

After getting the investment-stage decisions, the operation-stage decisions for all the DtGs as well as power transactions can also be obtained.

The dispatch results for the units in the year 2028 are shown in Fig. 6-7. In those figures, “EX” means the net power transaction between the MEMG and utility grid. It is equal to the amount of purchasing power subtract the selling power. “Power”, “Heat” and “Cooling” means the system power, heat and cooling loads.

Figure 5-5 Power Balance Condition in the Year 2028.

Figure 5-6. Thermal Balance Condition in the Year 2028.

From Figure 5-5 to Figure 5-6, all the heterogeneous DtGs coordinate with one another to supply the multi-energy demands. The RES outputs follow the maximal available active power as there is no RES curtailment. When the transaction prices are at valley periods, *i.e.*, 0:00 am-6:00 am, 22:00 pm-24:00 pm, more power would be transferred to heat via EBs or cooling via ECs to save money for supplying thermal demands. When the transaction prices are at peak periods, *i.e.*, 8:00 am-11:00 am, 17:00 pm-22:00 pm, more natural gas is consumed via CCHP plants to generate relatively cheaper power and thermal energy for the system multi-energy loads as well as sell the excess electricity

out to earn more from the utility grid. When the transaction prices are at medium periods, *i.e.*, 6:00 am-8:00 am, 11:00 am-17:00 pm, the program will decide the most economical way for the multi-energy coordination. The final NPV for the project plan is \$15.02 M, which means that this project should be implemented since its NPV is positive.

In terms of the solution speed, there are 1832653 continuous and 93096 discrete variables in the mathematical model, while the solution time is only 21.5 hours, which is fully computationally acceptable for a 12-year planning project.

5.4.7 Methods Comparison Results

After obtaining the simulation results for the proposed DtG placement method, to further verify its effectiveness, the comparisons with the traditional DtG placement methods are further done.

The simulation results of **Method #1** are given in Table 5-5.

Table 5-5 DG Placement Results of Method #1 (kW)

Year/Bus	3	6	9	12	18	22	25	27	30	33
DG-B										
5-8	0	0	120	120	0	0	0	0	120	0
9-12	0	0	240	120	0	0	0	0	240	0
GB-A										
1-4	0	0	0	0	0	175.1	0	175.1	0	0
5-8	191.9	162.2	0	305.6	0	177.5	132.9	175.1	123.6	100.0
9-12	191.9	459.0	176.7	305.6	194.8	314.1	132.9	271.7	326.9	233.3
GB-B										
1-12	143.3	111.6	115.4	128.9	114.9	0	0	0	0	254.9
GB-C										
1-12	641.2	463.0	537.3	409.1	0	0	679.5	424.7	0	0
PV-B										
1-12	137.6	137.6	126.7	126.7	126.7	137.6	183.5	183.5	169.0	171.0
WT-A										
1-12	80	80	80	0	0	0	80	0	0	0
WT-B										
1-12	0	120	120	0	240	120	240	0	0	240

It can be seen from Table 5-5 that, due to the similar operation performance with DG-A but lower unit investment cost, DG-B is installed to maintain the voltage reliability and supply the power loads. For thermal supply, all three types of GBs are installed but given the superior economic operation performance of GB-C, it has the largest invested capacity. However, when supplying the multi-energy loads, the DGs and GBs are of lower efficiency but higher operating cost, besides, there is no interaction between different energies at all, thus, the system cannot take the advantage of the price difference to effectively transfer

power to thermal energy to save money. Overall, the NPV for **Method #1** is much lower, which is only \$9.95M. The simulation results demonstrate the advantages of our proposed DtG placement in the 'multi-energy' scheme.

The simulation results for **Method #2** are shown in Table 5-6.

Table 5-6 DtG Placement Results of Method #2 (kW)

Year/Bus	3	6	9	12	18	22	25	27	30	33
Cap-65										
1-12	0	260	0	65	130	0	65	0	0	195
EB-A										
1-12	90.8	239.9	250.0	25.0	131.7	124.3	250.0	89.5	25.0	90.5
EC-A										
1-12	183.6	37.6	200.0	0	124.1	139.3	250.0	0	110.5	0
PV-B										
1-12	136.2	136.2	128.8	126.7	122.2	137.6	181.6	181.6	169.0	180.3
WT-B										
1-12	0	240	240	0	120	120	360	0	0	240
DE-B										
1-12	0	0	0	0	240	0	0	120	0	0

The NPV of **Method #2** is \$14.15M, which is also lower than our method. The reason is with the one-time investment, all the DtGs have to be installed prior to the project with large sizes, it would be a waste of capacity at early years and also result in lower salvage value. Besides, with much less choice for DtG types, the solution space of the programming model is limited. Thus, enabling the type and investment phase optimization benefits the project's economic performance.

The simulation results for **Method #3** are shown in Table 5-7.

Table 5-7 DG Placement Results of Method #3 (kW)

Year/Bus	3	6	9	12	18	22	25	27	30	33
Cap-65										
1-4	195	0	65	130	0	65	0	130	0	130
5-9	195	0	65	195	0	130	0	130	0	195
9-12	195	0	65	195	65	130	0	130	0	195
EB-A										
1-4	81.7	68.4	138.9	0	98.6	112.1	122.2	0	0	140.0
5-9	81.7	87.7	176.3	0	98.6	138.3	167.7	0	0	140.0
9-12	81.7	128.1	177.0	0	98.6	138.3	208.0	0	0	140.0
EB-B										
9-12	0	0	58.0	0	0	74.1	74.1	0	0	0
EC-A										
1-12	110.1	0	127.9	0	32.9	71.8	113.6	0	0	66.0
EC-B										
1-4	54.1	0.0	25.0	0	32.0	32.0	97.7	0	0	0
5-9	72.8	28.2	65.0	0	32.0	32.0	157.7	0	0	0
9-12	103.7	28.2	74.3	0	32.0	32.0	166.5	0	0	0
PV-B										
1-12	133.7	133.7	133.7	128.7	128.7	133.7	178.2	178.2	178.2	173.4
WT-A										
1-12	0	80	0	0	80	80	0	0	0	80
WT-B										
1-12	120	0	0	240	120	120	240	0	240	0

The NPV of **Method #3** is \$15.52M, which is slightly higher than our method. This is because the solution space is reduced and hence the NPV of our stochastic approach is lower considering the RES uncertainties in terms of scenarios. The cost difference between the deterministic approach (**Method #3**) and the stochastic approach is called the value of perfect information and it is used to help the system immune against the uncertainties.

However, when a set of 1000 random scenarios for the RES outputs of four typical days every year is used to check the robust performance of the planning decisions, the average NPV of all the scenarios of **Method #3** becomes \$14.55 M but the average NPV of our method is \$14.93 M. It means that with the real-time RES outputs (*i.e.*, the practical condition), our (stochastic) method has a higher potential in gaining more profits than the deterministic method. This result justifies the effectiveness of our stochastic DG placement method in immunizing against the practical RES fluctuations to reduce the system cost.

5.5 Conclusion and Future Work

This chapter develops an optimal two-stage placement method for the heterogeneous DtGs in a MEMG under the uncertainties from the RES. The DtG placement scheme is decomposed into three investment phases with the project NPV to be maximized. By employing the SO method, the RES uncertainties are incorporated and then handled in the system two-stage decision-making structure. Simulation results show that the project NPV of our method is positive, which means that this project can gain values and thus should be implemented. Besides, to further demonstrate the effectiveness of our proposed method, three conventional DtG placement methods are then compared, *i.e.*, separate DtG placement method, single-type single-investment-phase DtG placement method, and deterministic DtG placement method. The results show that our method, which considers the multi-energy coordination, multiple investment phase and type optimization in the DtG placement scheme would add extra flexibility for the system holistic energy supply and obtain a more economical and robust DtG placement plan.

As another indispensable unit, the heterogeneous energy storage system plays a key role in cost-saving and renewable integration. However, this chapter only deals with the planning problem of DtGs. Further planning research can be

done on the energy storage system.

6.) Optimal Deployment of Heterogeneous Energy Storage System in a Residential Multi-Energy Microgrid With Demand-Side Management

6.1 Introduction

Chapter 5 investigates the optimal planning of the DtGs under the diverse uncertainties, as another important component for the MEMG, the planning of the ES is of the same importance. ES is to capture the energy produced at one time for later use [127]. Its optimal deployment in the energy systems is essential for providing numerical benefits, such as tackling the intermittent power outputs from the RES, achieving higher energy utilization flexibility, shaving peak energy demands, improving the voltage profile, *etc.* [64],[128].

Thus, in this chapter, a new HES deployment model in the grid-tied residential multi-energy microgrids (RMEMGs) is proposed. Instead of focusing merely on the EES deployment like other traditional planning research, its integration with the TS and different energy properties are also investigated. Further, except for the traditional size and location planning, the investment phase selection is also considered, given there is an annual load growth rate, for a more comprehensive and flexible HES deployment. The diverse uncertainties not only from RES and power loads of the traditional power system but from the outdoor temperature and hot water needs of the thermal system are also taken into full account. Then, a scenario-based multi-stage adaptive stochastic approach is proposed to tackle all the uncertainties. The DSM for multiple energies is incorporated in the HES deployment, given its advantage in flexibilizing the system operation and reducing the energy bills. Especially for the thermal system, the DSM in terms of specific thermal modeling for the local residential buildings is built with thermal dynamics and thermal inertia combined. It makes this work more practical for the direct application in the emerging smart buildings/homes.

6.2 Residential Multi-Energy Microgrid Modelling

6.2.1 Residential Multi-Energy Microgrid Structure

In this chapter, the MEMG is based on residential buildings, that is, the RMEMG. The structure of a typical RMEMG is shown in Figure 6-1. The basic components like the DtGs and HES are the same as Chapter 3. Further, the residents are assumed to have signed a long-term contract with the RMEMG to save their energy bills.

Figure 6-1. Typical Structure of a RMEMG

All the units are coordinated to satisfy the multi-energy demands as well as maintain the system reliability and economy [18]. The RES generation, power demands, outdoor temperature, residential hot water needs, and demand response pattern data can all be collected by the smart meters equipped in each building. The collected data is then applied in the computation procedure as optimization parameters.

The detailed computation procedures are described in the following sections with the deployment decisions optimized from those procedures.

6.2.2 Heterogeneous Energy Storage (HES)

1) **For the electric energy storage (EES):** the BS is a kind of prevailing EES widely used in power system planning and operation. Compared with other types of EES such as the pumped storage and compressed air energy storage with capacities up to 100 MW, its power density range starts from a few kW to several MW. Thus, it is used in this study [129].

The model for the BS is the same as Chapter 3.

2) **For the thermal storage tank (TST):** The detailed typical TST model is shown in Figure 6-2. Its walls are composed of stainless steel, concrete, and heat insulation materials from inside to outside. The tank is well insulated for high operating efficiency [117]. The temperature in the tank can be roughly stratified into the hot water layer (Temperature: T_h , Volume: V_h) and cooling water layer (Temperature: T_c , Volume: V_c). In both layers, the temperature is the same as the corresponding water networks and remains constant. The TST absorbs or releases thermal energy by controlling the volume of hot or cold water. When it produces heat, the temperature of the supply water becomes

higher, in this light, the TST is called a heat storage tank; while for the cooling supply, the TST should be called a cooling storage tank with a higher temperature of return water.

Figure 6-2. Structure of the TST. SI, SO: inlet and outlet switch for supply water; RI, RO inlet and outlet switch for return water.

The absorbing and releasing power of the TST can be expressed as follows:

$$H_{TC}^t = C_{WR} \cdot \rho_{WR} \cdot V_H^t \cdot (T_H - T_C) \quad (6-1)$$

$$H_{TD}^t = -C_{WR} \cdot \rho_{WR} \cdot V_C^t \cdot (T_C - T_H) \quad (6-2)$$

The specific model between its energy and power is the same as Chapter3.

6.2.3 Price-Based Demand Response (PBDR) for Electricity

The PBDR is adopted for electricity DSM in the RMEMG. The reason lies in twofold: first, it allows customers to manage demand freely by themselves without partial loads being controlled directly by the system operator. In the PBDR, electricity prices of the following day are designed and delivered to the customers a day ahead, then the customers adjust their demands based on the prices. When the prices are high, the customers would reduce their demands to save usage bills. When they are low, customers would be incited to increase their demands; second, it contributes to the system reliability enhancement when there is a large penetration level of fluctuating renewable energies [80]. Currently, the PBDR has been widely applied in the power system planning, power market regulation, and economic dispatch, etc.

In the PBDR model, the relationship between the electricity price and demands can be expressed as follows:

$$P_{DL}^t = A \cdot (\chi_{PS})^\varepsilon \quad (6-3)$$

In Eq.(6-3), ε is the price elasticity of power demands, representing the

sensitivity of customer demand to the price of electricity; A is a constant. The specific calculation methods of ε and A are given by [130].

6.2.4 Thermal Loads Modelling with Thermal Inertia

For the DSM of thermal energy, the thermal dynamics and thermal inertia are employed in this thesis. To comprehensively model the thermal energy in a typical residential building, its typical structure is demonstrated in Figure 6-3 [122].

For the residents, their thermal demands mainly come from the following two parts:

1) **space thermal demands**, *i.e.*, space heating (usually in winter) and cooling (usually in summer) [131].

2) **residential hot water needs** (*usually in spring, autumn, and winter*) [132].

All the above thermal demands can be modeled considering the thermal dynamics.

Figure 6-3. Typical structure of a room in a residential building

1) Thermal Demand Classification

For space thermal demands, the thermal generation should compensate for any thermal loss to maintain suitable room temperature. The total thermal demands are calculated as [132]:

$$H_{TL}^t = H_{BH}^t + H_{AH}^t + H_{CN}^t + H_{CR}^t \quad (6-4)$$

The basic thermal transfer loss mainly includes the heat transfer from the building envelope such as doors, windows, walls, floors, and so on, which can be denoted as Eq.(6-5):

$$H_{BH}^t = \alpha_{BH} K_{HT} S_{BH} (T_{IN}^t - T_{OT}^t) \quad (6-5)$$

The additional thermal loss considers the loss brought by the wind blow, solar irradiation, and height of the building. It is calculated as:

$$H_{AH}^t = H_{BH}^t \cdot (\beta_{cx} + \beta_{jx}) \quad (6-6)$$

The infiltration thermal loss denotes the thermal demands to heat the cold air (mainly in winter) or cool the hot air (mainly in summer) from outside to inside via the door or window crack. It is formulated as:

$$H_{CN}^t = 0.364 \cdot I_{LE} A_{CL} (T_{IN}^t - T_{OT}^t) \quad (6-7)$$

The intrusion thermal loss describes the thermal demands that cool the hot air (mainly in summer) or heat the cold air (mainly in winter) from the casual opening of the doors or windows. It can be demonstrated as:

$$H_{CR}^t = H_{BH}^t \gamma_{it} \quad (6-8)$$

All the above thermal loss is related to the difference between inside and outside temperature, then the total thermal demands can be rewritten in a general form as:

$$H_{TL}^t = C_{AV} (T_{IN}^t - T_{OT}^t) \quad (6-9)$$

2) **Dynamic Thermal Demand Modelling**

According to the first law of thermodynamics [31], the thermal demands in Eqs.(6-4)-(6-9) can be modeled as a dynamic model with the temperature change as:

$$C_{Air} \rho_{Air} V_{RB} dT_{IN}^t / dt = H_{NET}^t \quad (6-10)$$

Due to the thermal inertia, the indoor temperature would vary slowly. Its variations during each short-term period, e.g., 1 hour can then be neglected [18], [122]. In this regard, the thermal dynamic model in Eq. (6-10) can be converted into an hourly state model as:

$$T_{IN}^t = H_{NET}^t \Delta t / (C_{Air} \rho_{Air} V_{RB}) + T_{IN}^{t-1} \quad (6-11)$$

Note that human activities, power appliances, *etc.*, may also impact the space thermal demands, but as the impact is little, they are ignored in this work [133].

3) **Hot water demands**

The hot water is mainly used for the showering or washing needs of the

residents. The corresponding thermal demands for hot water can be calculated as [131]:

$$H_{HW}^t = C_{WR} \rho_{WR} V_{HW}^t (T_{SW}^t - T_{IW}^t) \quad (6-12)$$

6.2.5 The DSM for Thermal Energy

Apart from the slow variation rate of thermal energy during short periods, the fact that residents can be comfortable within a certain indoor or hot-water temperature range constitutes another aspect of the thermal inertia [29]. This part is regarded as the DSM for thermal energy and it can be modeled as Eqs.(6-13) and (6-14).

$$T_{IN}^{set} - \Delta T_V \leq T_{IN}^\Delta \leq T_{IN}^{set} + \Delta T_V \quad (6-13)$$

$$T_{SW}^{set} + \Delta T_W \leq T_{SW}^\Delta \leq T_{SW}^{set} + \Delta T_W \quad (6-14)$$

6.3 Mathematical Modelling for HES Deployment

6.3.1 Multi-Stage HES Deployment Framework

In this study, the HES deployment can be decomposed into two main stages as Figure 6-4 with respective decisions:

Figure 6-4. Multi-stage HES deployment framework

1) **Investment stage:** decisions in this stage are related to the investment aspects, namely the HES location, size, and installation phase. As shown in Figure 6-4, 3 years is taken as a unit investment phase, and after every 3 years, there can be new HES installation decisions.

2) **Operation stage:** decisions in this stage include the optimal dispatch of the HES system, DtGs and DSM scheme. At this stage, the diverse uncertainties are handled via a further two-substage coordinated operation method. The first substage is the day-ahead dispatch stage, and the second substage is the intro-

day online dispatch stage. The details for the two substages are given in the following sections.

6.3.2 Mathematical Formulation

In this study, it is assumed there is a steady growth rate for the multi-energy demands every year. To evaluate the effectiveness of the method, the maximization of EDP is set as the objective. In finance, the EDP is defined as the profit per day of owning and operating an asset over its entire lifespan. It is calculated by dividing the net present value of a project by the present value of the daily factor. Then, the HES deployment model can be formulated as:

1) *Objective:*

$$MaxEDP = \frac{1}{365 \times N_p} \cdot \frac{dr(1+dr)^{N_p}}{(1+dr)^{N_p} - 1} \cdot \left[\underbrace{-F(z)}_{\text{Investment Stage}} + \underbrace{G(x)}_{\text{Operation Stage}} \right] \quad (6-15)$$

$$\text{s.t., } F(z) = \sum_{p \in N_p} \frac{C_{INV}^p}{(1+dr)^{p-1}} - \frac{C_{SAL}^{N_p}}{(1+dr)^{N_p-1}} \quad (6-16)$$

$$G(x) = \sum_{p \in N_p} \frac{(C_{REV}^p + C_{SUB}^p - C_{FC}^p - C_{TC}^p - C_{MC}^p - C_{EM}^p - C_{ST}^p - C_{SD}^p)}{(1+dr)^p} \quad (6-17)$$

$$C_{SAL}^{N_p} = \sum_{p \in N_p} \varepsilon_{SAL}^p C_{INV}^p \quad (6-18)$$

$$C_{INV}^p = \sum_{i \in N_B} \chi_{ES, INV} (S_{ES}^{p,i} - S_{ES}^{p-1,i}) \quad (6-19)$$

$$C_{REV}^p = \sum_{d \in N_D} \sum_{t \in N_T} \sum_{i \in N_B} (\chi_{PA}^{\Lambda} P_{DL}^{\Lambda} + \chi_{HS}^{\Lambda} H_{HL}^{\Lambda} + \chi_{CS}^{\Lambda} H_{CL}^{\Lambda}) \quad (6-20)$$

$$C_{SUB}^p = \sum_{d \in N_D} \sum_{t \in N_T} \sum_{i \in N_B} \chi_{SUB} (P_{WT}^{\Lambda} + P_{PV}^{\Lambda}) \quad (6-21)$$

$$C_{FC}^p = \sum_{d \in N_D} \sum_{t \in N_T} \sum_{i \in N_B} (\chi_{NG}^{\Lambda} P_{MT}^{\Lambda} / \eta_{MT}) \quad (6-22)$$

$$C_{TC}^p = \sum_{d \in N_D} \sum_{t \in N_T} \sum_{i \in N_B} (\chi_B^{\Lambda} P_{BX}^{\Lambda} - \chi_S^{\Lambda} P_{SX}^{\Lambda}) \quad (6-23)$$

$$C_{MC}^p = \sum_{i \in N_B} \sum_{d \in N_D} \sum_{t \in N_T} \chi_{DG, M} P_{DG}^{\Lambda} + \chi_{ES, M} P_{ES}^{\Lambda} \quad (6-24)$$

$$C_{EM}^p = \sum_{d \in N_D} \sum_{t \in N_T} \sum_{i \in N_B} \kappa_{MT} P_{MT}^{\Lambda} + \kappa_B P_{BX}^{\Lambda} \quad (6-25)$$

$$C_{ST}^p = \sum_{d \in N_d} \sum_{t \in N_T} \sum_{i \in N_B} \max[0, U_{DG}^{\Lambda} - U_{DG}^{p,d,t-1,i}] C_{DG}^U \quad (6-26)$$

$$C_{SD}^p = \sum_{d \in N_d} \sum_{t \in N_T} \sum_{i \in N_B} \max[0, U_{DG}^{p,d,t-1,i} - U_{DG}^{\Lambda}] C_{DG}^D \quad (6-27)$$

2) Constraints:

$$\text{Eqs. (6-1)-(6-14)} \quad (6-28)$$

$$S_{ES}^{p,i} \geq S_{ES}^{p-1,i} \quad (6-29)$$

$$U_{ES}^{p,i} \cdot S_{ES,MIN} \leq S_{ES}^{p,i} \leq U_{ES}^{p,i} \cdot S_{ES,MAX} \quad (6-30)$$

$$\sum_{i \in N_B} S_{ES}^{p,i} \leq S_{ES,ALL} \quad (6-31)$$

$$0 \leq P_{ESC}^{\Lambda} \leq \gamma_{ES,MAX} U_{ESC}^{\Lambda} S_{ES}^{p,i} \quad (6-32)$$

$$0 \leq P_{ESD}^{\Lambda} \leq \gamma_{ES,MAX} U_{ESD}^{\Lambda} S_{ES}^{p,i} \quad (6-33)$$

$$U_{ESC}^{\Lambda} + U_{ESD}^{\Lambda} \leq 1 \quad (6-34)$$

$$\sum_{i \in N_B} U_{ES}^{p,i} = 0 \quad (6-35)$$

$$E_{ES}^{p,d,0,i} = E_{ES}^{p,d,N_T,i} \quad (6-36)$$

$$\gamma_{DG,MIN} S_{DG}^{p,i} \leq P_{DG}^{\Lambda} \leq \gamma_{DG,MAX} S_{DG}^{p,i} \quad (6-37)$$

$$P_{DG}^{\Lambda} \leq P_{DG,REAL}^{\Lambda} \quad (6-38)$$

$$R_{DG,DN}^{\Lambda} \Delta t \leq P_{DG}^{\Lambda} - P_{DG}^{p,d,t-1,i} \leq R_{DG,UP}^{\Lambda} \Delta t \quad (6-39)$$

$$P_{PF}^{p,d,t,b+1} = P_{PF}^{p,d,t,b} - P_{PF}^{p,d,t,0,b+1} - P_{DL}^{\Lambda} + P_{MT}^{\Lambda} + P_{EP}^{\Lambda} - P_{CP}^{\Lambda} + P_{WT}^{\Lambda} + P_{PV}^{\Lambda} - P_{EB}^{\Lambda} - P_{EC}^{\Lambda} \quad (6-40)$$

$$Q_{PF}^{p,d,t,b+1} = Q_{PF}^{p,d,t,b} - Q_{PF}^{p,d,t,0,b+1} - Q_{DL}^{p,d,t,i} \quad (6-41)$$

$$V_{BUS}^{p,d,t,i+1} = V_{BUS}^{p,d,t,b} - (R^b P_{PF}^{p,d,t,b} + X^b Q_{PF}^{p,d,t,b}) / V_0 \quad (6-42)$$

$$1 - \Delta V_{BUS}^{\max} \leq V_{BUS}^{p,d,t,i} \leq 1 + \Delta V_{BUS}^{\max} \quad (6-43)$$

$$H_{TL}^{\Lambda} + H_{WR}^{\Lambda} = H_{MH}^{\Lambda} + H_{EB}^{\Lambda} + H_{MC}^{\Lambda} + H_{EC}^{\Lambda} + H_{TD}^{\Lambda} - H_{TC}^{\Lambda} \quad (6-44)$$

Eq.(6-15) denotes the system EDP, in which z and x denote the set of investment- and operation-stage decisions; $F(z)$ in Eq.(6-16) and $G(z)$ in Eq.(6-17) denote the cost from the investment- and operation- stage, respectively; Eq.(6-18) denotes the salvage value of the HES system; Eq.(6-19) presents the investment cost of the HES system; Eqs.(6-20) is the revenue from selling power and thermal energy to local customers; Eqs.(6-21) is the subsidy from the RES utilization; Eqs.(6-22)-(6-25) denote CCHP fuel cost, power transaction cost, maintenance cost from all the units as well as emission cost from CCHP plants and utility grid; Eqs.(6-26)-(6-27) are the start-up and shut-down cost for controllable generators; Eq.(6-29) means that the size of the HES system in the present year should be no less than that of the last year. It is

assumed that HES can be available in all variable sizes [46]; Eqs.(6-30) denotes HES size limits for each bus (for BS) or thermal group (for TST). Eqs. (6-31) describes the HES size limits for the whole system; Eqs.(6-32)-(6-36) denote all the HES operating constraints (subscript ES denotes the generalized abbreviation for the BS and TST); Eqs.(6-32) and (6-33) mean that the charging (absorbing) or discharging (releasing) power of HES should be within the capacity limits; Eq.(6-34) shows that HES cannot charge (absorb) and discharge (release) at the same time; Eq.(6-35) denotes that HES can only be installed at the candidate buses or thermal groups; Eq.(6-36) means that the HES starting energy is equal to its ending energy for the same scheduling flexibility of each dispatch horizon [131]; Eq.(6-37) denotes that the power output of each generator should be within their capacity limits (subscript DG is the generalized abbreviation for all the generators), while Eq.(6-38) shows that the RES power output should be less than available sources; Eq.(6-39) presents the ramp up and down rate limits for the controllable generators; Eqs.(6-40)-(6-42) are the distribution network's power flow, which is modeled based on the linearized Dist-Flow equations in [116]; Eq.(6-43) denotes that bus voltage should be maintained in a secure range; Eq.(6-44) denotes that thermal generation should be equal to its consumption [117].

In the HES deployment model, there are several nonlinear items such as Eqs. (6-3),(6-26)-(6-27) and (6-32)-(6-33). To reduce the computation burdens and improve the solution quality, those nonlinear items are linearized in the Appendix (Chapter 10, the specific equations are indicated). Then the proposed HES deployment model becomes a MILP problem.

6.4 Solution Method

6.4.1 Typical Seasonal Day Selection

Given that there are 365 days in a year, the HES deployment model is in excessively high dimension and thus computationally demanding. To prune the model's size and relieve the computational burden, a set of typical seasonal days is hence chosen to represent the yearly horizon.

Then the HES deployment model can be converted as:

$$NPV_s = \underset{z \in CF_z, x \in CG_x}{Max} \left[\underbrace{-F(z)}_{\text{Investment Stage}} + \underbrace{\sum_{c \in N_c} N_D^c \cdot G(x|c)}_{\text{Operation Stage}} \right] \quad (6-45)$$

$$s.t. \quad (6-1)-(6-44) \quad (6-46)$$

where N_D^c is the number of days in season c ; N_c is the number seasons; $G(x|c)$ is the objective of operation-stage in season c .

6.4.2 Scenario-Based Stochastic Operation Model

To handle the diverse system uncertainties, a two-substage stochastic operation method is proposed as Fig.5.

Figure 6-5. Two-stage coordinated operation framework

In Figure 6-5, the operation-stage is further decomposed into the day-ahead and intro-day online dispatch stages. Given that the HES system and PBDR are dynamic and sensitive to the holistic price information, their 24-hour dispatch decisions (with one hour as the unit dispatch interval [54]) are made in the day-ahead dispatch stage. In this stage, the diverse uncertainties are not revealed in real-time. In the intro-day online dispatch stage where the diverse uncertainties are realized, all the controllable generators that have faster response speeds are coordinated (with 15 minutes as the unit dispatch interval) to maintain the real-time balance of multi-energy generation and consumption.

1) Uncertainty Modelling

For the energy outputs of WTs and PVs, the uncertainty modeling are the same as Chapter 4.

As for the power demands, outdoor temperature and residential hot water needs, still the Normal distribution can be employed to represent their forecasting errors as Chapter 4[131]:

2) Scenario Generation and Reduction

The scenario generation and reduction method employed is the same as Chapter 4.

Then after the scenario generation and reduction, the SO model is finally modeled as a MILP problem as Eqs. (6-47)-(6-48):

$$\underset{x}{Min} G(x) = \underset{w, y_1, y_2, \dots, y_q}{Min} \left[S(w) + \sum_{q \in N_q} c_q L(y_q) \right] \quad (6-47)$$

$$\begin{aligned} s.t. \quad & w \in CS_w \mid z \\ & y_q \in CL(w, \omega_q), \forall q \end{aligned} \quad (6-48)$$

where q is the index of the forecasted scenarios; N_q is the total number of scenarios; c_q is the scenario possibility; $S(w)$ is objective of investment stage and day-ahead dispatch stage; w denotes the decision variables for size, location, investment phase and corresponding dispatch of the HES system as well as the PBDR scheme; CS_w is constraints associated with w ; $E[L(y_q)]$ is the expectation of cost from the controllable generators and power transaction between the RMEMG and utility grid; y_q denotes the corresponding decision variables for power flow, controllable generators and temperature for the rooms and hot water; ω_q is stochastic variation of system uncertain sources; $CL(w, \omega_q)$ is the constraints associated with y_q .

6.5 Simulation Results

6.5.1 Test System

The test grid-tied RMEMG is built with reference to the real conditions in Tianjin (38° N, 117° E), China, as shown in Figure 6-6. Its lifetime is 9 years with 3 years as the unit installation phase. The multiple energies are served mainly for the neighboring aggregated residential buildings, which are located in three regions. The heat networks among different thermal groups are not considered in this work since the long-distance thermal transmission will result in substantial thermal loss [134]. The predefined configuration of all the generators is shown in Table 6-1, while the substation capacity is set as 1.5 times the peak power in RMEMG [97] to guarantee that there is enough power supply when the faults occur inside. The technical details for the HES system are listed in Table 6-1 and Table 6-2. The studied RMEMG in Fig.6 is built based on the IEEE 33-bus standard test system in [135] with all the system data.

Figure 6-6. The IEEE 33-bus radial distribution system based RMEMG

Three typical days from the transition seasons (spring and autumn), summer and winter are used to represent the year. Based on the data of the year 2018 (Jan.-Dec.), Figure 6-7 shows the forecasting value of all the uncertain sources in the year 2019.

Figure 6-7. Forecasted RES output, outdoor temperature, and multi-energy demands

The system energy tariffs are shown in Table 6-3, which are extracted from [117], [73]-[74], [136]. For the thermal and power energy supplied to residents, the fixed pricing scheme is applied [2]. According to the electricity price and usage data in [137], the price elasticity of electricity demands is estimated as -0.75.

Table 6-1 Configuration of Distributed Generators (kW)

Node	WT	PV	CCHP	EB	EC
3	130	40	1200	650	500
6	162.5	80	0	0	0
10	162.5	64	1000	500	450
13	97.5	64	0	0	0
17	162.5	96	0	0	0
19	130	128	0	0	0
25	162.5	144	0	0	0
28	0	0	800	500	350
31	162.5	80	0	0	0

Table 6-2 Technical Details for the HES System [18]-[19]

Energy Storage	$\chi_{ES, INV}$	$\chi_{ES, M}$	$S_{ES, MIN}/S_{ES, MAX}$
Battery storage	120 (\$/kWh)	0.03 (\$/kWh)	0/1500(kWh)
Heat storage tank	36.7 (\$/kWh)	0.025 (\$/kWh)	0/1500(kWh)
Cooling storage tank	36.7 (\$/kWh)	0.025 (\$/kWh)	0/1500(kWh)

In the RMEMG, there are 16 buildings oriented South with 12 floors in each building; On each floor, there are two identical apartments, each with a floor area of 150 (15*10) m²; The area of north/south and east/west facing walls are 42 (15*2.8) m² and 28(10*2.8) m² respectively; The south and north walls are equipped with the double-glazed windows to the outside environment with areas of 10.5(3.75*0.7) m² and 8.4(3*0.56) m²; All the windows are of casement types without any blinds or shading devices; The area of the door on the east side is 2(2*1) m²; All the walls and flat roofs of the house are comprised of the same structural insulated panels [133].

The discount rate is 6% and load growth rates for power and thermal demands are set at 6.7% and 5% respectively [61].

Table 6-3 Energy Tariffs and Emission Prices [16], [18], [26]

Type	Price(\$/kW)	Type	Price(\$/kWh)	Period(h)
Local Power	0.17	Power Transaction	0.0468	0-6,23-24
Local Thermal	0.022		0.1029	6-8,11-17
Natural Gas	0.039		0.1785	8-11,17-22
Emission Price	CCHP	0.0057 (\$/kW)	Utility Grid	0.028(\$/kW)

Without loss of generality, any other real-world data can also be applied in the proposed without changing its effectiveness. The mathematical model is realized in GAMS and solved by the Cplex solver.

6.5.2 Investment-Stage Simulation Results & Discussion

In the simulation, 2000 scenarios are initially generated and then reduced to 10 representative ones with the corresponding possibilities. The total scenario generation and reduction time are 1.16 hours for each typical day, however, both processes can be done off-line. After the simulation, the HES deployment

results are shown in Table 6-4 and Table 6-5. The gray blocks mean that there are investment decisions at this phase and its subtraction with corresponding sizes in the last phase denotes the newly installed capacity.

Table 6-4 Deployment Results For Battery Storage (kWh)

Year/Bus	3	18	22	27	33
1-3	0	264.8	1500	0	338.8
4-6	0	264.8	1500	0	338.8
7-9	57.5	311.1	1500	247.3	338.8

Table 6-5 Deployment Results For Thermal Storage (kWh)

Year 1-9	Group 1	Group2	Group3
Cooling storage tank	0	0	0
Heat storage tank	1500	1500	1500

From the deployment results, it can be seen that:

1) Most capacities of the BS are installed on the terminal buses, i.e., Bus 18, 22 and 33. This is because their nearest power sources are renewable generators, which are stochastic and only account for a small portion of total power capacity. Thus, with an increment of power demands every year, the BS is installed on those buses to guarantee enough power supply and avoid voltage violations. Besides, BS can also shift energy from the valley-price periods to peak-price ones to gain profits. A similar function is taken by bus 6 and 27 for the BS, but on these two buses, since the generators can play the role for the voltage regulation, there is not so much installation.

2) There is no installation of the cooling storage tank but a full installation of a heat storage tank at the first installation phase in each thermal group. This is because the cooling storage tank works only on summer but the heat storage tank contribute to supplying heat both in transition seasons as well as winter days, thus, given the larger amount of heat demands, more utilization rate but the same unit installation cost with cooling storage tank, the invested capacity of heat storage tank is much larger and more widespread than the cooling one.

3) The investment phase selection plays a necessary role in the HES deployment scheme, as on bus 3, 18, 27, BS is installed at different phases. This contributes to avoiding any capacity redundancy at the early stage of the project, and thus enables a more economical and flexible HES deployment.

6.5.3 Operation-Stage Simulation Results & Discussions

To verify the effectiveness of the proposed method in the operation stage, the system dispatch results in the year 2023 are shown in Figure 6-8:

Figure 6-8. Energy balance condition in the year 2022.

It can be seen that all the units are coordinated to supply the multi-energy demands: when the transaction prices are low, the thermal energy is transferred by electricity via EBs or ECs instead of the CCHP plants to save the total fuel cost; when the transaction prices are high, the system thermal energy is served by the CCHP plants, and then the corresponding surplus power is sold to the utility grid to gain profits. As for the HES system, the BS charges at the low-price periods and discharges at high price periods to gain more profits from utility grid; For the TS, it makes the dispatch of the CCHP plants more flexible by absorbing its surplus thermal energy, when there is more power generation than required from the CCHP plants, and releasing thermal energy when not so much power is needed from CCHP plants. Besides, the DSM scheme shifts the multi-energy

demands to other periods for increasing the system profits. Its function for the cost-saving is verified in the next section.

The final EDP of the proposed method is positive as \$636.5 per day, which means that this project should be implemented as it will gain profit. In terms of the solution speed, there are 1098586 continuous and 138915 discrete variables in the HES deployment mathematical model, and the solution time is 5.74 hours, which is efficient enough for a 9-year project planning problem.

6.5.4 Methods Comparison

To fully demonstrate the advantage of the proposed method, three conventional HES deployment methods are compared:

Method #1: Separate energy storage deployment method, *i.e.*, the energy storage is installed in the respective single-energy microgrids. The GBs are utilized instead of CCHP plants, ECs and EBs for supplying the thermal demands, while the RES-based generators and transacted power from the utility grid serve the system power demands.

After the simulation, the results indicate that there is no TS installation and the deployment results for the BS are shown in Table 6-6.

Table 6-6 Deployment Results for Battery of Method #1 (kW)					
Year/Bus	3	6	18	22	33
1-3	382.4	0	0	1500	290.1
4-9	1500	437.5	772.4	1500	290.1

From the simulation results, as the GBs can just burn natural gas to generate thermal energy flexibly in the thermal system, there is no need to install thermal energy storage given that it will bring extra installation and operating costs; the generators for power in the microgrid is only the RES-based ones, whose outputs are intermittent and fluctuate, thus the BS is installed at different buses mainly to maintain the bus voltage in a secure range and at the same time, shift energy to gain profits. Since most of the power energy is obtained from the utility grid with a high price and the efficiency of the GBs is relatively low, the EDP for **Method #1** is much lower as only \$135.4 per day.

Therefore, the simulation results show that the multi-energy HES deployment can gain much more profits than the single-energy paradigm.

Method #2: The HES deployment without the multi-energy DSM, *i.e.*, the system power demands, indoor room temperature, and hot water

temperature are set as constant and fixed. The corresponding simulation results are shown in Table 6-7 and Table 6-8.

Table 6-7 Deployment Results for Battery of Method #2 (kWh)

Year/Bus	3	22	25
1-9	183.5	1500	1500

Table 6-8 Results for Thermal Storage of Method #2 (kWh)

Year 1-9	Group 1	Group2	Group3
Cooling storage tank	0	0	0
Heat storage tank	1500	1500	1500

Compared with our proposed method, as the power demands are not flexible anymore without the DSM scheme in **Method #2**, all the BS are installed at the first investment phase with lower salvage value, to shift the system power energy and maintain a safe voltage range for all the buses; As the thermal demands are not as flexible when the system is operating, there is the full installation of the TST to flexibilize the overall thermal energy operation and no installation of the cooling storage tank given its low usage rate as well as lower cooling demands. In this case, the resulted EDP for **Method #2** is lower than our method as \$612.5 per day. This is because the multi-energy DSM could provide additional flexibility for the system operation by actively responding to the energy prices and load conditions, and further, reduce system operating costs.

The simulation results show the involving the multi-energy DSM in the HES deployment model is effective in increasing the system profits.

Method #3: Deterministic deployment method, *i.e.*, the forecasting of the outputs from RES-based generators, outdoor temperature, and residential hot water needs are assumed as accurate. Then after the simulation, the HES deployment results are shown in Table 6-9 and Table 6-10.

Table 6-9 Deployment Results for Battery of Method #3 (kWh)

Year/Bus	3	6	18	22	25
1-3	1500	0	50.4	1500	1386.3
4-6	1500	0	50.4	1500	1386.3
7-9	1500	61.4	50.4	1500	1386.3

Table 6-10 Results for Thermal Storage of Method #3 (kWh)

Year 1-9	Group 1	Group2	Group3
Cooling storage tank	0	0	0
Heat storage tank	1500	1500	1500

From the results, without considering the system uncertainties, there the BS is still largely installed at different phases to shift the power for more profits and maintain the system voltage stability; though there are the same TS

deployment decisions, which play the same function as our method, the final EDP for **Method #3** is \$ 647.97 per day, which is slightly higher than our method. This is because considering the diverse uncertainties will highly reduce the overall solution space, and hence the corresponding EDP. The cost difference between the proposed method and the deterministic approach is called the *Value of Perfect Information*, which is used to immune against the system uncertainties.

However, to check the performance of the deterministic approach when the system uncertainties are realized, a set of 1000 random scenarios of typical days every year are utilized. The average EDP of **Method #3** is \$628.78 per day, while our method is \$637.54 per day. It means that, when the system is practically exposed to the uncertainty sources, the proposed (stochastic) method has a higher potential in gaining more profits than the deterministic one, as it already immunizes against the diverse uncertainties through the deployment process.

The results show that the proposed method can guarantee a more robust deployment plan.

6.6 Conclusions and Future Work

This chapter presents a multi-stage stochastic HES deployment method in a RMEMG considering multi-energy DSM as well as diverse uncertainties from RES-based generators, outdoor temperature, power loads and hot-water needs. The deployment scheme is decomposed into three investment phases with the EDP as the objective. By using the scenario-based multi-stage stochastic optimization method, the diverse uncertainties handled. The case study shows that the HES deployment can help gain values and thus should be implemented. Compared with three conventional deployment methods, the proposed method, which considers the system uncertainties, multi-energy coordination, and DSM, provides extra flexibility for system holistic energy supply and a more robust plan.

For the practical application, with the increasing penetration level of renewables and widespread installation of smart meters, this work could provide beneficial references for deploying the electric and thermal energy storage in the emerging smart homes, green buildings, *etc*, which have signed long-term

contracts for the multi-energy DSM.

To this end, the research on the land-based multi-energy systems, either the planning or the operation has been conducted. Then, the performance for the mobile multi-energy systems, especially the multi-energy ships, which is a new and emerging diagram both in industry and academia should be further studied.

7.) Multi-Objective Coordinated Energy Dispatch and Voyage Scheduling for a Multi-energy Ship Microgrid

7.1 Introduction

Chapter 3-6 study the optimal planning and operation of the land-based multi-energy systems, that is, the MEMGs, RMEMGs, however, given the rapid development of ship technologies and increasing desire for marine tourism [138], more and more cruising ships which are a form of the mobile multi-energy systems are needed. First of all, the ships are required to arrive punctually at the ports with bounded speed throughout the voyage. Besides, the cruising ships are mostly equipped with cinemas, clubs, dining halls or even swimming pools, *etc.* to provide the power, heat and cooling service for tourists. For this reason, the cruising ship can be regarded as a mobile isolated multi-energy microgrid, and its voyage scheduling and energy dispatch should be optimized concurrently [139]-[140].

In this context, this chapter aims at the multi-energy coordination of the MES microgrid. Firstly, a MES microgrid that combines the CCHP unit, TS, PtC unit and MEP system is studied. The introduction of the high-efficient units above is in line with a recent review [138], which calls for the more usage of gas-fired generators to reduce the emissions for shipboards. Further, a multi-objective coordinated voyage scheduling and energy dispatch method for the MES microgrid is proposed. This method aims to simultaneously optimize the ship operating cost and gas emissions. Last but not least, the original nonlinear problem is linearized as a MILP model, which can be solved by the commercial solvers. Besides, to simultaneously reduce the ship emission and cost, the AUGMECON is utilized.

7.2 Structure of the Multi-energy Ship (MES) Microgrid

The configuration of the MES microgrid is shown in Figure 7-1. It consists of the CCHP unit, EES, conventional DGs, MEP system, TS, and PtC unit. The CCHP unit burns the natural gas to generate thermal and power energy at the same time, while the TS and PtC unit could enhance the overall system dispatch flexibility by storing/releasing or converting energies [117]. All the units are coordinated to meet the propulsion and multi-energy service loads concurrently [90].

Figure 7-1. Proposed configuration of the MES system

In the MES microgrid, the propulsion motors are in charge of the ship propulsion loads, which are dependent on the cruising speed. The service loads mainly consist of power and thermal loads. The power loads come from powering all the appliances and thermal loads are mainly for space heating or cooling, tourists' showering needs, etc. All the loads are assumed to be forecasted with high accuracy on a half-hour base [92]-[93], [95]-[96].

7.3 Multi-Energy Cruising Ship Modelling

7.3.1 Voyage Modelling for Cruising Ships

The ship voyage demonstrated in Figure 7-2 usually includes the berthing periods (T_b) and cruising periods (T_c). During most cruising periods (T_m), the ship cruises with its full speed, for the periods right approaching (T_a) or departing (T_d) from the ports, it cruises at the partial speed [95]-[96].

Figure 7-2. Ship voyage pattern.

To ensure a punctual and safe voyage, the ship should cruise under several constraints as:

1) **Ship speed.** The shipping speed must be upper and lower bound for an efficient and safe voyage [92]-[96] as:

$$\chi_v^{\min} v_s^{\text{rate}} U_v^t \leq v_s^t \leq \chi_v^{\max} v_s^{\text{rate}} U_v^t \quad (7-1)$$

Note that the disturbances like the wind, wave, water density, etc., could

influence the shipping speed. They are necessary for the specific ship speed control or modeling research. However, this work aims to provide a general operation method for directly scheduling the shipping speed. Thus, the specific modeling of the shipping speed with influences from the above factors is not considered [95], [97].

2) **Cruising distance.** The cruising distance is the accumulation of the speed with corresponding cruising time as denoted in (7-2). The needs for the punctual arrival at the ports require the ship to have reached the vicinity of the ports during the berthing periods [95], [141] as Eq.(7-3).

$$D_s^t = D_s^{t-1} + v_s^t \Delta t \quad (7-2)$$

$$\chi_D^{min} D_s^{rate} \leq D_s^t \leq \chi_D^{max} D_s^{rate} \quad (7-3)$$

3) **Power for propulsion motors.** The cruising speed is driven by ship propulsion motors, whose power consumption is an exponential relationship with the speed [96] as:

$$P_{PL}^t = \alpha_{PL} (v_s^t)^{\beta_{PL}} \quad (7-4)$$

7.3.2 Multi-energy Photovoltaic (MEP) System

To reduce the ship emissions, the renewable energy-based generators are encouraged to be installed on the ship [92]. In this regard, the PV modules are installed on the ship deck and rooftops, as they are flexible in size. The PV modules can generate power and thermal energy simultaneously by absorbing solar irradiance [141], hence they can be regarded as s MEP system. The energy generation models for the MEP system are:

$$P_{PVP}^t = \eta_{PVP}^t A_{PV} G_{PV}^t \quad (7-5)$$

$$P_{PVT}^t = \eta_{PVT}^t A_{PV} G_{PV}^t \quad (7-6)$$

The referential efficiencies for the MES power and thermal outputs are [23]:

$$\eta_{PVP}^t = \eta_{PVP-ref} \gamma_{PF} \tau_P \eta_{MPPT} \left[1 - \beta_C (T_C^t - T_{C-ref}) \right] \quad (7-7)$$

$$\eta_{PVT} = \gamma_{PF} \tau_P - \alpha_1 (T_W - T_C^t) / G_{PV}^{std} - \alpha_2 (T_W - T_C^t)^2 / G_{PV}^{std} \quad (7-8)$$

For the MEP system, usually in the literature, the maximum power point tracking (MPPT) mode is employed [117].

7.3.3 Conventional Diesel Generators (DGs)

DGs could burn the diesel to generate electricity. They are currently the main

engine for the ship as they are fuel-efficient, small in size and flexible to control [94]-[95]. Their fuel cost and gas emissions depend on their power outputs, and can be approximated by second-order polynomials as [90], [143]:

$$F_{DG}^t = a_{DG}^f (P_{DG}^t)^2 + b_{DG}^f P_{DG}^t + c_{DG}^f U_{DG}^t \quad (7-9)$$

$$G_{DG}^t = a_{DG}^g (P_{DG}^t)^2 + b_{DG}^g P_{DG}^t + c_{DG}^g U_{DG}^t \quad (7-10)$$

7.3.4 Combined Cooling, Heat and Power (CCHP) Unit

As a candidate for tri-generation units, the CCHP unit mainly consists of three parts: a gas turbine (GT), an absorption chiller and a heat recovery unit. Usually, the Capstone's gas turbine [117], which has a high international market share, is utilized for real practice. Its electrical efficiency is modeled as:

$$\eta_{GT}^t = 0.08 (P_{GT}^t / P_{GT}^R)^3 - 0.31 (P_{GT}^t / P_{GT}^R)^2 + 0.42 P_{GT}^t / P_{GT}^R + 0.11 \quad (7-11)$$

Its thermal outputs can be modeled as:

$$Q_{GT}^t = \chi_{GT} P_{GT}^t \quad (7-12)$$

The corresponding fuel cost and gas emissions are:

$$F_{GT}^t = \xi_{NG} P_{GT}^t / \eta_{GT}^t \quad (7-13)$$

$$G_{GT}^t = \kappa_{GT} P_{GT}^t \quad (7-14)$$

7.3.5 Energy Storage System

The EES and TS used in the land-based multi-energy systems are also applicable for the mobile microgrids. The models for ES are similar for EES and TS as Chapter 3

7.3.6 Power to Thermal Conversion (PtC) Unit

Different types of PtC units share a similar operating model as Chapter 5.

7.4 Mathematical Modelling for MES Operation

The performance of the MES microgrid should be evaluated in terms of its operating cost and gas emissions. It constitutes a multi-objective problem as:

$$Obj1: MIN COST = \sum_{t \in N_T} (C_{FU}^t + C_{OM}^t) \Delta t + C_{ST}^t \quad (7-15)$$

$$Obj2: MIN EMI = \sum_{t \in N_T} G_{EM}^t \Delta t \quad (7-16)$$

$$\text{s.t., Eqs. (7-1)-(7-14)} \quad (7-17)$$

$$C_{FU}^t = F_{DG}^t + F_{GT}^t \quad (7-18)$$

$$C_{OM}^t = \left[\begin{aligned} &\xi_{PV}^m (P_{PVP}^t + P_{PVT}^t) + \sum_{j \in N_{DG}} \xi_{DG,j}^m P_{DG,j}^t + \xi_{GT}^m P_{GT}^t \\ &+ \xi_{ES}^m (P_{ESC}^t + P_{ESD}^t) + \xi_{PtC}^m P_{PtC}^t \end{aligned} \right] \quad (7-19)$$

$$C_{ST}^t = \sum_{j \in N_{DG}} \max[0, U_{DG,j}^t - U_{DG,j}^{t-1}] \xi_{DG,j}^U \quad (7-20)$$

$$G_{EM}^t = G_{DG}^t + G_{GT}^t \quad (7-21)$$

$$P_{DG,j}^{min} U_{DG,j}^t \leq P_{DG,j}^t \leq P_{DG,j}^{max} U_{DG,j}^t \quad (7-22)$$

$$R_{DG,j}^{min} \Delta t \leq P_{DG,j}^t - P_{DG,j}^{t-1} \leq R_{DG,j}^{max} \Delta t \quad (7-23)$$

$$(T_{DG,j}^{on,t-1} - T_{DG,j}^U)(U_{DG,j}^{t-1} - U_{DG,j}^t) \geq 0 \quad (7-24)$$

$$(T_{DG,j}^{off,t-1} - T_{DG,j}^D)(U_{DG,j}^t - U_{DG,j}^{t-1}) \geq 0 \quad (7-25)$$

$$U_{GT}^t P_{GT}^{min} \leq P_{GT}^t \leq P_{GT}^{max} U_{GT}^t \quad (7-26)$$

$$U_{PtC}^t P_{PtC}^{min} \leq P_{PtC}^t \leq P_{PtC}^{max} U_{PtC}^t \quad (7-27)$$

$$0 \leq P_{ESC}^t \leq \gamma_{ESC}^t P_{ESC}^{max} \quad (7-28)$$

$$0 \leq P_{ESD}^t \leq \gamma_{ESD}^t P_{ESD}^{max} \quad (7-29)$$

$$\gamma_{ESC}^t + \gamma_{ESD}^t \leq 1 \quad (7-30)$$

$$\chi_{ES}^{min} E_{ES}^{rate} \leq E_{ES}^t \leq \chi_{ES}^{max} E_{ES}^{rate} \quad (7-31)$$

$$E_{ES}^0 = E_{ES}^{N_T} \quad (7-32)$$

$$P_{PVP}^t + P_{DG}^t + P_{GT}^t + P_{EESD}^t - P_{EESC}^t - P_{PtC}^t = P_{PL}^t + P_{SL}^t \quad (7-33)$$

$$P_{PVT}^t + Q_{GT}^t + Q_{PtC}^t + P_{TSD}^t - P_{TSC}^t = Q_{SL}^t \quad (7-34)$$

$$\sum_{j \in N_{DG}} (P_{DG,j}^{max} - P_{DG,j}^t) + P_{GT}^{max} - P_{GT}^t + P_{EESD}^{max} - P_{EESD}^t \geq \chi_P^{RE} (P_{PL}^t + P_{SL}^t + P_{PtC}^t) \quad (7-35)$$

$$\chi_{GT} P_{GT}^{max} - Q_{GT}^t + P_{PtC}^{max} \chi_{PtC} - Q_{PtC}^t + P_{TSD}^{max} - P_{TSD}^t \geq \chi_Q^{RE} Q_{SL}^t \quad (7-36)$$

Eq.(7-15) and (7-16) denote the ship operating cost and CO2 emissions during the voyage. Eq.(7-18)-(7-20) are the fuel cost, maintenance cost and start-up cost of the conventional DGs [93]. Eq.(7-21) is the total ship gas emissions at each dispatch period. Eq.(7-22) denotes that the DG power outputs should be within a safe range. Eq.(7-23) is the ramp-up and -down limits for the DGs. Eq.(7-24)-(7-25) denote the minimal on- and off-time constraints for DGs. Eqs.(7-26)-(7-27) are the power output limits for the GT and PtC unit; Note that the GT and PtC unit are among the flexible DtGs, whose power outputs could be changed within seconds [117]. Thus, their ramp limits, minimum on/off time

constraints as well as start-up/shut-down cost can be ignored. Eq.(7-28)-(7-32) are the constraints for the energy storage. Eq.(7-28)-(7-29) denote the maximal charging and discharging power limits. Eq.(7-30) limits that energy storage cannot charge or discharge at the same time. Eq.(7-31) are the energy limits. Eq.(7-32) denotes that the energy stored in the storage should remain the same in the whole dispatch horizon to keep the dispatch flexibility. Eq.(7-33) and (7-34) denote that the ship should always be in the power and thermal balance. Eq.(7-35) and (7-36) indicate the ship spinning power and thermal reserve.

It should be noted that the dynamics such as the ship position, speed and torque are more about the ship control scheme. Thus, in this operation or optimization study, they are not considered [92], [94]. Besides, all the above equations without the terms for the newly introduced CCHP unit, TS, PtC unit, thermal outputs from the MEP system and thermal loads constitute the conventional power energy dispatch model [96]-[97].

There are some nonlinear equations such as Eqs.(7-4), (7-9)-(7-10), (7-12),(7-13), (7-20), (7-24)-(7-25). They make the ship operation model as a nonlinear programming problem, which would lead to heavy computation burdens and poor solution quality [117]. Thus, those nonlinear items are linearized in the Appendix. Then, the coordinated dispatch model becomes a MILP one and can be efficiently solved by some industry-proven solvers like Cplex and Gurobi.

7.4.1 Solution Methodology

To solve the multi-objective problem, the Pareto fronts are obtained first by the lexicographic optimization (LO)-based AUGMECON. Then the final single solution can be determined with the references from the decision-makers (DMs).

7.4.2 Augmented ϵ -Constraint Method (AUGMECON)

To solve the multi-objective optimization problems, the NSGA-II, weighted sum and (simple) ϵ -constraint methods are mostly utilized in the literature [143]. The NSGA-II method is one of the evolutionary algorithms. It is inspired by natural selection, such as reproduction, mutation, recombination, and selection [144]. The evolution of the population then takes place after the repeated application of the above operators. Though it is efficient for solving different kinds of problems, it is highly computationally demanded and would result in the

non-convergent as well as suboptimal solutions [117]. The weighted sum and (simple) ε -constraint methods are among the generation algorithms, which can avoid the above problems with the different solution mechanisms. However, for the weighted sum method, it is easy to implement but only applicable for convex problems and requires the scaling of the multiple objectives when applying the weights. Further, the Pareto fronts from the weighted sum method are not well-proportioned [143]. It is outperformed by the (simple) ε -constraint method which produces efficient solutions for both convex and non-convex problems. Nonetheless, its efficiency is not guaranteed since it may return weakly efficient solutions if the ranges of the objectives are not properly identified [145].

Thus, in this study, an improved version of the (simple) ε -constraint method, namely, the AUGMECON is used to solve the multi-objective problem. It transforms the objective constraints of the (simple) ε -constraint method to equalities using positive continuous slack variables s_p as:

$$\text{Min} \left[f_1(xd) + \varepsilon(s_2 + \dots + s_p) \right] \quad (7-37)$$

$$s.t. f_2(xd) + s_2 = e_2$$

...

$$f_p(xd) + s_p = e_p \quad (7-38)$$

$$xd \in Xd, \varepsilon \in [10^{-6}, 10^{-3}], s_p \in R^+$$

where $f_p(xd)$ is the p th objective; e_p is the p th objective limits; xd is the decision variable; ε is the coefficient.

Compared with the (simple) ε -constraint method, the AUGMECON introduces the slack variables to produce the only effective proportional Pareto optimal solutions [25], [27].

7.4.3 Lexicographic Optimization (LO)

To calculate the range of the objectives in Eqs.(7-37)-(7-38), the AUGMECON uses the LO to get the pay-off table. The LO method optimizes the objectives by adding optimal values of previous objectives consecutively as an equality constraint to guarantee the Pareto optimal solutions [25]. Afterward, the range of the objectives is divided into q intervals using $q+1$ grid points. Then, these points are used to vary the right hand of the objectives e_p to get the Pareto fronts with element x_{fe} as:

$$PF = \begin{bmatrix} x_{11} & \dots & x_{1e} & \dots & x_{1p} \\ \vdots & \ddots & & & \vdots \\ x_{f1} & & x_{fe} & & x_{pe} \\ & & & \ddots & \vdots \\ x_{q1} & \dots & x_{qe} & \dots & x_{qp} \end{bmatrix} \quad (7-39)$$

Note that in Eq. (7-39), each line represents an alternative solution, and each column is associated with an objective.

7.4.4 Solution Chosen Given the References

After the AUGMECON, a set of efficient solutions, which constitutes the Pareto fronts is obtained. On top of that, the DMs can intervene as well as decide one final solution according to their preferences.

Firstly, the obtained Pareto fronts are transformed into a non-dimensional attribute matrix (r_{fe}) to enable the comparison among different attributes. The normalization process is performed as (7-40)

$$r_{fe} = x_{fe} / \sqrt{\sum_{f \in q} x_{fe}^2} \quad (7-40)$$

After that, a set of weights $\omega = \{\omega_1, \dots, \omega_e, \dots, \omega_p\}$, $\sum_{e \in p} \omega_e = 1$ which presents the relative importance/preference of each objective are provided by DMs. The weighted normalized matrix with elements ψ_{fe} can be created by multiplying each column of Eq.(7-39) with elements r_{fe} by the corresponding weights ω_e .

Then, the ideal (ψ_e^+) and negative-ideal (ψ_e^-) solution vectors are selected as:

$$\psi_e^+ = \left\{ \left[\max_f (\psi_{fe}) \mid e \in E \right], \left[\min_e (\psi_{fe}) \mid e \in E' \right] \right\} \quad (7-41)$$

$\forall f = 1, 2, \dots, q-1, q$

$$\psi_e^- = \left\{ \left[\min_f (\psi_{fe}) \mid e \in E \right], \left[\max_e (\psi_{fe}) \mid e \in E' \right] \right\} \quad (7-42)$$

$\forall f = 1, 2, \dots, q-1, q$

where E is the set of objectives to be maximized; E' is the set of objectives to be minimized.

Further, the separation measure of each alternative solution from the ideal (D_f^+) and negative-ideal (D_f^-) solution is measured by the Euclidean distance as:

$$D_f^+ = \sqrt{\sum_{e \in p} (\psi_{fe} - \psi_e^+)^2}, \quad \forall f = 1, 2, \dots, q-1, q \quad (7-43)$$

$$D_f^- = \sqrt{\sum_{e \in p} (\psi_{fe} - \psi_e^-)^2}, \quad \forall f = 1, 2, \dots, q-1, q \quad (7-44)$$

Finally, the relative closeness to the ideal solution with respect to the similarity index (S_f^+) is selected as:

$$S_f^+ = \frac{D_f^-}{D_f^+ + D_f^-}, \quad \forall f = 1, 2, \dots, q-1, q \quad (7-45)$$

The final solution is the vector that corresponds to the maximal S_f^+ .

7.5 Case Study

7.5.1 Test System

The configuration of the test MES microgrid is the same as Figure 7-1. There are three DGs, one MEP system, one CCHP unit, one TS, one EES (BS) and one PtC unit installed. As shown in Fig. 3(a), the ship cruises back and forth between two ports, *i.e.*, Port A in Shangdong Province and Port B in Liaoning Province, China. Totally, there are 48 half-hour dispatch periods (24 hours). The information for nominal (partial) cruising speed, voyage distance and cruising periods are indicated in Figure 7-3 (b). This ship is designed mainly for sightseeing in summer days and after berthing at port B, the passengers would leave for a trip to the city near the port for 4 hours.

Figure 7-3. Voyage scheduling of the cruising ship.

For the MEP system, the outdoor temperature and solar irradiance are shown in Figure 7-4. Then, the corresponding power and thermal outputs of the MEP system can be obtained.

Figure 7-4 The forecasted solar irradiance and outdoor temperature.

The multi-energy service loads in summer days mainly consist of power and space thermal loads as shown in Figure 7-5.

Figure 7-5 Multi-energy service loads of the ship in summer days.

The technical parameters for the onboard units are shown in Table 7-1 to Table 7-4.

Table 7-1 Technical Parameters for Generators [15],[17],[19], [24]

Units	$P_{CG}^{max}/P_{CG}^{min}$	T_{CG}^U/T_{CG}^D	$R_{CG}^{max}/R_{CG}^{min}$	ξ_{CG}^m	ξ_{CG}^U
DG1	15/4	3/3	12/12	3.2	600
DG2-3	7.5/2.5	1.5/1.5	6/6	2.4	350
GT	15/3	0/0	-	2.5	-
PtC unit	5/0	0/0	-	1.0	-

* The CG in the first row of the Table. I denote all the controllable generators, i.e., the CCHP unit, conventional DGs and PtC unit.

Table 7-2 TECHNICAL PARAMETERS FOR ENERGY STORAGE [17], [19]-[20]

ES	$\chi_{ES}^{min}/\chi_{ES}^{max}$	$P_{ESC}^{max}/P_{ESD}^{max}$	η_{ESC}/η_{ESD}	T_{ES}	E_{ES}^{rate}	E_{ES}^0
EES	0.2/0.9	7.5/7.5	0.95/0.95	0.01	15	3
TS	0/0.9	7.5/7.5	0.85/0.85	0.04	18	0

Table 7-3 OTHER PARAMETERS FOR GENERATORS [12], [17]-[18]

Units	$a_{DG}^f, b_{DG}^f, c_{DG}^f$	$a_{DG}^g, b_{DG}^g, c_{DG}^g$
DG1	1.333, 145.666, 1.933	2.027, -100.214, 4191.562
DG2-3	2.747, 88.681, 1.565	11.076, -60.457, 1350.324
GT	ξ_{NG}	52.631
	K_{GT}	184kg

Table 7-4 Other System Parameters [12], [14], [17], [19]-[20], [22]-[23]

Name	Value	Name	Value	Name	Value
A_{PV}	4000	$\gamma_{PF} \& T_p$	0.95	T_{C-ref}	25
$\eta_{PVP-ref}$	30%	β_C	0.0048	G_{PV}^{std}	550
α_1	12	T_W	45	β_{PL}	3
α_2	0.01	α_{PL}	0.003	χ_{PtC}	3.5
χ_{GT}	2.18	χ_D^{min}	0.97	χ_v^{min}	0.8
$\chi_P^{RE} \& \chi_Q^{RE}$	0.1	χ_D^{max}	1.03	χ_v^{min}	1.2

All the relevant data are synthesized figures from available literature, reports, and commercial catalogs, without loss of generality, any other real-world data can also be applied without affecting the effectiveness of the proposed method. The simulation is conducted on an Intel(R) Xeon(R) E5-1630 3.70GHz 64-bit PC with 16G RAM and solved by the Cplex solver via the GAMS.

7.5.2 Pareto Fronts

In the simulation, the range of the objectives is divided into 50 intervals using 51 grid points, that is, 51 frontiers are in the Pareto fronts. Note that for the multi-objective problem, there are no strict limits on the number of the frontier in the

Pareto fronts. Usually, the number can be varied in a wide range from approximately 15 to 150 or more like [87], [95]-[96], [145]. However, more frontiers mean higher accuracy but much longer solution time. Thus, in this study, 51 frontiers are chosen for a trade-off between the solution time and accuracy. The simulation results are shown in Fig.6.

Figure 7-6. Pareto fronts of the proposed method.

There are two dimensions in the Pareto fronts in Figure 7-6, *i.e.*, ‘cost (k\$)’ and ‘emission (ton)’. Each frontier is bounded by two extreme solutions (A and B in the figure). The two solutions achieve the minimum value along with one objective and hence sacrificing the performance along the other with the maximum. Other frontiers are trade-offs between the two extreme ones. Given the Pareto fronts, the ideal solution with the preferences from certain DMs can be finally chosen.

In terms of the computational performance, the total solution time for the 51 frontiers is 5.37 hours, with each frontier only 6.31 minutes. The solution time is totally compatible with the day (24 hours)-ahead ship operation.

7.5.3 Final Single Solution Decision

The DM would like to weigh the cost and emissions as the equal importance, that is, the standardized ratios of cost and emissions are 0.5, 0.5, respectively. Then the corresponding voyage scheduling and energy dispatch decisions are:

(a) The onboard power energy dispatch

Figure 7-7. Voyage scheduling and energy dispatch results for the DM.

It can be seen from Figure 7-7 that all the units are scheduled with regards to their operational characteristics:

1) The MEP system follows the MPPT mode in its power and thermal generation. However, as currently its energy generation efficiency is low and no enough space for the large installation of PV modules on the ship, the energy generation only counts for a very small portion for the total energy consumption, see Fig. 7 (a)-(b).

2) Since the CCHP unit can output multiple energies at the same time but with the relatively higher unit operating cost and lower unit emission, it outputs energy at most periods, sees Figure 7-7 (a)-(b). Besides, as the more energy outputs from the CCHP unit, the lower its unit operating cost is. In this regard, usually, the CCHP unit generates more energies than required such as period 1-3, 5-8, 10, 14-18, 23, 25-27, 30, 33-37 in Figure 7-7 (a)-(b). The corresponding surplus thermal energy is stored by TS and then release it at the remaining periods. In this way, the TS contributes to flexibilizing the CCHP operation to further reduce the ship operating cost and gas emissions, see Figure 7-7 (b).

2: Due to lower unit operating cost but slightly higher unit gas emission of DG1 compared with DG2 and DG3, it operates at all the ship cruising periods (Tc) with the other two DGs works as supplements, see Figure 7-7 (a).

3: Given the high efficiency of the PtC unit, it would replace the CCHP unit

for the thermal supply at some periods, such as period 11-13, 37, 39 in Figure 7-7 (a)-(b). In this way, there can be more power generation space for DGs given its decreasing unit operating cost with its increasing outputs. However, as the unit DG operating cost and emission are generally high, no much energy is transferred by the PtC unit.

4: The EES collaborates with the CCHP unit and DGs to supply the power loads to avoid the frequent start-up of DGs, especially at the berthing periods when the propulsion loads are zero, see Figure 7-7 (a), (c).

5: The cruising speed is lower than the rated speed at T_c , this is because lower speed means fewer propulsion loads. Then there would be lower ship operating cost and gas emissions. However, given the distance limits, at periods of T_a and T_b , its speed is a bit higher than the rated partial speed, see Figure 7-7 (c).

To sum up, the voyage scheduling and energy dispatch are coordinated to simultaneously reduce the ship's operating cost and gas emissions. The final ship operating cost and gas emissions are 105.39k\$ and 120.33ton.

7.5.4 Methods Comparison

To fully demonstrate the advantages of our method, two conventional ship dispatch benchmarks are compared as:

Method #1: Separate dispatch method: this corresponds to the methods in [13]-[18] that the propulsion and service power loads are supplied by the PV cells, EES and 4 DGs (2*15MW and 2*7.5MW). The GB is used to satisfy the thermal loads [19]. The emission conversion factor for GB is 226kg/MWh. The resulted Pareto fronts are shown in Figure 7-8.

Figure 7-8. Pareto fronts of Method #1.

It shows that Pareto fronts of **Method #1** in Figure 7-8 are totally dominated

by our proposed multi-energy dispatch method in Figure 7-6, *i.e.*, the corresponding cost and emissions are both larger in **Method #1**. This is because with the low-efficient GB supplying the thermal loads separately, there is no coordination among the multiple energies, and hence more operating cost and gas emissions are resulted in. The simulation results prove that the multi-energy coordinated dispatch method outperforms the separate one.

For the DM, the final cost and emissions of **Method #1** are 106.28 k\$ and 168.78ton, respectively.

Method #2: Fixed voyage method [92]-[97]. In this method, there is no coordination between the energy dispatch and voyage scheduling. The ship follows the fixed routes and cruises at the rated speed. The results are shown in Figure 7-9 as:

Figure 7-9. Pareto fronts of Method #2.

As compared with Figure 7-6, Pareto fronts of the fixed voyage method are absolutely dominated by our proposed coordination method. This is because involving the voyage scheduling would add extra degrees of freedom for the ship energy dispatch, and hence greatly decrease the operating cost and emissions. The simulation results demonstrate that our coordinated dispatch method is efficient.

For the DM, the final cost and emissions of **Method #2** are 114.36k\$ and 130.88ton, which are also both larger than our proposed method as **Method #1**.

7.5.5 Sensitivity Analysis

To further demonstrate the effectiveness of our proposed method, sensitivity analysis is done in terms of the number of objective intervals p and preferences (standard ratios) from the DMs.

1) **Effect of the objective intervals or frontiers:** In the above case study,

50 objective intervals (51 frontiers) are chosen to make a trade-off between the computation time and solution accuracy. To show how the number of objective intervals or frontiers affects the ship operating results, the sensitivity analysis is done as Figure 7-10 to Figure 7-11.

Figure 7-10. Pareto fronts of the proposed method with 25 intervals.

Figure 7-11. Pareto fronts of the proposed method with 100 intervals.

In Figure 7-10 to Figure 7-11, there are 25 and 100 objective intervals in the respective Pareto fronts. It is seen that the Pareto fronts for the 25 intervals are sparser while the 100 intervals are much denser. It shows that solutions are more accurate with the increasing number of objective intervals. However, their trends are similar to Figure 7-6, besides, all the Pareto fronts in Figure 7-6, Figure 7-10 and Figure 7-11 dominate **Method #1** and **#2** in Figure 7-8 and Figure 7-9. As for the DM in the case study, the solution results are (105.52k\$, 119.89ton) and (105.39k\$, 120.33ton), respectively. The above results show that the number of objective intervals in AUGMECON won't influence the effectiveness of the proposed method.

However, the total solution time for Pareto fronts with 25 and 100 objective intervals are 2.42 hours and 12.74 hours with the unit computation time for each frontier as 5.81 minutes and 7.56 minutes. All of them are compatible with the

day-ahead ship operation, but the total solution time is much longer when the number of objective intervals increases. In this regard, when choosing the intervals in AUGMECON, there should be a trade-off between the solution accuracy and computation time.

2) Effect of the preference or standardized ratios from DMs: In the case study, the DM chooses the equal standard ratios for the cost and emission. However, there can be different preferences from various DMs. To indicate the effect of the preferences or standardized ratios from the DMs, the corresponding sensitivity analysis is done with the simulation results shown as Figure 7-12:

Figure 7-12. Sensitivity analysis of the cost and emission with the preferences

In Figure 7-12, the preferences for the cost (emission) are varied from 0-1 (1-0) with 0.1 as a unit interval. It can be seen from Figure 7-12 (a) that the ship operating cost is decreasing with its increasing standardized ratios, and from Figure 7-12(b), gas emissions have the same trend with their corresponding ratios as the cost. The results verify that if more importance is put on one objective, this objective would be more optimal, however, it would sacrifice the performance along with the other. The sensitivity analysis verifies that our method is effective for different DMs with various preferences.

7.6 Conclusions and Future Work

In this chapter, a MES microgrid is presented with the MEP system, conventional DGs, EES, CCHP unit, TS and PtC unit. Then a coordination method to jointly dispatch multiple energies and ship voyage is proposed. The proposed method is modeled as a multi-objective optimization problem to reduce the ship operating cost and gas emissions, simultaneously. To solve the problem, AUGMECON with the preferences from the DM is employed, and case studies are done to verify the effectiveness of the proposed method. It is concluded that our proposed multi-energy coordination method is effective in coordinating the energy dispatch and voyage scheduling, to simultaneously reduce the ship operating cost and gas emission. Besides, compared with the traditional separate dispatch method and fixed voyage method, our proposed method dominates them in both the cost-savings and emission-reduction aspects. Finally, sensitivity analysis is further done in terms of the number of objective intervals and different preferences from various DMs. The results show that the effectiveness of the proposed method won't be affected by the number of objective intervals and different preferences from the DMs.

The coordination of the energy dispatch and voyage scheduling is studied in this chapter still in the deterministic scope, that is, the forecasting value of the energy generation from renewable energies, multi-energy loads, etc., are all assumed accurate. However, this is not the case in the real world. Considering that safety is the first priority of the ship operation, then the methods for tackling the uncertainties should be sufficient enough to immune against any uncertainty realizations.

8.) Robust Operation of a Hybrid AC/DC Multi-energy Ship Microgrid with Flexible Voyage and Thermal Loads

8.1 Introduction

In Chapter 7, the multi-objective coordinated energy dispatch and voyage scheduling is investigated for the more economical and environmentally friendly ship system. The all-electric ship has been gaining their research attention among the shipping industry and academia communities recently, as it integrates techniques such as distributed generation, ES, renewable energies, *etc.*, to reduce the increasing amount of gas emissions and fuel consumption [147]. Driven by the propulsion motors, the ship voyage requires punctual arrival, safe speed. When cruising on the sea, the ship sustains itself, while at berth, it gets energy support from the land, which is the so-called ‘cold ironing’ [138].

In this chapter, a hybrid AC/DC MES system with a flexible voyage and thermal loads is proposed. The hybrid AC-DC system contributes to reducing levels of power conversions so as to increase system efficiency. Besides, the cold ironing technique is also introduced to support the ship when it is at berth. Then a coordinated operation method for voyage scheduling and energy dispatch of the MES is presented. The method deals with the uncertainties from solar power and thermal energy as well as multi-energy service loads through a two-stage RO approach. Further, the linearization methods are used to convert the coordination model to a MILP problem, which can then be solved efficiently by commercial solvers such as Cplex or Gurobi.

8.2 Hybrid AC/DC Multi-energy Ship System

8.2.1 Multi-Energy Ship Configuration and Energy Conversion

The proposed hybrid AC/DC MES embedded with the energy conversion block is depicted in Figure 8-1. All the units and loads are also clearly denoted with their AC/DC classification.

Figure 8-1. The hybrid AC/DC MES embedded with energy conversion block

Energy conversion block is a multi-carrier energy block, which provides functions of input, output, and conversion of multiple energy forms [147] such as electricity, cooling, and heat. Its general model is shown as Eq.(8-1).

$$\begin{bmatrix} P_{EL} \\ P_{HL} \\ P_{CL} \end{bmatrix} = \underbrace{\begin{bmatrix} \eta_{GT} & \eta_{DG} & 1 \\ \eta_{GH} & 0 & \eta_{EB} \\ \eta_{GC} & 0 & \eta_{EC} \end{bmatrix}}_{\text{Energy Conversion Block}} \begin{bmatrix} P_G \\ P_D \\ P_E \end{bmatrix} \quad (8-1)$$

Outputs Inputs

The inputs are electricity (P_E), diesel (P_D) and natural gas (P_G), where the electricity can be imported from the PV system, CCHP unit, and the seaport (land) by cold ironing. The outputs are the electricity (P_{EL}) for AC propulsion loads, DC service loads and heat (P_{HL}) or cooling (P_{CL}) energy for onboard thermal loads. The conversion from gas to electricity and thermal is realized by the CCHP unit, whose generator is a gas turbine and equipped with an absorption chiller and a heat recovery unit, $\eta_{GT}/\eta_{GH}/\eta_{GC}$ are its power/ heat /cooling conversion efficiency; The conversion from diesel to electricity is fulfilled by DGs with efficiency η_{DG} ; The conversion from AC to DC or DC to AC is managed by the bi-directional converters. To convert electricity to thermal energy, the PtC unit, *i.e.*, EB and EC are used, and η_{EB} and η_{EC} are its heat and cooling efficiencies.

A HES system consists of the BS and TS. The PV system in this study is also a tri-generation unit as the CCHP unit because it can output thermal and power energy at the same time.

8.2.2 Ship Voyage Modelling

The ship voyage modeling is the same as Chapter 7

8.2.3 Temperature-Dependent Thermal Loads Modelling

The onboard thermal loads are mainly for space heating or cooling. They

are highly dependent on the temperature difference between indoor and outdoor temperature, as the loads are closely related to the thermal conduction through the building shells like walls, floors or windows. The thermal loads by the thermal conduction can be modeled as:

$$P_{TL}^t = |\theta_{IN}^t - \theta_{OUT}^t| / R_T \quad (8-2)$$

Eq. (8-2) denotes the calculation of thermal loads under the steady indoor temperature, however, when the indoor temperature (or the thermal energy) changes, the thermal conduction model is dynamic with the following model:

$$C_{AIR} (d\theta_{IN}^t / dt) = P_{TG}^t - P_{TL}^t = P_{GT}^t - |\theta_{IN}^t - \theta_{OUT}^t| / R_T \quad (8-3)$$

Eq.(8-3) shows that the indoor thermal energy variation (the difference between the thermal generation and loads) leads to the indoor temperature variations. However, due to the thermal inertia, the indoor ambient temperature varies slowly so the change can be neglected for a relatively long timescale (30 minutes or longer) [146]. This way, the derivation model in Eq.(8-3) can be represented as a differential state model with the indoor temperature kept as constant:

$$C_{AIR} (\theta_{IN}^t - \theta_{IN}^{t-1}) / \Delta t = P_{TG}^t - |\theta_{IN}^t - \theta_{OUT}^t| / R_T \quad (8-4)$$

As the indoor temperature can be controlled in a range as Eq.(8-5) without violating human thermal comfort levels, the corresponding thermal loads are, in this regard, flexible.

$$\theta_{IN}^{min} \leq \theta_{IN}^t \leq \theta_{IN}^{max} \quad (8-5)$$

8.2.4 Robust Coordination Framework for MES

Given the uncertain weather conditions, solar irradiance, fluctuate outdoor temperature and random human electricity usage behaviors, the PV multi-energy outputs, thermal loads as well as the onboard power loads are all uncertain as a result. To eliminate the adverse impacts from the system uncertain sources, a two-stage robustly coordinated operation approach is presented in Figure 8-2.

Figure 8-2. Two-stage robust coordination model for the MES

In Figure 8-2, the inputs are the forecasted PV multi-energy generation, onboard thermal and power loads, ship voyage information in terms of the ship secure cruising speed and distance range. Then after the two-stage robust coordination model, the final outputs are the ship voyage scheduling and energy dispatch decisions.

In the two-stage robust coordination model, the first stage is the voyage-ahead operation, it has a relatively long dispatch timescale, *e.g.*, half a day or longer. With the inputs, the first-stage model is optimized by the RO method to obtain the scheduling of the voyage (cruising speed and distance), heterogeneous energy storage (charging/discharging) and on/off status for the conventional DGs. These decisions will be implemented during the following voyage.

The second stage has a relatively shorter dispatch timescale, *e.g.*, 1 hour or 30 minutes (set in this thesis) or even shorter, so this stage is called the 30mins-ahead or real-time operation. For this stage, the 30mins-ahead prediction of the uncertainties is applied. The output operation decisions are the power output of the CCHP unit, DGs, PtC unit, power transfer of bidirectional converter and cold ironing as well as the indoor temperature. These decisions are updated and performed every 30 minutes to complement the first-stage operation when the uncertainties are realized. Therefore, the second stage can track the uncertainties in a short timescale or even real-time to guarantee the operating robustness.

Note that the ship voyage is scheduled at the first stage as its speed is hard to change immediately given the large water resistance. The HES system is scheduled voyage-ahead so that the power and thermal generation can be

shifted in a large time horizon to match the load peaks, besides, the frequent charging or discharging of ES is harmful to their health.

8.3 Mathematical Formulation

In this study, the PV panels are installed on the walls and deck of the ship, and other types of renewables can also be considered if possible.

8.3.1 Deterministic MES Operation Model

For the MES, the aim is to reduce the ship operating cost with the following model:

$$\min_{P, E, V, D, T, U} \sum_{t \in N_T} (C_{FU}^t + C_{OM}^t + C_{ST}^t + C_{CI}^t + C_{GE}^t) \Delta t \quad (8-6)$$

$$\text{s.t.}, C_{FU}^t = \kappa_{GAS}^f P_{GT}^t + \sum_{j \in N_J} \kappa_{GT}^{f,j} P_{GT}^{t,j} \quad (8-7)$$

$$C_{OM}^t = \left[\begin{array}{l} \kappa_{DG}^m P_{DG}^t + \sum_{j \in N_J} \kappa_{GT}^{m,j} P_{GT}^{t,j} + \kappa_{PT}^m P_{PT}^t + \kappa_{AD}^m P_{AD}^t \\ \kappa_{BS}^m (P_{BC}^t + P_{BD}^t) + \kappa_{TS}^m (P_{TC}^t + P_{TD}^t) + \kappa_{AD}^m P_{DA}^t \end{array} \right] \quad (8-8)$$

$$C_{ST}^t = \max \sum_{j \in N_J} [0, U_{DG}^{t,j} - U_{DG}^{t-1,j}] \kappa_{DG}^{u,j} \quad (8-9)$$

$$C_{CI}^t = \kappa_{CI} P_{CI}^t \quad (8-10)$$

$$C_{GE}^t = \kappa_{GT}^e P_{GT}^t + \sum_{j \in N_J} \kappa_{DG}^{e,j} P_{DG}^{t,j} \quad (8-11)$$

$$\text{Eqs. (7-1)-(7-4), (8-4)-(8-5)} \quad (8-12)$$

$$P_{DG}^{min,j} U_{DG}^{t,j} \leq P_{DG}^{t,j} \leq P_{DG}^{max,j} U_{DG}^{t,j}, \forall t \in N_T, \forall j \in N_J \quad (8-13)$$

$$R_{DG}^{min,j} \Delta t \leq P_{DG}^{t,j} - P_{DG}^{t-1,j} \leq R_{DG}^{max,j} \Delta t, \forall t \in N_T, \forall j \in N_J \quad (8-14)$$

$$(T_{DG}^{on,t-1,j} - T_{DG}^{u,j}) (U_{DG}^{t-1,j} - U_{DG}^{t,j}) \geq 0, \forall t \in N_T, \forall j \in N_J \quad (8-15)$$

$$(T_{DG}^{off,t-1,j} - T_{DG}^{d,j}) (U_{DG}^{t,j} - U_{DG}^{t-1,j}) \geq 0, \forall t \in N_T, \forall j \in N_J \quad (8-16)$$

$$P_{GT}^{min} \leq P_{GT}^t \leq P_{GT}^{max}, \forall t \in N_T \quad (8-17)$$

$$P_{PT}^{min} \leq P_{PT}^t \leq P_{PT}^{max}, \forall t \in N_T \quad (8-18)$$

$$P_{GC}^t = \eta_{TE} P_{GT}^t, \forall t \in N_T \quad (8-19)$$

$$P_{PC}^t = \eta_{PC} P_{PT}^t, \forall t \in N_T \quad (8-20)$$

$$0 \leq P_{BC}^t \leq P_{BC}^{max}, \forall t \in N_T \quad (8-21)$$

$$0 \leq P_{BD}^t \leq P_{BD}^{max}, \forall t \in N_T \quad (8-22)$$

$$P_{BC}^t P_{BD}^t = 0, \forall t \in N_T \quad (8-23)$$

$$E_{BS}^t = E_{BS}^{t-1} (1 - \tau_{BS}) + \eta_{BC} P_{BC}^t - P_{BC}^t / \eta_{BD}, \forall t \in N_T \quad (8-24)$$

$$\chi_{BS}^{min} E_{BS}^{rate} \leq E_{BS}^t \leq \chi_{BS}^{max} E_{BS}^{rate}, \forall t \in N_T \quad (8-25)$$

$$E_{BS}^0 = E_{BS}^{N_T} \quad (8-26)$$

$$0 \leq P_{TC}^t \leq P_{TC}^{max}, \forall t \in N_T \quad (8-27)$$

$$0 \leq P_{TD}^t \leq P_{TD}^{max}, \forall t \in N_T \quad (8-28)$$

$$P_{TC}^t P_{TD}^t = 0, \forall t \in N_T \quad (8-29)$$

$$E_{TS}^t = E_{TS}^{t-1} (1 - \tau_{TS}) + \eta_{TC} P_{TC}^t - P_{TC}^t / \eta_{TD}, \forall t \in N_T \quad (8-30)$$

$$\chi_{TS}^{min} E_{TS}^{rate} \leq E_{TS}^t \leq \chi_{TS}^{max} E_{TS}^{rate}, \forall t \in N_T \quad (8-31)$$

$$E_{TS}^0 = E_{TS}^{N_T} \quad (8-32)$$

$$0 \leq P_{CI}^t \leq P_{CI}^{max}, \forall t \in N_B \quad (8-33)$$

$$0 \leq P_{DA}^t \leq P_{DA}^{max}, \forall t \in N_T \quad (8-34)$$

$$0 \leq P_{AD}^t \leq P_{AD}^{max}, \forall t \in N_T \quad (8-35)$$

$$P_{AD}^t P_{DA}^t = 0, \forall t \in N_T \quad (8-36)$$

$$\sum_{j \in N_J} P_{DG}^{t,j} + P_{GT}^t + P_{DA}^t \eta_{DA} - P_{AD}^t + P_{CI}^t = P_{PL}^t, \forall t \in N_T, \forall j \in N_J \quad (8-37)$$

$$P_{EP}^t + P_{BD}^t - P_{BC}^t - P_{PT}^t - P_{AD}^t \eta_{AD} + P_{DA}^t = P_{EL}^t, \forall t \in N_T \quad (8-38)$$

$$P_{HP}^t + P_{GC}^t + P_{PC}^t + P_{TD}^t - P_{TC}^t = P_{TG}^t, \forall t \in N_T \quad (8-39)$$

Eq.(8-6) denotes the ship operation objective, which minimizes the total operating cost; Eq.(8-7)-(8-11) are the ship fuel cost, maintenance cost, start-up cost for DGs and power purchasing cost from the land; Eqs.(7-22)-(8-16) show the power output, ramp up as well as the minimal on/off time limits of the DG; Eqs.(8-17)-(7-23) are the power output limits for the CCHP unit and PtC unit, compared with DGs, they are more flexible to control and start-up, i.e., they can change their power output from zero to maximum within several seconds, hence no ramp-up/-down limits or minimal on-off time are involved; Eqs.(8-19) and (8-20) denote the conversion from power to the thermal energy of the CCHP unit and PtC unit; Eqs. (7-28)-(8-26) are the operating constraints for BS in which Eqs.(7-28)-(7-29) are the maximal charging and discharging power limits, Eq.(8-23) means the BS cannot charge or discharge at the same time, Eq.(7-30) is the state model for its energy balance, Eq.(7-31) denotes the energy limits, while Eq.(8-26) guarantees the same dispatch flexibility during each voyage [17]; Eqs.(8-27)-(8-32) are the operating constraints for the TS corresponding to Eqs.(7-28)-(8-26) [15], [17]; Eq.(7-32) means that when the ship is at berth, the power support from the land is within a secure range; Eqs.(8-34)-(8-35) are the power limits for the bidirectional converter with Eq.(8-36) which limits that the power transfer from the AC to DC side and the other way around cannot happen at the same time; Eqs.(8-37)-(7-34) denote that the ship should maintain the balance of the AC power, DC power and thermal energy at all times.

In the above ship operation model, there are some nonlinear equations like Eqs.(7-4), (8-4), (8-9), (8-15)-(8-16), (8-23), (8-29) and (8-36) which make the ship operation a non-convex non-linear programming problem. To relieve the

computation burden and improve solution quality, the nonlinear items are linearized as the Appendix (Chapter 10).

After the linearization, the ship coordinated operation model becomes a MILP problem and can be efficiently solved by the industry-proven efficient solvers such as Cplex and Gurobi.

For the ease of presentation in subsequent discussions, the MES operation problem after the linearization is recast in the compact form as Eqs. (8-40)-(8-43):

$$\min_{\mathbf{x}, \mathbf{y}} \mathbf{c}^T \mathbf{x} + \mathbf{b}^T \mathbf{y} - \mathbf{e}^T \mathbf{d}_0 \quad (8-40)$$

$$\text{s.t.}, \mathbf{x} \in \chi \quad (8-41)$$

$$\mathbf{Ax} + \mathbf{By} \geq \mathbf{f} \quad (8-42)$$

$$\mathbf{Ex} + \mathbf{Fy} = \mathbf{d}_0 \quad (8-43)$$

Vector $\mathbf{x}$ represents the variable vectors: $\mathbf{v}_s$, $\mathbf{D}_s$, $\mathbf{P}_{PL}$, $\mathbf{P}_{BC}$, $\mathbf{P}_{BD}$, $\mathbf{E}_{BS}$, $\mathbf{P}_{TC}$, $\mathbf{P}_{TD}$, $\mathbf{E}_{TS}$, $\mathbf{U}_{DG}$ that are related to the first-stage operation. The vector $\mathbf{y}$ denotes the rest of the continuous variables regarding the second-stage operation. The vector $\mathbf{d}_0$ corresponds to the forecasted uncertainties. The term $\mathbf{c}^T \mathbf{x}$ denotes the maintenance cost for heterogeneous energy storage, the start-up cost of DGs and $\mathbf{b}^T \mathbf{y} - \mathbf{e}^T \mathbf{d}_0$ represents the power purchasing cost, fuel cost, emission cost as well as maintenance cost of all generators and bidirectional converter. χ is the feasible set of voyage-ahead decisions described by (7-1)-(7-4), (8-15)-(8-16), (7-28)-(8-31). Eq.(8-43) represents all the energy balance conditions of Eqs.(8-37)-(7-34). Eq.(8-42) summarizes all the linear constraints for the second-stage operation.

8.3.2 Two-Stage Robust Coordinated Operation Model

Given the robust coordination framework, the two-stage robust operation model can be formulated as:

$$\min_{\mathbf{x}} \mathbf{c}^T \mathbf{x} + \max_{\mathbf{d} \in \mathfrak{D}} L(\mathbf{x}, \mathbf{d}) \quad (8-44)$$

$$\text{s.t.}, \mathbf{x} \in \chi \quad (8-45)$$

$$\Upsilon(\mathbf{x}, \mathbf{d}) \neq \emptyset, \quad \forall \mathbf{d} \in \mathfrak{D} \quad (8-46)$$

where:

$$L(\mathbf{x}, \mathbf{d}) := \min_{\mathbf{y} \in \Upsilon(\mathbf{x}, \mathbf{d})} \mathbf{b}^T \mathbf{y} - \mathbf{e}^T \mathbf{d} \quad (8-47)$$

$$Y(\mathbf{x}, \mathbf{d}) := \left\{ \mathbf{y} \left| \begin{array}{l} \mathbf{Ax} + \mathbf{By} \geq \mathbf{f} \\ \mathbf{Ex} + \mathbf{Fy} = \mathbf{d} \end{array} \right. \right\} \quad (8-48)$$

Here, $\mathfrak{Z}$ denotes the uncertainty sets of the PV multi-energy outputs, onboard power loads and outdoor temperature. Usually, the uncertainty sets are polyhedrons, which guarantees the finite convergence of the solution algorithm [18]. Eqs.(8-47)-(8-48) denote that the second stage operation is optimized under the first-stage decision $\mathbf{x}$ and the constraint $Y(\mathbf{x}, \mathbf{d})$ with a given uncertainty scenario $\mathbf{d}$, which replaces the forecast load $\mathbf{d}_0$ to obtain the second-stage cost $L(\mathbf{x}, \mathbf{d})$. Then in Eq.(8-44), the uncertainty scenario that maximizes the minimum $L(\mathbf{x}, \mathbf{d})$ under the given first-stage decision $\mathbf{x}$ is obtained. This way, the robust program can find a solution that minimizes the first-stage cost and worst-case second-stage cost.

If the first-stage decision $\mathbf{x} \in \chi$ satisfies (8-46) (given such a decision $\mathbf{x}$, the system is feasible for any possible uncertainty scenario $\mathbf{d} \in \mathfrak{Z}$), then the first-stage decision is regarded robustly feasible. If no robustly feasible decision $\mathbf{x}$ exists (in other words, there is no feasible first-stage solution under a condition where the second stage is feasible for all possible uncertainties scenarios), then the robust program is infeasible. Thus, the feasibility check of the robust program should be done if the uncertainty set becomes large. However, if the model is not robustly feasible, in a realistic sense, the ship system should change its capacity to adapt to the large variation of the uncertain sources.

8.4 Solution Methodology

To solve the two-stage robust MES coordination model, the uncertainty set is modeled first for all the uncertainties. In this thesis, the column-and-constraint generation (C&CG) algorithm, which solves the problem by changing the robust model into the master and slave problems, is utilized.

8.4.1 Uncertain Sets Modelling

Take the onboard power loads as an example, its uncertainty degree is controlled in a set as:

$$\mathfrak{Z}_{EL} = \left\{ \mathbf{P}_{EL} \left| \begin{array}{l} P_{EL}^{\min} \leq P_{EL}^t \leq P_{EL}^{\max}, \\ \Gamma_{EL}^{\min} \leq \sum_{t \in N_T} P_{EL}^t / \sum_{t \in N_T} \tilde{P}_{EL}^t \leq \Gamma_{EL}^{\max} \end{array} \right. \right\} \quad (8-49)$$

In the uncertainty set, the real power loads can vary between the lower ($P_{EL}^{\min}$) and upper limits ($P_{EL}^{\max}$), while the overall variation is controlled by a user-defined lower ($\Gamma_{EL}^{\min}$) and upper ($\Gamma_{EL}^{\max}$) budget level. $\tilde{P}_{EL}^t$ means the forecasting value of the power loads

The uncertainty sets for the PV power, thermal outputs, and outdoor temperature are like power loads.

8.4.2 Master Problem of the First-stage Operation

The MES coordinated operation model can be rewritten in a robust optimization form with the master problem as:

$$\min_{\mathbf{x}, L} \mathbf{c}^T \mathbf{x} + L \quad (8-50)$$

$$\text{s.t., } \mathbf{x} \in \mathcal{X} \quad (8-51)$$

$$L \geq \mathbf{b}^T \mathbf{y} - \mathbf{e}^T \mathbf{d}^*, \forall \mathbf{d} \in \mathfrak{D} \quad (8-52)$$

$$\mathbf{y} \in \Upsilon(\mathbf{x}, \mathbf{d}) \quad (8-53)$$

$$L \geq 0 \quad (8-54)$$

$\mathbf{d}^*$ is the uncertainty vector obtained from the slave problem.

The solution for the master problem corresponds to the first-stage decisions $\mathbf{x}$. As all the constraints are linear, the master problem is a MILP problem.

8.4.3 Slave Problem of the First-Stage Operation

The slave problem in the C&CG algorithm aims to generate the worst-case scenario for the master problem and obtain an upper bound for the first stage. These goals are achieved by solving the following separation problem under the first stage decision $\mathbf{x}^*$ from the master problem as:

$$L(\mathbf{x}^*) := \max_{\mathbf{d} \in \mathfrak{D}} \min_{\mathbf{y}} \mathbf{b}^T \mathbf{y} - \mathbf{e}^T \mathbf{d} \quad (8-55)$$

$$\text{s.t., } \mathbf{B}\mathbf{y} \geq \mathbf{f} - \mathbf{A}\mathbf{x}^* \quad (8-56)$$

$$\mathbf{F}\mathbf{y} = \mathbf{d} - \mathbf{E}\mathbf{x}^* \quad (8-57)$$

Given $\mathbf{x}^*$, Eqs.(8-55)-(8-57) can find the worst-case uncertainty scenario $\mathbf{d}$ and corresponding second-stage decision $\mathbf{y}$.

To effectively solve the max-min problem in (8-55)-(8-57), Karush–Kuhn–Tucker (KKT) conditions are used to transfer it into a max problem and then it is linearized by the big-M method [147]. As all the constraints are linear, the slave problem also becomes a MILP problem.

8.4.4 Feasibility Check of the First-Stage Operation

For a given decision x^* , there is no guarantee that the slave problem is always feasible as there might exist a scenario d such that $L(x,d)$ is infeasible [150]. Hence, before solving the slave problem, whether the first-stage decision x^* is robustly feasible with the feasibility sub-problem must be checked as:

$$q(x^*) := \max_{d \in \mathcal{D}} \min_{y, mc, nc} mc + nc \quad (8-58)$$

$$\text{s.t., } By \geq f - Ax^* \quad (8-59)$$

$$Fy = d + (mc - nc)1 - Ex^* \quad (8-60)$$

$$mc, nc \geq 0 \quad (8-61)$$

The feasibility sub-problem adds the non-negative slack and surplus variables mc and nc to the system equations with uncertainty sources and they are adjusted according to the infeasibility of the slave problem. If $q(e^*) > 0$, there exists an uncertainty scenario d^* where there is no feasible solution, then, the new first stage decisions should be regained or in a realistic sense, the ship system should be re-planned. Otherwise, the decision x^* is robustly feasible for all uncertainty scenarios. This feasibility check problem is also a MILP problem.

8.4.5 Second-Stage Operation

With the decisions x^* and realization of the uncertainties d_0 from the short-lead-time prediction, the second-stage model is:

$$L(x^*) := \min_y b^T y - e^T d_0 \quad (8-62)$$

$$\text{s.t., } By \geq f - Ax^* \quad (8-63)$$

$$Fy = d_0 - Ex^* \quad (8-64)$$

The second-stage operation can be optimized by some classical deterministic optimization methods. Again, the second-stage problem is a MILP problem.

8.5 Case Study

8.5.1 Test System

The configuration of the hybrid AC/DC MES is shown in Figure 7-1. The PV system coordinates with the CCHP unit, DGs, PtC unit and heterogeneous energy storage to drive the voyage. The ship voyage information is shown in Figure 8-3, it is designed for sightseeing and equipped with clubs, cinemas, bars, hotels, swimming pools, dining rooms, etc. The ship cruises from Penang, Malaysia (Port A) at 4:00 am to Langkawi, Malaysia (Port B) at 8:00 am and stays there until 12:00 pm, then stops at Phuket, Thailand (Port C) at 22:30 pm.

Figure 8-3. Voyage information the test hybrid AC/DC multi-energy cruising ship.

For the ship operation, the unit dispatch interval is half an hour [92], i.e., $N_{T,1}=38$. As the ship cruises in tropical areas, only the cooling loads are needed. The voyage-ahead interval predictions of the PV multi-energy outputs, onboard power loads and outdoor temperature are shown in Figure 8-4, where the middle line denotes the expected values [64].

Figure 8-4. Interval predictions for the system uncertainties.

Parameters for the generators and HES system are shown in Table 8-1 to Table 8-2.

Table 8-1 Technical Parameters for the Generators [93], [95],[97]

Units	$P^{\max}/P^{\min}(\text{MW})$	$T_{\text{on}}/T_{\text{off}}(\text{h})$	$K_m(\$/\text{MW})$	$K_u(\$)$
DG1-3	(15,10,10)/(3,1.5,1.5)	(2,1,1)/(2,1,1)	3.2,2.4,2.4	600,350,400
PtC unit	6/0	-	1.0	-
CCHP unit	15/0	-	2.5	-

Table 8-2 Technical Parameters for Energy Storage [117]

ES	$\chi_{B/TS}^{\min}/\chi_{ETS}^{\max}$	$P_{B/TS}^{\max}/P_{ETS}^{\max}$	$\eta_{B/TS}/\eta_{ETS}$	$T_{B/TS}$	$E_{B/TS}^{\text{rate}}$	$E_{B/TS}^0$
BS	0.2/0.9	7.5/7.5(MW)	0.98/0.98	0.01	20(MWh)	4(MWh)
TS	0.1/0.9	8/8(MW)	0.95/0.95	0.04	25(MWh)	2.5(MWh)

Note that without the loss of generality, any other data collected from real life can also be applied. The simulation is conducted on an Intel(R) Xeon(R) E5-

1630 3.70GHz 64-bit PC with 16G RAM and solved by the Cplex solver via the GAMS platform.

8.5.2 First-Stage Ship Operation Results

With the interval predictions, the first-stage decision is obtained with a total MES operating cost of \$78772.3, which may be further reduced when the worst case does not occur in the second stage. The system energy dispatch and voyage scheduling under the worst-case are shown in Figure 8-5:

Figure 8-5. MES worst-case energy dispatch and voyage scheduling decisions

It can be seen that the multiple energies are coordinated under the worst-case multi-energy supply in Figure 8-5 (a)-(c): as the CCHP unit can generate power and thermal energy at the same time with high energy efficiency, it operates all the time [Figure 8-5(a),(c)]; The TS is coupled with the CCHP unit by storing its excess thermal outputs [Fig.6(c), Period:2-8], and when the ship is at berth, TS releases energy and supplies the onboard thermal loads with the PtC unit [Figure 8-5(c), Period:9-12]; Thus, the operation of CCHP unit is flexibilized by the coordination of TS and PtC unit; As DGs are the main source for the MES power supply and given its minimum on- and off-time constraints, there are always power outputs from them [Figure 8-5 (a)]; However, to avoid the cost from the frequent start-up of DGs, the BS stores their power generation when the ship is at berth [Figure 8-5(c), Period:13-16] and the release it when the ship is cruising [Figure 8-5(c), Period:13-16]; For the bidirectional converters,

as the main generators are at the AC side, only power flowing from AC to DC to supply the onboard power loads.

As for the voyage, it is flexible in terms of the speed and distance as shown in Fig.6 (d), in this regard, the propulsion loads are also flexibilized for the energy dispatch, *i.e.*, the energy dispatch and voyage scheduling are coordinated.

In terms of computational efficiency, the solution time is 20.1 minutes which is acceptable for voyage-ahead operation.

8.5.3 Second-Stage Ship Operation Results

For the real-time (second-stage) operation, the point forecasting values for multi-energy outputs of the PV system, onboard service power loads and outdoor temperature are obtained 30mins-ahead. Then, the second-stage decisions are shown in Figure 8-6 with the first-stage results as a comparison.

As the uncertainty realizations differ from the worst-case uncertainties in the first stage, MES re-dispatches the power generation or consumption of CCHP unit, DGs, PtC unit, ‘cold ironing’ and bidirectional converters [Figure 8-6(a)-(f)]. Besides, the indoor temperature is controlled to a different level [Figure 8-6(g)]. In this light, the final MES operating cost is decreased to \$75142.4 with a calculation time of 5.3s, which is practical for the online ship operation. Further, the result demonstrates that the second-stage operation compensates the first stage effectively, given the voyage-ahead prediction errors, to reduce the MES operating cost.

8.5.4 Methods Comparison

To verify the advantage of our proposed method, two conventional ship dispatch benchmarks are compared as:

Method #1: Fixed voyage and indoor temperature scheduling method [3]-[5]: the ship cruises at the rated speed, while the indoor temperature is kept as a fixed value.

Method #2: Deterministic dispatch method [92]-[97]: no uncertainties involved, *i.e.*, assume the predictions are accurate.

The operating cost and solution time are listed in Table 8-3.

Table 8-3 Ship Operating Cost and Solution Time

	Method #1		Method #2	
	Cost	Solution time	Cost	Solution time
First stage	\$84211.2	29.0s	\$74457.1	3.1s
Second stage	\$80474.1	1.8s	\$74998.7	1.7s

The solution time for all the methods is compatible with the practical ship operation. From the results of **Method #1**, the flexible voyage and thermal loads contribute much to the ship cost reduction as it adds extra degrees of dispatch freedom; compared with **Method #2**, though the first-stage cost of our method

is much higher, the second-stage cost is similar with the deterministic method, which verifies that the second-stage operation could compensate for the prediction errors in the first-stage operation effectively to reduce the ship operation cost.

8.5.5 Feasibility Check

To demonstrate the advantage of our robust method over the deterministic one, the feasibility check is further implemented. A group of 2000 scenarios, which denote the uncertainty realization, are generated by the Latin hypercube sampling. For all the uncertainty cases, the lower and upper limits of the uncertain sources are the same as Figure 8-4. The uncertainty budget for PV power and thermal outputs, onboard power loads and outdoor temperature are given in Table 8-4.

Table 8-4 Feasibility Check Results

	Method # 2	Our Method
First-stage operating cost	\$74457.1	\$78772.3
LHS Group1: ($\Gamma^{\min}$, $\Gamma^{\max}$): (0.8,1.2), (0.8,1.2), (0.925,1.075), (0.95,1.05)		
The average second-stage operating cost of feasible cases	\$75059.7	\$75251.2
Infeasible cases percentage	19.8%	0%

From Table 8-4, it can be seen that though our proposed method has a higher voyage-ahead operating cost than the deterministic method, as it is obtained under the worst case, the realized cost (average second-stage operating cost) of both methods are quite similar. This is in line with the principle of the RO method that the first-stage decisions are made under the worst case, while the second stage acts as a compensation for it. Second, in terms of feasibility performance, **Method #2** is infeasible for some cases, *i.e.*, the system should cut a part of loads to maintain the energy balance. However, our proposed method is feasible for all the cases, *i.e.* no loads need to be cut, which verifies that our robust solutions are against any uncertainty realizations.

8.5.6 Sensitivity Analysis

To further investigate the effectiveness and robustness of our proposed method, two cases in which both larger (Case 1) and smaller (Case 2) variations of uncertainty sources are considered. For both cases, the voyage-ahead interval predictions for diverse uncertainties are shown in Fig.8-7.

The corresponding budgets for diverse uncertainties in both cases are listed in Table 8-5.

Table 8-5 The Budgets for the Diverse Uncertainties in Both Cases

Index	$\Gamma_{EP}^{\min}$	$\Gamma_{EP}^{\max}$	$\Gamma_{TP}^{\min}$	$\Gamma_{TP}^{\max}$	$\Gamma_{OUT}^{\min}$	$\Gamma_{OUT}^{\max}$	$\Gamma_{EL}^{\min}$	$\Gamma_{EL}^{\max}$
Case 1	0.7	1.3	0.7	1.3	0.9	1.1	0.875	1.125
Case 2	0.9	1.1	0.9	1.1	0.975	1.025	0.95	1.05

The simulation results are shown in Table 8-6.

From the sensitivity analysis results above, it can be seen that:

1) The robustness of the RO method can be validated as it could guarantee reliable ship operation under different uncertainty levels.

2) The two-stage RO method is effective in handling the uncertainties. This is because compared with the deterministic method (**Method #2**) in different cases, there are no infeasible cases in real-time operation.

Table 8-6 Feasibility Check Results of Both Cases

Index	Method # 2 for Case 1	RO Method for Case 1	Method # 2 for Case 2	RO Method for Case 2
First-stage cost	\$74457.1	\$81070.1	\$74457.1	\$76859.2
First-stage time	3.1s	18.7 mins	3.1s	22.3 mins
Second-stage cost	\$75091.2	\$77241.6	\$74736.1	\$75119.8
Second-stage time	1.9s	5.6s	1.8s	5.9s
Average second-stage cost of feasible cases	\$75128.2	\$77319.7	\$75021.8	\$75124.9
Infeasible case percentage	24.6%	0%	15.2%	0%

3) For the RO method in different cases, the first-stage cost increase with the level of uncertainties. This verifies that the RO method can find the worst-case uncertainty realizations and the higher level of uncertainty results in even worse cases.

4) The solution time for all the methods in different cases is compatible with the respective operation.

8.6 Conclusions and Future Work

This chapter proposes a novel hybrid AC/DC multi-energy ship configuration with a flexible voyage and thermal loads. To address the system uncertainties from the renewables, onboard power loads and outdoor temperature, the robust coordination method is further proposed for the ship. Then, the proposed method is tested on a hybrid AC/DC MES system and compared with the conventional ship operation benchmarks to check its performance. The simulation results show that flexibilizing the voyage and loads can significantly reduce the operating cost as it adds extra dispatch flexibility for the system. Besides, compared with the deterministic method, the proposed robust coordination method can minimize the operating cost without violating the operating constraints, indicating that our method has high robustness for practical applications with various uncertainties.

In summary, the proposed robust coordination method for the proposed hybrid AC/DC MES system with flexible voyages and thermal loads can achieve low operating costs and arrive at robustly optimal solutions against uncertainties.

More to mention is that, in this chapter, the uncertainty of the energy generation of renewable energy sources, multi-energy loads are tackled effectively, however, to further consider the ship operation property, the uncertainties from the ship swinging should also be taken into consideration in the future work.

9.) Conclusion and Recommendations

9.1 Conclusion

This thesis investigates the optimal planning and operation of multi-energy systems in land-based (such as the MEMGs, RMEMGs, etc) and mobile (such as MEP microgrids) forms. By introducing different distributed generators, heterogeneous energy storage as well as by incorporating the DSM scheme, the system dispatch flexibility is greatly enhanced; Through the coordination of multiple units, the system energy utilization efficiency is largely improved; via the handling of diverse uncertainties, the system is more reliable and robust against the fluctuations; last but not least, the system cost and emission are largely reduced because of the optimal planning and operation scheme.

The current research indicates that the multi-energy systems would be beneficial for future energy systems with its high energy utilization efficiency and low operating cost and emission. Currently, with increasing penetration of RES and widespread installation of smart meters, growing investment of land-based or mobile multi-energy systems, the proposed methods in this thesis can provide insightful guidance for the real-world application.

9.2 Recommendations for further research

For future research, the author would like to go deeper into the multi-energy research, at the same time focusing a bit more on its application. The specific recommendations are:

1. Investigate on the coordination of the multi-energy networks, such as the power, gas, heat, transportation, *etc.*, network. As different networks share various properties, to fully study their coordination would contribute to more economic/resilient system operation.
2. Explore more uncertainty sources except for those solely from the power system, such as the natural gas price, ocean wave speed, *etc.* The uncertainties influence a lot on system reliability. Exploring and tacking more uncertainty sources could guarantee more reliable system operation.
3. Apply the more advanced solution methods or algorithms to speed up the solution process. In the literature, apart from the stochastic and robust optimization method, there are more other advanced methods such as

distributionally RO, artificial intelligence algorithms, approximate dynamic programming, stochastic robust optimization, deep reinforcement learning methods, etc. Using those novel methods would save the solution time and improve the solution quality.

4. Incorporate social science into the planning and operation of smart buildings and smart homes. For the smart buildings, except for space thermal and power loads, the social behavior of humans would add a great degree of uncertainty to the system operation. Consequently, exploring the social behavior pattern of all humans would contribute to more economic /comprehensive research.
5. Study the optimal planning of the ship system and/or seaport for a clean and economic future ship system. The planning of the ship system would be another promising topic for future research as currently, more and more countries all over the world had put much focus on the shipping industry in terms of ship tourism, ship transportation, etc. In this light, a better ship system planning would guarantee a more economic and environmentally friendly ship system.

10.)Appendix

10.1 Model Linearization

In some chapters, the nonlinear models are hard to be solved directly. in order to reduce the computation burdens and improve the solution quality, they can be linearized for more efficient and effective solutions. The linearization process can be categorized as the following:

10.1.1 Linearization of the Polynomial Functions

The nonlinear polynomial equations in this thesis are Eqs. (3-2),(3-3), (3-11) (4-2),(4-5),(7-4), (7-9), (7-10), (7-13).(7-9),(7-10), (7-12),(7-13), *etc.* Then, the thermal outputs of the CCHP plants, as well as the fuel cost for CCHP plants and FCs, are taken as examples to show the linearization process.

The fuel cost curves of the CCHP plants and FCs in Eqs. (3-11) are plotted as the solid line in Figure 10-1(a), the heat/cooling outputs curves of the CCHP plants in Eqs. (3-2),(3-3) are plotted as the solid line in Figure 10-1 (b). N_L blocks of linear functions in dash lines are used to approximate the origin nonlinear functions by introducing a binary variable and a continuous variable in each block [60]-[61].

Figure 10-1. Piecewise linearization of the nonlinear items.

The piecewise-linear functions for the fuel cost and heat/cooling outputs of the CCHP plants are

$$\bar{f}(t) = \sum_{k=1}^{N_L} (\alpha_k P_k^t + \beta_k B_k^t) \quad (10-1)$$

$$\alpha_k = [f(P_{k+1}) - f(P_k)] / (P_{k+1} - P_k) \quad (10-2)$$

$$\beta_k = f(P_k) - P_k \alpha_k \quad (10-3)$$

$$P_k B_k^t \leq P_k^t \leq B_k^t P_{k+1} \quad (10-4)$$

$$U_j^t = \sum_{k=1}^{N_L} B_k^t \leq 1 \quad (10-5)$$

10.1.2 Linearization of the Max Function

The start-up/shut-down cost functions in all the above chapters like Eqs. (3-13), (3-14), (4-8)-(4-9), (5-20),(5-21), (6-26), (6-27), (7-20),(8-16) are also nonlinear with the max function. It can be achieved by separating the max function into two individual parts as (Take Chapter 3 as an example)

$$\begin{cases} C_{ST}^t \geq 0 \\ C_{ST}^t \geq \sum_{j=1}^{N_{CG}} (U_j^t - U_j^{t-1}) C_{ST,j}^U \end{cases} \quad (10-6)$$

$$\begin{cases} C_{SD}^t \geq 0 \\ C_{SD}^t \geq \sum_{j=1}^{N_{CG}} (U_j^{t-1} - U_j^t) C_{SD,j}^D \end{cases} \quad (10-7)$$

10.1.3 Linearization of the Bilinear Item

The bilinear items can be seen in Eq.(5-23), (6-32), (6-33), *etc*: Take $z=Ax$ as an example in which A is a continuous variable which is bounded below by zero and above by $\bar{A}$ (or any Big M) and x is a binary variable, then z can be linearized as:

$$z \leq \bar{A} \cdot x; \quad z \leq A; \quad z \geq A - (1-x) \cdot \bar{A}; \quad z \geq 0 \quad (10-8)$$

10.1.4 Linearization of the Exponential Item

The stepwise price-elastic demand curve uses different price level rates to represent the price elasticity of power demands as Eqs. (6-3), with these price and demand response levels, the real and reactive power demands can be calculated/linearized as (assuming power factors are fixed) [2]:

$$P_{DL}^t = P_{DL,Pr}^t \cdot \sum_{j=1}^{N_J} \alpha^{t,j} \cdot L_{PL}^{t,j} \quad (10-9)$$

$$Q_{DL}^t = Q_{DL,Pr}^t \cdot \sum_{j=1}^{N_J} \alpha^{t,j} \cdot L_{QL}^{t,j} \quad (10-10)$$

10.1.5 Linearization of the Absolute Value

In Eq. (8-4), as the onboard thermal loads are for either the space heat (in winter days) or cooling (in summer days), the absolute value can be removed for the real case. However, to represent the general thermal dynamics, the absolute value sign is kept.

10.1.6 For the Minimum Up-/Down-Time Constraints

The original nonlinear minimum up-/down-time constraints for the DGs are explained in Eqs.(7-24),(7-25), (8-15),(8-16), the linearization process is as:

$$\sum_{t \in G_j} (1 - U_{DG,j}^t) = 0, G_j = \text{Min} \left[N_T, (T_{DG,j}^U - T_{DG,j}^{U0}) U_{DG,j}^0 \right] \quad (10-11)$$

$$\sum_{n \in (t, t+T_{DG,j}^U-1)} U_{DG,j}^n \geq T_{DG,j}^U [U_{DG,j}^t - U_{DG,j}^{t-1}], k = G_j + 1 \dots N_T - T_{DG,j}^U + 1 \quad (10-12)$$

$$\sum_{n \in (t, N_T)} [U_{DG,j}^n - (U_{DG,j}^t - U_{DG,j}^{t-1})] \geq 0 \quad k = N_T - T_{DG,j}^U + 2 \dots N_T \quad (10-13)$$

$$\sum_{t \in L_j} U_{DG,j}^t = 0, L_j = \text{Min} \left[N_T, (T_{DG,j}^D - T_{DG,j}^{D0}) (1 - U_{DG,j}^0) \right] \quad (10-14)$$

$$\sum_{n \in (t, t+T_{DG,j}^D-1)} [1 - U_{DG,j}^n] \geq T_{DG,j}^D [U_{DG,j}^{t-1} - U_{DG,j}^t], k = L_j + 1 \dots N_T - T_{DG,j}^D + 1 \quad (10-15)$$

$$\sum_{n \in (t, N_T)} [1 - U_{DG,j}^n - (U_{DG,j}^{t-1} - U_{DG,j}^t)] \geq 0 \quad k = N_T - T_{DG,j}^D + 2 \dots N_T \quad (10-16)$$

10.1.7 For the Simultaneous Charging and Discharging of HES

Equations (8-23), (8-29) and (8-36) are bilinear items, however, they can be directly removed. Here, Eq.(8-23) is taken to prove this theorem:

The objective function [Eqs.(8-6) and (8-8)] is monotonic increasing with P_{BD}^t and P_{BC}^t as $\kappa_{BS} > 0$. It can be simplified with regard only to P_{BD}^t and P_{BC}^t as:

$$\min_{P_{BC}, P_{BD}} \sum_{t \in N_T} [\kappa_{BS} (P_{BC}^t + P_{BD}^t) + C_{OT}^t] \Delta t \quad (10-17)$$

where C_{OT}^t is the cost irrespective of P_{BD}^t and P_{BC}^t .

Similarly, the constraint (8-38) can be simplified as:

$$P_{BD}^t - P_{BC}^t = P_{OT}^t, \forall t \in N_T \quad (10-18)$$

where P_{OT}^t is net power irrespective of P_{BD}^t and P_{BC}^t .

Then for the objective with regard to P_{BD}^t and P_{BC}^t in Eq.(10-17), it can be rewritten with Eq.(8-23) removed as:

$$\min_{P_{BC}, P_{BD}} \sum_{t \in N_T} [\kappa_{BS} (P_{OT}^t + 2P_{BC}^t) + C_{OT}^t] \Delta t$$

or

$$\min_{P_{BC}, P_{BD}} \sum_{t \in N_T} [\kappa_{BS} (-P_{OT}^t + 2P_{BD}^t) + C_{OT}^t] \Delta t$$

s.t., $P_{BD}^t > 0, P_{BC}^t > 0$

Since P_{OT}^t and C_{OT}^t are fixed values for the optimization problem regarding P_{BD}^t and P_{BC}^t , the optimal solution lies in either the $P_{BD}^t=0$ or $P_{BC}^t=0$. The proof is finished.

11.) Author's Publications

11.1 Journal Publication

- [1] Z. Li, Y. Xu, et al. Multi-objective Coordinated Voyage Scheduling and Energy Dispatch for the Multi-energy Cruising Ship System with Renewable Energies, *IEEE Transactions on Industrial Applications*, 2019.
- [2] Z. Li, Y. Xu, et al. Robust Operation of a Hybrid AC/DC Multi-energy Ship Microgrid with Flexible Voyage and Thermal Loads, *IEEE Transactions on Smart Grid*, 2020.
- [3] Z. Li, Y. Xu, et al. Optimal Deployment of Heterogeneous Energy Storage System in a Residential Multi-Energy Microgrid with Demand Side Management, *IEEE Transactions on Industrial Informatics*, 2020.
- [4] Z. Li, Y. Xu, et al. Optimal Placement of Heterogeneous Distributed Generators in a Grid-Connected Multi-Energy Microgrid under Uncertainties, *IET Renewable Power Generation (RPG)*, 2019.
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- [14] S. Fang, Y. Xu, Z. Li, "Optimal Sizing of Shipboard Carbon Capture System for Maritime Greenhouse Emission Control", *IEEE Transactions on Industrial Applications*. (Accepted)
- [15] Y. Wang, Y. Xu, Z. Li, "Cyber-Physical Design and Implementation of Distributed Event-Triggered Secondary Control in Islanded Microgrids", *IEEE Transactions on Industrial Applications*. (Accepted)

11.2 Conference Publications

- [1] Z. Li, Y. Xu, Sidun F, et al., "Multi-objective Coordinated Energy Dispatch and Voyage Scheduling for a Multi-energy Cruising Ship, in *Proceedings of 2019 IEEE/IAS 55th Industrial and Commercial Power Systems Technical Conference (I&CPS)*, May 2019, Calgary, Canada.
- [2] Z. Li, Y. Xu, "Dynamic dispatch of grid-connected multi-energy microgrids considering opportunity profit" in *Proceedings of 2017 IEEE Power & Energy Society General Meeting*, July 2017, Chicago.

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- [3] Y. Wang, Y. Xu, **Z. Li**, et al., "Distributed Event-Triggered Control for Islanded Microgrids: Cyber-Physical Design and Implementation" in *Proceedings of 2019 IEEE/IAS 55th Industrial and Commercial Power Systems Technical Conference (I&CPS)*, May 2019, Calgary, Canada.
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11.3 Paper under Review or Revision

- [16] **Z. Li**, Y Xu, et al. Multi-Objective Temporal Coordination of Energy Dispatch and Voyage Scheduling for A Multi-energy Ship Microgrid with Diverse Uncertainties, *IEEE Transactions on Smart Grid*. (To be submitted soon)
- [17] Y. Chen, Y. Xu, **Z. Li**, et al. Multi-stage coordinated operational dispatch of a multi-energy microgrid under uncertainty, *International Journal of Electrical Power & Energy Systems* (Under review)

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