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SINGAPORE

**OPTIMAL SCHEDULING OF ENERGY SYSTEMS
INCORPORATING LOAD MANAGEMENT SCHEMES**

ASHOK KRISHNAN

SCHOOL OF ELECTRICAL & ELECTRONIC ENGINEERING

2019

**OPTIMAL SCHEDULING OF ENERGY SYSTEMS
INCORPORATING LOAD MANAGEMENT SCHEMES**

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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

2019

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.

12/01/2019
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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.

12/01/2019
Date

[Assoc. Prof. H. B. Gooi]

Authorship Attribution Statement

This thesis contains material from three papers published/under review in the following peer-reviewed journals where I was/am the first author.

Chapter 4 is published as Ashok Krishnan, Y. S. Foo Eddy, H. B. Gooi, M. Q. Wang, and P. H. Cheah, “Optimal Load Management in a Shipyard Drydock,” *IEEE Transactions on Industrial Informatics*. DOI: 10.1109/TII.2018.2877703.

The contributions of the co-authors are as follows:

- Assoc. Prof. H. B. Gooi and Dr. Y. S. Foo Eddy provided the initial project direction and proofread the manuscript drafts.
- I prepared and edited the manuscript drafts and carried out the simulation studies using MATLAB.
- Mr. P. H. Cheah assisted in the design of the load forecasting module.
- Assoc. Prof. M. Q. Wang assisted in the formulation of the pump scheduling optimization scheme.

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The contributions of the co-authors are as follows:

- Assoc. Prof. H. B. Gooi and Dr. Y. S. Foo Eddy provided the initial project direction. Dr. Foo also proofread the manuscript drafts.
- I prepared and edited the manuscript drafts. I also performed all the simulation studies using MATLAB.
- Mr. L. P. M. I. Sampath assisted in integrating the optimal scheduling and the optimal power flow stages of the energy management system. Mr. Sampath also proofread the manuscript.

Chapter 6 is under review for possible publication as Ashok Krishnan, B. V. Patil, Y. S. Foo Eddy, and H. B. Gooi, "Optimal Scheduling of Multi-Energy Systems with Flexible Electrical and Thermal Loads," *IEEE Systems Journal*.

The contributions of the co-authors are as follows:

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- I prepared and edited the manuscript drafts. I also performed all the simulation studies using MATLAB.
- Dr. B. V. Patil assisted in the formulation of the optimal scheduling problem.

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Abstract

The advent of enabling smart grid technologies has resulted in the proliferation of heterogeneous power generation networks. In this context, the concept of microgrids has gained popularity in recent years due to their ability to integrate renewable energy sources with the power system. As such, many industrial units are increasingly displaying characteristics similar to grid-connected microgrids. Consequently, the traditional day-ahead scheduling (unit commitment) problem solved in power systems needs to account for the increasingly heterogeneous nature of the generators. Furthermore, deregulated electricity market concepts such as load management need to be incorporated in the scheduling problem. As such, there exists a need to formulate optimization models for modern energy systems which can account for the heterogeneity in the generation and the flexibility in the load.

This thesis is broadly divided into four parts. The first part develops accurate scheduling models of the components which constitute the energy systems considered in the later chapters of the thesis. The mixed logical dynamical modelling framework is used to develop scheduling models of the gas turbines, steam turbines, boilers, diesel generators, battery energy storage systems, thermal energy storage systems and interruptible loads. The scheduling models of the gas turbines, the steam turbines and the boilers include the power trajectories followed by these components while undergoing the hot, warm and cold start-up processes. A detailed treatment of the modelling of an exemplar conventional fossil fuel based generating unit using the mixed logical dynamical framework is also provided.

The second part of this thesis proposes a shipyard energy management system (SEMS) to optimize the cost of operating a typical shipyard drydock. The SEMS comprises three modules - load forecasting, contracted capacity optimization and optimal scheduling. The load forecasting module uses artificial neural networks (ANN) to generate short term and medium term load forecasts. Historical load demand data and ship arrival schedules are provided as inputs to the ANN. The inclusion of the ship arrival schedule as an input to the ANN enhances the accuracy

of the load forecast. The optimal scheduling module minimizes the electricity cost incurred by the drydock operator. A pump scheduling optimization model is proposed within the optimal scheduling module which minimizes the uncontracted capacity cost incurred by the drydock operator.

The third part of the thesis enhances the optimal scheduling module of the SEMS. The microgrid considered in this context comprises diesel generators, battery energy storage systems, renewable energy sources, flexible pump loads and interruptible loads. A two-stage energy management system architecture is proposed wherein an optimal, day-ahead scheduling problem similar to that of the SEMS is solved in the first stage. Subsequently, the results from the first stage are used to solve an optimal power flow problem in the second stage. This is done to account for the network losses and to verify the feasibility of the optimal schedule generated in the first stage with respect to the network constraints. This is unlike conventional unit commitment formulations which ignore the AC network constraints. Thereafter, the two stages are coordinated using an iterative procedure. The utility of the proposed optimization model is demonstrated using illustrative case studies.

The final part of this thesis proposes a detailed optimal scheduling model for an exemplar multi-energy system comprising combined cycle power plants (each constituted by one gas turbine and one steam turbine), battery energy storage systems, renewable energy sources, boilers, thermal energy storage systems, electric loads and thermal loads. The electric and thermal energy streams are linked through the combined cycle power plants which produce electricity and waste heat. A practical, multi-energy load management scheme is proposed which utilizes the flexibility offered by the flexible electrical pump loads, the electrical interruptible loads and a lumped flexible thermal load to reduce the overall energy cost of the system. The efficacy of the proposed model in reducing the energy cost of the system is demonstrated in the context of a day-ahead scheduling problem using four illustrative scenarios.

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Nomenclature and Acronyms

Nomenclature

k	Index of time intervals
n	Index of start-up methods
f	Index of gas turbines, steam turbines, diesel generators and boilers
$P_{\text{soak},1}, P_{\text{soak},2} \dots P_{\text{soak},n}$	Electrical power outputs from the corresponding unit during stages 1, 2...n of the soak phase respectively
$P_{\text{soak},k}^f$	Electrical power produced by a unit f undergoing the soak phase during hour k
$w_{\text{synch},k}^{n,f}$	Binary auxiliary variable which represents the synchronization phase status of the start-up method n of unit f during interval k
$w_{\text{start-up},k}^{n,f}$	Binary auxiliary variable which is set to 1 if start-up method n of unit f is initiated during hour k
$t_{\text{synch}}^{n,f}$	Duration of the synchronization phase of the start-up method n of unit f
$w_{\text{soak},k}^{n,f}$	Binary auxiliary variable which represents the soak phase status of start-up method n of unit f during interval k .
$t_{\text{soak}}^{n,f}$	Duration of the soak phase of start-up method n of unit f
GT, ST, BR	Sets of gas turbines, steam turbines and boilers respectively
$\mathcal{F}$	Set of diesel generators in the system
$\mathcal{N}$	Set of start-up methods
$\mathcal{K}$	Set of optimization intervals
$w_{\text{desyn},k}^f$	Binary auxiliary variable which represents the desynchronization phase status of unit f during interval k
$w_{\text{off},k}^f$	Binary auxiliary variable which is set to 1 if the electrical power output from unit f drops to 0MW during interval k

t_{desyn}^f	Duration of the desynchronization phase of unit f
$P_{\text{e},k}^f$	Electrical power (real power) produced by unit f during interval k in MW
$P_{\text{e},\text{max}}^f$	Upper bound on the electrical power produced by unit f in MW
$x_{\text{disp},k}^f$	Binary state variable which is set to 1 if unit f is in the dispatch phase during interval k
$P_{\text{h},k}^f$	Thermal power output from unit f during interval k in MW
$w_{\text{br},k}^f$	Fuel (natural gas) consumed by boiler f during hour k in mcf
a_0^f, a_1^f	Constant coefficients of the electrical power - thermal power curve for GT f
b_0^f	Conversion factor which relates the fuel consumed by boiler f to its thermal power production
h_k^f	Thermal power consumed by ST f during hour k in MW
b_1^f, b_2^f	Constant coefficients of the electrical power - thermal power curve for ST f
$P_{\text{bc},k}, P_{\text{bd},k}$	BESS charging and discharging powers respectively during interval k
$P_{1\text{C}}$	Power required to charge the BESS 100% in 1 hour i.e. 1C rate
$(\cdot)_{\text{min}}, (\cdot)_{\text{max}}$	Minimum and maximum bounds of the corresponding parameter respectively
N	BESS lifetime in hours
$T_{\text{bc}}, T_{\text{bd}}$	Average number of BESS charging and discharging hours in a day respectively
$\eta_{\text{c}}, \eta_{\text{d}}$	BESS charging and discharging efficiencies respectively
I	Capital cost (in \$/kWh) of purchasing the BESS
B_{cap}	BESS capacity in kWh
H_k^p	Continuous state variable which represents the storage level of TESS p during interval k
$\mathcal{P}$	Set of all the TESSs in the system
p	Index of TESSs in the system
$Q_{\text{in},k}^p$	Thermal power input to TESS p during interval k
$Q_{\text{out},k}^p$	Thermal power output from TESS p during interval k
γ_k^p	Psychological discharge of TESS p during interval k
v_{wind}	Wind velocity
C_{p}	Power coefficient which is a function of the tip speed ratio
a_{den}	Air density

A	Area swept by the rotor blades
$P_{\text{RES},k}$	Aggregated electrical power output from all the RESs in the system during interval k
$\mathcal{M}$	Set of pumps in the system
Q_k^m	Flow rate of pump m during interval k
m	Index of pumps in the system
$P_{m,k}$	Power consumed by a pump m during interval k
C_m	Rated power of pump m
u_k^m	Commitment status of pump m during interval k
V_d	Total liquid volume required to be pumped within the optimization period
$w_{\text{SU},k}^m$	Start-up status of pump m during interval k
$w_{\text{SU},\text{max}}^m$	Maximum number of times that pump m is permitted to start-up during the optimization period
$b_{\text{SU},k}^f$	Binary variable which represents the start-up status of DG f during interval k
C_{SU}^f	Start-up cost coefficient of DG f
$b_{\text{DG},k}^f$	Commitment status of DG f during interval k
$P_{\text{DG},k}^f$	Real power output from DG f during interval k
c_0^f, c_1^f, c_2^f	Fuel cost curve coefficients of DG f
$b_{\text{SD},k}^f$	Binary variable which represents the shutdown status of DG f during interval k
$P_{\text{EIL},\text{hour-max}}^h, P_{\text{EIL},\text{day-max}}^h$	Limits on the usage of IL h during each interval and day respectively
$P_{\text{EIL},k}^h$	Quantum of IL h utilized during interval k
h	Index of interruptible loads in the system
$\mathcal{H}$	Set of interruptible loads in the system
$C_{\text{pe},k}$	Price (in \$/MWh) at which electricity is purchased from the main utility grid during interval k
DR	Percentage of the nominal thermal load which is rescheduled during interval k
$P_{\text{Dh},k}^0$	Nominal thermal load demand
$P_{\text{Dh},k}$	Adjusted thermal load demand
$P_{\text{Shift},k}$	Thermal load which has been shifted to the current interval k from the other intervals of the optimization period

q	Index of the months in a year
$\mathcal{Q} = \{1, 2 \dots Q_{\text{end}}\}$	Set of Q_{end} months which are considered by the CCO problem
p^{CC}	Contracted capacity price
p^{UC}	Uncontracted capacity price
C^{opt}	Optimized contracted capacity
D_q^{max}	Forecasted maximum load demand during month q
$P_{\text{eb},k}$	Electricity imported from the main utility grid during interval k in MW
$P_{\text{es},k}$	Electricity sold to the utility grid during interval k in MW
$C_{\text{s},k}$	Price at which electricity is sold to the main utility grid during interval k in \$/MWh
$C_{\text{p},k}$	Price at which electricity is purchased from the main utility grid during interval k in \$/MWh
P_{UC}	Uncontracted capacity in MW
P_{CC}	Contracted capacity in MW
$b_{h,k}^{\text{IL}}$	Binary input variable which is set to 1 if IL h is interrupted during interval k
D_k	Forecasted load demand (excluding the pump loads) of the drydock in MW
$P_{\text{D},k}$	Total active power demand in the MG (Chapter 5)
$P_{\text{e},k}^{\text{loss}}$	Total electrical power losses in the network during hour k
z	Index of RESs in the system
$\mathcal{Z}$	Set of RESs in the system
e	Index of BESSs in the system
$\mathcal{E}$	Set of BESSs in the system
$P_{\text{hb},k}$	Thermal power purchased from external sources during hour k in MW
C_{sd}^f	Shutdown cost coefficient of unit f in dollars (\$)
$C_{\text{cold}}^f, C_{\text{warm}}^f$ and C_{hot}^f	Cost coefficients of unit f for the cold, warm and hot start-up methods respectively in dollars (\$)
$D_{\text{e},k}$	Total electrical load demand in the multi-energy system excluding the flexible pump loads during hour k
$P_{\text{Dh},k}$	Total thermal load demand in the multi-energy system during hour k
$P_{\text{De},k}$	Total electrical load demand in the multi-energy system

	during hour k
SR_k^f	Spinning reserve contributed by unit f during hour k
SR_k	Total system spinning reserve requirement during hour k
MSR^f	Maximum spinning rate of unit f in MW/min
c_2^f , c_1^f and c_0^f	Fuel cost curve coefficients of GT f in \$/MW ² , \$/MW and \$ respectively
P_{sync}	Power generated during the synchronization phase

Acronyms

ANN	Artificial Neural Network
BESS	Battery Energy Storage System
CCGT	Combined Cycle Gas Turbine
CCHP	Combined Cooling, Heat and Power
CCO	Contracted Capacity Optimization
CCPP	Combined Cycle Power Plant
CG	Conventional Generator
CHP	Combined Heat and Power
DG	Diesel Generator
EIP	Eco-Industrial Park
EMS	Energy Management System
GT	Gas Turbine
HRSG	Heat Recovery Steam Generator
HYSDEL	Hybrid System Description Language
IL	Interruptible Load
ISO	Independent System Operator
LF	Load Forecast
MAPE	Mean Absolute Percentage Error
MG	Microgrid
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Nonlinear Programming
MIQP	Mixed Integer Quadratic Programming
MLD	Mixed Logical Dynamical
MPC	Model Predictive Control
MSE	Mean Squared Error

MTLF	Medium Term Load Forecast
OPF	Optimal Power Flow
PCC	Point of Common Coupling
PSO	Pump Scheduling Optimization
PV	Photovoltaic
RES	Renewable Energy Source
SEMS	Shipyards Energy Management System
SOC	State of Charge
ST	Steam Turbine
STLF	Short Term Load Forecast
TESS	Thermal Energy Storage System
UC	Unit Commitment

Chapter 1

Introduction

1.1 Background and Motivation

The optimal scheduling of generators is an essential function of EMSs. The origin of the optimal scheduling problem in modern energy systems lies in the traditional UC problem solved by utilities. As such, the UC problem has interested researchers for many decades [4]. In this context, ‘turning on’ a unit implies that the unit needs to be brought upto speed (traditional generators), synchronized with the grid and connected with the grid to deliver power to consumers. The UC problem is an economic scheduling problem at its core. Optimally running the generators in the system helps the operator to save money. Many earlier works used Lagrangian Relaxation (LR) algorithms to solve the UC problem in power systems (see for example [5] and [6]). Apart from this, other early researchers proposed approaches based on the mixed integer programming method (see for example [7]). Some early examples of commercially used UC formulations can be found in [8] and [9].

With vast advancements in computational solvers, MILP based approaches for formulating power system optimization problems have taken precedence in recent years. A number of interesting works applying MILP based formulations for the UC problem are reviewed later in this chapter. Aided by government incentives and policies, the percentage of RESs in the energy mix has also grown exponentially in recent years. This has spawned the rise of numerous solution approaches to mitigate the intermittencies of RESs in the power system. Some examples of such approaches include the deployment of BESSs, the open cycle operation of GTs and

the increase of transmission capacity [10], [11]. In general, there is a rising trend in favour of increasing the heterogeneity of energy systems along with a wide range of flexible options to deal with various operating scenarios. In this context, demand response strategies have the potential to smooth out the demand curve and provide the system operator with a lot of flexibility [12].

On the other hand, many countries such as Singapore still rely heavily on fossil-fuel based generators such as CCPPs for their energy requirements [13]. While there is certainly a shift towards decarbonizing the generation of energy, fossil-fuel based units are expected to play a key role for many years to come due to a variety of reasons. Considering the heterogeneous nature of modern energy systems, there exists a need to adapt and re-formulate the traditional UC problem. Developing such scheduling problem formulations is a non-trivial task due to the changing nature of the power system architecture and the presence of numerous energy streams, types of generators and loads. Furthermore, the widespread introduction of intermittent RESs could require the traditional generating units which may have conventionally served only the base load, to start up and shut down more often. Consequently, the ramping constraints of traditional generating units also need to be given due consideration while formulating any optimal scheduling problem.

Another interesting development in the modern power system has been the proliferation of MGs. MGs have numerous advantages [14], [15]. MGs help in integrating greater capacities of RESs in the power system. They reduce transmission losses by bringing the generators and consumers closer. They provide flexibility by being able to operate in the grid-connected and islanded modes. Finally, MGs increase the reliability of the system. It is observed that numerous industrial units also exhibit characteristics similar to grid-connected MGs. Individual industrial parks also exhibit characteristics similar to grid-connected multi-energy MGs.

The above discussions clearly indicate the need to reformulate and adapt the traditional unit commitment problem to meet the needs of the modern heterogeneous power system. The optimization models need to account for the unique characteristics of all the constituent components and should be compatible with the other EMS modules. Such formulations will enable the system operator to minimize the cost of operating the power system. This thesis proposes optimal scheduling models for heterogeneous industrial energy systems which comprise a variety of generators and loads. This thesis focuses on industrial energy systems which

exhibit behaviours resembling grid-connected MGs. Optimal scheduling models are proposed for both single energy and multi-energy systems. Load management schemes form a key feature of all the optimal scheduling models presented in this thesis. The efficacies of the optimal scheduling models presented in this thesis are also largely demonstrated through the prism of the proposed load management schemes. Specifically, an energy management system is proposed to optimize the operations of a shipyard drydock with the overall aim of avoiding exorbitant un-contracted capacity costs. Subsequently, a two-stage energy management system architecture is proposed to incorporate the AC optimal power flow constraints in the optimal scheduling problem. Finally, an optimal scheduling model is proposed for a multi-energy industrial park energy system wherein the electrical and thermal energy streams are linked via combined cycle power plants. The following sections review some existing literature which is relevant to the scope of the various topics covered in this thesis.

1.2 Ramping Constraints of Thermal Units

The power output of a thermal unit is broadly restricted by three types of ramping constraints [1]:

- Ramp up and ramp down rate limits during the operation of the thermal unit.
- An increasing power trajectory during the start-up process of the thermal unit.
- A decreasing power trajectory during the shutdown process of the thermal unit.

The first constraint refers to an increase or decrease in the output power of a unit between any two successive time periods when the unit is in the dispatch phase. The second constraint refers to the increasing power trajectory followed by the thermal unit when it is started up. While starting up, a thermal unit may pass through several intermediate stages before finally reaching the technical minimum power output and the dispatch phase. The third constraint refers to the trajectory

TABLE 1.1: Summary of system model considered in [1]

Thermal Unit #1								
Arroyo and Conejo	Start-up(Defined as soak phase only)							
	Normal	Time (h)	Hot	Time (h)	Warm	Time (h)	Cold	Time (h)
Initial Output Power	112 MW	0h	0 MW	0h	0 MW	0h	0 MW	0h
$P_{\text{soak},1}$			37 MW	1h	37 MW	1h	37 MW	1h
$P_{\text{soak},2}$			75 MW	2h	75 MW	2h	75 MW	2h
Min. Power Output	112 MW	1h	112 MW	3h	112 MW	3h	112 MW	3h
Max. Power Output	294MW		294MW		294MW		294MW	
Min. Downtime	3h		3h		3h		3h	
Min. Uptime	3h		3h		3h		3h	
Synchronization Time	0h		1h		1h		1h	
Soak Time	0h		2h		2h		2h	

followed by a thermal unit when it is shut down. During the shutdown process, the output power of the unit initially reduces to the technical minimum level before dropping to 0 MW.

A rigorous thermal unit scheduling model is essential in the context of modern-day competitive electricity markets. To obtain a rigorous model of a thermal unit, it is necessary to understand its detailed operating characteristics. This includes a detailed consideration of the aforementioned ramping constraints. Much work has been done over the years to develop accurate scheduling models of thermal units. A short summary detailing the progress made by researchers in the modelling of thermal units is provided in the following paragraphs.

Arroyo and Conejo [1] were among the first to introduce a mixed integer linear (MIL) formulation for the UC problem which included most of the relevant ramping constraints. The self-scheduling problem of a thermal unit was solved in [1]. When compared with LR algorithm, MILP approaches guarantee a globally optimal solution. Furthermore, recent advances in solver technology has meant that even Regional Transmission Organization (RTO) level UC problems can be solved efficiently in the MILP framework. However, the start-up trajectory described in [1] did not account for the prior downtime of the unit which is often important in determining the time required by the unit to reach the technical minimum power output. A brief summary of the model in [1] is presented in Table 1.1. Further details on the various phases of the thermal unit start-up process are provided in the later chapters of this thesis.

Carrion and Arroyo [16] improved on the optimization model presented in [1]

TABLE 1.2: Summary of system model considered in [2]

Thermal Unit #2								
Simoglou	Start-up(Defined as soak phase only)							
	Normal	Time (h)	Hot	Time (h)	Warm	Time (h)	Cold	Time (h)
Initial Output Power	250 MW	0h	135 MW	0h	0 MW	0h	0 MW	0h
$P_{\text{soak},1}$			135 MW	0h	100 MW	1h	100 MW	3h
$P_{\text{soak},2}$					135 MW	1.5h	135 MW	4.5h
$P_{\text{soak},3}$								
Min. Output Power	250 MW	1h	250 MW	1h	250 MW	2h	250 MW	6h
Max. Output Power	476 MW		476 MW		476 MW		476 MW	
Off Time	0h		0h<OT<5h		5h<OT<12h		OT>12h	
Min. Downtime	3h		3h		3h		3h	
Min. Uptime	4h		4h		4h		4h	
Synchronization Time	0h		0h		1h		3h	
Soak Time	0h		1h		1h		3h	

by proposing a more computationally efficient formulation comprising fewer constraints and binary variables. The other highlights of the optimization model presented in [16] include the modelling of time dependent start-up costs and the inclusion of important unit constraints such as the minimum uptime, the minimum downtime and the generation limits. A single type of binary variable was used to model the constraints, the spinning reserve contributions and the start-up costs in [16] while three types of variables were used in [1]. The authors of [17] and [18] briefly mentioned various time-dependent start-up methods but did not consider these in detail while formulating the self-scheduling problem for an exemplar thermal unit.

Simoglou et al. [2] claimed to be the first researchers to consider different start-up methods based on the prior downtime in the scheduling model of a thermal unit. A detailed model of the various operating stages of a thermal unit was included in [2]. The operating stages considered in [2] included the synchronization, soak, dispatch and desynchronization phases. Based on the model in [2], constraints which render a unit unavailable for reserve contribution when it is undergoing the synchronization, soak and desynchronization phases can be formulated. Based on the prior unit downtime, three start-up methods were modelled in [2] - hot, warm and cold. The thermal unit model in [2] also allows the generator to earn revenues during the soak phase by accounting for the power produced during the soak phase in the scheduling problem. As opposed to the fixed start-up costs considered by traditional UC formulations, [2] considered different start-up costs for different start-up methods. A summary of the model presented in [2] is provided in Table 1.2.

Ostrowski et al. [19] provided an improved formulation of the UC problem based on the 3-variable model presented in [1]. Reference [19] also considered various generator constraints such as the generation limits, the ramp up and ramp down limits and the minimum uptime and downtime constraints. The authors of [19] conducted studies to demonstrate the efficiency of the formulation proposed in [1] when compared with [16] in the presence of ramping constraints. Reference [19] proposed groups of inequalities which strengthened the LP relaxation of the UC problem. This was done by studying the convex hull of the power generation schedule. The authors proposed a tighter formulation for expressing the upper bounds of the output power and the ramping constraints. These constraints reduced the computation time when compared with the conventional ramping constraints and the upper bounds considered in [1]. Reference [19] overcame some limitations of the model in [16] by using the 3-binary variable formulation in [1]. However, the inequalities proposed in [19] need to be introduced dynamically during the solution process. Furthermore, the introduction of the additional inequalities in [19] requires the user to configure the solution strategy. While [19] introduced a tighter UC problem formulation, it omitted a detailed consideration of different start-up methods.

Morales et al. [20] proposed a tighter formulation for the start-up and shutdown ramps in the UC problem with the aim of reducing the computational burden. The formulation presented in [20] required the use of only continuous variables while considering the different start-up trajectories. Reference [20] also avoided any large increases in number of constraints and variables while considering a single power trajectory for the start-up and shutdown processes. The self-scheduling problem of a single thermal unit was solved in [20]. Compared to previously reported UC problem formulations in the literature, the formulation proposed in [20] reduced the total computation time, thereby making it feasible for larger UC problems. Reference [20] demonstrated the economic benefits gained by including the start-up and shutdown power trajectories in the UC formulation. A brief summary of the model presented in [3] is shown in Table 1.3.

The authors of [20] extended their results to solve a thermal UC problem in [3]. The formulation used in [3] was tighter and more compact when compared with earlier UC formulations such as those used in [16] and [19] which used the 3-binary variable model and 1-binary variable model respectively. The tighter formulation

TABLE 1.3: Summary of system model considered in [3]

Thermal Unit #3								
Morales	Start-up(Defined as soak phase only)							
	Normal	Time (h)	Hot	Time (h)	Warm	Time (h)	Cold	Time (h)
Initial Output Power	150 MW	0h	0 MW	0h	0 MW	0h	0 MW	0h
$P_{\text{soak},1}$			50MW	1h	50MW	1h	50MW	1h
$P_{\text{soak},2}$					100MW	2h	83.33MW	2h
$P_{\text{soak},3}$							116.67MW	3h
Min. Output Power	150 MW	1h	150 MW	2h	150 MW	3h	150 MW	4h
Max. Output Power (rated capacity)	378 MW		378 MW		378 MW		378 MW	
Off Time(OT)	0h<OT<4h		4h<OT<6h		6h<OT<8h		OT≥8h	
Min. Downtime	4h		4h		4h		4h	
Min. Uptime	4h		4h		4h		4h	
Synchronization Time	0h		1h		1h		1h	
Soak Time	0h		1h		2h		3h	

in [3] helped in reducing the search space for the solver and also increased the search speed. The formulation in [3] was tested on several standard thermal UC problems. The number of binary variables used in [3] was five times the number of binary variables used in the 1-binary variable formulation proposed in [16]. The number of constraints and nonzeros were reduced by two-thirds in [3], thereby making it a more compact formulation. Overall, the performance of the formulation in [3] was superior in terms of both optimality and computation time when compared with the 3-binary variable and the 1-binary variable UC formulations. The superiority was particularly pronounced in larger systems. The authors of [3] also thoroughly analyzed the computational complexity involved in solving MILPs when the number of constraints and variables increases.

1.3 Shipyard Energy Management System

Shipyard drydocks can be regarded as low voltage distribution level MGs comprising heterogeneous generators and loads [21, 22]. The electricity cost constitutes a significant percentage of the total operating cost of a drydock [23]. Large pumps are deployed in drydocks to pump out water from the drydock prior to performing repairs on ships. These pumps constitute a significant percentage of the overall load demand of the drydock. The capacities of the pumps used in drydocks are typically in the region of a few MWs owing to the high volume of water which needs to be pumped out within a specific time frame [24]. Consequently, the maximum load demand of a drydock is affected by the operation of these pumps. A drydock operator incurs an exorbitant uncontracted capacity charge if the maximum load demand of the drydock exceeds the contracted capacity at any time [21]. Load

forecasting techniques are used for predicting the day and month ahead load demands in the shipyard drydock. This enables the drydock operator to optimally schedule the local generators and loads in a manner which minimizes the import of uncontracted capacity from the main utility grid. In this context, PSO and the deployment of ILs aid in lowering the maximum load demand of the drydock. This results in lower electricity costs for the drydock operator.

Contestable consumers (large power consumers such as drydocks) in Singapore are permitted to purchase electricity directly from the wholesale electricity market through SP Services Limited [25]. The wholesale electricity market prices are updated every 30 minutes. In this scenario, drydocks need to handle the uncertainties and risks associated with the fluctuating electricity prices. Energy charges and capacity charges are the two components of a contestable consumer's electricity bill. The product of the electricity consumed over a period and the electricity price determines the energy charge. The product of the contracted capacity and the contracted capacity price determines the capacity charge. The capacity charge is computed on a monthly basis. The uncontracted capacity charge is computed as the product of the uncontracted capacity and the uncontracted capacity charge.

With the growing adoption of enabling smart grid technology, the development of efficient load management strategies has been an active area of research in recent years. Reference [26] presented an excellent review and analysis of various demand side management strategies. A detailed survey of the various models and approaches used for demand response can be found in [27]. A probabilistic scheduling model for energy hubs was presented in [28]. The optimal scheduling model presented in [28] included a multi-energy demand side management strategy and examined the economic benefits gained by including flexible electrical and thermal loads in the system. Reference [29] proposed an optimal pump scheduling problem for a rural two-stage water pumping station. In [29], the operations of the pumps were optimized on the basis of time-of-use prices to reduce the total electricity cost of the system. An MILP formulation for a home energy management system was presented in [30]. The framework in [30] jointly optimized the scheduling of household tasks and energy while taking into consideration the thermal comfort requirements of the residents and the dynamic electrical constraints. An industrial load management model incorporated into an energy hub management system was proposed in [31] for scheduling processes in flour mills, water pumping stations

and other industrial settings. The test cases presented in [31] dealt with issues such as load control, voltage optimization and peak demand control. An integer programming approach for managing the load in a flour mill while accounting for all the relevant operational constraints was proposed in [32]. The MLD - hybrid MPC framework was employed in [33] for solving the optimal scheduling problem of a district heating network including boilers, TESSs and flexible thermal loads. The objective of the scheduling problem in [33] minimized the operations and maintenance cost of the district heating network. The increasing popularity of electric vehicles (EVs) has led to the proliferation of numerous charging stations. The optimal management of these charging stations has emerged as a key problem in modern electrical power systems [34]. In this context, a few key research areas which have emerged include the management of EV charging load while optimizing the charging station operating cost and the aggregation of EV loads for load frequency control applications [35], [36]. Thermostatically controlled appliances were scheduled using a load management strategy in [37]. Price and load forecasts were employed in [37] for scheduling the appliances while taking into consideration various objectives such as the minimization of cost and the maximization of user comfort. Another recent work developed a district EMS which aimed at minimizing the total cost while respecting the users' comfort preferences [38].

Energy Management Systems require load forecasts to solve the optimal scheduling problem of the energy system they are supervising [39]. Load forecasts can have prediction horizons ranging from a few minutes to several days and even months. STLFs typically have prediction horizons ranging from about 15 minutes to a few hours. MTLFs can be used to forecast peak load demands over time periods ranging from a few months to a year. The forecasting algorithm has a significant bearing on the accuracy of the load forecast. Accurate load forecasting methods can provide significant economic benefits to the system operator apart from contributing to improved system security [39]. Several researchers have proposed methodologies for obtaining STLFs over the years (see for instance [40], [41], [42], [43] and [44]). Reference [45] investigated the effects of demand response strategies on the load forecast. Numerous techniques including extrapolation, Kalman filtering, support vector regression, fuzzy logic, auto-regressive models and neural networks have been utilized for obtaining STLFs (see [40], [41] and [46]). As explained in the later chapters, ANNs have been used in this thesis for generating STLFs and MTLFs. ANNs deliver good performance due to their ability to learn complex non-linear

relationships [39]. The authors of [47] reviewed numerous ANN-based approaches used for generating STLFs. References [48] and [49] also presented ANN-based approaches for generating STLFs. In the context of load forecasts, random events and system disturbances contribute to uncertainties which adversely affect the quality of the generated forecast. Conversely, predictable events such as the ship arrival schedule in the context of the drydock lead to an improvement in the load forecast accuracy. In Singapore, there is very little variation in the weather during the year. As such, the influence of the weather conditions on the load forecast is minimal and is usually ignored [41].

The above discussions indicate that the design and development of EMSs for different industrial applications has been an active research area in recent years. However, the existing EMS designs and formulations are ill-suited for a drydock as they do not consider the unique features and requirements of the drydock. Furthermore, several EMS formulations such as those proposed in [28] and [33] arbitrarily perform load shifting without considering the unique requirements of the specific application for which they are designed.

1.3.1 Network Constraints

Apart from the aforementioned load management techniques and optimal scheduling routines, EMSs also need to account for the network constraints while dispatching the MG components. Solving an OPF problem within the EMS framework ensures that the schedule generated by the EMS does not violate any network constraints [50]. As such, designing an EMS is a non-trivial task due to the complexities involved in integrating and solving the optimal scheduling and the OPF problems. A common practice in many research works is to formulate the optimal scheduling problem in the EMS by ignoring the network constraints. Consequently, the network losses also get ignored. The optimal scheduling problem in the EMS thereby takes the form of a standard MILP or MIQP which can be solved using commercial solvers. However, the results of the optimal scheduling problem in this context may not be feasible since the network constraints could get violated. Furthermore, the network losses are also unaccounted.

Distributed computational approaches have been adopted by researchers to reduce the computational burden while solving the optimal scheduling problem in the

EMS. Reference [51] proposed a dynamic programming based constraint management approach for designing the EMS of a MG comprising a solar PV plant and a BESS. Reference [51] aimed at maximizing the import of energy from the main grid while minimizing the cash flows by optimally dispatching the BESS. The Lagrangian relaxation based optimality condition decomposition approach combined with the unlimited point algorithm was used in [52] to reduce the computational burden of the optimization problem solved in power systems. This approach was used in [52] to coordinate the operations of intermittent RESs and BESSs in multiple control areas. Reference [53] proposed a centralized EMS incorporating an MPC-based algorithm to coordinate the operations of a network of MGs. The MPC-based algorithm in [53] used point forecasts for the load demand, the RES generation and the energy market prices to optimize the schedules of the power exchanges between individual MGs in the multi-MG system. Apart from this, optimal schedules for the charging/discharging of the BESSs and the exchange of power with the main grid were also generated by the MPC-based algorithm in [53]. Many MG EMS formulations including [53] do not consider the presence of dispatchable sources such as DGs and microturbines in the MG which is a common feature of remote MGs. The presence of such dispatchable sources makes the optimal scheduling problem more complex to solve. Furthermore, there is scant regard for the network losses in such EMS formulations, thereby potentially rendering the optimal schedule infeasible. This is because the network losses may not be insignificant in many MGs.

Numerous other MPC based schemes have also been proposed for the optimal scheduling of energy systems. Some examples of such schemes can be found in [54], [55] and [56]. However, the vast majority of these schemes including those found in [54] and [55] do not consider any network constraints due to the complexities involved in solving the resulting optimization problem. As such, the optimal scheduling problem and the OPF problem are solved separately in such schemes. Some works have tried to integrate the optimal scheduling and the OPF problems in the EMS. The optimal scheduling and the OPF problems were integrated in [57] for a conventional power system which did not include any BESSs, RESs and ILs. A centralized, cooperative multi-area scheme for the optimal scheduling of a standalone MG was proposed in [58]. The schedules of the MG components such as the conventional generators, the RESs and the BESSs were obtained while considering the network constraints and the ramp rates in [58]. A jump and shift approach was

proposed in [59] to iteratively solve the optimal scheduling and the OPF problems to account for the network constraints in a MG including BESSs and RESs. Furthermore, the iterative procedure in [59] also included a provision to account for the MG network losses in the optimal scheduling problem. The author's previous work in [60] adapted and modified the jump and shift approach in [59] to perform the optimal scheduling of a multi-MG system while also permitting the trading of energy between the individual MGs constituting the multi-MG system.

1.4 Multi-Energy Systems

Industrial units are constantly evaluating measures to improve their operational efficiencies. There is a universal desire among industrial units to maximize production while using the least amount of resources. Concurrently, increasing awareness about environmental issues has resulted in greater emphasis on lowering the environmental impact of industrial activities. In this context, the concept of EIPs has gained popularity [61]. An EIP can be broadly described as an industrial park wherein businesses cooperate with each other and with the local community to reduce wastage and improve process efficiencies by sharing resources without sacrificing their legitimate business interests [62]. A key factor in the realization of an EIP is the efficient recycling of waste materials, energy and water being used in the industrial park. These elements need to be redirected in an optimal manner post recycling to benefit other users [61].

Numerous researchers have studied various aspects of EIPs over the years. In this context, an excellent survey of the quantitative tools used to analyze the exchange of water, heat, power and materials in existing industrial parks can be found in [61]. However, from [61], it is evident that the vast majority of studies thus far have focused exclusively on a single domain (i.e water, heat, materials or power). There is very limited literature available which analyzes the interactions between these domains. In the context of heat and energy, many studies have focused on analyzing the heat exchange networks (HENs) in industrial parks. A few examples of such studies can be found in [63], [64], [65] and [66]. A 'nearest neighbour' algorithm was proposed in [63] to generate multiple designs for an energy network on the basis of carbon emission reduction. MILP models were used in [64] to analyze the heat captured from steam and waste water for achieving economic and environmental

optimization of the network. R-curves were adapted by the authors of [65] to incorporate carbon emissions and economic considerations while retrofitting utility networks or while finalizing the initial designs for utility networks. Reference [66] proposed the use of Pareto fronts for optimizing HENs with restrictions on the exchange of heat between independent subsystems.

Many entities including large petrochemical plants are located in mega industrial parks such as Singapore's Jurong Island and the Yeosu Industrial Park in the Republic of Korea [67], [68]. According to Singapore's Energy Market Authority, 95% of Singapore's electricity is produced using natural gas. Most of this electricity is generated using the CCPP technology [13]. CCPPs exhibit higher energy efficiencies by producing electricity and recyclable waste heat from a single fuel [69]. The system operator can operate the CCPPs in several modes [70]. As such, CCPPs offer a lot of flexibility to the system operators. Many studies related to CCPPs study optimal designs which minimize the cost for the plant owner [71, 72]. Developing a model to analyze the energy flows across the entire industrial park is a potential enabler for realizing EIPs. In industrial parks where CCPPs generate the bulk of the electricity, there are multiple energy streams which are coupled. The energy streams include electricity, heat and possibly even cooling. Consequently, CCPPs may be used as bridges to link these energy streams. The optimal management of these multiple energy streams becomes vital in ensuring the efficient operation of the industrial park.

Traditionally, energy flows have been analyzed separately from both operational and planning viewpoints despite the significant interactions which exist between them [73]. Multi-energy systems offer technical, economic and environmental advantages when compared with independently analyzed energy systems [73]. The management of multi-energy systems is a non-trivial problem due to the existence of significant interactions between the electrical and thermal energy streams [74]. For example, the performances of the topping and bottoming cycles in a CCPP are closely linked. Consequently, the optimal management of multi-energy systems has attracted the attention of numerous researchers in recent years. Specifically, many researchers have studied the optimal operation of MG scale multi-energy systems. Such systems are typically based on micro CHP or CCHP plants. The participation of a portfolio of generators including wind power plants and CHP plants in the Nordic two-price balancing market was discussed in [75]. An optimal scheduling

model for operating CCHP plants to satisfy electrical and cooling loads in a MG scenario was proposed and solved in [74] and [76] respectively. The optimal coordinated scheduling of microturbines and other distributed generators was performed in [77] to satisfy electrical and cooling loads in a MG setup. An earlier work by the authors of [77] used an energy transfer matrix to model the multiple energy flows between the components of a MG [78]. A CCHP-based optimal scheduling model for the multi-energy MG was also presented in [78]. A multi-energy load management scheme for the optimal management of energy hubs incorporating CHP plants was formulated in [28]. The impact of uncertain energy market prices on the optimal management of a CHP-based multi-energy MG was handled using a robust optimization framework in [79]. An optimal dispatch strategy using an ANN-based approach was proposed for residential multi-energy systems in [80]. Reference [80] also proposed a mechanism to handle uncertainties in the load demand forecast. The optimal management of a grid-connected MG comprising multiple residential micro CHP plants was examined in [81]. The scheme proposed in [81] permitted smaller subgroups of generators within the MG to exchange electrical and thermal power. A recent work proposed a two-layer optimal dispatch scheme for CCHP-based MGs [82]. A rolling horizon framework was used to schedule the operation of the MG based on the latest load demand and renewable generation forecast information in the first layer of [82]. A short-term error prediction based correction model was embedded in the second layer to handle any dispatch adjustments and forecast errors while meeting the load demand in [82]. A two-stage robust optimization model was developed for optimally scheduling a CCHP-based MG in [83]. A price-based demand side management scheme along with temperature control was used in [83] to introduce flexibility in the electrical and thermal loads. Subsequently, [83] proposed a two-stage coordination method to operate the MG components under uncertainties. A multi-stage stochastic MILP framework was used to capture energy market price uncertainties while determining an optimal schedule for the participation of a CHP plant and a TESS in multiple, sequential electricity markets [84].

The optimal management of larger multi-energy systems such as those found in EIPs or other industrial entities has not been fully explored by researchers. Some formulations of such problems can be found in [85–88] among others. Kim et. al presented an MINLP formulation for the optimal scheduling of the multi-energy system in a university campus [85]. A detailed component-wise scheduling model

was developed in [85] for each element of the multi-energy system including detailed power trajectory models for the start-up and shutdown procedures of the GTs, STs and boilers. An approximated mixed integer formulation of the optimal multi-energy scheduling problem for a system comprising both CCPPs and conventional thermal units was presented in [86]. The author's recent work in [87] consolidated elements from previous works [56, 89] apart from [85, 86]. In [87], an MIQP formulation was developed for the multi-energy scheduling problem. The effectiveness of an industrial load management technique (PSO) in reducing the overall electricity cost of the system was demonstrated in [87]. An optimal, day-ahead scheduling problem for a system comprising CHPs, boilers, BESSs and TESSs was formulated and solved in [88]. The optimal scheduling problem formulated in [88] also considered security constraints.

The start-up/shutdown power trajectories of large generators are largely ignored in conventional optimal power system scheduling problem formulations. As highlighted by Morales-Espana in [90, 91], these formulations fail to allocate a large quantum of energy which is present in real time. Consequently, the load balance and reserve requirements in the system are distorted. Economic losses and inefficiencies may result from ignoring the start-up/shutdown power trajectories [92]. Despite this, the start-up/shutdown power trajectories are largely ignored in conventional power system scheduling problem formulations due to the high computational capacity required to solve the resulting optimization problem. EIPs are usually smaller than bulk power systems in terms of the number of generators. The start-up/shutdown power trajectories are also intrinsic to boilers which are important constituents of many multi-energy systems such as EIPs. Computationally inexpensive approaches have also been proposed recently to handle the start-up/shutdown trajectories in optimal power system scheduling problems [92], [93].

References [86]-[88] do not include detailed models for the start-up/shutdown trajectories of the CCPP components (GTs and STs) and boilers. The start-up/shutdown trajectories were included in the models of the CCPPs and boilers in [85] and [87]. However, [85] and [87] did not study the interactions between the CCPPs/boilers and other multi-energy system components such as the BESS, the TESS, the RESs and the flexible electrical and thermal loads. Moreover, [28] recently proposed a multi-energy load management scheme within the overarching framework

of an optimal multi-energy scheduling problem. However, the multi-energy load management scheme proposed in [28] was rather generic in nature without going into any modelling details of the specific industrial load management application.

1.5 Contributions

The salient contributions of this thesis are summarized below:

1. An SEMS is proposed for minimizing the electricity cost of a drydock. The proposed SEMS comprises three modules - LF, CCO and an optimal scheduling module which incorporates a PSO model. The drydock considered in this thesis resembles a grid-connected MG with heterogeneous generation sources and flexible loads. The coordination between the drydock MG components to meet the load demand is a key highlight of this contribution.
2. The capabilities of the aforementioned optimal scheduling module are enhanced by incorporating an OPF problem through a two-stage EMS architecture. The proposed EMS solves the optimal scheduling and OPF problems iteratively, thereby generating a feasible MG schedule which conforms to all the network constraints. Furthermore, the EMS also enables the network losses to be accounted for in the optimal schedule.
3. An optimal scheduling framework is proposed for an exemplar multi-energy system comprising heterogeneous generators and loads. Importantly, the multi-energy system scheduling model includes a detailed consideration of the start-up and shutdown trajectories which are intrinsic to the CCPPs (GTs and STs) and the boilers in the system. Another key highlight of this contribution is a proposed multi-energy load management scheme which utilizes the flexibility offered by system components such as the ILs, the pump loads and the flexible thermal loads to reduce the cost of the system. Finally, the coordination between the multi-energy system components to meet the electrical and the thermal load demands in the system is also studied.

1.6 Thesis Organization

The remainder of this thesis is organized as described below.

The scheduling models of the various components constituting the energy systems studied in this thesis are developed in Chapter 2. This is aligned with the component-based modelling approach adopted in this thesis. The scheduling models of the GTs, the STs and the boilers include detailed considerations of the start-up ramp constraints, the shutdown ramp constraints and the ramp constraints during the dispatch phase. The hybrid system based MLD modelling approach is briefly introduced in Chapter 2. In this thesis, the MLD approach has been used to model the GTs, the STs, the boilers, the BESSs, the TESSs, the DGs and the exchange of electrical power with the main utility grid.

Chapter 3 uses the MLD framework introduced in Chapter 2 to develop the scheduling model of an exemplar thermal unit. Detailed explanations are provided about the logical statements which are used to develop the thermal unit scheduling model. The model is developed by considering normal, hot, warm and cold start-up methods for the thermal unit. The utility of the model is demonstrated by solving an optimal self-scheduling problem and a simple UC problem involving five thermal units.

Chapter 4 proposes an SEMS containing three key modules: LF, CCO and an optimal scheduling module incorporating a PSO model. The three modules are designed on the basis of real data from a shipyard drydock in Singapore. The optimal scheduling module models the drydock as a grid-connected MG comprising DGs, BESSs, RESs, pump loads and ILs. The component models developed in Chapter 2 are used to develop optimal scheduling models for the MGs considered in Chapters 4 and 5. The PSO optimally schedules the drydock pumps. The optimal scheduling module coordinates the operations of the drydock pumps with those of the other drydock MG components including the ILs, the DGs and the RESs apart from leveraging on the fluctuating prices of electricity in the energy market. Case studies are used to demonstrate the improvement obtained in the STLF accuracy by providing the ship arrival schedule as an input to the ANN used to generate the STLFs in the LF module. Five scenarios are simulated on the basis of the proposed load management strategy to demonstrate the potential of the PSO and the ILs in reducing the operating cost of the drydock MG.

Chapter 5 extends the optimal scheduling framework presented in Chapter 4. A two-stage EMS architecture along the lines of [60] and [59] is proposed in Chapter 5 to minimize the cost of operating the MG without violating any network constraints. The load management scheme proposed in the optimal scheduling module of the SEMS in Chapter 4 is also incorporated within the optimal scheduling problem solved by the EMS proposed in Chapter 5. Case studies based on the load management scheme are performed to determine the optimal day-ahead schedules of two exemplar MGs which are based on a modified IEEE 30-bus system and a modified IEEE 57-bus system respectively. The case studies demonstrate the utility of the proposed EMS architecture.

In Chapter 6, an exemplar multi-energy system model is built using the component scheduling models developed in Chapter 2 of this thesis. The multi-energy system comprises CCPPs (each comprising 1 GT and 1 ST), boilers, BESS, RES, TESSs, flexible pump loads (from Chapter 4), ILs and flexible thermal loads. An optimal day-ahead scheduling problem is formulated and solved for the multi-energy system. A multi-energy load management scheme is proposed and included in the optimal scheduling problem formulation. The multi-energy load management model utilizes the flexibility offered by the pump loads, ILs and flexible thermal loads to reduce the cost of operating the system. Four case studies are simulated to demonstrate the potential of the proposed load management scheme in reducing the cost of the system. Finally, the coordination between the various components of the multi-energy system to service the electrical and thermal loads in the system is studied.

Chapter 7 concludes the thesis and provides some recommendations for future research.

Chapter 2

System Modelling

2.1 Introduction

The optimal scheduling of different energy systems is performed in the later chapters of this thesis. Each energy system modelled in this thesis comprises heterogeneous generation sources and loads.

The optimal scheduling of energy systems involves the solution of an optimization problem comprising binary and continuous decision variables. Typically, in a simple energy system scheduling problem, the binary variables represent the ON/OFF decisions for the various components in the energy system while the continuous variables represent the dispatch values for all the dispatchable components. Apart from this, the continuous decision variables can also represent the fuel consumed by the conventional generators in the system and the number of hours spent by the corresponding energy system component in various operational modes. As such, owing to the presence of continuous and binary decision variables in the optimization model, hybrid system modelling approaches present attractive options for modelling and formulating the optimal scheduling problems of energy systems. In this context, among the various hybrid system modelling approaches, the MLD framework has been used by several researchers to develop optimal scheduling problem formulations for energy systems [94]. A few typical examples of such formulations are reviewed in the following paragraphs.

The MLD framework was used to formulate the optimal scheduling models for the MG components in [54], [95] and [55]. The optimal MG scheduling problems in these works were subsequently solved in the hybrid MPC framework. Furthermore, a scheduling model for BESSs in the MLD framework was developed in [54]. An older work utilized the MLD framework to formulate an optimal self-scheduling problem for a CCGT in the hybrid MPC framework [17]. Interestingly, [17] modelled four different start-up methods (hot, warm, normal and cold) for the GT and the ST constituting a CCGT using the MLD framework. The hybrid MPC framework was also used to optimize the operational schedule of a two-generator power system comprising a solar PV plant and a fuel cell in [96]. In [96], the system description was derived using the MLD framework. A recent work in [33] used the MLD framework to describe the operations of a district heating network. Apart from these examples, the author's previous works also employed the MLD-hybrid MPC framework for describing and solving the optimal scheduling problems of various energy systems [87], [89], [97].

Reference [97] presented a short term self-scheduling problem for an exemplar CCGT. In [97], the scheduling model of the CCGT was developed using the MLD framework. The scheduling model of the CCGT in [97] considered four start-up methods, namely normal, hot, warm and cold. Furthermore, a branch and bound scheme was also proposed in [97] to solve the MINLP optimal self-scheduling problem of the CCGT in the MPC framework. The nonlinearity resulted from the consideration of the valve point effect in the CCGT fuel cost function. Subsequently, a generalized scheduling model was developed for thermal units in the MLD framework [89]. The scheduling model formulated in [89] included the trajectories of four different start-up methods and a shutdown trajectory. The utility of the scheduling model in [89] was demonstrated through a day-ahead self-scheduling problem for a single thermal unit which was solved in the hybrid MPC framework. Subsequently, an optimal scheduling problem was formulated and solved for a system comprising five thermal units. The author's recent work in [87] solved the optimal day-ahead scheduling problem for an exemplar multi-energy system comprising two CCPPs, three conventional STs, two boilers and flexible pump loads. Moreover, [87] also demonstrated the benefits accrued by including flexible loads in the multi-energy system through illustrative case studies.

A summary of the various approaches adopted by ISOs such as ERCOT, PJM and

NYISO to model CCPPs is provided in [98]. These approaches include the aggregate modelling approach, the pseudo unit modelling approach, the configuration-based modelling approach and the physical unit modelling (component-based modelling) approach. The CCPP is modelled as a set of mutually exclusive combinations of GTs and STs in the configuration-based modelling approach [99], [93]. The switching between operating modes is performed according to predefined transition paths. Each component of the CCPP is modelled individually in the component-based approach. The advantages of the component-based approach include the consideration of the minimum on/off time and the ramp limits for each component, cost benefits and the inclusion of models for auxiliary equipment such as boilers and duct burners [86].

This chapter extends the aforementioned component-based modelling approach for developing detailed scheduling models of the different generators and loads which constitute the energy systems modelled in this thesis. The component-based approach is used to individually model the GTs and the STs which constitute a typical CCPP. The boiler associated with each CCPP is also modelled using the component-based approach. The models of the energy systems considered in the subsequent chapters of this thesis are generated on the basis of the component wise scheduling models developed in this chapter. Furthermore, the MLD approach has been adopted in this thesis for generating the scheduling models of the CCPPs (including GTs and STs), the boilers, the BESSs, the TESSs, the DGs and the exchange of electrical power with the main utility grid.

The remainder of this chapter is organized as follows. Section 2.2 develops detailed, first principle scheduling models of the CCPPs and the boilers which are components of the energy systems modelled in the later chapters of this thesis. Subsequently, the scheduling models of the BESSs and the TESSs are developed in Sections 2.3 and 2.4 respectively. The mathematical models of the wind power plants and solar PV power plants are provided in Section 2.5. The scheduling models of the flexible pump loads, the DGs, the ILs and the flexible thermal loads are formulated in Sections 2.6, 2.7, 2.8 and 2.9 respectively. Section 2.10 discusses some salient features of the MLD modelling approach used in this thesis. Finally, some concluding remarks are provided in Section 2.11.

2.2 Combined Cycle Power Plant (CCPP) Components

In this thesis, 1 GT, 1 ST and 1 HRSG constitute each CCPP. Furthermore, each CCPP has 1 boiler and 1 TESS associated with it. Owing to the presence of two thermodynamic cycles (Brayton cycle for the GT and Rankine cycle for the ST), the energy efficiency of CCPPs is usually 20-30% higher than single cycle thermal power plants. Two CCPPs are included as components of the multi-energy system modelled in Chapter 6 of this thesis.

In a CCPP, the HRSG functions as a heat exchanger between the two thermodynamic cycles and enables the recovery of the waste heat emitted by the GT. The output from the HRSG is high pressure steam. The boiler associated with the corresponding CCPP generates steam to supplement the HRSG output during periods of high thermal load demand.

Fig. 2.1 illustrates all the operating modes of the GTs, STs and boilers modelled in this thesis. In the context of electrical power systems, the ramping constraints of conventional generators are usually classified into three categories: 1) Operating ramp constraint, 2) Start-up ramp constraint and 3) Shutdown ramp constraint [1]. In the context of multi-energy systems, these ramping constraints are applicable to the GTs and STs which constitute the CCPPs apart from the boilers. The start-up ramp constraint refers to a predefined trajectory followed by the corresponding unit during the start-up process wherein the electrical (thermal) power output from the unit gradually increases to the technical minimum level in steps. In this thesis, hot, warm and cold start-up methods are modelled for each GT, ST and boiler. The model of each GT, ST and boiler is constructed such that the correct start-up method is identified depending on the prior downtime of the unit [56]. The models of the GTs and the STs specify unique electrical power trajectories for each start-up method. The shutdown ramp constraint refers to a predefined trajectory followed by the corresponding unit during the unit shutdown process wherein the electrical power output from the unit initially reduces to the technical minimum level before reducing to 0MW. Furthermore, in this thesis, it is assumed that no thermal power is produced by the boilers during the start-up and shutdown processes.

As illustrated in Fig. 2.1, each unit typically operates in four distinct phases - synchronization phase, soak phase, dispatch phase and desynchronization phase ([85], [20], [2]). The synchronization and soak phases constitute the start-up trajectory while the desynchronization phase constitutes the shutdown trajectory.

A generalized illustration of the operation of a thermal unit is presented in Fig. 2.1. The exemplar start-up trajectory shown in Fig. 2.1 illustrates that the time required to enter the dispatch phase increases as the downtime prior to commitment increases. This is true for each GT, ST and boiler and is essential to avoid any mechanical stresses. The STs commence the soak phase after grid synchronization (synchronization phase). The GTs commence the soak phase on being committed. During the soak phase, the electrical power output from each GT and ST increases in steps to reach the technical minimum power level. In this thesis, it is assumed that a constant electrical power, $P_{\text{soak},k}^f$ is produced by a unit f undergoing the soak phase during hour k . The soak phase is followed by the dispatch phase wherein the unit operates between its technical minimum and maximum electrical power outputs. Similarly, during the shutdown process, a unit first undergoes the desynchronization phase. Subsequently, the electrical power output of the unit drops to zero.

All the boilers also pass through the soak phase while starting up. Once a boiler is committed, the soak phase duration determines the time needed by the boiler to reach the dispatch phase. The scheduling model of each boiler needs to account for the soak phase duration. Furthermore, the boilers do not undergo synchronization and desynchronization with the utility grid. The following paragraphs detail the mathematical scheduling models of the GTs, the STs and the boilers considered in this thesis.

2.2.1 Synchronization and Soak Phases

The identification of the synchronization phase of start-up method n is performed as shown below:

$$w_{\text{synch},k}^{n,f} = \sum_{\tau=k-t_{\text{synch}}^{n,f}+1}^k w_{\text{start-up},\tau}^{n,f}, \quad \forall k \in \mathcal{K}, \forall f \in \{ST\}, \forall n \in \mathcal{N} \quad (2.1)$$

FIGURE 2.1: Typical start-up and shutdown power trajectories of a thermal unit

The identification of the soak phase of start-up method n is performed as shown below:

$$w_{\text{soak},k}^{n,f} = \sum_{\tau=k-t_{\text{synch}}^{n,f}-t_{\text{soak}}^{n,f}+1}^{k-t_{\text{synch}}^{n,f}} w_{\text{start-up},\tau}^{n,f}, \quad \forall k \in \mathcal{K}, \forall f \in \{GT, ST, BR\}, \forall n \in \mathcal{N} \quad (2.2)$$

The identification of the desynchronization phase of unit f is performed as shown below:

$$w_{\text{desyn},k}^f = \sum_{\tau=k+1}^{k+t_{\text{desyn}}^f} w_{\text{off},\tau}^f, \quad \forall k \in \mathcal{K}, \forall f \in \{GT, ST\} \quad (2.3)$$

2.2.2 Ramping Constraints in Dispatch Phase

The electrical power output from ST f is limited by the ramping constraint in (2.4). The GTs are fast ramping units and are not subjected to ramping constraints.

$$-0.5P_{e,\max}^f \leq P_{e,k}^f x_{\text{disp},k}^f - P_{e,k-1}^f x_{\text{disp},k-1}^f \leq 0.5P_{e,\max}^f, \quad \forall k \in \mathcal{K}, \forall f \in ST \quad (2.4)$$

2.2.3 Thermal Power Generation Constraints

The performances of the topping and bottoming cycles in a CCPP are closely inter-linked. As mentioned earlier in this chapter, the waste heat recovered by the HRSG

is supplemented by the boiler associated with the corresponding CCPP. The total heat produced by each CCPP-boiler pair can be utilized either to produce electricity using the corresponding ST or to service the thermal load demand in the system via a heat distribution network. Any excess heat which is generated can either be stored in the associated TESS for future use or emitted to the environment.

$$P_{h,k}^f = a_0^f P_{e,k}^f x_{\text{disp},k}^f + a_1^f, \quad \forall k \in K, \forall f \in GT \quad (2.5)$$

$$P_{h,k}^f = b_0^f w_{\text{br},k}^f, \quad \forall k \in K, \quad \forall f \in BR \quad (2.6)$$

$$h_k^f = b_1^f P_{e,k}^f + b_2^f, \quad \forall k \in K, \quad \forall f \in ST \quad (2.7)$$

$$P_{h,k}^{\text{GT1}} + P_{h,k}^{\text{Boiler 1}} \geq h_k^{\text{ST1}} \quad (2.8)$$

$$P_{h,k}^{\text{GT2}} + P_{h,k}^{\text{Boiler 2}} \geq h_k^{\text{ST2}} \quad (2.9)$$

The following parameter values are applicable for the 2 CCPPs considered in Chapter 6 of this thesis: $a_0^{\text{GT1}} = 1.35$, $a_1^{\text{GT1}} = 97.09$; $a_0^{\text{GT2}} = 1.14$, $a_1^{\text{GT2}} = 96.32$; $b_0^{\text{BR1}} = 0.0004$; $b_0^{\text{BR2}} = 0.0003$; $b_1^{\text{ST1}} = 1.74$, $b_2^{\text{ST1}} = 72.05$; $b_1^{\text{ST2}} = 0.82$, $b_2^{\text{ST2}} = 85.58$.

2.3 Battery Energy Storage System

A practical BESS is modelled in this thesis. The BESS model includes constraints on the intertemporal evolution of the SOC apart from operational bounds on the SOC, charging power and discharging power. Furthermore, a battery degradation cost function which reflects the BESS capital cost based on its charging and discharging events is formulated. The complete BESS model used in this thesis is shown below [100], [101].

$$SOC_{k+1} = SOC_k + (\eta_c P_{\text{bc},k} - P_{\text{bd},k}/\eta_d)/P_{1C}, \quad \forall k \in K \quad (2.10)$$

$$SOC_{\min} \leq SOC_{k+1} \leq SOC_{\max}, \quad \forall k \in K \quad (2.11)$$

$$0 \leq P_{\text{bc},k} \leq P_{\text{bc},\max}, \quad \forall k \in K \quad (2.12)$$

$$0 \leq P_{\text{bd},k} \leq P_{\text{bd},\max}, \quad \forall k \in K \quad (2.13)$$

The BESS degradation cost function is shown below:

$$C_{\text{BESS}} = \sum_{k \in \mathcal{K}} \frac{I}{2B_{\text{cap}}N} \left(\frac{P_{\text{bc},k}}{T_{\text{bc}}} + \frac{P_{\text{bd},k}}{T_{\text{bd}}} \right) \quad (2.14)$$

The BESS SOC evolves in accordance with (2.10). Equations (2.11) - (2.13) represent the constraints on the BESS SOC, charging power and discharging power respectively.

2.4 Thermal Energy Storage System

TESSs such as accumulator tanks have high levels of insulation. The operation of a TESS is analogous to the operation of a BESS which stores electricity. The following discrete time, state space model is used to describe each TESS in this thesis:

$$H_{k+1}^p = H_k^p + Q_{\text{in},k}^p - Q_{\text{out},k}^p - \gamma_k^p, \forall k \in \mathcal{K}, \forall p \in \mathcal{P} \quad (2.15)$$

The following constraints need to be considered while operating TESS p :

$$H_{\min}^p \leq H_k^p \leq H_{\max}^p, \forall k \in \mathcal{K}, \forall p \in \mathcal{P} \quad (2.16)$$

$$0 \leq \gamma_k^p \leq \gamma_{\max}^p, \forall k \in \mathcal{K}, \forall p \in \mathcal{P} \quad (2.17)$$

$$Q_{\text{in},k}^1 \leq P_{\text{h},k}^{\text{GT1}} + P_{\text{h},k}^{\text{Boiler 1}} - h_k^{\text{ST1}}, \forall k \in \mathcal{K} \quad (2.18)$$

$$Q_{\text{in},k}^2 \leq P_{\text{h},k}^{\text{GT2}} + P_{\text{h},k}^{\text{Boiler 2}} - h_k^{\text{ST2}}, \forall k \in \mathcal{K} \quad (2.19)$$

Equation (2.15) describes the evolution of the SOC of TESS p while (2.16) describes the bounds on the SOC of TESS p during interval k . Equation (2.17) describes the bounds on the psychological discharge of TESS p during interval k . The upper bounds on the thermal power inputs to TESS 1 and TESS 2 are described by (2.18) and (2.19) respectively. The thermal power produced by GT1 and Boiler 1 can be either used by ST1 to produce electricity, stored in TESS 1 or emitted to the environment. Similarly, the thermal power produced by GT2 and Boiler 2 can be either used by ST2 to produce electricity, stored in TESS 2 or emitted to the environment. Two identical TESSs (TESS 1 and TESS 2) are modelled and used in this thesis. Both the TESSs have the following parameter values: $H_{\min}^p = 90\text{MW}$; $H_{\max}^p = 200\text{MW}$ and $\gamma_{\max}^p = 20\text{MW}$.

2.5 Renewable Energy Sources

Solar PV and/or wind power plants are considered to be components of all the energy systems modelled in this thesis. It is assumed that the operating cost of the RESs is 0 [60]. The modelling of the solar PV and wind power plants is briefly outlined in the following paragraphs.

The electrical power output of a wind power plant is directly proportional to the cube of the wind velocity and is calculated as shown below:

$$P_{\text{wind}} = 0.5C_p k a_{\text{den}} A (v_{\text{wind}})^3 \quad (2.20)$$

The five-parameter array performance model is a popular PV performance model among researchers. The current-voltage (I-V) curve and the maximum power point (MPP) are extracted from the PV performance model. These parameters can aid in improving the overall performance of the PV system. The steady-state performance of a PV module can be described as shown below [102]:

$$I_L - I_S \{ \exp[\alpha(v_{\text{pv}} + R_S i_{\text{pv}})] - 1 \} - \frac{v_{\text{pv}} + R_S i_{\text{pv}}}{R_{\text{Sh}}} - i_{\text{pv}} = 0 \quad (2.21)$$

$$P_{\text{pv}} = v_{\text{pv}} i_{\text{pv}} \quad (2.22)$$

where $\alpha = q/n_s k_{\text{bc}} T$ represents the ideality factor. Additionally, $k_{\text{bc}} = 1.38 \times 10^{-23} \text{ J/K}$ represents the Boltzmann's constant; $q = 1.6022 \times 10^{-19}$ represents the electronic charge; $K = 298 \text{ K}$ represents the temperature and n_s represents the number of cells arranged in series. Further details about the solar PV and the wind power plant models can be obtained from [102] and the references therein. All the solar PV and wind power plant generation forecasts used in this thesis were obtained from [103].

2.6 Flexible Pump Loads

Industrial loads can be scheduled and operated in a manner which reduces the overall electricity cost of the system. In this thesis, large pumps used in shipyards

are modelled as exemplar industrial (electrical) loads. The pump loads are schedulable, thereby providing the system operator with a lot of flexibility in terms of scheduling the generators and the electric power exchanges with the main utility grid. As demonstrated in the later chapters, the flexible pump loads also assist the system operator in avoiding uncontracted capacity costs. The flexible pump loads are subject to the following operational constraints:

$$\sum_{\substack{k \in \mathcal{K} \\ m \in \mathcal{M}}} Q^m u_k^m \geq V_d \quad (2.23)$$

The constraint in (2.23) requires a certain volume of liquid to be pumped out within the optimization period. The power consumed by a pump m during interval k is calculated as follows:

$$P_{m,k} = C_m u_k^m, \forall m \in \mathcal{M}, k \in \mathcal{K} \quad (2.24)$$

It is assumed that the pump speeds cannot be varied. This means that all the pumps operate at rated power if they are scheduled. Pumps are affected by the water hammer effect when they are turned on. Pumps with large capacities are not permitted to start up and shut down frequently during the optimization period due to their large inertias. Consequently, the total number of start-up events permitted during the optimization period for pump m is restricted as follows:

$$\sum_{k \in \mathcal{K}} w_{\text{SU},k}^m \leq w_{\text{SU},\text{max}}^m, \forall m \in \mathcal{M} \quad (2.25)$$

$$\text{and, } w_{\text{SU},k}^m = u_k^m (u_k^m - u_{k-1}^m), \forall k \in \mathcal{K}, \forall m \in \mathcal{M} \quad (2.26)$$

Equation (2.26) is linearized as follows:

$$w_{\text{SU},k}^m \leq (u_k^m + 1 - u_{k-1}^m)/2 \quad (2.27)$$

$$w_{\text{SU},k}^m \geq (u_k^m - u_{k-1}^m)/2 \quad (2.28)$$

2.7 Diesel Generators

DGs are controllable in nature. A quadratic function of the real power output is used to determine the fuel cost of each DG f . Apart from the fuel cost, each

TABLE 2.1: Technical parameters of the DGs modelled in this thesis

DG #	c_0^f (\$)	c_1^f (\$/MW)	c_2^f (\$/MW ²)	Min $P_{DG,k}^f$ (MW)	Max $P_{DG,k}^f$ (MW)	C_{SU}^f (\$)	Min. UT/ DT (h)
1	80	30	1	0.1	3	50	3
2	200	60	2	0.1	3	30	3
3	1000	50	3	0.1	3	5	3

DG also incurs a start-up cost. The operation of each DG is subject to minimum uptime and downtime constraints. The total cost incurred by the system operator for operating all the DGs in the system is evaluated as shown in (2.29):

$$C_{DG} = \sum_{\substack{k \in \mathcal{K} \\ f \in \{DG1, DG2, DG3\}}} \left[b_{SU,k}^f C_{SU}^f + b_{DG,k}^f \left(c_0^f + c_1^f P_{DG,k}^f + c_2^f (P_{DG,k}^f)^2 \right) \right] \quad (2.29)$$

The first term of (2.29) represents the start-up cost of DG f while the second term represents the fuel cost. The technical parameters of the three DGs modelled in this thesis are provided in Table 2.1.

The minimum uptime (UT) and the minimum downtime (DT) constraints impact the operation of each DG f as expressed in (2.30) - (2.31):

$$\sum_{\tau=k}^{k+UT-1} b_{DG,\tau}^f \geq UT[b_{SU,k}^f - b_{SU,k-1}^f], \quad \forall k \in \mathcal{K}, \forall f \in \{DG1, DG2, DG3\} \quad (2.30)$$

$$\sum_{\tau=k}^{k+DT-1} [1 - b_{DG,\tau}^f] \geq DT[b_{SD,k-1}^f - b_{SD,k}^f], \quad \forall k \in \mathcal{K}, \forall f \in \{DG1, DG2, DG3\} \quad (2.31)$$

2.8 Interruptible Electrical Loads

Lower priority electrical loads can be curtailed if they are monetarily compensated. Such loads are called ILs. The operation of each IL h during interval k is

constrained as follows:

$$0 \leq P_{\text{EIL},k}^h \leq P_{\text{EIL},\text{hour-max}}^h, \quad \forall k \in \mathcal{K}, \quad \forall h \in \{\text{IL1}, \text{IL2}, \text{IL3}\} \quad (2.32)$$

$$\sum_{k \in \mathcal{K}} P_{\text{EIL},k}^h \leq P_{\text{EIL},\text{day-max}}^h, \quad \forall h \in \{\text{IL1}, \text{IL2}, \text{IL3}\} \quad (2.33)$$

Equations (2.32) and (2.33) represent the constraints on the utilization of IL h during each interval and day respectively. The total cost incurred by the system operator for compensating the curtailed ILs is calculated as follows:

$$C_{\text{EIL}} = \sum_{\substack{k \in \mathcal{K} \\ h \in \{\text{IL1}, \text{IL2}, \text{IL3}\}}} 1.5 C_{\text{pe},k} P_{\text{EIL},k}^h \quad (2.34)$$

2.9 Flexible Thermal Load

During each interval, a certain percentage of the thermal load demand is considered to be reschedulable. The utilization of the flexible thermal load in the system is constrained as shown below:

$$P_{\text{Dh},k} = (1 - DR_k) P_{\text{Dh},k}^0 + P_{\text{Shift},k}, \quad \forall k \in \mathcal{K} \quad (2.35)$$

$$0 \leq DR_k \leq 0.1 \quad (2.36)$$

$$0 \leq P_{\text{Shift},k} \quad (2.37)$$

$$\sum_{k \in \mathcal{K}} P_{\text{Dh},k} = \sum_{k \in \mathcal{K}} P_{\text{Dh},k}^0 \quad (2.38)$$

Equations (2.36) and (2.37) bound the percentage of thermal load which is rescheduled during interval k and the quantum of the thermal load transferred to interval k from the other intervals of the optimization period.

2.10 Mixed Logical Dynamical Approach

In [104], Heemels et. al described five classes of hybrid systems and established the equivalences which exist among these classes. The MLD framework is one of the five classes of hybrid systems mentioned in [104]. The MLD framework has been used in this thesis for modelling various energy system components such as CCPs,

boilers, BESSs, TESSs and DGs. Furthermore, the MLD framework has also been used in this thesis to model the electricity exchanged with the main utility grid. The seminal work on the MLD framework by Bemporad et. al describes an MLD system using the following equations [94]:

$$x(k+1) = Ax(k) + B_u u(k) + B_{aux} w(k) + B_{aff} \quad (2.39)$$

$$E_x x(k) + E_u u(k) + E_{aux} w(k) \leq E_{aff} \quad (2.40)$$

where $x = [x_c \ x_b]^T$, $x_c \in \mathbb{R}^{n_c}$, $x_b \in \{0, 1\}^{n_b}$ represents the continuous and binary states of the system; $u = [u_c \ u_b]^T$, $u_c \in \mathbb{R}^{n_u}$, $u_b \in \{0, 1\}^{n_u}$ represents the continuous and binary inputs to the system and $w = [w_c \ w_b]^T$, $w_c \in \mathbb{R}^{n_w}$, $w_b \in \{0, 1\}^{n_w}$ represents the continuous and binary auxiliary variables. The auxiliary variables are used in the MLD framework to represent the product between linear functions and logic variables. The conversion of propositional logic to linear inequalities of the form (2.40) is achieved through the use of auxiliary variables [94]. The interactions between the states of the system, the inputs to the system and the auxiliary variables are described using the constant matrices A , B_u , B_{aux} , B_{aff} , E_x , E_u , E_{aux} and E_{aff} . The auxiliary variables $w(k)$ are solved using (2.40). Subsequently, $w(k)$ is used along with the current system state $x(k)$ and the system input $u(k)$ to determine the evolution of the system state according to (2.39). Interested readers may refer to [94] for a detailed treatment of the MLD framework.

This thesis uses HYSDEL [105] to formulate all the system component models in the MLD framework. The HYSDEL compiler is used to generate all the constant matrices of the MLD model described in (2.39)-(2.40) from a high-level description of the system behaviour. In this thesis, each system component is modelled using an individual HYSDEL slave file. Subsequently, the MODULE section in HYSDEL 3.0 is used to combine all the individual slave files in a master file, thereby generating the system model. The master file is also used to detail the interactions between the various system components. A detailed description of the modelling of CCPs and thermal units in the MLD framework using HYSDEL can be found in the author's previous works [56, 89]. MLD models have proven to be successful in recasting hybrid dynamic optimization problems into MILP or MIQP problems which can be solved using commercially available solvers such as CPLEX and GUROBI. Furthermore, detailed descriptions of the modelling of BESSs and the

exchange of electricity with the main utility grid in the MLD framework can be found in [54].

2.11 Summary

This chapter developed first principle scheduling models for the components which constitute the various energy systems modelled in this thesis. The scheduling models of the components developed in this chapter are embedded in the respective optimal scheduling problems for the various energy systems modelled in this thesis. Detailed scheduling models including the hot, warm and cold start-up methods were developed for the boilers and CCPP components such as the GTs and the STs. Furthermore, scheduling models were developed for other system components such as BESSs, TESSs, RESs, flexible pump loads, DGs, ILs and flexible thermal loads. A brief introduction to the MLD framework was provided. The MLD framework has been used to model the CCPPs, boilers, BESSs, DGs and TESSs in this thesis. Apart from these components, the MLD framework has also been used in this thesis to model the exchange of electricity with the main utility grid.

Chapter 3

Hybrid Model Predictive Control Framework for the Thermal UC Problem including Start-up and Shutdown Power Trajectories

3.1 Introduction

This chapter details the development of the scheduling model for a thermal unit using logical statements in the MLD framework. Towards this endeavour, the thermal units considered in this chapter exhibit behaviour patterns along the lines of Fig. 2.1. As such, this chapter develops a generalized thermal unit model including detailed start-up and shutdown trajectories. Logical statements compatible with the MLD framework described in Chapter 2 are used to describe the start-up and shutdown trajectories of the thermal units considered in this chapter. Consequently, the utility of the auxiliary variables in the MLD framework is also demonstrated. Subsequently, a hybrid MPC framework is adapted to solve the self-scheduling problem of an exemplar thermal unit based on point forecasts for the load demand and the energy market prices. As explained in Chapter 2, each start-up method has a predefined power trajectory based on the prior unit downtime. Moreover, different costs are associated with different start-up methods. Finally, the optimal

scheduling problem of a five generator system is also solved to test the scalability of the modelling approach for small to medium size power networks.

The rest of this chapter is organized as follows: Section 3.2 describes the application of the MLD framework in building a logical scheduling model for a thermal unit including detailed descriptions of the start-up and shutdown trajectories presented in Chapter 2. The objective function for the self-scheduling problem of a thermal unit is formulated in Section 3.3. The simulation results of this self-scheduling problem are shown in Section 3.4. The self-scheduling problem described in Section 3.3 is extended to consider a system of five thermal units in Section 3.5. Finally, some important conclusions are drawn in Section 3.6.

3.2 Hybrid Model of a Thermal Unit Including Start-up Trajectories

This section details the modelling of an exemplar thermal unit including the logical statements used to model the start-up and shutdown power trajectories.

3.2.1 Hybrid Features of a Thermal Unit

Some features of a thermal unit which make hybrid system based modelling approaches promising options are detailed below:

- The thermal unit undergoes different start-up methods depending on its prior downtime. Four start-up methods have been considered in this chapter. They are normal, hot, warm and cold.
- The electric power output and the fuel consumed are continuous valued quantities which evolve over time.
- The decision whether to turn on or turn off the unit is a binary decision.

As mentioned in Chapter 2, the MLD approach has been adopted for generating the scheduling models of all the conventional generating units in this thesis. All

the aforementioned features of a thermal unit can be easily incorporated in the MLD framework.

With reference to (2.39)-(2.40), let the basic inputs to the thermal unit be u_1 which represents the output power setpoint for the thermal unit expressed as a percentage of its rated (maximum) output power and ul which represents the commitment status for the unit. It is pertinent to mention here that the notations and variable names used in this chapter differ from those used in the remaining chapters. The mathematical descriptions of the GT, ST and boiler behaviours discussed in Chapter 2 have been expressed in this chapter using logical statements.

3.2.2 MLD Model of a Thermal Unit Incorporating Start-up and Shutdown Trajectories

As mentioned in Chapter 2, the HYSDEL compiler generates the MLD matrices from a high level description of the system behavior [105]. HYSDEL automates the process of representing hybrid systems in the MLD form. An important step in deriving the MLD form of a hybrid system is to associate a binary variable with a logical statement S , which can either be true or false [17]. The binary variable takes the value of 1 if and only if S is true. Boolean operators such as $AND(\wedge)$, $OR(\vee)$ and $NOT(!)$ are used to combine several such statements into a compound statement. This compound statement can then be represented as linear inequalities over the associated binary variables. The formation of these inequalities from the compound statement is described in [94]. For most thermal units, their respective start-up diagrams show that the time required to commence the dispatch phase after the initial commitment increases as the prior downtime of the unit increases. This is essential to avoid mechanical stresses in the turbine. Gradual heating of the mechanical components helps in avoiding these stresses. This leads to the four different start-up methods shown in Table 3.1. The four start-up methods are modelled in detail by considering the power produced during each stage of the start-up trajectory. The start-up trajectory of each thermal unit considered in this chapter can be broadly divided into the synchronization and soak phases as shown in Fig. 2.1. At the end of the soak phase, the unit produces the technical minimum power output. During the desynchronization phase, the output power first drops to the technical minimum value before dropping to 0 MW.

TABLE 3.1: Details of Four Start-up Methods

Start-up Type	Normal	Hot	Warm	Cold
Min. up-time (h)	3	3	3	3
Min. down-time (h)	2	2	2	2
Off-Time (OT) (h)	$0 < OT < 4$	$4 \leq OT < 6$	$6 \leq OT < 8$	$OT \geq 8$
Start-up Cost (\$)	16	28	36	40
P_{sync} (MW)	NA	50	50	50
$P_{\text{soak},1}$ (MW)	NA	NA	100	83.33
$P_{\text{soak},2}$ (MW)	NA	NA	NA	116.67
Start-up duration (h)	1	2	3	4

In this chapter, the basic MLD model of an exemplar thermal unit is developed along the lines of the description provided in [17]. However, several additional features which have been added to the model consider the different start-up and shutdown trajectories. The model formulated in this chapter has three important continuous state variables which effectively act as counters. They are described below.

t_{on} : This is a continuous state variable which counts the number of consecutive hours the unit has been undergoing the dispatch phase. If the unit is producing power in the dispatch phase, the state is updated as follows:

$$t_{\text{on}}(k+1) = t_{\text{on}}(k) + 1 \quad (3.1)$$

In the context of this chapter, k represents the hour of the day.

t_{off} : This is a continuous state variable which counts the number of consecutive hours the unit has been undergoing either the desynchronization, synchronization, soak or off phases. This state variable is updated as follows:

$$t_{\text{off}}(k+1) = t_{\text{off}}(k) + 1 \quad (3.2)$$

t_{lat} : This is a continuous state variable which stores the time spent by the unit in the start-up phase, i.e. the time between the unit being first committed and the unit entering the dispatch phase. In this chapter, the model has been defined such that the thermal unit enters the dispatch phase only when the value of $t_{\text{lat}}(k)$ drops below -1 . To select the appropriate start-up method among the hot, warm and cold start-up methods respectively, the following binary auxiliary variables are

defined:

$$d_h(k) = 1 \Leftrightarrow t_{\text{off}}(k) \geq 4h \quad (3.3)$$

$$d_w(k) = 1 \Leftrightarrow t_{\text{off}}(k) \geq 6h \quad (3.4)$$

$$d_c(k) = 1 \Leftrightarrow t_{\text{off}}(k) \geq 8h \quad (3.5)$$

where $d_h(k)$, $d_w(k)$ and $d_c(k)$ are used to identify and select the hot, warm and cold start-up methods respectively.

These binary auxiliary variables along with a continuous auxiliary variable z_{lat} are subsequently used in the state update of t_{lat} as follows:

$$\text{IF } ul(k) = 1 \text{ THEN } z_{\text{lat}}(k) = t_{\text{lat}}(k) - 1 \quad (3.6)$$

$$\text{ELSE } z_{\text{lat}}(k) = d_h(k) + d_w(k) + d_c(k) \quad (3.7)$$

$$t_{\text{lat}}(k+1) = z_{\text{lat}}(k) \quad (3.8)$$

where z_{lat} represents the number of hours left for the thermal unit to reach the dispatch phase based on the start-up method. The start-up method is determined on the basis of the prior downtime of the unit which is inclusive of the desynchronization and off (zero power output) phases. For example, if the initial state of the unit is such that $t_{\text{off}}(k) = 9h$, then $d_h(k)$, $d_c(k)$ and $d_w(k)$ are equal to 1 provided that the input $ul(k) = 0$. Therefore, the state update for $t_{\text{lat}}(k)$ is $t_{\text{lat}}(k+1) = z_{\text{lat}}(k) = 3h$. This means that the unit requires 4 hours to reach the minimum power output and that there are 3 intermediate stages between initial commitment and the unit reaching the minimum power output.

Finally, $xl_1(k)$ is a state variable which is introduced to track the number of consecutive hours for which the input command $ul(k) = 1$ is given to the thermal unit. Effectively, this state tracks the time spent by the thermal unit in the synchronization, soak and dispatch phases. This state variable is updated as follows:

$$\text{IF } ul(k) = 1 \text{ THEN } z_{\text{lat}1}(k) = xl_1(k) + 1 \quad (3.9)$$

$$\text{ELSE } z_{\text{lat}1}(k) = 0 \quad (3.10)$$

$$xl_1(k+1) = z_{\text{lat}1}(k) \quad (3.11)$$

where $z_{\text{lat}1}(k)$ is a continuous auxiliary variable which checks whether the logical condition required to increment $xl_1(k)$ is TRUE. $z_{\text{lat}1}(k)$ is assigned to $xl_1(k) + 1$

only if $ul(k)=1$. Otherwise, it remains at 0.

The following binary auxiliary variables are introduced to track the value of the state $xl_1(k)$. These variables are used to determine which phase of the start-up process the unit is undergoing. This facilitates the determination of the power setpoint applicable for that phase of the start-up method based on the predefined power trajectory.

$$d_{\text{start1}}(k) = 1 \Leftrightarrow xl_1(k) \geq 2h \quad (3.12)$$

$$d_{\text{start2}}(k) = 1 \Leftrightarrow xl_1(k) \geq 1h \quad (3.13)$$

$$d_{\text{start3}}(k) = 1 \Leftrightarrow xl_1(k) \geq 3h \quad (3.14)$$

For example, in the case of a cold start-up, d_{start1} may be used to indicate the start of the third phase of the start-up method. Once this scenario is identified, the appropriate output power setpoint for the thermal unit is determined on the basis of the pre-defined start-up power trajectory. It is now possible to define a logical statement whereby, in a cold start-up, if $d_{\text{start2}}(k) = 1$ (true for any value of $xl_1(k) \geq 1h$) and $xl_1(k)$ is not greater than $2h$ (true if $d_{\text{start1}}(k) = 0$), based on the trajectory, the output power setpoint for the thermal unit is assigned as 50 MW.

In order to pin-point the exact state of the unit during the start-up process, the following binary auxiliary variables track the state t_{lat} :

$$d_{\text{lat1}}(k) = 1 \Leftrightarrow t_{\text{lat}}(k) \geq 3h \quad (3.15)$$

$$d_{\text{lat2}}(k) = 1 \Leftrightarrow t_{\text{lat}}(k) \geq 2h \quad (3.16)$$

$$d_{\text{lat3}}(k) = 1 \Leftrightarrow t_{\text{lat}}(k) \geq 1h \quad (3.17)$$

These variables are required since the value of the state t_{lat} keeps evolving during the start-up process. These variables are used along with $d_{\text{start1}}(k)$, $d_{\text{start2}}(k)$ and $d_{\text{start3}}(k)$ to formulate logical statements which identify the start-up method and the phase of the start-up method the thermal unit is undergoing. For example, the following four logical equations may be used to describe the various phases of the

cold start-up method:

$$d_1(k) = ul(k) \wedge d_{lat1}(k) \quad (3.18)$$

$$d_5(k) = ul(k) \wedge d_{lat2}(k) \wedge (!d_{lat1}(k)) \wedge d_{start2}(k) \wedge (!d_{start1}(k)) \wedge (!d_{start3}(k)) \quad (3.19)$$

$$d_8(k) = ul(k) \wedge d_{lat3}(k) \wedge (!d_{lat2}(k)) \wedge (!d_{lat1}(k)) \wedge d_{start1}(k) \wedge (!d_{start3}(k)) \quad (3.20)$$

$$d_{10}(k) = ul(k) \wedge d_{lat4}(k) \wedge (!d_{lat3}(k)) \wedge (!d_{lat2}(k)) \wedge (!d_{lat1}(k)) \wedge d_{start3}(k) \quad (3.21)$$

where $d_1(k)$, $d_5(k)$, $d_8(k)$ and $d_{10}(k)$ are binary auxiliary variables which represent the synchronization phase, soak phase 1, soak phase 2 and soak phase 3 respectively of the thermal unit for the cold start-up method. For example, $d_5(k)$ checks whether the binary input to the system is 1 and whether $t_{lat}(k) = 2h$ (by checking the values of $d_{lat2}(k)$ and $d_{lat1}(k)$) and $x_{l1}(k) = 1h$ (by checking $d_{start1}(k)$, $d_{start2}(k)$ and $d_{start3}(k)$). This means that while $ul(k) = 1$, the variable $d_5(k)$ is used to check whether the unit is undergoing the second stage of the cold start-up method. This is possible in the cold start-up method only if $t_{lat}(k)$ drops to 2h from 3h and $ul(k-1) = 1$. The phases of the remaining start-up methods are similarly represented using three, two and one logical statements respectively. These are detailed below:

i) Warm start-up:

$$d_2(k) = ul(k) \wedge d_{lat2}(k) \wedge (!d_{lat1}(k)) \wedge (!d_{start1}(k)) \wedge (!d_{start2}(k)) \wedge (!d_{start3}(k)) \quad (3.22)$$

$$d_6(k) = ul(k) \wedge d_{lat3}(k) \wedge (!d_{lat2}(k)) \wedge (!d_{lat1}(k)) \wedge (!d_{start1}(k)) \wedge d_{start2}(k) \wedge (!d_{start3}(k)) \quad (3.23)$$

$$d_9(k) = ul(k) \wedge d_{lat4}(k) \wedge (!d_{lat3}(k)) \wedge (!d_{lat2}(k)) \wedge (!d_{lat1}(k)) \wedge d_{start1}(k) \wedge (!d_{start3}(k)) \quad (3.24)$$

ii) Hot start-up:

$$d_3(k) = ul(k) \wedge d_{lat3}(k) \wedge (!d_{lat2}(k)) \wedge (!d_{lat1}(k)) \wedge (!d_{start1}(k)) \wedge (!d_{start2}(k)) \wedge (!d_{start3}(k)) \quad (3.25)$$

$$d_7(k) = ul(k) \wedge d_{lat4}(k) \wedge (!d_{lat3}(k)) \wedge (!d_{lat2}(k)) \wedge (!d_{lat1}(k)) \wedge d_{start2}(k) \wedge (!d_{start1}(k)) \wedge (!d_{start3}(k)) \quad (3.26)$$

iii) Normal start-up:

$$d_4(k) = ul(k) \wedge d_{lat4}(k) \wedge (!d_{lat3}(k)) \wedge (!d_{lat2}(k)) \\ \wedge (!d_{lat1}(k)) \wedge (!d_{start2}(k)) \wedge (!d_{start1}(k)) \wedge (!d_{start3}(k)) \quad (3.27)$$

It is pertinent to note here that in the case of the cold start-up method, the logical statements are framed in such a way that during any particular time interval, only one variable among $d_1(k)$, $d_5(k)$, $d_8(k)$ and $d_{10}(k)$ equals 1. Therefore, it logically follows that the output power of the thermal unit follows these variables during the start-up process. The output power is fixed for the various phases of the four start-up methods as shown in Table 3.1. These variables can also be utilized to implement variable start-up costs. This means that each start-up method will have a unique cost associated with it. For instance, if the statement $(delta_{11}(k) = d_1(k) \vee d_5(k) \vee d_8(k) \vee d_{10}(k))$ is true, then the cost associated with the cold start-up method can be imposed during that particular time interval using the auxiliary binary variable $delta_{11}(k)$. This statement being true implies that the unit is undergoing one of the phases of the cold start-up during the corresponding time interval. Similar procedures may be adopted to express the costs incurred for the other start-up methods.

The shutdown trajectory can also be modelled in a similar manner to the start-up power trajectories. However, this is a relatively easier task since there is only one fixed shutdown trajectory. Initially, the binary auxiliary variables $d_{down3}(k)$ and $d_{down1}(k)$ are defined as follows:

$$d_{down3}(k) = 1 \Leftrightarrow t_{off}(k) \geq 2h \quad (3.28)$$

$$d_{down1}(k) = 1 \Leftrightarrow t_{off}(k) \geq 1h \quad (3.29)$$

These variables are used to detect both stages in the shutdown process. Initially, the output power from the thermal unit drops to the technical minimum value. Subsequently, it drops to 0 MW. These two stages can be detected by tracking the t_{off} state. This is because t_{off} starts incrementing as soon as the off command ($ul(k) = 0$) is given to the thermal unit. Additionally, the following binary auxiliary

variables are defined:

$$d_{\text{off1}}(k) = (!ul(k)) \wedge xl(k) \quad (3.30)$$

$$d_{\text{off2}}(k) = (!ul(k)) \wedge d_{\text{down1}}(k) \wedge (!d_{\text{down3}}(k)) \quad (3.31)$$

where $xl(k)$ is a binary state variable which is set to 1 if the unit is in the dispatch phase. Thus, the variable $d_{\text{off1}}(k)$ detects when the off command is given to the thermal unit. It takes the value of 1 only if the unit is in the dispatch phase when the off command is issued. The variable $d_{\text{off1}}(k)$ is then subsequently used to decrease the units output power to the technical minimum value. The next phase of the shutdown trajectory reduces the generator output power to 0 MW. To detect this phase, $d_{\text{off2}}(k)$ is utilized. As soon as the binary input $ul(k)$ is set to 0, the continuous state variable $t_{\text{off}}(k)$ starts incrementing. The binary auxiliary variable $d_{\text{down1}}(k)$ detects the condition when $t_{\text{off}}(k)$ equals 1. It achieves this by checking if the input $ul(k)$ is still 0 and $t_{\text{off}}(k)$ is equal to 1. Furthermore, it naturally follows that the output power of the unit is set to 0 MW if $d_{\text{off2}}(k)$ equals 1. Finally, the shutdown cost is added to the overall cost function if either $d_{\text{off2}}(k)$ or $d_{\text{off1}}(k)$ is equal to 1.

In total, the model has two inputs and 7 states. Owing to their large sizes, the matrices obtained from the HYSDEL compiler are omitted for the sake of brevity. The total number of inequalities of the form (2.40) in this model is 198.

3.3 Objective Function

The hybrid MPC framework has been successfully applied in several industrial systems (see for instance [106] and [107]). In the hybrid MPC framework, a finite horizon open-loop optimization problem is solved with the system being initialized with its current state. To perform optimal scheduling, a cost function is minimized during each hour k . This cost function accounts for the different costs associated with operating the thermal unit. A sequence of optimal inputs for the entire optimization horizon is generated along with predictions on how the system states are expected to evolve over the optimization horizon. From this sequence, only the first set of inputs is chosen and applied to the system. During the next hour $k + 1$, the optimization problem is reformulated and solved while the horizon is

moved. Feedback control action is provided by this problem reformulation. This section presents a hybrid MPC scheme for the optimal self-scheduling problem of a thermal unit. The hybrid MPC scheme presented in this chapter differs slightly from the hybrid MPC scheme used in the remainder of this thesis. The hybrid MPC scheme in this chapter incorporates a moving horizon mechanism unlike the remainder of this thesis.

3.3.1 Cost Function

The overall cost function is defined as follows:

$$J = C_{\text{Fuel}} + C_{\text{Start-up}} + C_{\text{Shutdown}} \quad (3.32)$$

Let k be the current hour and P be the length of the prediction horizon. Let $f(t|k)$ denote a time varying function f which is defined for time $t \geq k$ and also depends on the current time instant k . The various terms of the cost function in (3.32) are defined as shown below.

C_{Fuel} is the cost incurred due to the fuel consumed by the thermal unit. The fuel can be coal, oil or natural gas. C_{Fuel} in this chapter is calculated as follows:

$$C_{\text{Fuel}} = \sum_{t=k}^{k+P} a(y_1(t|k))^2 + b(y_1(t|k)) + c \quad (3.33)$$

where $a = \$0.00194/\text{MW}^2$, $b = \$7.85/\text{MW}$ and $c = \$310$ are the fuel cost curve coefficients. y_1 is the output power in MW.

$C_{\text{Start-up}}$ calculates the costs incurred during the start-up process of the thermal unit. Different start-up costs are used for the four start-up methods as shown below:

$$\begin{aligned} C_{\text{Start-up}} = & \sum_{t=k}^{k+P} C_{\text{cold}} * \text{delta}_{11}(t|k) + C_{\text{warm}} * \text{delta}_{21}(t|k) \\ & + C_{\text{hot}} * \text{delta}_{31}(t|k) + C_{\text{normal}} * \text{delta}_{41}(t|k) \end{aligned} \quad (3.34)$$

where delta_{11} , delta_{21} , delta_{31} and delta_{41} are binary auxiliary variables which indicate whether the unit is undergoing any phase of the cold, warm, hot and

normal start-ups respectively during that time interval. C_{cold} , C_{warm} , C_{hot} and C_{normal} are the cost coefficients for the cold, warm, hot and normal start-up methods respectively in dollars (\$).

C_{Shutdown} calculates the cost incurred during the shutdown process of the thermal unit. This term is active during the hours when the thermal unit power first decreases to the technical minimum output power and subsequently to 0 MW.

$$C_{\text{Shutdown}} = \sum_{t=k}^{k+P} C_{\text{SD}} * d_{\text{off1}}(t|k) + C_{\text{SD}} * d_{\text{off2}}(t|k) \quad (3.35)$$

Therefore, the overall optimal self-scheduling problem for the thermal unit considered in this chapter may be defined as follows:

$$\begin{aligned} \min_{u,x,w} \quad & J = C_{\text{Fuel}} + C_{\text{Start-up}} + C_{\text{Shutdown}} \\ \text{subject to} \quad & \\ & x(k|k) = x_k \quad (3.36) \\ & \text{and} \quad k = 0, \dots, k + P - 1 \text{ to} \\ & \text{MLD form shown in (2.39) and (2.40)} \end{aligned}$$

Furthermore, the optimal self-scheduling problem is also subject to thermal constraints such as the minimum up and down times mentioned in Table 3.1 and the ramping constraints in the dispatch phase [4]. The ramp limit for the thermal unit is set at 80 MW/h. Moreover, the power balance constraint results in the meeting of the load demand only by the generators undergoing the dispatch phase. The load profile was adapted from [3] with 300 MW as the peak load.

3.4 Simulation Results

The optimization problem formulated in Section 3.3 turns out to be an MIQP problem. The optimization problem was formulated using YALMIP [108] in MATLAB and solved using CPLEX. A prediction horizon of 5h was chosen to cover all the four start-up methods. The load forecast used in the optimal self-scheduling problem is shown in Fig. 3.1. In Fig. 3.1, it is observed that there are 5 hours of

FIGURE 3.1: Typical load demand profile

no load demand prior to the 24-hour period under consideration. The load profile was designed in the manner to demonstrate the start-up trajectory of the thermal unit. There is a 2 hour period at the end of the load profile where the demand is 0 MW to demonstrate the shutdown trajectory. The system states were initialized as follows: $t_{\text{on}} = 0\text{h}$, $t_{\text{off}} = 9\text{h}$ and $t_{\text{lat}} = 3\text{h}$. Since the unit was shutdown for 9 hours, a cold start-up was necessary. From Fig. 3.1 and Fig. 3.2, it is clear that even though the load demand in the initial 5 hours is zero, the thermal unit still produces output power in accordance with the start-up power trajectory for the cold start-up method. During the dispatch phase, due to the power balance constraint, the output power curve in Fig. 3.2 follows the load profile in Fig. 3.1. During the last two hours, the thermal unit initially drops its production to the technical minimum output power and thereafter to 0 MW. Fig. 3.3 shows the evolution of the system states t_{on} , t_{off} and t_{lat} . The unit enters the dispatch phase when t_{lat} drops to -2. Concurrently, t_{off} drops to 0h and t_{on} starts to rise. The converse happens during the unit shutdown wherein t_{lat} rises to 0, t_{on} drops to 0h and t_{off} starts to rise from 0h. During the first 5 hours, while the unit is still starting up, t_{off} rises till the unit reaches the dispatch phase while t_{on} remains at 0h and t_{lat} starts to drop from its initial value of 3. The evolution of the system states is thereby aligned with the output power produced by the thermal unit.

3.5 Optimal Scheduling of a 5-Generator System

In this section, the simulation study presented in the previous section for the optimal self-scheduling of a single thermal unit is extended to consider a system

FIGURE 3.2: Thermal unit output power for given load profile

FIGURE 3.3: Evolution of system states

comprising five units. The objective function used in this study is similar to the one described in Section 3.3. Modular features introduced in HYSDEL 3.0 were utilized in order to extend the study presented in the previous section to a system comprising 5 thermal units [105]. Fig. 3.4 shows the load forecast over a 26-hour period which was considered for this study. The first 4 hours and the last 2 hours in Fig. 3.4 were deliberately considered as no load periods to demonstrate the start-up and shutdown trajectories. The ratings of the thermal units used in this study are shown in Table 3.2 while the simulation study results are presented in Table 3.3 and Fig. 3.5. Table 3.2 also provides the other details of the thermal units considered in this study such as the minimum uptime and downtime, the start-up costs for the different start-up methods and the shutdown costs. The

overall objective function may be summarized as follows:

$$J = \sum_{f=1}^5 C_{\text{Fixed}}^f + C_{\text{Marginal}}^f + C_{\text{Start-up}}^f + C_{\text{Shutdown}}^f \quad (3.37)$$

where f represents the index of the thermal units being considered. The terms $C_{\text{Start-up}}$ and C_{Shutdown} are similar to the descriptions provided in Section 3.3. The remaining terms of (3.37) are described below:

$$C_{\text{Fixed}} = \sum_{t=k}^{k+P} C_{\text{NL}} * u_1(t|k) \quad (3.38)$$

$$C_{\text{Marginal}} = \sum_{t=k}^{k+P} C_{\text{LV}} * x_1(t|k+1) \quad (3.39)$$

where C_{NL} represents the no-load cost coefficient in \$/h. C_{LV} represents the linear variable production cost coefficient in \$/MWh. C_{Fixed} accounts for all the fixed costs such as the operation and maintenance costs which would be incurred if the turbine was running. C_{Marginal} represents the linearized fuel cost incurred for producing each MWh of energy. The cost coefficients are adapted from [3] and [16] and are shown in Table 3.2. x_1 is a continuous state variable which represents the thermal unit output power in MW.

FIGURE 3.4: Load demand profile for the 5-unit study

The hybrid MPC framework used earlier in this chapter was utilized for generating the optimal schedule. All the five units were initialized with the following states: $t_{\text{off}} = 9\text{h}$, $t_{\text{lat}} = 3\text{h}$ and $t_{\text{on}} = 0\text{h}$. All the generators therefore required a cold start-up. The power balance constraint was defined such that only those units undergoing the dispatch phase were used to satisfy the load demand. The overall

FIGURE 3.5: Output power generated by 5 units

TABLE 3.2: Technical and cost data of thermal units

Technical Information				Cost Coefficients (\$)						
Gen.	$P_{\max}$ (MW)	$P_{\min}$ (MW)	Min. UT/ DT (h)	C_{NL}	C_{LV}	C_{cold}	C_{warm}	C_{hot}	C_{normal}	C_{SD}
1	455	150	3	1000	16.19	9000	6750	4500	2250	4500
2	130	20	3	700	16.60	1100	825	550	275	550
3	455	150	3	970	17.26	10000	7500	5000	2500	5000
4	130	20	3	680	16.50	1120	840	560	280	560
5	162	25	3	450	19.70	1800	1350	900	450	900

optimal scheduling problem turned out to be an MILP problem. The optimization problem was formulated in MATLAB using YALMIP [108] and solved using CPLEX. From the scheduling results shown in Table 3.3, it is observed that the load is mostly shared between the first, third and fifth units for the first few hours. The second unit is started up at the 11th hour when the system load demand starts exceeding the combined capacity of the first, third and fifth units. The fourth unit is the last to get committed. It is used only when the load demand peaks towards the end of the optimization horizon under consideration. The other four units which are started up earlier remain committed till the end since the load demand mostly increases over the optimization horizon under consideration. During the last two hours, the load demand drops to 0 MW and all the units initially drop their generation to their respective technical minimum output power levels.

TABLE 3.3: Day ahead schedule for 5 thermal units (1-ON, 0-OFF)

Unit	Hours (1-26)
1	1 0 0
2	0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 0 0
3	1 0 0
4	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0
5	1 0 0

Subsequently, they ramp down their generation further to 0 MW.

3.6 Conclusion

In this chapter, a generalized MLD-based modelling approach for thermal units was presented. This model presented in this chapter can be easily adapted for other generators such as combined cycle power plants and DGs. A self-scheduling problem for a single thermal unit was formulated and solved. The self-scheduling problem was extended to solve the optimal scheduling problem for a system comprising five thermal units.

Chapter 4

Optimal Scheduling of a Shipyard Drydock

4.1 Introduction

Industrial power networks may comprise fossil fuel based generators such as DGs or microturbines, RESs, BESSs and different types of loads [24]. As such, industrial power networks can be treated as grid-connected MGs comprising heterogeneous generators and loads. An EMS facilitates the efficient operation of a MG by minimizing the total electricity cost. In Singapore, minimizing the uncontracted capacity consumption is essential for reducing the electricity cost of industrial entities such as shipyard drydocks. Typically, the EMS determines an optimal schedule and dispatch for each generator, BESS, flexible load and IL in the MG which respects all the applicable technical and operational constraints. Consequently, an SEMS is proposed in this chapter for optimally managing an exemplar drydock MG. The proposed SEMS comprises the following three modules: i) LF, ii) CCO, and iii) Optimal Scheduling including PSO. The three SEMS modules are developed on the basis of real data from a shipyard drydock in Singapore.

The remainder of this chapter is organized as follows: Section 4.2 describes the architecture of the SEMS proposed in this chapter. Subsequently, Section 4.3 details the configuration of the drydock MG considered in this chapter. The parameters of the BESS present in the drydock MG are also provided in Section 4.3. Section 4.4 discusses the proposed LF module in the SEMS along with a case study to

demonstrate the advantages of providing the ship arrival schedule as an input to the ANN used for generating the STLFs. Section 4.5 describes the formulation of the CCO problem along with a case study. The mathematical formulation of the uncontracted capacity cost incurred by the drydock MG operator is also provided in Section 4.5. The optimal scheduling problem solved by the SEMS is formulated in Section 4.6. Section 4.7 presents the results from five scenario-based case studies which demonstrate the efficacy of the proposed optimal scheduling module in the SEMS. Finally, Section 4.8 provides some concluding remarks for this chapter.

4.2 SEMS Architecture

This section describes the architecture of the proposed SEMS. The SEMS proposed in this chapter comprises the following three modules: i) LF ii) CCO and iii) Optimal Scheduling including PSO. The interactions between these three modules is illustrated in Fig. 4.1. The LF module generates STLFs and MTLFs for the drydock. Historical load data and ship arrival schedules are provided as inputs to the ANNs used to perform the forecasting in the LF module. The MTLF generated by the LF module is used as an input by the CCO module to optimize the contracted capacity of the drydock. The optimized contracted capacity estimated by the CCO and the STLF from the LF module are used as inputs by the optimal scheduling module to generate optimal schedules for all the generators, BESSs, pump loads and ILs in the drydock MG. Furthermore, the optimal scheduling module also generates a schedule for the exchange of power between the drydock MG and the main utility grid. Detailed descriptions of all the three modules are provided in the later sections of this chapter.

FIGURE 4.1: Overview of the SEMS modules

4.3 Drydock MG

With the advent of enabling technological innovations, many industries including shipyards have been sourcing their electricity requirements from increasingly diverse sources such as captive fossil fuel based generators, utility grid supply, RESs and BESSs. Additionally, drydocks may contain different types of loads such as critical loads, schedulable loads and ILs. As such, drydocks may be treated as grid-connected MGs.

The drydock MG modelled in this chapter comprises the three DGs whose technical parameters were provided in Table 2.1. DG1, DG2 and DG3 of Table 2.1 are denoted as CG 1, CG 2 and CG 3 respectively in this chapter. In addition to the DGs, the drydock MG also contains one BESS, one solar PV power plant, three main pumps, four auxiliary pumps and three ILs. The three ILs are denoted as IL 1, IL 2 and IL 3 in this chapter. The parameters of the ILs and the pump loads are provided in the later sections of this chapter. A detailed description of the constraints which the operations of the DGs, the BESS, the ILs and the pump loads in the drydock MG are subject to was provided in Chapter 2 of this thesis.

The technical parameters of the BESS present in the drydock MG considered in this chapter are as follows: $P_{bc,max} = P_{bd,max} = 300\text{kW}$, $B_{cap} = 1,020\text{kWh}$, $N = 6,000\text{h}$, $P_{1C} = 1,020\text{kW}$, $SOC_{min} = 0.2$, $\eta_c = \eta_d = 0.95$, $SOC_{max} = 0.9$ and $I = \$408,000$.

4.4 Artificial Neural Network - Load Forecasting Module

An ANN uses mathematical representations to process information in a manner similar to the human brain. An ANN comprises numerous interconnected processing entities called neurons which solve problems in a parallel fashion. The neurons are interconnected by adjustable synaptic weights. An ANN can be trained to understand the complex relationships between the inputs and the specific target output. The difference between the actual output and the targeted output is used as the basis for adjusting the synaptic weights. The synaptic weights are adjusted using an iterative process till the actual and the targeted outputs match. In this

scenario, a large number of input-targeted output data pairs are needed to train the ANN [39].

The backpropagation algorithm is commonly used in feed-forward networks as a supervised learning method. In this algorithm, the ANN is supplied with training data comprising sample inputs and targeted outputs. The difference between the output and the targeted output is defined as the error. The calculated error is backpropagated from the output layer to the input layer. Random weights are initially assigned to the ANN during the training process. The backpropagation algorithm minimizes the error by iteratively adjusting the weights until the ANN fully learns the training data.

The procedure outlined in Fig. 4.2 is used to generate the STLFs and the MTLFs for the drydock under consideration in this chapter. Historical peak demand data and the ship arrival schedules from July 2011 to October 2011 are provided as inputs to the ANN used for generating the MTLFs. Furthermore, historical total demand data and ship arrival schedules from July 2011 to October 2011 are provided as inputs to the ANN used for generating the STLFs. Subsequently, data preprocessing techniques are used to deal with missing, irregular or bad data which may exist due to malfunctioning metering equipment. Curve fitting techniques are adopted during data preprocessing to handle data spikes and missing/redundant data elements as a result of which typical curve values are used to replace the bad data. All the data elements are scaled using the following equation to fall within the $[0,1]$ range:

$$Y_n = \frac{Y_{\text{act}} - Y_{\text{min}}}{Y_{\text{max}} - Y_{\text{min}}} \quad (4.1)$$

where Y_n represents the scaled data element; Y_{act} represents the actual data element and Y_{max} and Y_{min} represent the maximum and minimum data elements respectively.

The preprocessed load data is divided into three datasets for training, validation and forecasting respectively. The objective behind forming the training and validation datasets is to apply early stopping (ES) and to avoid overfitting the data. First, the training data is utilized to calculate the gradient and to update the weights and biases of the neural network. The adjustment of the weights is carried out using the gradient descent method. The validation set uses the updated

FIGURE 4.2: STLF/MTLF Procedure

network weights and biases to calculate the MSE. The training is stopped if the maximum number of iterations exceeds the maximum number of epochs. Apart from this, the training can also be stopped if the MSE meets the preset training goal or if the maximum validation check value is exceeded. The training process is repeated iteratively using the adjusted weights and biases till the MSE is minimized. Normally, a decreasing trend is observed in the MSE during the initial stages of the training process. When the ANN starts overfitting the data, the MSE starts to show an increasing trend. Validation checks verify whether the MSE in the current iteration exceeds the MSE in the previous iteration. If the check is affirmative for a number of iterations which exceeds a predefined maximum value, the training is stopped. The validation check prevents the ANN from overfitting the data and falling into memorizing mode. The ANN is finally used for forecasting wherein data postprocessing is performed to scale the output data elements up to their normal values. The latest four weeks of historical load data elements from

the database are grouped according to the days of the week to generate the STLTF. The ship arrival schedule contains the ship tonnage information which can be used to estimate the load demand of each ship.

4.4.1 Ship Arrival Schedule

The day/month/year ahead information about the arrival of ships at the drydock is communicated using the ship arrival schedule. The ship arrival schedule includes information such as the name, tonnage, size, docking time and undocking date of each ship arriving at the drydock. Fig. 4.3 shows an exemplar ship arrival schedule. The drydock operator anticipates the arrival of ships at the docks using the ship arrival schedule. As such, the ship arrival schedule can help the drydock operator in better forecasting the maximum load demand of the drydock.

FIGURE 4.3: Exemplar ship arrival schedule

4.4.2 STLTF Case Study

The power meters in the drydock provide the historical load data records which are used as inputs to the ANN for generating the STLTF. Fig. 4.4 shows the historical load data for the period April 2011 - December 2011. This historical load database contains 26,401 readings with the load being measured every 15 minutes. Six missing readings in the database are represented as 0kW in Fig. 4.4. During data preprocessing, the missing readings are replaced by typical mean values and scaled using (4.1). For the historical load database, the mean and standard deviation are 6,177.15kW and 1,864.45kW respectively.

The ship arrival schedule is used along with the historical load data as an input to the STLTF ANN. The day-ahead load demand is predicted at 15-minute intervals

FIGURE 4.4: Historical load data for the past nine months

using the STLF ANN. The ANN configuration used in this case study is shown in Fig. 4.5. The ANN used in this case study has five input neurons. The first four input neurons each contain a column of 96 data records which represent the load demand at 15-minute intervals from four Mondays (or any other day of the week). The final input neuron contains Monday's ship arrival schedule data at 15-minute intervals. The data format of the output node follows the input node. Consequently, the output node contains a column of 96 data points which represent the STLF for Monday at 15-minute intervals. The ANN contains one hidden layer. The ANN is trained using five hidden neurons prior to being utilized to generate the STLF. The number of hidden neurons is finalized through trial and error. If the number of hidden neurons is too low, the ANN may be incapable of learning. If there are too many hidden neurons, the ANN may lost its generalizing properties and overfit the data. The user can adjust the remaining ANN parameters. In this chapter, the ANN learning rate is set to 0.8. The convergence time can be reduced without affecting the system stability by selecting suitable learning rates. The maximum number of epochs for the ANN is set to 300. Finally, the training goal and maximum validation check are set to 10^{-7} and five times respectively.

FIGURE 4.5: STLF ANN configuration with ship arrival schedule

Fig. 4.6 shows the STLF result for Monday at 15-minute intervals. The STLF generated when the ship arrival schedule is provided as an input to the ANN has an average MAPE of 7.18%. The average MAPE of the STLF generated without providing the ship arrival schedule as an input to the ANN is 8.7%. In general, it is observed from Table 4.1 that the average MAPE of the STLF generated when the ship arrival schedule is provided as an input to the ANN is lower than the average MAPE of the STLF generated without providing the ship arrival schedule as an input to the ANN. The average MAPE of the STLF generated for Sunday improved by 4.35% from 22.31% to 17.96% when the ship arrival schedule was provided as an input to the ANN. The average MAPE showed an increase only for Friday when the ship arrival schedule was provided as an input to the ANN. This anomaly can be attributed to a significant mismatch between the ship arrival schedule and the actual arrival of ships at the drydock on Friday. The average MAPE of the STLF generated for Friday with the ship arrival schedule provided as an input to the ANN can be decreased by correcting this mismatch. Overall, the results shown in Table 4.1 highlight the advantages offered by the inclusion of the ship arrival schedule as an input to the STLF ANN.

FIGURE 4.6: Comparison of load forecast results with and without ship arrival schedule for Monday

4.5 Contracted Capacity Optimization

A high contracted capacity leads to a high contracted capacity charge but lowers the uncontracted capacity charge. As such, a trade-off exists between the contracted and uncontracted capacities. Usually, the uncontracted capacity price is much higher than the contracted capacity price. To minimize the capacity charge

TABLE 4.1: Short Term Load Forecast Results

Day	Average MAPE without ship schedule (%)	Average MAPE with ship schedule (%)
Monday	8.71	7.18
Tuesday	14.06	13.79
Wednesday	10.17	8.14
Thursday	11.19	7.73
Friday	11.02	11.73
Saturday	14.37	13.12
Sunday	22.31	17.96
Average MAPE	13.12	11.38

incurred by the drydock operator, a CCO module in the SEMS optimizes the contracted capacity. The CCO problem solved in this chapter assumes that the entire load demand in the drydock is met by drawing electricity from the main utility grid. The CCO problem formulation can be suitably modified to accommodate any captive generators within the drydock. The objective function for the CCO problem is formulated as shown below:

$$\min_{b_q, C^{\text{opt}}} \sum_{q \in \mathcal{Q}} [p^{\text{CC}} C^{\text{opt}} + p^{\text{UC}} b_q (D_q^{\text{max}} - C^{\text{opt}})] \quad (4.2)$$

As shown below, b_q represents a binary variable which is set to 1 if uncontracted capacity is imported from the main utility grid to satisfy the load demand during month q .

$$b_q = \begin{cases} 1, & D_q^{\text{max}} - C^{\text{opt}} > 0 \\ 0, & D_q^{\text{max}} - C^{\text{opt}} \leq 0 \end{cases} \quad (4.3)$$

Equation (4.3) can be linearized as follows:

$$\frac{D_q^{\max} - C^{\text{opt}}}{\sum_{q \in \mathcal{Q}} D_q^{\max}} \leq b_q \leq 1 + \frac{D_q^{\max} - C^{\text{opt}}}{\sum_{q \in \mathcal{Q}} D_q^{\max}} \quad (4.4)$$

The overall CCO problem turns out to be an MILP problem. In this thesis, the CCO problem was formulated in MATLAB using YALMIP [108] and solved using CPLEX.

The MTLF ANN embedded in the SEMS LF module generates the maximum monthly load demand forecast shown in Fig. 4.7. A CCO problem is solved using the monthly maximum demand forecast shown in Fig. 4.7. The optimized contracted capacity aids the shipyard drydock operator in negotiating an electricity supply contract with the suppliers on the local wholesale electricity market. The

FIGURE 4.7: Monthly maximum demand forecast obtained from the MTLF module

following parameter values were used for this case study: $M = 12$; $p^{\text{CC}} = \$8.57/\text{kW}/\text{month}$; $p^{\text{UC}} = \$12.86/\text{kW}/\text{month}$. Table 4.2 displays the results of the CCO case study.

TABLE 4.2: CCO Case Study Results

C^{opt} (MW)	13.06
Capacity Charge (\$/year)	1342987
Uncontracted Capacity Charge (\$/year)	72132
Total Capacity Charge (\$/year)	1415119

4.5.1 Uncontracted Capacity Cost

The electricity imported by the shipyard from the main utility grid over and above the contracted capacity is called uncontracted capacity. The following equation is used to calculate the uncontracted capacity:

$$P_{UC} = \max \left\{ 0, \max_{1 \leq k \leq K} \left\{ \sum_{m \in \mathcal{M}} P_{m,k} + D_k - \sum_{h \in \mathcal{H}} b_{h,k}^{IL} P_{EIL,k}^h - C^{\text{opt}} \right\} \right\} \quad (4.5)$$

Equation (4.5) may be reformulated and linearized as shown below [109]:

$$\begin{cases} P_{UC} \geq \sum_{m \in \mathcal{M}} P_{m,k} + D_k - \sum_{h \in \mathcal{H}} b_{h,k}^{IL} P_{EIL,k}^h - C^{\text{opt}}, \forall k \in \mathcal{K} \\ P_{UC} \geq 0 \end{cases} \quad (4.6)$$

The cost incurred by the system operator due to the uncontracted capacity is calculated as follows:

$$C_{UC} = 12860 * U_{CC} \quad (4.7)$$

where \$12,860 is the uncontracted capacity price in \$/MW/month.

4.6 Objective Function

The objective function for the optimal drydock scheduling problem solved by the SEMS is formulated as shown below:

$$\min J = C_{CG} + C_{BESS} + C_{IL} + C_{UC} + C_{p,k} P_{eb,k} - C_{s,k} P_{es,k} \quad (4.8)$$

subject to (2.23), (2.27), (2.28), (2.32), (2.33), (2.39), (2.40), (4.6) and

$$D_k + P_{es,k} + P_{bc,k} + \sum_{m \in \mathcal{M}} P_{m,k} - \sum_{h \in \{\text{IL } 1, \text{IL } 2, \text{IL } 3\}} b_{h,k}^{IL} P_{EIL,k}^h \leq \sum_{f \in \mathcal{F}} P_{CG,k}^f + P_{RES,k} + P_{eb,k} + P_{bd,k} \quad (4.9)$$

$$0 \leq P_{eb,k} \leq 4\text{MWh} \quad (4.10)$$

$$0 \leq P_{es,k} \leq 4\text{MWh} \quad (4.11)$$

Finally, $P_{EIL, \text{hour-max}}^h = 0.4\text{MWh}$ and $P_{EIL, \text{day-max}}^h = 1\text{MWh}$ for IL 1, IL 2 and IL 3 in this chapter.

Furthermore, BESS operation is constrained by the following [74], [77]:

$$SOC_1 = SOC_{13} \quad (4.12)$$

The optimal drydock scheduling problem formulated in (4.8)-(4.12) turns out to be a MIQP problem. In this thesis, the optimal drydock scheduling problem was formulated in MATLAB using YALMIP [108] and solved using CPLEX.

4.7 PSO Case Studies

The five operational scenarios enumerated below are simulated in this chapter to highlight the efficacy of the optimal drydock scheduling problem formulated in (4.8)-(4.12).

1. PSO is not included in the optimal drydock scheduling problem formulation and the pumping of the water is done in the least possible time using the 3 main pumps alone.
2. PSO is included in the optimal drydock scheduling problem formulation and the pumping is done using the 3 main pumps alone.
3. PSO is included in the optimal drydock scheduling problem formulation and the pumping is done using the 3 main pumps and the 4 auxiliary pumps.
4. PSO is included in the optimal drydock scheduling problem formulation and the pumping is done using the 3 main pumps and the ILs.
5. PSO is included in the optimal drydock scheduling problem formulation and the pumping is done using the 3 main pumps, the 4 auxiliary pumps and the ILs.

The forecasts for D_k and $P_{RES,k}$ used under Scenarios 1-5 are shown in Figs. 4.8(a) and 4.8(b) respectively. The electricity price forecasts shown in Fig. 4.8(c) were adapted from [110]. Furthermore, $C^{opt} = 0.7\text{MW}$ under Scenarios 1-5. The optimal drydock scheduling problem formulated in (4.8)-(4.12) is solved at 30-minute

intervals under Scenarios 1-5 to align the operations of the drydock with the National Electricity Market of Singapore. The optimization period for the optimal drydock scheduling problem formulated in (4.8) - (4.12) is 6 hours in accordance with the operational requirements of the drydock. The technical parameters of all the main and auxiliary pumps considered in this chapter are shown in Table 4.3.

TABLE 4.3: Parameters for the main and auxiliary pumps

	Number	Capacity (MW)	Water Flow Rate (m ³ /h)	Energy Utilization Rate (kWh/m ³)	Allowable Start up Number
Main Pump	3	1.45	24,000	0.06	1
Auxiliary Pump	4	0.11	1,200	0.09	10

TABLE 4.4: Total cost under Scenarios 1-5

Scenario Number	Uncontracted Capacity (MW)	Uncontracted Capacity Charge (\$)	Interruptible Load Cost (\$)	Fuel Cost (\$)	Total Payment (\$)
1	2.003	25,753.44	0	15,616.2	41,369.63
2	0.315	4,052.1	0	19,269.02	19,269.02
3	0	0	0	19,264.25	19,264.25
4	0	0	392.45	17,265.47	17,657.91
5	0	0	345.71	17,285.21	17,630.91

The schedules of CG 1, CG 2 and CG 3 under Scenario 1 are shown in Fig. 4.9. Fig. 4.10 shows the power exchanged by the drydock MG with the main utility grid

TABLE 4.5: Pump commitment status under Scenarios 1-5 for each interval in the optimization period. 0s and 1s represent the ON and OFF status respectively of the corresponding pump

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Main Pump 1	(111111000000)	(000000001110)	(0110000000000)	(000000011000)	(000000000111)
Main Pump 2	(1,1,1,1,1,0,0,0,0,0)	(011111111111)	(011111111111)	(011111111111)	(000011111111)
Main Pump 3	(111110000000)	(0111100000000)	(000000001110)	(011110000000)	(000000011111)
Auxiliary Pump 1	NA	NA	(000100010100)	NA	(000011100000)
Auxiliary Pump 2	NA	NA	(000100010010)	NA	(000011000001)
Auxiliary Pump 3	NA	NA	(000100010110)	NA	(000011100001)
Auxiliary Pump 4	NA	NA	(000100010110)	NA	(000011100001)

FIGURE 4.8: Forecasts of (a) Load Demand (b) RES Generation (c) Electricity prices

under Scenarios 1-5. Fig. 4.11 shows the charge and discharge profiles of the BESS under Scenarios 1-5 while Fig. 4.12 shows the evolution of the BESS SOC under Scenarios 1-5. As mentioned earlier, the PSO is not implemented under Scenario 1. Consequently, from Table 4.4, it is observed that the total cost is the highest under Scenario 1. A major contributing factor to the higher cost under Scenario 1 is the uncontracted capacity charge. Furthermore, the time varying electricity prices are also not leveraged for operating the pumps under Scenario 1. As such, from Table 4.5, it is observed that the three main pumps are operated together during the first five intervals of the optimization period to pump out the water in the quickest possible time under Scenario 1. From Fig. 4.8(a), it is also observed that the load demand in the system is high during the first five intervals of the optimization period. This results in a situation wherein the system operator is forced to import uncontracted capacity from the main utility grid under Scenario 1. Subsequently, the system operator continues importing electricity from the main utility grid at levels higher than the contracted capacity even when the load demand reduces. This phenomenon can be explained by the formulation of the uncontracted capacity presented in (4.6). Consequently, it is observed from Fig. 4.9 that CG 2 and CG 3 are shutdown from intervals 6 and 10 respectively after being committed at the start of the optimization period under Scenario 1. From Fig. 4.9, it is also observed that CG 1 is operated throughout the optimization period at full capacity since it is the cheapest among the three CGs.

The schedules of CG 1, CG 2 and CG 3 under Scenario 2 are shown in Fig. 4.13. As observed from Table 4.5, the PSO implemented under Scenario 2 results in the

FIGURE 4.9: Dispatch of CG 1, CG 2 and CG 3 under Scenario 1

FIGURE 4.10: Power exchanged with the utility grid under Scenarios 1-5

FIGURE 4.11: BESS charge and discharge profiles under Scenarios 1-5

operations of the three main pumps being spread out across the entire optimization period. Consequently, the three main pumps are never operated together under Scenario 2. This eliminates the need for the system operator to import uncontracted capacity from the main utility grid. It is observed from Fig. 4.13 that CG 1 and CG 2 operate throughout the optimization period under Scenario 2. Furthermore, it is also observed from Fig. 4.13 that CG 3 is operated from the second interval till the tenth interval when there is a drop in the forecasted load demand. It is also observed from Fig. 4.11 that the usage of the BESS under Scenario 2 is

FIGURE 4.12: BESS SOC evolution under Scenarios 1-5

lower than under Scenario 1.

FIGURE 4.13: Dispatch of CG 1, CG 2 and CG 3 under Scenario 2

The schedules of CG 1, CG 2 and CG 3 under Scenario 3 are shown in Fig. 4.14. From Table 4.4, a marginal reduction in the total cost is observed under Scenario 3. This is despite the lower pumping efficiency of the auxiliary pumps which are deployed under Scenario 3. The auxiliary pumps provide additional flexibility to the system operator due to their lower capacities and higher number of permitted start-up events. Consequently, it is observed from Table 4.5 that the usage of the main pumps reduces by one hour under Scenario 3 when compared with Scenario 2. It is also observed from Fig. 4.14 that the schedules of CG 1, CG 2 and CG 3 are similar under Scenarios 2 and 3.

The schedules of CG 1, CG 2 and CG 3 under Scenario 4 are shown in Fig. 4.15. Fig. 4.16 shows the schedules of IL 1, IL 2 and IL 3 under Scenario 4. The optimal drydock scheduling problem is relaxed by the introduction of the ILs under Scenario 4 leading to a reduction in the total cost by \$1,606 when compared with Scenario 3. The ILs provide additional flexibility to the SEMS. As a result, it is observed from Fig. 4.15 that the utilization of the expensive CG 3 reduces under Scenario

FIGURE 4.14: Dispatch of CG 1, CG 2 and CG 3 under Scenario 3

4 when compared with Scenarios 2 and 3. It is observed from Fig. 4.11 that there is an increase in the usage of the BESS under Scenario 4. This provides the system operator with an increased level of flexibility to deal with various operational situations.

FIGURE 4.15: Dispatch of CG 1, CG 2 and CG 3 under Scenario 4

FIGURE 4.16: IL usage under Scenario 4

The schedules of CG 1, CG 2 and CG 3 under Scenario 5 are shown in Fig. 4.17. From Table 4.4, it is observed that the lowest operating cost is incurred under Scenario 5. As observed from Table 4.5, the flexibility offered by the ILs and the

auxiliary pumps under Scenario 5 permits the three main pumps to be operated during the last three intervals of the optimization period when the system load demand is low. As seen in Fig. 4.17, CG 3 is operated from the fourth interval to provide sufficient generation capacity in the system when the main pumps are operated under Scenario 5. As observed from Figs. 4.11 and 4.18, the usage of the flexible auxiliary pumps under Scenario 5 leads to a reduction in the usage of the ILs and the BESS when compared with that of Scenario 4. It is observed that the utilization of the ILs mainly happens during the last five intervals of the optimization period under Scenario 5. This coincides with the intervals during which either two or three main pumps are operated together under Scenario 5.

FIGURE 4.17: Dispatch of CG 1, CG 2 and CG 3 under Scenario 5

FIGURE 4.18: IL usage under Scenario 5

4.7.1 Discussions

The late night hours (12 midnight to 6am) are usually preferred by the drydock operator to operate the pumps. This is done to avoid drawing uncontracted capacity from the main utility grid since the load demand is relatively lower during

these hours. Despite this, the drydock operator is oftentimes forced to operate the pumps during the other hours of the day to cater to the ship arrival schedule. As such, in this context, the drydock operator can incur very high uncontracted capacity charges as observed under Scenario 1. It is observed from Figs. 4.8(a) and 4.8(c) that the main pump operation under Scenario 1 coincides with high electricity purchase prices and high overall drydock load demand. Consequently, the drydock operator incurs a high electrical power import cost and uncontracted capacity charges. As observed from Table 4.4, this results in a high electricity cost under Scenario 1. Scenarios 2-5 demonstrated the potential of PSO and flexible system components such as the ILs and the auxiliary pumps in reducing the total electricity cost of the drydock.

The introduction of PSO under Scenario 2 nullifies the need for the drydock to import uncontracted capacity from the main utility grid. This is largely achieved by shifting the usage of the main pumps to the low load demand intervals. This results in a steep reduction in the total electricity cost of the system under Scenario 2 when compared with Scenario 1. The introduction of flexible system components such as the auxiliary pumps and the ILs to the drydock configuration results in further reductions in the electricity cost of the drydock. Compared with Scenario 1, the deployments of PSO and the ILs under Scenario 5 resulted in a 57% reduction in the electricity cost of the drydock MG. Under Scenario 3, the ILs were not deployed while PSO delivered a 53% reduction in the total electricity cost when compared with that of Scenario 1. The results obtained under Scenarios 1-5 suggest that the auxiliary pumps have a marginal impact on the total electricity cost due to their higher energy utilization rates when compared with the main pumps. The potential of the optimal scheduling problem formulation presented in this chapter in lowering the total electricity cost of the drydock was highlighted using the five scenarios. As such, the cost difference between Scenarios 1 and 5 represents the cost difference between the worst case and best case operational scenarios respectively.

4.8 Summary

This chapter presented the framework and design of an SEMS using real data from a local shipyard drydock in Singapore. The SEMS comprised three modules - LF, CCO and optimal scheduling. The LF module was used to generate STLFs and

MTLFs for the drydock. A case study was used to validate the improvement in the accuracy of the STLF obtained when the ship arrival schedule was included as an input to the STLF ANN. The CCO module was used to optimize the contracted capacity by utilizing the MTLF generated by the LF module, thereby reducing the capacity charge paid by the drydock. This chapter utilized the component models developed in Chapter 2 to construct the model of an exemplar drydock MG system. The drydock MG considered in this chapter comprised CGs, BESS, RES, pump loads and ILs. The drydock MG model was used in the optimal scheduling module of the SEMS. An optimal scheduling problem was formulated to generate schedules for all the drydock MG components including the pump loads. To demonstrate the efficacy and the utility of the optimal scheduling problem formulation developed in this chapter, five scenarios based on the deployment of PSO, the auxiliary pumps and the ILs were simulated. The results of the case studies clearly demonstrated the value of including flexible components such as auxiliary pumps and ILs in the MG configuration. Finally, it was observed that Scenario 5 which involved the deployment of the ILs and PSO for the 3 main pumps and the 4 auxiliary pumps incurred the lowest electricity cost among all the scenarios.

Chapter 5

Optimal MG Scheduling including Pump Scheduling Optimization and Network Constraints

5.1 Introduction

This chapter leverages on the component models formulated in Chapter 2 to build the model of two exemplar MG systems based on a modified IEEE 30-bus network and a modified IEEE 57-bus network respectively. The exemplar MG systems considered in this chapter comprise DGs, BESSs, RESs and ILs. In addition, the pump loads used in the SEMS described in Chapter 4 are considered to be flexible electrical loads which are present in the exemplar MG systems considered in this chapter. Subsequently, an optimal day-ahead scheduling problem is formulated for the MGs wherein point forecasts for the load demand, RES generation and energy market prices are provided as inputs to the optimal scheduling problem. A two-stage EMS architecture is proposed along the lines of [59] and [60] to integrate the optimal scheduling and the OPF problems, thereby ensuring a feasible schedule which does not violate any network constraints. Apart from the deployment of ILs, the optimal scheduling problem formulations in the EMSs also include the PSO strategy described in Chapter 4. The proposed EMS architecture minimizes the operating cost of the MG while respecting all the technical constraints. Illustrative case studies under different operational scenarios are used to demonstrate the

efficiency of the proposed EMS architecture in reducing the operating cost of the MG. Finally, the financial gains accrued by including demand side management techniques such as the PSO scheme and the deployment of ILs in the EMS are analyzed.

The remainder of this chapter is organized as follows: Section 5.2 describes the formulation of the optimal scheduling problem solved by the EMS. A detailed description of the iterative solution approach implemented in the EMS is also presented in Section 5.2. Section 5.3 presents the numerical results obtained from the case studies performed to demonstrate the efficacy of the proposed optimization model. Finally, Section 5.4 provides some concluding remarks.

5.2 Energy Management System Architecture

The exemplar MGs considered in this chapter comprise three DGs (described in Table 2.1), BESSs, RESs, three ILs and flexible pump loads. The exact locations of the MG components in the respective MGs are detailed in the later sections of this chapter. The technical parameters and the configurations of the BESSs and the pump loads constituting the MGs in this chapter are identical to those used in Chapter 4. Finally, $P_{\text{EIL, hour-max}}^h = 0.4\text{MWh}$ and $P_{\text{EIL, day-max}}^h = 1\text{MWh}$ for IL 1, IL 2 and IL 3 in this chapter.

The proposed EMS comprises two sequential stages for minimizing the total MG operating cost. The motivation behind adopting this two-stage approach is to decrease the complexity of the overall optimization problem, thereby ensuring that it is solved in reasonable time. The two stages of the proposed EMS are described below.

5.2.1 Stage 1 - Unit Commitment

Optimal schedules for all the DGs, BESSs, pumps and ILs in the MG are generated by solving a UC problem in Stage 1. The UC problem in Stage 1 is constrained to satisfy the active power demand in the MG. The optimal scheduling problem

solved in Stage 1 is described below:

$$\begin{aligned}
 \min_{u,x,w} J &= C_{\text{DG}} + C_{\text{BESS}} + C_{\text{UCC}} + C_{\text{Grid}} + C_{\text{EIL}} \\
 &\text{subject to (2.39), (2.40)} \\
 u_{\min} &\leq u \leq u_{\max}; x_{\min} \leq x \leq x_{\max}; w_{\min} \leq w \leq w_{\max} \\
 P_{\text{D},k} - \sum_{h \in \mathcal{H}} P_{\text{EIL},k}^h + P_{\text{e},k}^{\text{loss}} + \sum_{m \in \mathcal{M}} P_{m,k} &= \sum_{f \in \mathcal{F}} P_{\text{DG},k}^f + P_{\text{eb},k} - P_{\text{es},k} + \\
 &\sum_{e \in \mathcal{E}} (P_{\text{bd},k}^e - P_{\text{bc},k}^e) + \sum_{z \in \mathcal{Z}} P_{\text{RES},k}^z, \forall k \in \mathcal{K} \quad (5.1)
 \end{aligned}$$

where the first constraint defines the bounds on the system states, the system inputs and the auxiliary variables. The power balance constraint for the UC problem is described in (5.1). The following paragraphs describe the unexplained terms of (5.1).

C_{Grid} evaluates the cost incurred by the MG system operator for purchasing electricity from the main utility grid. The revenue earned by the system operator for selling electricity to the main utility grid is also included in C_{Grid} . The formulation of C_{Grid} is shown below:

$$C_{\text{Grid}} = \sum_{k \in \mathcal{K}} (C_{\text{p},k} P_{\text{eb},k} - C_{\text{s},k} P_{\text{es},k}) \quad (5.2)$$

C_{UCC} is used to calculate the cost incurred by the MG system operator due to the purchase of uncontracted capacity from the main utility grid. The maximum demand is used to calculate the uncontracted capacity as shown below [87]:

$$P_{\text{UC}} = \max\{0, \max_{1 \leq k \leq 24} \{P_{\text{eb},k} - P_{\text{CC}}\}\} \quad (5.3)$$

Equation (5.3) is linearized as follows:

$$P_{\text{UC}} \geq P_{\text{eb},k} - P_{\text{CC}}, \forall k \in \mathcal{K} \quad (5.4)$$

$$P_{\text{UC}} \geq 0 \quad (5.5)$$

$$\text{and } C_{\text{UCC}} = U_{\text{CC}} P_{\text{UC}} \quad (5.6)$$

where $U_{\text{CC}} = \$12,860/\text{MW}/\text{month}$ and $P_{\text{CC}} = 0.7\text{MW}$.

The optimal scheduling problem described above is solved in a hybrid MPC framework with a prediction horizon of 24 hours (day-ahead scheduling). The optimization problem solved in Stage 1 turns out to be an MIQP problem. This MIQP problem is described using YALMIP [108] in MATLAB and solved using CPLEX.

5.2.2 Stage 2: Optimal Power Flow

The optimal power flow (OPF) is an important optimization function in power system operations. It is used to calculate the optimal operating setpoints for the system variables. OPF usually minimizes the cost of generating electrical power to satisfy the load demand in the system. The OPF problem is subject to numerous generator and network constraints. Since the OPF problem also accounts for the power losses in the system, the objective function of the OPF problem can be formulated to minimize the power losses in the system.

The system load demand varies with time. As such, it is imperative that the OPF problem is solved within a reasonable time. The OPF problem is an NP-hard nonconvex, nonlinear optimization problem [60]. Global optimization routines are computationally expensive and may not be viable options to solve the OPF problem within the prescribed time limit. Owing to their fast computational speeds, gradient based methods have been widely used by researchers to solve the OPF problem despite the suboptimal nature of the solution obtained using gradient based methods. Among gradient based methods, the quadratic programming method [111] and several variants of the interior point method [59, 112, 113] have been popular among researchers due to their fast computational speeds.

5.2.2.1 Network Model

Let $\mathcal{G}$ represent the set of G buses in the MG. Let $\mathcal{L}$ represent the set of L lines in the MG. The generators in the MG are connected to a subset of $\mathcal{G}$. The solutions of multiple OPF problems are found during different hours in this chapter. Therefore, all the time varying variables and parameters in the OPF problem are denoted by $(\cdot)_k$ during hour k . The polar form of the bus voltage in this formulation is represented as $v_k^i = V_k^i e^{j\delta_k^i}$ wherein V_k^i and δ_k^i are the magnitude and phase angle respectively of the voltage phasor v_k^i at bus $i \in \mathcal{G}$. The vector of complex power

injections is denoted by $s_k \in \mathbb{C}^G$ such that $s_k^i = P_{e,k}^i + jQ_{e,k}^i$ for bus $i \in \mathcal{G}$, where $P_{e,k}^i$ and $Q_{e,k}^i$ represent the generated real and reactive powers respectively. The standard π -model is used to model all the transmission lines in the MG. For transmission line l connecting buses i and j ; $l = (i, j) \in \mathcal{L}$, let $Y \in \mathbb{C}^L$ represent the branch admittance matrix having components $Y_{ij} = g_{ij} + jb_{ij}$; g_{ij} and b_{ij} represent the series conductance and susceptance respectively, and b_{ij}^{sh} represents the line charging susceptance. Furthermore, $d_k \in \mathbb{C}^G$ such that $d_k^i = P_{d,k}^i + jQ_{d,k}^i$ for bus i , where $P_{d,k}^i$ and $Q_{d,k}^i$ represent the active and reactive power demands at bus i respectively such that $P_{D,k} = \sum_{i \in \mathcal{G}} P_{d,k}^i$ and $Q_{D,k} = \sum_{i \in \mathcal{G}} Q_{d,k}^i$.

5.2.2.2 OPF Problem Formulation

The OPF problem is subject to constraints which conform to Kirchoff's laws and ensure that the active and reactive power balances are maintained at each bus while respecting the generation and voltage bounds. The constraints for the OPF problem are listed below:

1) Active power balance at bus i :

$$P_{e,k}^{ij} = g_{ij}(V_k^i)^2 - g_{ij}V_k^iV_k^j \cos(\delta_k^{ij}) + b_{ij}V_k^iV_k^j \sin(\delta_k^{ij}); \quad i, j \in \mathcal{G}, \quad \forall l \in \mathcal{L} \quad (5.7a)$$

$$\begin{aligned} P_{e,k}^i &= \sum_{f \in \mathcal{F}(i)} P_{\text{DG},k}^f + \sum_{e \in \mathcal{E}(i)} P_{\text{BESS},k}^e + P_{\text{Grid},k} + \sum_{z \in \mathcal{Z}(i)} P_{\text{RES},k}^z \\ &\quad - P_{d,k}^i + \sum_{h \in \mathcal{H}(i)} P_{\text{EIL},k}^h - \sum_{m \in \mathcal{M}(i)} P_{m,k} \end{aligned} \quad (5.7b)$$

$$P_{e,k}^i = \sum_{j \in \mathcal{G}(i)} P_{e,k}^{ij}; \quad \forall i \in \mathcal{G} \quad (5.7c)$$

$$P_{\text{BESS},k}^e = P_{\text{bd},k}^e - P_{\text{bc},k}^e; \quad \forall e \in \mathcal{E} \quad (5.7d)$$

$$P_{\text{Grid},k} = P_{\text{eb},k} - P_{\text{es},k} \quad (5.7e)$$

2) Reactive power balance at bus i :

$$Q_{e,k}^{ij} = (b_{ij} + b_{ij}^{\text{sh}}/2)(V_k^i)^2 - b_{ij}V_k^iV_k^j \cos(\delta_k^{ij}) - g_{ij}V_k^iV_k^j \sin(\delta_k^{ij}); i, j \in \mathcal{G}, \forall l \in \mathcal{L} \quad (5.8a)$$

$$Q_{e,k}^i = \sum_{f \in \mathcal{F}(i)} Q_{\text{DG},k}^f + \sum_{e \in \mathcal{E}(i)} Q_{\text{BESS},k}^e + Q_{\text{Grid},k} + \sum_{z \in \mathcal{Z}(i)} Q_{\text{RES},k}^z - Q_{\text{d},k}^i + \sum_{h \in \mathcal{H}(i)} Q_{\text{EIL},k}^h - \sum_{m \in \mathcal{M}(i)} Q_{m,k} \quad (5.8b)$$

$$Q_{e,k}^i = \sum_{j \in \mathcal{G}(i)} Q_{e,k}^{ij}; \forall i \in \mathcal{G} \quad (5.8c)$$

$$Q_{\text{BESS},k}^e = Q_{\text{bd},k}^e - Q_{\text{bc},k}^e; \forall e \in \mathcal{E} \quad (5.8d)$$

$$Q_{\text{Grid},k} = Q_{\text{eb},k} - Q_{\text{es},k} \quad (5.8e)$$

where the active and reactive power flows through line l connecting buses i and j can be represented as $(P_{e,k}^{ij})$ and $(Q_{e,k}^{ij})$ respectively. Equations (5.7a) and (5.8a) satisfy the physical power flow laws. Furthermore, $\delta_k^{ij} = \delta_k^i - \delta_k^j$. The active power and reactive power injections (positive) or extractions (negative) at bus i are represented by $P_{e,k}^i$ and $Q_{e,k}^i$ respectively. In this chapter, all the variables associated with reactive power (denoted using Q) follow the notation used for the variables associated with real power (denoted using P).

It is assumed that the reactive power consumption of the pump loads and the ILs is equal to 50% of the active power consumption. Furthermore, it is assumed that the power converters associated with the BESS and the RESs are capable of maintaining a minimum power factor of 0.7. $\mathcal{F}(i)$, $\mathcal{E}(i)$, $\mathcal{Z}(i)$, $\mathcal{H}(i)$ and $\mathcal{M}(i)$ are used to denote the sets of DGs, BESSs, RESs, ILs and pumps connected to bus i respectively. $\mathcal{G}(i)$ denotes the set of buses connected to bus i with transmission lines. Here, $\mathcal{F}(i) \subset \mathcal{F}$, $\mathcal{E}(i) \subset \mathcal{E}$, $\mathcal{Z}(i) \subset \mathcal{Z}$, $\mathcal{H}(i) \subset \mathcal{H}$, $\mathcal{M}(i) \subset \mathcal{M}$ and $\mathcal{G}(i) \subset \mathcal{G}$. At each bus, the active and reactive power balances are represented using (5.7c) and (5.8c) respectively. The additional variables $P_{e,k}^{ij}$, $Q_{e,k}^{ij}$, $P_{e,k}^i$ and $Q_{e,k}^i$ are excluded during the implementation.

3) Bounds on the active and reactive power generation by each generator (Discussed in Section 5.2.3).

4) Bounds on the voltage at bus i :

$$V_k^i \in [V_{\min}^i, V_{\max}^i]; \forall i \in \mathcal{G} \quad (5.9)$$

where $(\cdot)_{\min}$ and $(\cdot)_{\max}$ are used to denote the lower and upper bounds respectively of the corresponding variable.

5.2.3 Coordination between Stage 1 and Stage 2

Stage 1 and Stage 2 are solved by the EMS alternately. The binary commitment statuses and the continuous dispatch setpoints for all the DGs, the BESS, the pumps and the ILs in the MG are determined in Stage 1. Furthermore, the schedule for exchanging power with the main utility grid is also determined in Stage 1. Along with the schedule for exchanging power with the main utility grid, the dispatch setpoints for the DGs, the BESS, the pumps and the ILs determined in Stage 1 are shared with the OPF problem solved in Stage 2. The OPF problem formulation in Stage 2 permits a small degree of freedom around the scheduled main utility grid power exchange values and the dispatch setpoints for the DGs and the BESS which are determined in Stage 1. The power losses in the MG are evaluated and the power flow convergence is verified in Stage 2. The network power losses evaluated in Stage 2 are shared with the optimal scheduling problem solved in Stage 1 which solves the optimal scheduling problem again incorporating the network power losses. The results of the optimal scheduling problem solved in Stage 1 are shared with Stage 2 which reevaluates the network power losses and rechecks the power flow convergence in the MG. This iterative process continues till convergence and is illustrated in Fig. 5.1.

Initially, $(P_{e,k}^{\text{loss}}) = 0\text{MW}$ during each hour is used to solve the first optimal scheduling problem in Stage 1. Based on the results of the optimal scheduling problem received from Stage 1, the bounds of the dispatch variables of the controllable sources (DGs, BESS and main utility grid supply) in the MG are modified as shown below by the OPF problem in Stage 2.

Let $\hat{P}_{e,k}^g$, $\hat{u}_k^g$ and $\hat{P}_{\text{BESS},k}^e$ be the dispatch setpoint for generator g , the commitment status of generator g and the power flow from BESS e during hour k respectively. The values of $\hat{P}_{e,k}^g$, $\hat{u}_k^g$ and $\hat{P}_{\text{BESS},k}^e$ are received by Stage 2 from Stage 1.

For the f^{th} DG:

$$P_{e,k}^f \geq \hat{u}_k^f \max\{(1 - \alpha)\hat{P}_{e,k}^f, P_{e,\min}^f\}, \quad \forall k \in K, \quad \forall f \in \mathcal{F} \quad (5.10a)$$

$$P_{e,k}^f \leq \hat{u}_k^f \min\{(1 + \alpha)\hat{P}_{e,k}^f, P_{e,\max}^f\}, \quad \forall k \in K, \quad \forall f \in \mathcal{F} \quad (5.10b)$$

$$\hat{u}_k^f Q_{e,\min}^f \leq Q_{e,k}^f \leq \hat{u}_k^f Q_{e,\max}^f, \quad \forall k \in K, \quad \forall f \in \mathcal{F} \quad (5.10c)$$

The BESS and the main utility grid are bidirectional elements in the MG. The following definition is used for the shifted domain based on the direction of the power flow:

For the e^{th} BESS:

$$Q_{\text{BESS},\min,k}^e \leq Q_{\text{BESS},k}^e \leq Q_{\text{BESS},\max,k}^e; \quad \forall e \in \mathcal{E} \quad (5.11)$$

1. If $\hat{P}_{\text{bd},k}^e \geq 0$ ($\hat{P}_{\text{BESS},k}^e \geq 0$)

$$P_{\text{BESS},k}^e \geq \max\{(1 - \alpha)\hat{P}_{\text{BESS},k}^e, 0\} \quad (5.12a)$$

$$P_{\text{BESS},k}^e \leq \min\{(1 + \alpha)\hat{P}_{\text{BESS},k}^e, P_{\text{bd},\max}^e\} \quad (5.12b)$$

2. If $\hat{P}_{\text{bc},k}^e \geq 0$ ($\hat{P}_{\text{BESS},k}^e \leq 0$)

$$P_{\text{BESS},k}^e \geq \min\{(1 - \alpha)\hat{P}_{\text{BESS},k}^e, 0\} \quad (5.13a)$$

$$P_{\text{BESS},k}^e \leq \max\{(1 + \alpha)\hat{P}_{\text{BESS},k}^e, -P_{\text{bc},\max}^e\} \quad (5.13b)$$

Based on the direction of the power flow, the shifted domains of the main utility grid power supply can also be defined in a similar fashion to (5.11)–(5.13).

The small degree of freedom permitted around the optimal dispatch values (calculated in Stage 1) for the controllable sources in the MG is denoted by the positive parameter α . If the parameter α is too low, the convergence would be slower. As such, α needs to be decided carefully. In this chapter, $\alpha = 0.03$. The uncontrollable MG generators such as the RESs are fixed in a similar fashion to Stage 1.

Parallel computation techniques can be used to enhance the computational performance of the OPF problems in Stage 2 which are decoupled from each other. The network power loss during each hour is computed by the OPF problem in Stage 2 as shown in (5.14a) below. The network power losses are shared with the optimal

FIGURE 5.1: Flowchart illustrating the computations in the EMS layer

scheduling problem in Stage 1. Subsequently, in the next iteration, the optimal scheduling problem is solved again in Stage 1 and the results are shared with Stage 2.

The total power loss ($P_{e,k}^{\text{loss}}$) during each hour k is conveyed to the UC problem in Stage 1 for the next iteration. Thereafter, the UC problem is solved again in Stage 1 with the losses included and the dispatch values are shared with Stage 2.

$$P_{e,k}^{\text{loss}} = \sum_{l \in \mathcal{L}} [P_{e,k}^{ij} + P_{e,k}^{ji}] ; i, j \in \mathcal{G}, \forall l = (i, j) \in \mathcal{L}, \forall k \in \mathcal{K} \quad (5.14a)$$

This iterative method continues till the power losses and the optimal scheduling results converge. Interested readers may refer to [59] for the proof of convergence for this method.

5.3 Case Studies

The efficacy of the EMS framework proposed in this chapter is demonstrated by performing the optimal hourly, day-ahead scheduling of an exemplar modified IEEE 30-bus MG under the following possible operational scenarios.

1. The ILs are not deployed and PSO is not performed. The water is pumped out in the least possible time using the three main pumps alone.
2. PSO is performed and the water is pumped out using the three main pumps alone. The ILs are not deployed in this scenario.
3. PSO is performed and the water is pumped out using the three main pumps and the four auxiliary pumps. The ILs are not deployed in this scenario.
4. PSO is performed and the water is pumped out using the three main pumps alone. The three ILs are also deployed in this scenario.
5. PSO is performed and the water is pumped out using the three main pumps and the four auxiliary pumps. The three ILs are also deployed in this scenario.

Subsequently, the optimal scheduling of a modified IEEE 57-bus MG system is performed under Scenario 5 to further validate the utility of the EMS framework proposed in this chapter.

5.3.1 Case Study 1 - Optimal Scheduling of a Modified IEEE 30-bus System

The standard MATPOWER case file for the IEEE 30-bus system is modified and used as an exemplar MG for the purpose of this case study [114]. The base value of the 30-bus MG is set to 8000kVA. The line resistance and reactance values for the 30-bus MG are obtained by multiplying the line resistance and reactance values provided in the original MATPOWER IEEE 30-bus case file by 3 and 1.5 respectively. The three DGs (denoted as DG 1, DG 2 and DG 3 in this chapter) are connected to buses 27, 2 and 3 respectively in the 30-bus MG. Furthermore, the BESS and wind power plant are both connected to bus 22 while the solar PV

power plant is connected to bus 13. The PCC with the main utility grid is bus 1. All the main pumps are connected to bus 27 while the auxiliary pumps are connected to bus 29. The aggregate IL is distributed among the load buses in the same proportion as the nominal load demand.

5.3.1.1 System Initialization

The main pumps are initialized to be switched off prior to the commencement of the optimization period under all the simulation scenarios. The auxiliary pumps are also initialized to be switched off prior to the start of the optimization period under Scenarios 3 and 5. Furthermore, the initial SOC of the BESS is set to 0.6. Finally, all the DGs in the MG are initialized to be switched off prior to the start of the optimization period under all the simulation scenarios.

Scenarios 1-5 are simulated under the assumption that accurate point forecasts for the MG load consumption (excluding the pump loads), electricity prices and RES generation are available. Figs. 5.2 (a), (b) and (c) show the point forecasts for the MG load consumption (excluding the pump loads), the RES generation and the electricity prices respectively. The electricity price profiles shown in Fig. 5.2 were adapted from the pricing information provided on the website of the Energy Market Company of Singapore and [115].

FIGURE 5.2: Point forecasts of (a) MG load consumption (excluding pump loads) (b) RES Generation (c) Electricity prices

5.3.1.2 Optimal Scheduling Results

Fig. 5.3(a) shows the dispatch values of the DGs under Scenario 1. The charge and discharge profiles of the BESS under Scenario 1 are shown in Fig. 5.3(b). The electricity purchased by the MG from the main utility grid under Scenario 1 is shown in Fig. 5.3(c). Table 5.1 lists the schedules of the main pumps under Scenarios 1-5 while Table 5.2 lists the schedules of the auxiliary pumps under Scenarios 3 and 5. Under Scenario 1, the 3 main pumps are operated during the first 3 hours of the optimization period. This is done to complete the pumping of the water in the least possible time. However, as observed from Table 5.3, the operation of the main pumps under Scenario 1 negatively impacts the total cost since the total MG load demand is high during the first 3 hours of the optimization period. It is observed from Fig. 5.3(c) that P_{eb} exceeds 0.7MW (contracted capacity) during the first three hours of the optimization period. Consequently, an uncontracted capacity charge of \$11,991.5 is incurred by the MG operator. Furthermore, from Fig. 5.3(c), it is observed that the EMS continues importing uncontracted capacity from the main utility grid even when the MG load demand reduces. This phenomenon can be explained by the methodology used to calculate the uncontracted capacity cost described earlier in this thesis. As a result, it is observed from Fig. 5.3(a) that DG 3 is shutdown from hour 6 to the end of the optimization period while DG 2 is not operated between hours 14-17. DG 2 is operated at full capacity from hour 18 onwards when the MG load demand begins to increase. DG 1 is relatively cheaper and is operated throughout the optimization period. Under Scenario 5, the optimal scheduling problem has 9194 constraints, 2222 variables (including 125 binary variables). The integrality tolerance is 1e-05.

Fig. 5.4(a) shows the dispatch values of the DGs under Scenario 2. The charge and discharge profiles of the BESS under Scenario 2 are shown in Fig. 5.4(b). The electricity purchased by the MG from the main utility grid under Scenario 2 is shown in Fig. 5.4(c). As evidenced by Table 5.3, the introduction of pump scheduling under Scenario 2 obviates the need to import uncontracted capacity from the main utility grid. It is observed from Fig. 5.4(a) that DG 1, DG 2 and DG 3 are operated during the peak load demand hours (hours 0-10 and 20-24) under Scenario 2. From Fig. 5.4(c), it is observed that the maximum electricity imported from the main utility grid does not exceed the contracted capacity of 0.7MW. As seen in Fig. 5.4(b), the BESS usage under Scenario 2 is lower when compared with

FIGURE 5.3: Scenario 1 - (a) Dispatch values of DG 1, DG 2 and DG 3 (b) BESS charge and discharge profiles (c) P_{eb}

Scenario 1. The EMS imported uncontracted capacity during the first three hours of the optimization period under Scenario 1 to meet the high MG load demand. As such, the EMS continued importing uncontracted capacity from the main utility grid during the low load demand hours in the optimization period under Scenario 1. Owing to the elimination of the uncontracted capacity under Scenario 2, it is observed from Fig. 5.4(a) that DG 2 is operated throughout the optimization period. Furthermore, as observed from Table 5.1, the pump scheduling introduced under Scenario 2 ensures that only one pump is scheduled for operation at a time to avoid the import of uncontracted capacity from the main utility grid. From Table 5.1, it is observed that Main Pumps 1 and 3 are scheduled for operation during the first four hours and the last four hours of the optimization period respectively under Scenario 2. From Fig. 5.4(a), it is observed that all the three DGs are scheduled for operation during these hours, thereby ensuring sufficient running capacity in the MG to accommodate the load demand from the main pumps.

Fig. 5.5(a) shows the dispatch values of the DGs under Scenario 3. The charge and discharge profiles of the BESS under Scenario 3 are shown in Fig. 5.5(b). The electricity purchased by the MG from the main utility grid under Scenario 3 is shown in Fig. 5.5(c). As observed in Tables 5.1 and 5.2, the introduction of the auxiliary pumps reduces the usage of the main pumps by one hour under Scenario 3 when compared with Scenario 2. Consequently, in Table 5.3, a small reduction (\$53) in the total cost is observed under Scenario 3 when compared with Scenario 2. Furthermore, it is observed from Fig. 5.5 that the schedules of the main pumps,

FIGURE 5.4: Scenario 2 - (a) Dispatch values of DG 1, DG 2 and DG 3 (b) BESS charge and discharge profiles (c) P_{eb}

the BESS, the DGs and the purchase of electricity from the main utility grid under Scenario 3 are similar to Scenario 2.

FIGURE 5.5: Scenario 3 - (a) Dispatch values of DG 1, DG 2 and DG 3 (b) BESS charge and discharge profiles (c) P_{eb}

Fig. 5.6(a) shows the dispatch values of the DGs under Scenario 4. The charge and discharge profiles of the BESS under Scenario 4 are shown in Fig. 5.6(b). The electricity purchased by the MG from the main utility grid under Scenario 4 is shown in Fig. 5.6(c). From Table 5.3, it is observed that the introduction of the ILs under Scenario 4 reduces the total cost by \$6,949 when compared with Scenario 3. It is clear from Fig. 5.7 that the ILs are used primarily during the first three hours and the last five hours of the optimization period under Scenario 4 when the load demand is high. From Fig. 5.6(a), it is observed that the usage of the expensive DG 3 is less under Scenario 4 when compared with Scenarios 1-3.

From Fig. 5.6(a), it is observed that the EMS keeps DG 3 turned off during the first three hours of the optimization period under Scenario 4. Subsequently, DG 3 is switched on during hour 4 since the total permitted curtailment for each IL is capped at 2MWh per day. From Fig. 5.6(c), it is seen that the electricity imported from the main utility grid is used to compensate for any shortfalls in the local MG generation as and when required without exceeding the contracted capacity under Scenario 4. From Table 5.1, it is observed that the EMS operates the main pumps mainly during the valley periods in the load profile under Scenario 4.

FIGURE 5.6: Scenario 4 - (a) Dispatch values of DG 1, DG 2 and DG 3 (b) BESS charge and discharge profiles (c) P_{eb}

FIGURE 5.7: Curtailment of ILs under Scenario 4

Fig. 5.8(a) shows the dispatch values of the DGs under Scenario 5. The charge and discharge profiles of the BESS under Scenario 5 are shown in Fig. 5.8(b). The electricity purchased by the MG from the main utility grid under Scenario 5 is shown in Fig. 5.8(c). The profiles shown in Figs. 5.8(a) - (c) are similar to the profiles in Figs. 5.6(a) - (c). From Table 5.3, a marginal decrease in the total cost is observed under Scenario 5 when compared with Scenario 4 due to the introduction of the auxiliary pumps. From Table 5.3, it is observed that Scenario 5 is the best scenario, wherein the total cost is 33.99% lower when compared with

that of Scenario 1 which is the worst scenario. From Table 5.1, it is observed that the main pumps are not operated during hour 5 under Scenario 5 unlike Scenario 4. Consequently, from Fig. 5.8(b), it is observed that there is no import of electric power from the main utility grid during hour 5 under Scenario 5. Furthermore, from Fig. 5.9, it is observed that there is no IL curtailment during hour 5 under Scenario 5.

FIGURE 5.8: Scenario 5 - (a) Dispatch values of DG 1, DG 2 and DG 3 (b) BESS charge and discharge profiles (c) P_{eb}

FIGURE 5.9: Curtailment of ILs under Scenario 5

The convergence of the 2-stage EMS architecture described in Section 5.2.3 is illustrated in Fig. 5.10. From Fig. 5.10, it is observed that Scenario 3 takes the largest number of iterations to converge among all the simulated scenarios. From Fig. 5.10, it is observed that the total operating cost approaches the final value after three iterations under all the five scenarios. Furthermore, it is observed that the trajectories of the total operating cost and total power loss are similar. It is also noteworthy that the sale of electricity to the main utility grid was not observed under any of the simulated scenarios. A brief sensitivity analysis of the α parameter under Scenario 5 is presented in Fig. 5.11. The number of iterations reduces to 5 when α is increased to 0.045. The number of iterations for convergence increases

to 7 when α is reduced to 0.01. It is clear that the value of α influences the number of iterations required for convergence. As mentioned earlier in this chapter, the value of α needs to be carefully selected through a trial and error process. The convergence of the unit commitment solutions of DG 2 and DG 3 under Scenario 5 are shown in Figs. 5.12 and 5.13 respectively. The output of DG 1 remains at 3 MW throughout the optimization period for all the 6 iterations under Scenario 5.

FIGURE 5.10: Evolution of (a) Total operating cost and (b) Total power loss over 24 hours

FIGURE 5.11: Sensitivity analysis of α parameter

FIGURE 5.12: Convergence of the unit commitment results of DG 2

FIGURE 5.13: Convergence of the unit commitment results of DG 3

5.3.2 Case Study 2 - Optimal Scheduling of a Modified IEEE 57-bus System

The standard MATPOWER case file for the IEEE 57-bus system is modified and used as an exemplar MG for the purpose of this case study [114]. The optimal scheduling of this 57-bus MG is performed under Scenario 5 in this case study. The base value of the 57-bus MG is set to 7000kVA. The line reactance values for the 57-bus MG are obtained by multiplying the line reactance p.u values provided in the original MATPOWER IEEE 57-bus case file by 0.5 respectively. In the 57-bus MG used in this case study, the three DGs are connected to buses 1, 8 and 9 respectively. The wind power plants are connected to buses 2 and 12 respectively. The BESSs are also connected to buses 2 and 12 respectively. The solar PV power plant is connected to bus 3. The PCC with the main utility grid is bus 6. All the

main pumps are connected to bus 2 while the auxiliary pumps are connected to bus 1. The aggregate IL is distributed among the load buses in the same proportion as the nominal load demand

5.3.2.1 System Initialization

In this case study, the main pumps and the auxiliary pumps are initialized to be switched off prior to the commencement of the optimization period. Furthermore, the initial SOC of the two BESSs in the 57-bus MG are set to 0.6 and 0.5 respectively. Finally, all the DGs in the MG are initialized to be switched off prior to the start of the optimization period in this case study.

In this case study, Scenario 5 is simulated under the assumption that accurate point forecasts for the MG load consumption (excluding the pump loads), electricity prices and RES generation are available. Figs. 5.14 shows the point forecasts for the MG load consumption (excluding the pump loads) in this case study. Fig. 5.2(b) shows the point forecasts for the electrical power generation from the solar PV plant and the first wind power plant. The point forecast for the electrical power generation from the second wind power plant is shown in Fig. 5.14.

FIGURE 5.14: Point forecasts of the MG load demand and wind power plant generation for Case Study 2

5.3.2.2 Optimal Scheduling Results

Fig. 5.15(a) shows the dispatch values of the DGs in Case Study 2. The charge and discharge profiles of the BESS in Case Study 2 are shown in Fig. 5.15 (b). The electricity purchased by the MG from the main utility grid under Scenario 5 in Case Study 2 is shown in Fig. 5.8 (c). In Case Study 2, the main pumps are operated as

follows under Scenario 5: Main Pump 1 during hours 16-18; Main Pump 2 during hour 19 and Main Pump 3 during hours 12-15. The auxiliary pumps are operated as follows under Scenario 5 in this case study: Auxiliary Pump 1 during hours 15, 17 and 18; Auxiliary Pump 2 during hours 11 and 15; Auxiliary Pump 3 during hour 15 and Auxiliary Pump 4 during hour 11.

The scheduling results of Case Study 2 are in line with those of Case Study 1. The operation of the pumps happens during the valley periods in the MG load consumption profile which generally coincides with the late night hours. For example, one main pump and three auxiliary pumps are operated during hour 15 when the MG load demand is the lowest. From Fig. 5.15(a), it is observed that the operation of DG 3 is avoided due to the higher availability of electric power from the RESs in Case Study 2. Furthermore, it is also observed that DGs 1 and 2 are operated near their full capacities throughout the optimization period in Case Study 2. From Fig. 5.16, it is observed that the utilization of the ILs happens during the hours of peak load demand in Case Study 2. The EMS also resorts to electricity imports from the main utility grid during these hours. However, the imports are maintained below the contracted capacity threshold of 0.8MW. From Fig. 5.15(b), it is observed that the discharging of the BESSs happens during the hours of peak load demand while the charging of the BESSs takes place during the valley periods in the MG load consumption profile. In Case Study 2, the total MG operational cost was \$15842.79 while the computational time taken was 154.59s. The lower cost in this case study can be attributed to the higher contribution from the RESs.

The convergence of the 2-stage EMS scheduling algorithm is illustrated in Fig. 5.17. From Fig. 5.17, it is observed that the EMS takes more iterations to converge in Case Study 2 when compared with all the scenarios in Case Study 1 except Scenario 3. The sale of electricity to the main utility grid was not observed in Case Study 2 under Scenario 5.

The potential of the load management strategies used in this chapter such as pump scheduling and the usage of the ILs in reducing the total electricity cost of the MG was clearly established in Case Study 1. It was assumed that the main pumps operate during the first three hours of the optimization period to pump out the water in the least possible time. Even if this assumption was not strictly true, the load management strategies presented in this chapter such as the PSO and the

FIGURE 5.15: Optimal scheduling of the modified IEEE 57-bus system in Case Study 2 - (a) Dispatch values of DG 1, DG 2 and DG 3 (b) Charge and discharge profiles of BESSs (c) P_{eb}

FIGURE 5.16: Curtailment of ILs in Case Study 2

FIGURE 5.17: Evolution of (a) Total operating cost and (b) Total power loss over 24 hours in Case Study 2

deployment of the ILs would still ensure the least possible operating cost for the MG without violating any operational constraints.

The MLD approach used to model the MG components results in a state-space

representation of the system as shown in (2.39). As such, the initial states of the system provide a snapshot of the MG prior to the start of the optimization period. The initial states of the system need to be determined carefully without violating any operational constraints. This means that the initial operating point of the MG must be a feasible operating point. Furthermore, the tractability of the optimization problem should not be affected. The initial states of the MGs in this chapter were determined while respecting these requirements. However, the selection of a different set of initial system states would result in a different evolution of the system according to (2.39) and (2.40). The scheduling results thereby obtained would also differ from the scheduling results presented in this chapter.

5.4 Summary

The component models developed in Chapter 2 of this thesis were used to develop optimal scheduling models for two exemplar MGs. The MGs considered in this chapter comprised DGs, BESSs, pump loads and ILs. A 2-stage EMS was proposed in this chapter for optimally scheduling the operations of the MGs. An iterative procedure was used in the 2-stage EMS for integrating the UC and OPF problems, thereby scheduling the MGs while satisfying their respective network constraints. The 2-stage EMS adopted efficient load management strategies such as PSO and IL deployment to reduce the total electricity cost incurred by the MG operator. Five illustrative operational scenarios were used to demonstrate the efficacy of the EMS on a modified IEEE 30-bus network MG. From the optimal schedules of the MG under the five scenarios, it was observed that significant uncontracted capacity charges were incurred by the MG operator when efficient load management strategies were not included in the EMS framework. Furthermore, it was also observed that including the optimal pump scheduling in the EMS framework led to a significant reduction in the total electricity cost through the elimination (reduction) of uncontracted capacity. Finally, the optimal scheduling results under the five scenarios also demonstrated the impacts of including the auxiliary pumps and the ILs in the EMS framework. While the curtailment of the ILs led to significant cost savings for the MG operator, the usage of the auxiliary pumps only had a marginal impact on the total electricity cost. The scalability and efficacy of the EMS were

also demonstrated on an exemplar 57-bus MG. The results of the optimal scheduling problem solved for the 57-bus MG served to validate the results obtained for the 30-bus MG while also adequately demonstrating the scalability of the EMS architecture.

TABLE 5.1: Schedules of all the main pumps under Scenarios 1-5. The sequence of 0s and 1s represents the ON/OFF status of the respective pump during hours 1-24

Scenario	Main Pump 1	Main Pump 2	Main Pump 3
1	[1,1,1,0,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,0,0,0,0]	[1,1,1,0,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,0,0,0,0]	[1,1,1,0,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,0,0,0,0]
2	[0,0,0,0,0,0,0,0,0,1,0,0, 0,0,0,0,0,0,0,0,0,0]	[1,1,1,1,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,0,0,0,0]	[0,0,0,0,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,0,1,1,1]
3	[0,0,0,0,0,0,0,0,0,0,1,0,0, 0,0,0,0,0,0,0,0,0,0]	[0,0,0,0,0,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,0,0,1,1,1]	[1,1,1,0,0,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,0,0,0,0]
4	[0,0,0,0,0,0,0,0,1,1,0,0,0, 0,0,0,0,0,0,0,0,0,0]	[0,0,0,0,0,0,0,0,0,0,0,0,0, 0,1,1,1,1,1,0,0,0,0,0]	[0,0,0,1,1,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,0,0,0,0]
5	[0,0,0,0,1,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,0,0,0,0]	[0,0,0,0,0,0,0,0,0,0,0,0,0, 0,1,1,1,1,1,0,0,0,0,0]	[0,0,0,0,0,0,0,0,1,1,0,0,0, 0,0,0,0,0,0,0,0,0,0]

TABLE 5.2: Schedules of all the auxiliary pumps under Scenarios 3 and 5. The sequence of 0s and 1s represents the ON/OFF status of the respective pump during hours 1-24

Scenario	Aux. Pump 1	Aux. Pump 2	Aux. Pump 3	Aux. Pump 4
3	[0,0,0,1,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,0,0,0,0,0]	[0,0,0,1,0,0,0,0,1,0,0,0, 0,0,0,0,0,0,0,0,0,0,0]	[0,0,0,0,0,0,0,0,0,0,0,0, 0,0,0,0,1,0,0,0,0,0,0]	[0,0,0,0,0,0,0,0,0,0,1,0,0,0, 0,0,0,1,0,1,0,0,0,0,0]
5	[0,0,0,0,1,0,0,0,0,0,0,1, 0,0,0,0,0,1,0,0,0,0,0]	[0,0,0,0,0,0,0,0,0,0,0,1, 0,0,0,0,0,0,1,0,0,0,0]	[0,0,0,0,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,1,0,0,0,0]	[0,0,0,0,0,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,1,0,0,0,0]

TABLE 5.3: Cost breakdown and computational times for Scenarios 1-5

Scenario #	Uncontracted Capacity Cost (\$)	Interruptible Load Cost (\$)	Total Cost (\$)	Percentage Reduction in Total Cost	Computational Time (s)
1	11,991.50	-	34,710.10	-	38.11
2	0	-	29,997.80	13.58%	60.59
3	0	-	29,945.11	13.73%	136.04
4	0	864.21	22,995.63	33.75%	60.81
5	0	861.90	22,911.79	33.99%	108.53

Chapter 6

Optimal Scheduling of Multi-Energy Systems with Flexible Electrical and Thermal Loads

6.1 Introduction

Industrial parks such as Singapore's Jurong Island oftentimes comprise electrical and thermal generators and loads, thereby making them multi-energy systems. Apart from the aforementioned interactions between the different energy streams in multi-energy systems, the increasingly heterogeneous nature of the energy generation makes the optimal management of multi-energy systems a non-trivial problem. However, a true estimate of the energy efficiency gains which can be accrued through the optimal management of multi-energy systems requires a comprehensive model of the energy generation and supply systems which account for the interactions between the various energy streams constituting the multi-energy system. As an initial step towards realizing such a model, this chapter focuses on the optimal scheduling of the generators and loads which constitute an exemplar multi-energy system.

A detailed optimal scheduling model of an exemplar multi-energy system is developed in this chapter using the component models developed in Chapter 2. This

chapter subsequently examines the optimal coordinated operation of CCPPs, boilers, RESs, BESS, TESS, ILs and flexible electrical and thermal loads to meet the thermal and electrical load demands in the exemplar multi-energy system. Furthermore, a multi-energy load management scheme is proposed including a practical industrial pump scheduling problem. Apart from optimizing the pump schedules, the proposed load management scheme also utilizes the flexibility offered by system components such as the ILs and the flexible thermal load. The efficacy of the proposed optimal scheduling problem formulation is demonstrated using illustrative numerical case studies.

The remainder of this chapter is organized as follows: The configuration of the multi-energy system along with the parameter values of its constituent components is provided in Section 6.2. The optimal scheduling problem for the exemplar multi-energy system considered in this chapter including all the relevant constraints is formulated in Section 6.3. Section 6.4 presents the results of the numerical case studies performed to demonstrate the efficacy and the utility of the optimization model developed in this chapter. Finally, some concluding remarks are presented in Section 6.5.

6.2 System Model

An overview of the exemplar multi-energy system considered in this chapter is shown in Fig. 6.1. As shown in Fig. 6.1, the CCPPs act as bridges between the electrical and the thermal energy streams in the multi-energy system. The RESs produce only electrical energy while the boilers produce only thermal energy. The BESS and TESS are capable of producing and storing electrical and thermal energy respectively. Apart from this, as shown in Fig. 6.1, the multi-energy system also contains different types of loads which only consume energy. The multi-energy system considered in this chapter comprises 2 CCPPs (each comprising 1 GT and 1 ST), 2 boilers, a BESS, 2 wind power plants (RESs), 2 TESSs, flexible industrial pump loads, a lumped flexible thermal load and 3 ILs. The multi-energy system is also empowered to exchange (buy/sell) power with the main utility grid. There is also an option to purchase thermal energy from external producers to fulfill the thermal load demand. The scheduling models of the CCPPs, the boilers, the BESS,

the TESSs, the flexible industrial pump loads, the flexible thermal load and the ILs were provided in Chapter 2 of this thesis.

FIGURE 6.1: Overview of an exemplar multi-energy system

The parameters of the BESS used in this chapter are as follows: $N = 6,000\text{h}$, $P_{bc,\max} = 7,386.645\text{kWh}$, $P_{bd,\max} = 7,615.095\text{kWh}$, $\eta_c = \eta_d = 0.97$, $P_{1C} = 3.73\text{MW} \cdot 15 = 55.965\text{MW}$, $SOC_{\min} = 0.2$ and $SOC_{\max} = 0.8$.

To the best of the author's knowledge, a BESS with 30MW power capacity is not available as a single commercial system for ready deployment. However, BESSs with 2MW power capacity and 3.7MWh energy capacity are available in the market [116]. With the help of series-parallel combinations of such BESSs, a multi-modular BESS with 30MW capacity can be realized. Similar systems can be found installed at several locations [117]. Based on recent quotations obtained for such grid scale BESSs, the cost of the BESS used in this chapter is estimated to be \$450/kWh.

The multi-energy system considered in this chapter includes a total of 7 pump loads - 3 main pumps and 4 auxiliary pumps. The parameters of the pump loads considered in this chapter are as follows: Water flow rate = 72,000 m³/h and $w_{SU,\max}^m = 1$ for all the main pumps; Water flow rate = 3,600 m³/h and $w_{SU,\max}^m = 10$ for all the auxiliary pumps and $V_d = 600,000 \text{ m}^3$. In this chapter, energy utilization rate = 0.06kWh/m³ for all the main pumps and energy utilization rate = 0.09kWh/m³ for all the auxiliary pumps.

Furthermore, the technical parameters of the CCPPs and the boilers included in the exemplar multi-energy system considered in this chapter are provided in Appendix

A of this thesis. The parameters of the TESS used in this chapter were provided in Chapter 2 of this thesis.

The quantum of IL h curtailed during hour k is constrained as follows:

$$0 \leq P_{\text{EIL},k}^h \leq 2.5\text{MWh}, \forall k \in \mathcal{K}, \forall h \in \{\text{IL1}, \text{IL2}, \text{IL3}\} \quad (6.1)$$

$$\sum_{h \in \{\text{IL1}, \text{IL2}, \text{IL3}\}} P_{\text{EIL},k}^h \leq 0.05D_{\text{e},k}, \forall k \in \mathcal{K} \quad (6.2)$$

$$\sum_{k \in \mathcal{K}} P_{\text{EIL},k}^h \leq 10\text{MWh}, \forall h \in \{\text{IL 1}, \text{IL 2}, \text{IL 3}\} \quad (6.3)$$

where represents the .

6.3 Optimal Multi-Energy Scheduling Problem Formulation

This section describes the formulation of the optimal multi-energy scheduling problem solved in this chapter. Optimal schedules are generated for all the components which constitute the exemplar multi-energy system as described in Section 6.2. The optimal, day-ahead multi-energy scheduling problem (hereinafter referred to as the ‘optimal scheduling problem’ throughout this chapter) is formulated to satisfy all the electrical and thermal loads in the system while respecting the various technical and operational constraints associated with the multi-energy system components as described in Chapter 2. Furthermore, the optimal scheduling problem is also subject to several other constraints which are outlined below. It is assumed that accurate point forecasts for the thermal load demand, electrical load demand, RES generation and energy market prices are available. These forecasts are provided as inputs to the various scenario-based optimal scheduling problems solved in this chapter. The following paragraphs formulate the terms of the objective function which were not formulated in Chapter 2.

6.3.0.1 Reserve Constraints

The spinning reserve constraints (electrical) for the exemplar multi-energy system considered in this chapter are formulated as shown below:

$$(50 - P_{\text{eb},k}) + \sum_{f \in \{GT, ST\}} SR_k^f x_{\text{disp},k}^f \geq SR_k, \quad \forall k \in \mathcal{K} \quad (6.4)$$

$$SR_k^f x_{\text{disp},k}^f \leq 10MSR^f, \quad \forall k \in \mathcal{K}, \forall f \in \{GT, ST\} \quad (6.5)$$

$$SR_k^f x_{\text{disp},k}^f + P_{\text{e},k}^f x_{\text{disp},k}^f \leq P_{\text{e},\text{max}}^f, \quad \forall k \in \mathcal{K}, \forall f \in \{GT, ST\} \quad (6.6)$$

C_{Fuel} represents the cost incurred by the system operator due to the consumption of natural gas by the GTs in the system. The fuel cost is formulated as a quadratic function of the electrical power generated by the GT.

$$C_{\text{Fuel}} = \sum_{\substack{k \in \mathcal{K} \\ f \in GT}} x_{\text{disp},k}^f \left(c_2^f \left(P_{\text{e},k}^f \right)^2 + c_1^f P_{\text{e},k}^f + c_0^f \right) \quad (6.7)$$

C_{SU} evaluates the cost incurred during the start-up of all the GTs, STs and boilers in the system. Variable costs are used for the hot, warm and cold start-up methods as shown below.

$$C_{\text{SU}} = \sum_{\substack{k \in \mathcal{K} \\ f \in \{GT, ST, BR\}}} \left(C_{\text{cold}}^f \left(w_{\text{synch},k}^{\text{cold},f} + w_{\text{soak},k}^{\text{cold},f} \right) + C_{\text{warm}}^f \left(w_{\text{synch},k}^{\text{warm},f} + w_{\text{soak},k}^{\text{warm},f} \right) + C_{\text{hot}}^f w_{\text{soak},k}^{\text{hot},f} \right) \quad (6.8)$$

C_{SD} evaluates the cost incurred during the shutdown process of all the GTs, STs and boilers in the system. C_{SD} is calculated as follows:

$$C_{\text{SD}} = \sum_{\substack{k \in \mathcal{K} \\ f \in \{GT, ST, BR\}}} C_{\text{sd}}^f w_{\text{desyn},k}^f \quad (6.9)$$

C_{UCC} is the uncontracted capacity cost. The uncontracted capacity is calculated as follows:

$$P_{\text{UC}} = \max\{0, \max_{1 \leq k \leq 24} \{P_{\text{eb},k} - P_{\text{CC}}\}\} \quad (6.10)$$

Equation (6.10) is linearized as follows:

$$P_{UC} \geq P_{eb,k} - P_{CC}, \quad \forall k \in \mathcal{K} \quad (6.11)$$

$$P_{UC} \geq 0 \quad (6.12)$$

$$\text{and } C_{UCC} = U_{CC}P_{UC} \quad (6.13)$$

where $U_{CC} = \$12,860/\text{MW}/\text{month}$ and $P_{CC} = 25 \text{ MW}$.

C_{Boiler} evaluates the boiler fuel cost. It is assumed that all the boilers modelled in this chapter use natural gas as fuel to produce thermal energy. The price of natural gas is considered to be $\$3.81/\text{mcf}$ in this chapter.

$$C_{\text{Boiler}} = \sum_{\substack{k \in \mathcal{K} \\ f \in BR}} 3.81 w_{br,k}^f \quad (6.14)$$

C_{Grid} accounts for the cost incurred due to the purchase of electrical and thermal power from external sources such as the utility grid. C_{Grid} also includes the revenue earned from the sale of electrical power to the main utility grid. C_{Grid} is calculated as follows:

$$C_{\text{Grid}} = \sum_{k \in \mathcal{K}} (C_{p,k}P_{eb,k} - C_{s,k}P_{es,k} + C_{\text{heat}}P_{hb,k}) \quad (6.15)$$

Finally, $C_{\text{heat}} = \$100/\text{MW}$ is the price at which thermal power is purchased from external sources.

The overall optimal scheduling problem for the multi-energy system described in this paper is summarized as follows:

$$\begin{aligned}
 \min_{u,x,w} J &= C_{\text{Fuel}} + C_{\text{BESS}} + C_{\text{SU}} + C_{\text{SD}} + C_{\text{UCC}} + C_{\text{Boiler}} + C_{\text{Grid}} + C_{\text{EIL}} \quad (6.16) \\
 &\text{subject to Equations (2.4), (2.8), (2.9), (2.23), (2.25), (2.27), (2.28),} \\
 &\quad (2.35) - (2.38), (2.39), (2.40), (6.1) - (6.3), (6.4) - (6.6), (6.11), (6.12) \\
 P_{\text{De},k} + \sum_{m \in \mathcal{M}} P_k^m - \sum_{h \in \mathcal{H}} P_{\text{EIL},k}^h &\leq \sum_{f \in \{GT, ST\}} \left(P_{e,k}^f + P_{\text{soak},k}^f \right) + P_{\text{eb},k} - P_{\text{es},k} \\
 &\quad + P_{\text{bd},k} - P_{\text{bc},k} + P_{\text{RES},k} \quad (6.17) \\
 P_{\text{Dh},k} + \sum_{f \in ST} h_k^f &\leq \sum_{f \in \{GT, BR\}} \left(P_{h,k}^f \right) + P_{\text{hb},k} - Q_{\text{in},k}^1 - Q_{\text{in},k}^2 + Q_{\text{out},k}^1 + Q_{\text{out},k}^2 \quad (6.18) \\
 u_{\min} &\leq u(k) \leq u_{\max} \quad (6.19) \\
 x_{\min} &\leq x(k) \leq x_{\max} \quad (6.20) \\
 w_{\min} &\leq w(k) \leq w_{\max} \quad (6.21) \\
 0 &\leq P_{\text{eb},k} \leq 50, \quad 0 \leq P_{\text{eb},k} \leq 50, \quad 0 \leq P_{\text{hb},k} \leq 80 \quad (6.22)
 \end{aligned}$$

Equations (6.17) and (6.18) represent the electrical and thermal power balance constraints respectively. The overall optimization problem turns out to be an MIQP problem which is formulated in MATLAB using YALMIP [108] and solved using CPLEX.

6.4 Case Studies

To demonstrate the efficacy of the optimal scheduling problem formulated earlier in this chapter, the following scenarios are simulated:

1. Load scheduling is not performed. The water is pumped out in the fastest possible time using only the main pumps. The auxiliary pumps, the flexible thermal load and the ILs are not included in the optimal scheduling problem formulation solved under this scenario while the schedules of the main pumps are fixed. The entire electrical and thermal load demands are assumed to be made up of critical loads.
2. Load scheduling is performed to demonstrate the flexibility offered by the PSO scheme. All the main pumps and the auxiliary pumps participate in the

PSO scheme. The flexible thermal load and the ILs are not included in the optimal scheduling problem formulation solved under this scenario.

3. In addition to the PSO scheme, this scenario considers the presence of the ILs which relaxes the optimal scheduling problem and provides further flexibility to the system operator. The flexible thermal load is not included in the optimal scheduling problem formulation under this scenario.
4. In addition to the PSO scheme and the ILs, the flexible thermal load is included in the optimal scheduling problem formulation solved under this scenario. As demonstrated later in this chapter, this scenario offers the maximum flexibility to the system operator, thereby resulting in the lowest energy cost among all the simulated scenarios.

6.4.1 System Initialization

Initially, it is assumed that GT1, GT2, ST1, ST2, ST3, Boiler 1 and Boiler 2 are already in the dispatch phase. Furthermore, $SOC_1 = 0.6$ and $H_1^1 = H_1^2 = 171.643\text{MW}$. All the main and auxiliary pumps are assumed to be in the OFF position prior to the start of the optimization horizon. The initial system states have been carefully chosen to ensure a feasible operating point for the system prior to the start of the optimization horizon. It is also appropriate to mention here that the initial states of the system have a significant bearing on the final system trajectory and the scheduling results obtained. However, the system initialization does not significantly alter the general trends observed in the results presented later in this chapter.

6.4.2 Results and Discussions

The inputs to the optimal scheduling problem are shown in Fig. 6.2(a) - Fig. 6.2(d). The point forecasts for the electrical and the thermal load demands are shown in Figs. 6.2(a) and 6.2(b) respectively. The point forecasts for the electricity prices (obtained from [110]) and the RES generation are shown in Figs. 6.2(c) and 6.2(d) respectively. The results of the optimal scheduling problem solved under all the four scenarios are presented in Fig. 6.3 - Fig. 6.6 and Tables 6.1 and 6.2.

Figs. 6.3(a), 6.3(b) and 6.4(a) indicate that GT1, GT2 and ST3 service the electrical base load demand under all the four scenarios. As such, they operate at full capacity throughout the optimization horizon under all the four scenarios. From Figs. 6.3(c) and 6.3(d), the effect of including the start-up/shutdown power trajectories in the scheduling models of the STs constituting the CCPPs can be clearly observed. From Fig. 6.3(c), it is observed that ST1 is unused between hours 10-18 under all the four scenarios due to the low electrical load demand during those hours. The pump schedules in Table 6.1 also show that the pumps are operated during hours 16-20 under Scenarios 2-4 to avoid uncontracted capacity costs. Fig. 6.4(d) indicates that the usage of the BESS follows a similar trend under Scenarios 1-4. In general, it is observed that the BESS charging takes place during the hours when the electrical load demand is low.

Under Scenario 1, the main pumps are operated during the first 3 hours of the optimization horizon. From Fig. 6.3(c), it is observed that the utilization of ST1 is higher during the first 4 hours under Scenario 1 when compared with that of the other scenarios. This is to cater to the additional electricity demand caused by the operation of the main pumps during these hours. From Fig. 6.6(d), it is observed that the dependence on imported thermal energy is the highest under Scenario 1, especially during the first 8 hours. This is due to the high utilization of the STs coinciding with the high thermal load demand during these hours. As observed in Fig. 6.5(a), imported electricity from the main utility grid is used to mitigate the shortfall in the electricity generated within the multi-energy system during the first few hours of the optimization horizon. This leads to the consumption of uncontracted capacity which entails a huge cost to the system operator. As observed in Fig. 6.4(d), the BESS utilization (in discharging mode) during the first 2 hours is also quite high under Scenario 1. This is to cope with the additional electricity demand during these hours.

Compared with Scenario 1, the PSO performed under Scenario 2 eliminates the uncontracted capacity cost, thereby leading to a reduction in the total energy cost of the system as shown in Table 6.2. As shown in Table 6.1, this cost reduction is achieved by shifting the usage of the pumps to the off-peak hours (hours 16-19) from the peak hours. Consequently, as observed from Figs. 6.4(d) and 6.3(b), there is a decrease in the usage of the BESS and ST1 respectively. The reduced usage of ST1 leads to a slight decrease in the requirement of imported thermal energy

during the first 8 hours as seen in Fig. 6.6(d). There is also a significant quantity of thermal energy imported during hours 21-23 under Scenario 1 and hours 23-24 under Scenario 2. This is to cater to the high thermal load demand experienced during these hours. From Figs. 6.6(a) and 6.6(b), it is observed that thermal energy is also drawn from the TESSs during these hours under Scenarios 1 and 2. From Figs. 6.4(b) and 6.4(c), it is seen that both Boiler 1 and Boiler 2 are also operated at full capacity during these hours under Scenarios 1 and 2. The BESS is also used in the discharging mode during hours 22-23 as seen in Fig. 6.4(d). From Fig. 6.3(c), it is observed that the utilization of ST1 is lower under Scenario 3 than that under Scenario 1 during hours 1-5 and lower than that under Scenario 2 during hours 3 and 5. This is mainly due to the utilization of the ILs as observed from Figs. 6.5(b) - 6.5(d). A similar phenomenon is also observed during hours 21-23 under Scenario 3. During hour 24, only IL1 is utilized under Scenario 3. This leads to an increased utilization of ST1 during hour 24. Furthermore, as seen from Fig. 6.4(d), the BESS also discharges during hours 21 and 22 under Scenario 3 to cope with the higher electrical load demand. Under Scenario 3, from Fig. 6.6(d), it is observed that thermal energy is imported during hour 23. Furthermore, from Figs. 6.6(b) and 6.6(c), it is observed that the TESSs supply thermal energy during hours 21-24 under Scenario 3 to cope with the higher thermal load demand.

Under Scenario 4, the purchase of expensive thermal energy from external producers is the least among the four scenarios as observed in Fig. 6.6(d). This can be largely attributed to the introduction of the flexible thermal load in the problem formulation under Scenario 4 which causes some of the thermal load demand during the peak load hours to be shifted to the off-peak hours as shown in Fig. 6.6(c). For instance, it is observed that the profile of P_{Dh} has distinct spikes during hours 16 and 18. This can be attributed to the shifting of the thermal load to these hours from the peak loading hours. Additionally, unlike the other scenarios, it is observed in Fig. 6.4(c) that the usage of Boiler 2 also rises during hours 16 and 18 under Scenario 4 to cater to the additional thermal load demand. Furthermore, from Fig. 6.4(b), it is observed that Boiler 1 is also operated at full capacity during the entire optimization horizon under Scenario 4. From Figs. 6.5(b) - 6.5(d), it is observed that the ILs are also mainly utilized between hours 2-6 and during hour 9 under Scenario 4 to relax the optimal scheduling problem and to compensate for any shortfall in the electricity production without resorting to uncontracted capacity consumption. The utilization of ST1 during hours 4-6 under Scenario 4

is the lowest among all the four scenarios due to the usage of the ILs during these hours. The combined effect of the ILs and the flexible thermal load causes the electrical and thermal load demands during the peak load (electrical and thermal) hours to reduce, thereby obviating the need to import uncontracted capacity and large quantities of thermal energy from external sources. Consequently, Scenario 4 has the lowest energy cost among all the simulated scenarios as seen in Table 6.2. Compared with Scenario 1 (the worst-case scenario), the energy cost under Scenario 4 is 18.6% lower. As the flexibility available to the system operator is progressively increased under Scenarios 2-4, the cost progressively declines. The greater flexibility allows the system operator to better manage the load demand using locally available generation while sparingly resorting to energy imports as and when necessary.

FIGURE 6.2: Point forecasts for: (a) P_{De} (b) P_{Dh}^0 (c) c_s and c_p and (d) RES generation

6.5 Conclusions

This chapter presented an optimal, day-ahead scheduling problem for an exemplar multi-energy system comprising CCPPs, boilers, RESs, BESS, TESSs, flexible thermal load, flexible pump loads and ILs. The multi-energy system model was constructed using the individual component models developed in Chapter 2 of this thesis. Furthermore, a multi-energy load management scheme was included in the optimal scheduling model. The multi-energy load management model took advantage of the flexibility offered by the PSO scheme, the flexible thermal load and the ILs to drive down the energy cost of the system. The efficacy and cost reduction

FIGURE 6.3: Electrical power dispatch values under Scenarios 1-4 of: (a) GT1 (b) GT2 (c) ST1 and (d) ST2. The legend for (a), (b), (c) and (d) is as follows: Scenario 1 - blue *, Scenario 2 - magenta +, Scenario 3 - black circle and Scenario 4 - red square

FIGURE 6.4: Profiles (under Scenarios 1-4) of: (a) Electrical power dispatch of ST3 (b) Fuel consumption of Boiler 1 (c) Fuel consumption of Boiler 2 and (d) BESS usage represented by $P_{bd} - P_{bc}$. The legend for (a), (b), (c) and (d) is as follows: Scenario 1 - blue *, Scenario 2 - magenta +, Scenario 3 - black circle and Scenario 4 - red square

potential of the optimal scheduling model was demonstrated using four illustrative simulation scenarios. The best-case scenario involving flexible electrical and thermal loads delivered an 18.6% cost reduction when compared with the worst-case scenario. The simulated scenarios were analyzed to demonstrate how the optimal scheduling model played a role in reducing the energy cost of the system.

FIGURE 6.5: Profiles (under Scenarios 1-4) of: (a) Electricity exchanged with the main grid represented by $P_{eb} - P_{es}$ (b) Usage of IL1 (c) Usage of IL2 and (d) Usage of IL3. The legend for (a) is as follows: Scenario 1 - blue *, Scenario 2 - magenta +, Scenario 3 - black circle and Scenario 4 - red square. The legend for (b), (c) and (d) is as follows: Scenario 3 - blue * and Scenario 4 - magenta +

FIGURE 6.6: Profiles (under Scenarios 1-4) of: (a) Usage of TESS 1 (b) Usage of TESS 2 (c) P_{Dh} and P_{Dh}^0 and (d) P_{hb} . The legend for (a), (b) and (d) is as follows: Scenario 1 - blue *, Scenario 2 - magenta +, Scenario 3 - black circle and Scenario 4 - red square. The legend for (c) is as follows: P_{Dh} - blue * and P_{Dh}^0 - magenta +

TABLE 6.1: Pump schedules under Scenarios 1-4. The sequence of 0s and 1s represents the ON/OFF status of the respective pump during hours 1-24

Pump No	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Main	111000000000	000000000000	000000000000	000000000000
Pump 1	000000000000	000111100000	000011100000	000001110000
Main	111000000000	000000000000	000000000000	000000000000
Pump 2	000000000000	000011000000	000011100000	000001100000
Main	111000000000	000000000000	000000000000	000000000000
Pump 3	000000000000	000011000000	000011000000	000001110000
Auxiliary	000000000000	000000000000	000000000000	000000000000
Pump 1	000000000000	000001000000	000001000000	000000100000
Auxiliary	000000000000	000000000000	000000000000	000000000000
Pump 2	000000000000	000011000000	000011000000	000000100000
Auxiliary	000000000000	000000000000	000000000000	000000000000
Pump 3	000000000000	000011000000	000011000000	000001100000
Auxiliary	000000000000	000000000000	000000000000	000000000000
Pump 4	000000000000	000011000000	000011000000	000001100000

TABLE 6.2: Cost comparison under Scenarios 1-4

Scenario	Uncontracted Capacity Cost (\$)	Total Cost (\$)	Percentage Reduction with respect to Scenario 1
1	8,558.18	298,822.8	-
2	0	285,881.83	4.33
3	0	282,769.35	5.37
4	0	243,183.54	18.62

Chapter 7

Conclusions and Recommendations for Future Work

7.1 Conclusions

This thesis formulated and solved the optimal scheduling problems of various heterogeneous energy systems comprising conventional generation sources, RESs, energy storage systems, flexible loads and ILs. A component-wise modelling approach was used to construct the models of the energy systems considered in this thesis. This thesis highlighted the importance of well-designed EMSs in the optimal and secure operation of various energy systems. The importance of load management techniques in reducing the overall cost of operating the energy system was especially highlighted. The importance of coordinating the operations of the various energy system components to meet the load demand was demonstrated. Importantly, this thesis developed a framework for studying the operation of an exemplar multi-energy system with electrical and thermal energy streams. The research work performed in this thesis has the potential to open up several vistas for future research which are also highlighted in the second part of this chapter. A chapter-wise summary of the highlights of this thesis is provided in the following paragraphs.

Chapter 1 provided a broad literature review relevant to the topics covered in this thesis. The literature review was then used to motivate the contributions of this

thesis. First principle scheduling models for all the energy system components in this thesis were developed in Chapter 2. The component-wise modelling approach was used throughout the thesis to develop the scheduling models of the energy systems. The scheduling models of the GTs, the STs and the boilers included a detailed consideration of the hot, warm and cold start-up methods apart from a shutdown power trajectory. A brief introduction to the MLD modelling framework was provided in Chapter 2. The MLD framework was used to model the CCPP components, the boilers, the BESSs, the DGs and the TESSs. The exchange of electricity with the main grid was also modelled using the MLD framework. A detailed description of the application of the MLD framework in the modelling of thermal units was presented in Chapter 3. The logical statements used to model the behaviour of the thermal units in the MLD framework was also presented in Chapter 3. Subsequently, a self-scheduling problem for an exemplar thermal unit was formulated and solved. Thereafter, the optimal scheduling problem of a five-generator system was also formulated and solved to test the suitability of the MLD modelling approach for small to medium sized systems.

Chapter 4 described the design of an SEMS for optimizing the operations of a shipyard drydock. The SEMS was designed using data from a real shipyard in Singapore. The SEMS comprised three modules - LF, CCO and optimal scheduling. The inclusion of the ship arrival schedule as an input to the ANN used to generate the STLFS improved the accuracy of the STLF. The drydock MG in Chapter 4 comprised CGs, a BESS, an RES and flexible pump loads. The inclusion of a PSO model within the framework of the optimal scheduling problem eliminated the consumption of uncontracted capacity by the shipyard drydock, thereby leading to a significantly lower operating cost. The advantages of the PSO model and of deploying the ILs were demonstrated through suitable case studies. Among the five scenarios used as case studies in Chapter 4, the lowest operating cost was observed under the scenario wherein the PSO for the main and auxiliary pumps was used in conjunction with the ILs.

An exemplar industrial MG comprising DGs, BESSs, pump loads and ILs was modelled in Chapter 5 using the component models developed in Chapter 2. A two-stage iterative EMS architecture proposed in this chapter decoupled the optimal scheduling and the OPF problems. The optimal scheduling problem formulation in Chapter 5 included load management strategies such as PSO and the use of ILs.

The inclusion of an OPF problem in the EMS architecture helped in accounting for the network constraints and the losses in the MG. Five operational scenarios were simulated to test the efficacy of the optimal scheduling problem formulation. The results of the case studies showed the potential of the ILs in reducing the operating cost of the MG. The results of the case studies also indicated that the deployment of the auxiliary pumps only had a marginal impact on the operating cost of the MG owing to their lower efficiencies. Importantly, the PSO was observed to eliminate the usage of uncontracted capacity, thereby leading to a significant reduction in the operating cost of the system. The EMS architecture was tested on two exemplar MGs which were derived from a modified IEEE 30-bus system and a modified IEEE 57-bus system respectively.

Chapter 6 formulated and solved the optimal day-ahead scheduling problem for an exemplar multi-energy system comprising CCPPs, TESSs, BESSs, flexible thermal loads, ILs and the flexible pump loads described in Chapter 4. The individual component models developed in Chapter 2 were used to construct the system model in Chapter 6. A multi-energy load management scheme involving the flexible thermal loads, the pump loads and the ILs was proposed to be included as a part of the optimal scheduling problem formulation in Chapter 6. The combined flexibility offered by the pump loads, the ILs, the energy storage systems and the flexible thermal loads was utilized by the system operator to obtain the lowest operating cost for the multi-energy system. The coordination between the components of the multi-energy system to meet the electrical and the thermal load in the system was also analyzed. Four representative scenarios were simulated to demonstrate the effectiveness of the multi-energy load management model in reducing the operating cost of the system. The best-case scenario including the multi-energy load management scheme delivered an 18.6% reduction in the operating cost of the system over the worst-case scenario wherein load management schemes were not considered in the optimal scheduling problem formulation.

7.2 Recommendations for future research

The arrival of ships at the shipyard drydock considered in this thesis was not affected by factors such as the tide, weather and congestion at the main shipyard.

These factors may affect the ship arrival schedule at other drydocks. As such, subject to the availability of adequate data, the accuracy of the LF module embedded in the SEMS can be enhanced further by considering the impact of these factors on the ship arrival schedule. Moreover, the SEMS presented in this thesis focused on the optimal management of electricity within the drydock of a local shipyard. The SEMS was designed after carefully considering the operational requirements of the local shipyard. However, as highlighted in [23], many shipyards are actually multi-energy systems. As such, the SEMS formulation presented in this thesis can be adapted to jointly optimize the supply of electrical and thermal energy in the shipyard. In this context, CHP plants can be utilized to bridge the thermal and electrical energy streams.

The multi-energy scheduling problem formulated and solved in this thesis did not consider any electrical and thermal network constraints. This could potentially affect the feasibility of the multi-energy system schedule. Consequently, an interesting direction for future research is the inclusion of the electrical and thermal network constraints in the optimal multi-energy scheduling problem. This would truly facilitate a detailed study of the energy flows in the multi-energy system. Subsequently, the optimal routing of multiple energy streams to achieve economic and environmental benefits can also be realized. The J-Park simulator (<http://www.jparksimulator.com/>) is a next-generation tool for the design, analysis, optimization and operation of eco-industrial parks. The author proposes to leverage his connections with the Cambridge CARES project to study the performance of the optimal scheduling model in the J-Park simulator. This would enable the development of accurate load models which are relevant to the petrochemical industry. Furthermore, the J-Park simulator would also allow the study energy flows between various units in the industrial park. The optimal scheduling problem for multi-energy systems can be formulated as a multi-objective problem with appropriate weight factors for economic and environmental benefits. Furthermore, linear relationships were used to describe the thermal energy generated by the GTs and the thermal energy consumed by the STs constituting the CCPPs. Future work can examine more accurate non-linear or piecewise linear models for describing these relationships.

In this thesis, all the optimal scheduling problems were solved under the assumption that accurate point forecasts for the electrical load demand, thermal load demand,

renewable energy generation and energy market prices are available. If there are uncertainties in any of these forecasts, the optimal schedule generated may be suboptimal or even infeasible. Spinning reserves in the system can be optimally allocated among the different generators to manage the uncertainties to some extent. As such, an important direction for future research in the context of all the optimal scheduling problems presented in this thesis is the development of a scenario-based robust optimization framework in the EMS for handling all the uncertain forecasts. Some initial results of the author's work in this direction can be found in [118]. In [118], a robust optimization framework is proposed for a multi-microgrid systems to account for the uncertainties in the forecasts of the renewable energy generation, electricity market prices and load demand. Unlike other works in the literature, the framework in [118] preserves the nonanticipativity in reserve scheduling. The proposed robust optimization framework also includes a cooperative bidding-based trading scheme to facilitate the sharing of energy and reserves between the constituent MGs of the MMG system. The robust optimization framework proposed in [118] can also be extended to the multi-energy system presented in this thesis. Furthermore, the possibility of considering an industrial park as a multi-energy, multi-microgrid system can be explored using the cooperative bidding mechanism proposed in [118].

This thesis has not considered the recent proliferation of electric vehicles. An interesting direction for future research would be to perform complexity driven simulations to study the effects of electric vehicles on the results of the optimal scheduling problems solved in this thesis. In this context, multi-agent simulations using publicly available traffic pattern studies can be conducted to estimate the loading on the electrical power network due to the charging of electric vehicles. Software tools such as Netlogo or Artisoc can be used to conduct the multi-agent simulations. Some initial results related to such studies can be found in the author's recent collaborative work in [34]. While some links were established with the electrical power grid using the MATPOWER tool in [34], it would be interesting to study the effects of the multi-agent simulation on various aspects of power system operation such as optimal scheduling, power flow and congestion management.

Appendix A

Technical Parameters of GTs, STs and boilers

TABLE A.1: Technical Parameters of GTs, STs and boilers

	GT1	GT2	ST1	ST2	ST3	Boiler 1	Boiler 2
$P_{e,max}^f$ (MW)	42	32.2	25	25	55	NA	NA
$P_{soak,k}^f$ (MW)	8.4	6.4	3	3	10	NA	NA
$t_{synch}^{cold,f}$ (h)	0	0	2	2	2	NA	NA
$t_{synch}^{warm,f}$ (h)	0	0	1	1	1	NA	NA
$t_{synch}^{hot,f}$ (h)	0	0	0	0	0	NA	NA
$t_{soak}^{cold,f}$ (h)	3	3	3	3	3	3	3
$t_{soak}^{warm,f}$ (h)	2	2	2	2	2	2	2
$t_{soak}^{hot,f}$ (h)	1	1	1	1	1	1	1
t_{desyn}^f (h)	2	2	1	1	1	NA	NA
C_{cold}^f (\$)	1673	1189	0	0	900	964	1834
C_{warm}^f (\$)	1115	793	0	0	675	643	1223
C_{hot}^f (\$)	558	396	0	0	450	321	611
C_{sd}^f (\$)	1467	1048	440	440	440	390	964
$t_1^{cold,f}, t_{\alpha}^{cold,f}$ (h)	≥ 10	≥ 10	≥ 10	≥ 10	≥ 10	≥ 10	≥ 10
$t_1^{warm,f}, t_{\alpha}^{warm,f}$ (h)	[5,9]	[5,9]	[5,9]	[5,9]	[5,9]	[5,9]	[5,9]
$t_1^{hot,f}, t_{\alpha}^{hot,f}$ (h)	< 5	< 5	< 5	< 5	< 5	< 5	< 5
c_2^f (\$/MW ²)	0.016087	0.001534	0	0	0.002	NA	NA
c_1^f (\$/MW)	5.5818	7.1079	0	0	7.5247	NA	NA
c_0^f (\$)	463.023	509.78	0	0	468.825	NA	NA

NA - Not Applicable

Appendix B

Author's Vita

Ashok Krishnan was born in 1990 in Kochi, India. He received the Bachelor of Technology degree in Electrical and Electronics Engineering from Amrita Vishwa Vidyapeetham University, India, in 2012. From 2012 to 2013, he was a Projects Executive with Mytrah Energy India Limited, a leading Independent Power Producer. His research interests include power system scheduling, microgrids and multi-energy systems.

A selected list of the author's publications is provided below:

Journal Publications

1. **Ashok Krishnan**, Y. S. Foo Eddy, H. B. Gooi, M. Q. Wang, and P. H. Cheah, "Optimal Load Management in a Shipyard Drydock," in *IEEE Transactions on Industrial Informatics*. doi: 10.1109/TII.2018.2877703.
2. **Ashok Krishnan**, L. P. M. I. Sampath, Y. S. Foo Eddy, and H. B. Gooi, "Optimal Scheduling of a Microgrid Including Pump Scheduling and Network Constraints," in *Complexity*, vol. 2018, Article ID 9842025, 20 pages, 2018. doi: 10.1155/2018/9842025.
3. K. S. Chaudhari, N. K. Kandasamy, **Ashok Krishnan**, A. Ukil and H. B. Gooi, "Agent Based Aggregated Behavior Modelling For Electric Vehicle Charging Load," in *IEEE Transactions on Industrial Informatics*. doi: 10.1109/TII.2018.2823321.

4. Bhagyesh V. Patil, L. P. M. I. Sampath, **Ashok Krishnan**, Jan Maciejowski, K. V. Ling, and H. B. Gooi, "Experiments with hybrid Bernstein global optimization algorithm for the OPF problem in power systems," in *Engineering Optimization*. doi: 10.1080/0305215X.2018.1521399.
5. **Ashok Krishnan**, B. V. Patil, Y. S. Foo Eddy, and H. B. Gooi, "Optimal Scheduling of Multi-Energy Systems with Flexible Electrical and Thermal Loads," in *IEEE Systems Journal (Under review)*.
6. L. P. M. I. Sampath, **Ashok Krishnan**, Y. S. Foo Eddy, and H. B. Gooi, "Optimal Scheduling of Multi-Energy Systems with Flexible Loads and Network Constraints," in *IEEE Transactions on Smart Grid (Under review)*.

Conference Publications

1. **Ashok Krishnan**, B. V. Patil, H. B. Gooi and K. V. Ling, "Predictive control based framework for optimal scheduling of combined cycle gas turbines," *2016 American Control Conference (ACC)*, Boston, MA, 2016, pp. 6066-6072.
2. **Ashok Krishnan**, Foo Y.S. Eddy, Bhagyesh V. Patil, "Hybrid Model Predictive Control Framework for the Thermal Unit Commitment Problem including Start-up and Shutdown Power Trajectories," *IFAC-PapersOnLine*, Volume 50, Issue 1, pp. 9329-9335, 2017. 20th IFAC World Congress, Toulouse, France.
3. L. P. M. I. Sampath, **Ashok Krishnan**, K. Chaudhari, H. B. Gooi and A. Ukil, "A control architecture for optimal power sharing among interconnected microgrids," *2017 IEEE Power & Energy Society General Meeting*, Chicago, IL, 2017, pp. 1-5.
4. **Ashok Krishnan**, L. P. M. I. Sampath, Foo Y.S. Eddy, B. V. Patil, and H. B. Gooi, "Multi-Energy Scheduling Using a Hybrid Systems Approach," *2018 IFAC Conference on Analysis & Design of Hybrid Systems*, Oxford, UK, 2018.

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