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A Process Systems Approach on the Optimisation of Water and Power Networks using a Discrete-Time Framework

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UNIVERSITY OF THE
WITWATERSRAND,
JOHANNESBURG

A Process Systems Approach on the Optimisation of Water and Power Networks using a Discrete-Time Framework

by

David Kazengura

A dissertation submitted in fulfilment of the requirements for the degree

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Declaraction of Authorship

I declare that this dissertation is my own unaided work. It is being submitted for the Degree of Master of Science in Chemical Engineering to the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination to any other University.



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David Kazengura

02 day of September in the year 2025

Abstract

Rising water and energy demands due to the increasing global population and economies have necessitated solutions for sustainable management of water and power distribution networks. Drawing from the concept of the water-energy nexus, studies have integrated the operation of water and power distribution networks to increase efficiencies of the other. The inherent flexibility of power intensive operations in the water distribution network can improve power grid stability through demand-side management. Concomitantly, the water distribution network can take advantage of time-varying electricity prices offered by the power distribution network to reduce operating costs, as well as improve their energy efficiency through optimal scheduling. In this work, a discrete-time MINLP model is proposed to solve a short-term scheduling problem resulting from the integration of water and power distribution networks. The developed model ensures that detailed modelling of storage facilities in the integrated networks, as well as complete capture of the water-energy nexus between water and power distribution networks are achieved. An illustrative example is used to show the applicability of the model. Results showed a 2.88% increase in cost savings for the detailed modelling of the storage facilities in comparison to a black-box model, whereas the complete capture of the water-energy nexus led to an increase of 0.57% in the overall operational costs.

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Contents

Declaraction of Authorship **ii**

Abstract **iii**

Acknowledgements **iv**

Contents **v**

List of Figures **viii**

List of Tables **xi**

List of Abbreviations **xii**

Nomenclature **xiv**

1 Introduction **1**

1.1 Background 1

1.2 Motivation 4

1.3 Research Objectives 6

1.4 Problem Statement 7

1.5 Dissertation Structure 7

2 Literature Review **9**

2.1 Introduction 9

2.2 Process Integration 9

2.2.1 Definition and Background 9

2.2.2 Graphical-Based Approaches 10
2.2.3 Mathematical Optimisation-Based Approaches 11
2.3 Mathematical Optimisation 12
2.3.1 Definition 12
2.3.2 Classification 14
2.3.3 Convexity and Nonconvexity 14
2.4 Water-Energy Nexus 18
2.4.1 Water for Energy 19
2.4.2 Energy for Water 25
2.5 Demand-Side Management 29
2.5.1 Definition 30
2.5.2 Classification 31
2.6 Scheduling in PSE 35
2.6.1 Definition 35
2.6.2 Continuous versus Batch Processing 36
2.6.3 Modelling of Time 38
2.6.4 Scheduling of the DSM in Process Industries 39
2.7 Integrated Water and Power Distribution Networks 41
2.7.1 Brief Review of Power Distribution Networks 41
2.7.2 Mathematical Optimisation of Power Distribution Networks 42
2.7.3 Brief Review of Water Distribution Networks 45
2.7.4 Mathematical Optimisation of Water Distribution Networks 46
2.7.5 State-of-the-Art of Mathematical Optimisation Models for Integrated Water and Power Distribution Networks . 48
2.8 Global Optimisation Algorithms and Techniques for MINLP Problems 51
2.8.1 Convexification Techniques 52
2.8.2 Deterministic Approaches 54
2.8.3 Stochastic Approaches 58

2.8.4 Global Optimisation Solver Software for MINLP Problems 59
2.8.5 Modelling Systems 60
2.9 Summary 61

3 Model Development 63
3.1 Superstructure 63
3.2 Time Representation 66
3.3 Water Distribution Network Constraints 66
3.3.1 Material Balance Constraints 66
3.3.2 Pressure Loss Constraints 67
3.3.3 Water Storage Tank Constraints 69
3.4 Power Distribution Network Constraints 72
3.4.1 Branch Flow Constraints 72
3.4.2 BESS Constraints 75
3.5 Linking Constraints 77
3.5.1 Water Treatment Facility Power Consumption 77
3.5.2 Thermoelectric Power Plant Water Consumption 78
3.6 Objective Function 78

4 Model Application 80
4.1 Illustrative Example 80
4.2 Results and Discussion 89

5 Concluding Remarks 100
5.1 Conclusions 100
5.2 Recommendations for Future Works 101

References 103

List of Figures

1.1 Typical integrated water and power distribution network with one-way interdependency. 5
1.2 Improved integrated water and power distribution network with two-way interdependency, and detailed BESS and water storage tank. 5

2.1 Graphical illustration of a feasible region (region within the shaded area) (Edgar & Himmelblau, 2001). 13
2.2 Different classes of mathematical optimisation models (Lin et al., 2012). 15
2.3 Graphical illustrations of convex and nonconvex sets (Hendrix & G.-Toth, 2010). 15
2.4 Graphical illustrations of convex and nonconvex functions (Grossmann, 2021). 16
2.5 Illustration of local minima and global optimum in a minimisation problem (Dantzig & Thapa, 2003). 17
2.6 Illustration of the water for energy and energy for water concepts (Panagopoulos, 2021). 19
2.7 Plot showing the increasing number of WEN related publications in literature (Ding et al., 2020). 20
2.8 Water-related processes in the water supply system (IEA, 2016). 26
2.9 Energy use for various water-related processes (IEA, 2016). . . . 26
2.10 Power system operator and electricity consumer perspectives on DSM (Zhang & Grossmann, 2016). 31

2.11 Classification of DSM methods (Alotaibi et al., 2020). 32
2.12 Illustration of the differences between batch and continuous tasks (Harjunkoski et al., 2014). 37
2.13 Discrete-time representation (Majozi et al., 2017). 38
2.14 Continuous-time representation (Majozi et al., 2017). 39
2.15 Illustration of a power grid (Zhang & Grossmann, 2016). 41
2.16 An illustration of a 13-Node Test Feeder (Li, 2016). 45
2.17 Graphical representation of a nonconvex function with its piecewise linear approximation (Belotti et al., 2013). 55
2.18 Flowchart of a general sBB algorithm (Bajaj & Hasan, 2020). . 56
2.19 Flowchart showing the general steps involved in Decomposition Algorithms (Grossmann, 2021). 58

3.1 Integrated water and power distribution network superstructure for the proposed mathematical optimisation model. 64
3.2 Illustration of the operation of a typical elevated storage tank (Verleye & Aghezzaf, 2013). 69
3.3 A typical radial power distribution network structure. 73
3.4 Illustration of the operation of a typical BESS. 75

4.1 Topology of a 13-bus power distribution network integrated with an 8-node water distribution network. 81
4.2 Forecasted energy time-of-use tariffs charged by the power utility operators (Xiao et al., 2022). 84
4.3 Forecasted real time pricing of the electricity from the grid (Oikonomou & Parvania, 2020). 84
4.4 Power consumption profile of pump *wtf1n2* for Scenario C. . . . 92
4.5 Gantt chart for Scenario C. 93
4.6 Optimal integrated water and power distribution network of the Scenario B at time interval t=6. 94
4.7 Optimal integrated water and power distribution network of the Scenario B at time interval t=13. 95

4.8 Optimal integrated water and power distribution network of the Scenario B at time interval t=20. 96
4.9 Optimal integrated water and power distribution network of the Scenario C at time interval t=6. 97
4.10 Optimal integrated water and power distribution network of the Scenario C at time interval t=13. 98
4.11 Optimal integrated water and power distribution network of the Scenario C at time interval t=20. 99

List of Tables

2.1 Non-global solvers for MINLP problems. 62
2.2 Global solvers for MINLP problems. 62

4.1 BESS parameters (Li et al., 2019) 83
4.2 Other water distribution network parameters (Verleye & Aghezzaf, 2013). 83
4.3 Forecasted solar power. 85
4.4 Forecasted water demands. 86
4.5 Forecasted active power demands. 87
4.6 Forecasted reactive power demands. 88
4.7 Results obtained from the illustrative example. 89

List of Abbreviations

AIMMS	Advanced Interactive Multidimensional Modeling System.
Alpha-ECP	Alpha-Extended Cutting Plane.
AMPL	A Mathematical Programming Language.
ANTIGONE	Algorithms for coNTinuous/Integer Global Optimisation of Nonlinear Equations.
AOA	AIMMS Outer Approximation.
BARON	Branch-and-Reduce Optimisation Navigator.
BB	Branch-and-Bound.
BESS	Battery Energy Storage System.
BONMIN	Basic Open-source Nonlinear Mixed Integer Programming.
Couenne	Convex Over and Under Envelopes for Nonlinear Estimation.
CSP	Concentrated Solar Power.
DICOPT	Discrete and Continuous OPTimiser.
DSM	Demand-Side Management.
ECP	Extended Cutting Plane.
GAMS	General Algebraic Modeling System.
GBD	Generalized Benders Decomposition.
IEA	International Energy Agency.
IEEE PES	Institute of Electrical and Electronics Engineers Power and Energy Society.

LP	Linear Program.
LP/NLP BB	Linear Program/Nonlinear Program-Branch-and-Bound.
MILP	Mixed-Integer Linear Program.
MINLP	Mixed-Integer Nonlinear Program.
MIP	Mixed-Integer Program.
MIQCQP	Mixed-Integer Quadratically-Constrained Quadratic Program.
NEOS	Network-Enabled Optimisation System.
NLP	Nonlinear Program.
OA	Outer Approximation.
PSE	Process Systems Engineering.
PV	Photovoltaic.
QC	Quadratic Convex.
QCQP	Quadratically-Constrained Quadratic Program.
R/X	resistance/reactance.
sBB	Spatial Branch-and-Bound.
SCIP	Solving Constraint Integer Programs.
SDP	Semi-Definite Programming.
SOCP	Second Order Cone Programming.
US DOE	United States Department of Energy.
WEN	Water-Energy Nexus.

Nomenclature

Sets

$i \in I$	buses
$ji \in IJ$	branches/distribution lines
$k \in K$	pipes
$n \in N$	nodes
$t \in T$	time intervals

Subsets

$ib \in IB$	buses connected to a BESS
$id \in ID$	buses connected to a power demand/load
$ig \in IG$	buses connected to the power grid
$ip \in IP$	buses connected to a pump
$it \in IT$	buses connected to a thermoelectric power plant
$kp \in KP$	pipes with a pump
$kw \in KW$	pipes with no pump
$nd \in ND$	nodes connected to a water treatment facility
$nf \in NF$	nodes connected to a water treatment facility
$nt \in NT$	nodes connected to a storage tank

Parameters

η_{ib}^{CH}	Charging efficiency of BESS at bus ib
η_{ib}^{DCH}	Discharging efficiency of BESS at bus ib
η_{kp}	Pump efficiency of pump kp
ρ	Water density (kg/m^3)
σ_{ib}	Hourly self-discharge rate of BESS at bus ib $\left(\frac{1}{h}\right)$
τ_t	Length of period (h)

A_{kp}	Head coefficients for pump kp (m^{-5})
A_{nt}	The surface area of a storage tank at node nt (m^2)
B_{kp}	Head coefficients for pump kp (m^{-2})
C_{kp}	Head coefficients for pump kp (m)
CPP_t	Forecasted electricity price of power from the grid at time interval t $\left(\frac{\$}{kWh}\right)$
CPW_t	Forecasted time of use tariffs at time interval t $\left(\frac{\$}{kWh}\right)$
CTP_{it}	Operating cost of generating energy at thermoelectric power plant it $\left(\frac{\$}{kWh}\right)$
$CWCI_{it}$	Water consumption intensity of thermoelectric power plant it $\left(\frac{m^3/h}{kW}\right)$
D_k	Diameter of pipe k (mm)
E_{ib}^{INI}	Initial amount of electric energy of the BESS at bus ib (kWh)
E_{ib}^{L}	Minimum energy capacity of BESS at bus ib (kWh)
E_{ib}^{U}	Maximum energy capacity of BESS at bus ib (kWh)
F_k^f	Friction factor of the pipe k
F_{kp}^{L}	Minimum flowrate in pump kp (m^3/h)
F_k^L	Minimum flowrate in pipe k (m^3/h)
F_{kp}^{U}	Maximum flowrate in pump kp (m^3/h)
F_k^U	Maximum flowrate in pipe k (m^3/h)
$F_{nd,t}$	Water demand at node nd at time interval t (m^3/h)
g	Acceleration due to gravity (m/s^2)
H_{nt}^{FL}	Level of storage tank floor at node nt (m)
H_{nt}^{IN}	Level of inflow in a storage tank at node nt (m)
H_n^L	Minimum pressure head at any node n in the water distribution network (m)
H_n^U	Maximum pressure head at any node n in the water distribution network (m)
IC_{ji}^{L}	Minimum square of current magnitude in line ji (A^2)
IC_{ji}^{U}	Maximum square of current magnitude in line ji (A^2)
kk	Material-dependent roughness of pipe k (mm)
L_{nt}^{INI}	Initial level in the storage tank at node nt (m)

L_{nt}^{L} Minimum level in the storage tank at node nt (m)

L_{nt}^{U} Maximum level in the storage tank at node nt (m)

L_{k} Length of pipe k (m)

$P_{i,t}^{L}$ Active electric power load at bus i at time interval t (kW)

P_{ig}^{L} Minimum active power from the grid at bus ig (kW)

$P_{i,t}^{RE}$ Active power output of renewable energy source at bus i at time interval t (kW)

P_{ib}^{U} Maximum charging or discharging power of BESS at bus ib (kVA)

P_{ig}^{U} Maximum active power from the grid at bus ig (kW)

P_{it}^{U} Maximum active power from the thermoelectric power plant at bus it (kW)

PCI_{nf} Power consumption intensity of water treatment facility nf $\left(\frac{kW}{m^3/h}\right)$

PF_{kp} Power factor of pump kp (kW)

$Q_{i,t}^{L}$ Reactive electric power load at bus i at time interval t (kW)

Q_{ig}^{L} Minimum reactive power from the grid at bus ig (kVA)

Q_{ig}^{U} Maximum reactive power from the grid at bus ig (kVA)

Q_{it}^{U} Maximum reactive power from the thermoelectric power plant at bus it (kVA)

R_{ji} Resistance of line ji $(Ohms)$

R_{k} Head loss coefficient of pipe k (s^2/m^5)

S_{ji} Capacity limit of branch ji (kVA)

V_{i}^{L} Minimum square of voltage magnitude at bus i (V^2)

V_{i}^{U} Maximum square of voltage magnitude at bus i (V^2)

v_{k}^{U} Maximum velocity of flow in every pipe k (m/s)

X_{ji} Reactance of line ji $(Ohms)$

Z_{n} Geographic height at node n (m)

Continuous variables

$\ell_{ji,t}$ Square of current magnitude in line ji at time interval t (A^2)

$e_{ib,t}$ Amount of electric energy stored in BESS at bus ib at the end of time interval t (kWh)

$f_{it,t}^{D}$ Water demand of thermoelectric power plant it at time interval t

	(m^3/h)
$f^{IN}_{nt,t}$	Water inflow at the entrance of storage tank nt at time interval t (m^3/h)
$f^{OUT}_{nt,t}$	Water outflow at the entrance of storage tank nt at time interval t (m^3/h)
$f_{k,t}$	Water flow in pipe k at time interval t (m^3/h)
$f_{nf,t}$	Water outflow at water treatment facility nf at time interval t (m^3/h)
$h^M_{nt,t}$	Average head of storage tank nt in time interval t (m)
$h_{kp,t}$	Head gain imposed by the pump kp at time interval t (m)
$h_{n,t}$	Water head at node n at time interval t (m)
$l_{nt,t}$	Level of water inside the storage tank nt at the end of time interval t (m)
$p^{CH}_{ib,t}$	Active power charged to a BESS at bus ib at time interval t (kW)
$p^{DCH}_{ib,t}$	Active power discharged from a BESS at bus ib at time interval t (kW)
$p^{G}_{ig,t}$	Active power from the grid at bus ig at time interval t (kW)
$p^{WTF}_{nf,t}$	Active power load of water treatment facility at node nf at time interval t (kW)
$p_{it,t}$	Active power from thermoelectric power plant at bus it at time interval t (kW)
$p_{ji,t}$	Active branch power in line ji at time interval t (kW)
$p_{kp,t}$	Active power consumption of the pump kp at time interval t (kW)
$q^{CH}_{ib,t}$	Reactive power charged to a BESS at bus ib at time interval t (kVA)
$q^{DCH}_{ib,t}$	Reactive power discharged from a BESS at bus ib at time interval t (kVA)
$q^{G}_{ig,t}$	Reactive power from the grid at bus ig at time interval t (kVA)
$q_{it,t}$	Reactive power from thermoelectric power plant at bus it at time interval t (kVA)
$q_{ji,t}$	Reactive branch power in line ji at time interval t (kVA)

$q_{kp,t}$ Reactive power consumption of the pump kp at time interval t (kVA)

$qs_{nt,t}$ Amount of water in storage tank nt at the end of time interval t (m^3)

$v_{i,t}$ Square of voltage magnitude at bus i and time interval t (kVA)

$Cost^{Total}$ Total operating costs along the whole scheduling horizon (objective function) ($)

Binary variables

$y^{IN}_{nt,t}$ Binary variable indicating if the inflow at storage tank nt is active or not at time interval t

$y^{OUT}_{nt,t}$ Binary variable indicating if the outflow at storage tank nt is active or not at time interval t

$y^{PCH}_{ib,t}$ Binary variable indicating if the BESS at bus ib is actively discharging or not at time interval t

$y^{PDCH}_{ib,t}$ Binary variable indicating if the BESS ib is actively charging or not at time interval t

$y^{QCH}_{ib,t}$ Binary variable indicating if the BESS ib is reactively charging or not at time interval t

$y^{QDCH}_{ib,t}$ Binary variable indicating if the BESS at bus ib is reactively discharging or not at time interval t

$y_{kp,t}$ Binary variable indicating if the pump kp is active or not at time interval t

Chapter 1

Introduction

This chapter gives the background of the problem that is tackled in this dissertation. The basis of the motivation is explored. The research objectives are then described. Finally, the problem is formalised into a problem statement.

1.1 Background

Water and energy are indispensable and interdependent resources that are required for the survival of human life. These resources have played a vital role in the advancement of civilisation and economies. However, as the global population has been rapidly increasing, demands for water and energy have also increased dramatically. It has also been projected that by 2050, global energy demands will increase by nearly 50% (Sourmehi, 2021), while global water demands will increase by 20%-30% (Boretti & Rosa, 2019). This will intensify the dependency of water on energy and vice-versa. Thus, it has become imperative to seek holistic solution approaches that consider the dependency between water and energy for sustainable management and conservation of the water and energy resources.

The mutual interdependencies between water and energy systems are called water-energy nexus (WEN). Energy systems need water for cooling, power generation, and fossil fuel extraction, while water systems need energy to treat and distribute water. Various systems involved with water and energy resources,

such as water desalination (Santhosh et al., 2014), shale gas exploration (Oke et al., 2018), and eco-industrial parks (Gou et al., 2022) have been optimised successfully, through the concept of the WEN. The application of a WEN concept on water and power distribution networks has also proven to be one way of sustainably managing water and energy resources (Zamzam et al., 2019).

Water and power distribution networks are vital infrastructures that require efficient management to guarantee reliable channelling of water and energy, from water and power utilities to the consumers. These distribution networks are also inextricably interdependent on one another. On one hand, water utilities need electric energy for pumping and treating water. Pumping activities require vast amounts of energy for the flow of water to overcome changes in elevation and friction in pipes. This can lead to operational costs as high as 65% for water utilities (do Egito et al., 2023). Moreover, the treatment of water can be energy intensive, especially when technologies, such as water desalination are used. On the other hand, most power utilities heavily rely on water for cooling, particularly thermal power plants. Thermal power plants require huge amounts of water for cooling the exhaust steam from turbines to achieve safe and efficient power generation (Pan et al., 2018). Lohrmann et al. (2022) presented that around 88% of active thermal power plants use water-based cooling technologies, such as once through cooling systems and wet cooling towers. These cooling systems are dependent on pumps and water storage tanks in water distribution networks for water supply. As these mutual interdependencies continue to strengthen, the integration of water and power distribution networks has been considered as a promising opportunity to design and operate these networks synergistically.

Integration of water and power distribution networks offers benefits to both networks. Power distribution networks are an integral part of the power grid that delivers electricity to individual consumers. Nowadays, the power grid is faced with a growing challenge of grid balancing (Zhang, Sundaramoorthy, et al., 2016). This is occurring due to the increasing penetration of variable renewable energy resources and new electricity demand patterns in power

distribution networks (Zsiborács et al., 2021). To solve this challenge, the flexibility in power grids needs to be increased. Through integration with power distribution networks, water distribution networks can increase flexibility in power grids. For instance, energy intensive operations in water distribution networks such as, pumping and treating water can be shifted to off-peak hours in demand-side management schemes (DSM) (Zamzam et al., 2019). This can be done in tandem with water storage tanks which ensure that water delivery to the water consumers are met without any disruptions. To leverage the operational flexibility offered by water storage tanks, the usage of advanced smart metering and communication infrastructure is also necessary (Paterakis et al., 2017; Zohrabian et al., 2021). This is because real-time information will be needed for both water and power utility operators to ensure smooth coordination between both networks. Despite the need for capital expenditure to install smart metering and communication infrastructure, the efficiency of water utilisation in the water distribution networks will increase (Davies et al., 2014). Moreover, water distribution networks achieve reduced operational costs through integration with power distribution networks, particularly when time-varying electricity prices are involved (Li et al., 2019).

The growing interest in DSM has led to the development of mathematical optimisation models with the objective to improve the cost efficiency and sustainable management of both distribution networks. The models provide a reliable basis for the implementation of DSM schemes. The problem of integrating water and power distribution takes the form of a short-term scheduling problem with a scheduling horizon of 24 hours. Mathematical optimisation models for solving this short-term scheduling problem are inherently nonconvex mixed integer nonlinear programs (MINLP). Consequently, most studies have proposed mathematical techniques that deal with the nonconvexities found in the problem to improve tractability and achieve solutions with shorter CPU times.

Integrating water and power distribution networks is a multidisciplinary problem. This has allowed researchers from different fields to propose different approaches to the problem. Among these fields, the field of Process Systems

Engineering (PSE) is well equipped with process integration methods that provide a holistic approach when tackling such systematic problems. Moreover, the problem is analogous to the batch process optimisation problem in the field of PSE. At the same time, a few studies have proposed mathematical optimisation models with the earliest study on the topic by Zamzam et al. (2019).

1.2 Motivation

A few literature studies have proposed mathematical optimisation models that demonstrate the benefits of the integrated operation of the water and power distribution networks. The integration of water and power distribution networks is based on the concept of the WEN which refers to the mutual interdependencies between water and energy systems. However, literature studies do not fully capture the mutual interdependencies between water and power distribution networks. The integration between water and power distribution networks only appears through the pumps receiving power from the power distribution network, as shown in Figure 1.1. This leads to a one-way interdependency between the water and power distribution network, despite possible connections, such as thermoelectric power plants receiving water for cooling from the water distribution network, and water treatment facilities receiving power from the power distribution network. Consequently, this results in the incomplete capture of the WEN which is the basis of the integrated water and power distribution networks problem.

In addition, studies in literature either neglect the consideration of storage facilities, such as water storage tanks and battery energy storage systems (BESSs) in the problem or when they consider them, do not capture their detailed operation. The operation of the BESS and water storage tank are captured using black box models. This is usually justified by their simplicity and computational inexpensiveness (Jakata & Majozi, 2022). However, to satisfy water and power demands reliably, water storage tanks and battery energy

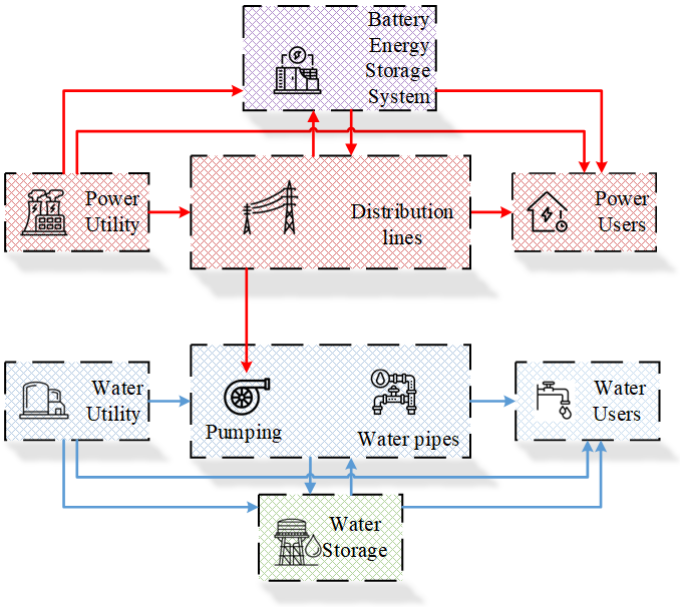


Figure 1.1: Typical integrated water and power distribution network with one-way interdependency.

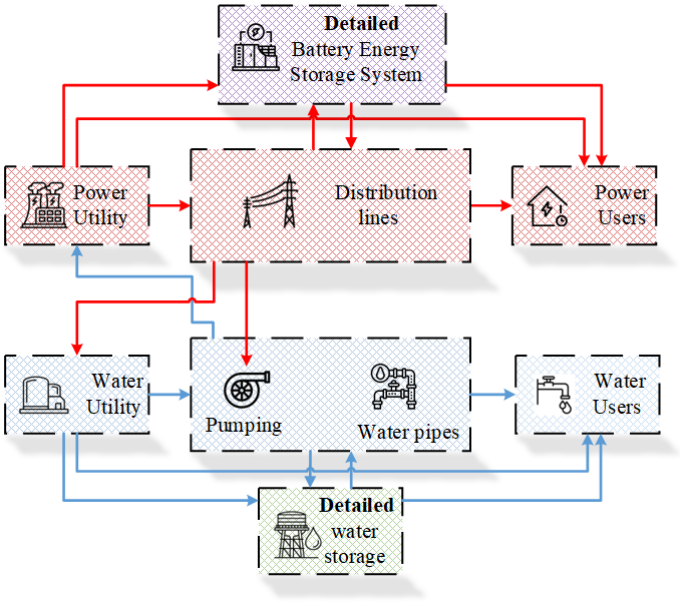


Figure 1.2: Improved integrated water and power distribution network with two-way interdependency, and detailed BESS and water storage tank.

storage systems (BESSs) act as vital buffers in the integrated operation of water and power distribution networks. Simple representation of the operation of the water storage tanks and BESS can adversely affect their flexible capabilities over a given scheduling horizon, especially when time-varying electricity prices associated with deregulated electricity markets are considered. This results in suboptimal operating schedules, which inherently lead to inaccurate operational costs thereby lowering the applicability of the optimisation model.

This dissertation addresses these drawbacks by developing an improved mathematical optimisation model that completely captures the WEN, and the detailed operation of the BESS and water storage tanks, as shown in Figure 1.2.

1.3 Research Objectives

The objectives of this research can be summarised as follows:

- Develop an optimisation model where all the possible interconnections between the water and power distribution networks are considered thereby fully capturing the WEN in an integrated water and power distribution network,
- Incorporation of detailed models for the operation of the storage facilities in the optimisation model of an integrated water and power distribution network,
- The developed optimisation model generates an overall formulation that can determine the optimal schedule, as well as the minimum total operating cost of an integrated water and power distribution network,
- Evaluation of the optimisation model using an illustrative example from literature.

1.4 Problem Statement

The problem addressed in this dissertation considers the optimal operation of an integrated water and power distribution network.

Given:

(i) The detailed water and power distribution networks, i.e., characteristics of water pipes, pumps, and power distribution lines, etc.,

(ii) The forecasted water and power demands,

(iii) The forecasted electricity prices,

(iv) The initial conditions and capacities of available BESS and water storage tanks,

(v) The capacity and water consumption intensity of the thermoelectric power plant,

(vi) The capacity and power consumption intensity of the water treatment facility,

(vii) The time horizon of interest.

Determine the optimal schedule for the operation of an integrated water and power distribution network that yields the minimum operation cost while meeting the water and power demands during a given time horizon of interest.

1.5 Dissertation Structure

The remainder of the dissertation is structured as follows:

Chapter 2 provides the literature review, where a detailed survey of the related topics in this research are discussed. A broad overview of process integration, mathematical optimisation, WEN, scheduling in PSE, DSM, mathematical optimisation of integrated water and power distribution networks, and global optimisation algorithms and techniques is given.

Chapter 3 presents the model development of the proposed optimisation model for an integrated water and power distribution network. Using a superstructure as the basis of the proposed model, the detailed explanation of water distribution network constraints, power distribution network constraints, linking constraints, and the objective function is given.

In **Chapter 4**, the proposed optimisation model is applied to an illustrative example and obtained results are discussed.

In **Chapter 5**, key findings of the research are presented. Recommendations indicating opportunities for future work are given based on the limitations of this research.

Chapter 2

Literature Review

2.1 Introduction

The study in this dissertation contributes towards the sustainable management of water and power distribution networks through mathematical optimisation techniques. The aim of the study is to optimise the operation of integrated water and power distribution networks under DSM programs. This chapter provides the literature review of the pertinent subject matter that is related to the integration of water and power distribution networks, as well as the process integration and mathematical optimisation techniques used in the discipline of PSE. The major sections of this chapter include process integration, WEN, mathematical optimisation, DSM, scheduling in PSE, state-of-art on integrated water and power distribution networks mathematical optimisation models, as well as the global optimisation algorithms and techniques used to optimise MINLP problems.

2.2 Process Integration

2.2.1 Definition and Background

Process integration is a holistic approach to process design and operation that focuses on the unity of a process (El-Halwagi, 1997). This approach considers

all the possible interactions between the process units, streams, and objectives of a process, as well as the exploitation of these interactions to optimise the entire process. Process integration methodologies have been developed in the PSE discipline since the 1970s in response to the oil crisis which caused fuel scarcity and expensive energy costs (Klemeš, 2013). In the form of pinch analysis, process integration was used to increase energy efficiency and energy savings in process systems. Subsequently, the approach was applied to various processes to provide a comprehensive analysis of process systems and this allowed the development of cost-effective and sustainable solutions for processes (Dunn & El-Halwagi, 2003; Foo & Tan, 2015). Process integration methodologies are broadly classified as graphical-based techniques and mathematical optimisation-based techniques.

2.2.2 Graphical-Based Approaches

Graphical-based approaches rely on a structure independent approach that is used for setting performance targets before committing to a particular process design. These techniques allow the designer to guide the optimisation process since they are graphical in nature (Majozi, 2010). The most common graphical-based approach is called pinch analysis. It was introduced by Linnhoff (1979) with the aim to target minimum energy consumption within the process through maximum heat recovery between process-process heat exchange before resorting to external utilities. Subsequently, the application of pinch analysis was extended to other processes, such as water networks (Wang & Smith, 1994), hydrogen networks (Alves & Towler, 2002), and utility gas networks (Foo & Manan, 2006). Despite the need for significant problem simplifications and assumptions, as well as their limitation to two dimensions, graphical-based approaches remain as some of the most useful tools for process integration in PSE. Yuan and Mao (2024) provides an excellent review on the topic of graphical-based approaches of process integration.

2.2.3 Mathematical Optimisation-Based Approaches

Mathematical optimisation-based approaches allow for detailed handling of complex problems through mathematical optimisation models. They involve three major steps: (i) the development of a framework that incorporates all the possible configurations of a process called a superstructure, (ii) the mathematical formulation of the process of interest to produce a mathematical optimisation model, and (iii) the determination of an optimal solution using a suitable optimisation algorithm (solver) (Chen & Grossmann, 2017; Grossmann et al., 2000).

To ensure that a good mathematical optimisation model is formulated, a thorough analysis of the problem is necessary before developing the superstructure. This avoids the exclusion of any potential optimal configurations thereby avoiding cases where suboptimal solutions may be obtained. It is also important to note that, the final solution generally indicates the optimal operational conditions of the problem (e.g. optimal schedule, temperature, pressure,etc.). Unlike the graphical-based approaches which are limited to two dimensions, mathematical optimisation-based approaches offer the flexibility of incorporating more dimensions in mathematical optimisation models. Various constraints of practical relevance such as cost functions, physical relationships, and logical dependencies can be incorporated. Therefore, mathematical optimisation-based approaches provide a more robust and rigorous approach than graphical based approaches. Sensitivity analyses can also be performed by varying the parameters to assess the correlations between parameters and objective(s) (Budak Duhbacı et al., 2021). However, mathematical optimisation-based approaches require computational effort and sophisticated optimisation algorithms, particularly in cases where the constraints in the optimisation model have nonconvexities.

It should be noted that, in some cases superstructures may also be used to make the modelling process easier and general. For instance, Castro et al. (2009) used a superstructure to build a scheduling model for the operation

of continuous plants. The authors noted that, despite the usage of the superstructure not being absolutely necessary, it proved to be highly useful for generalising and making it easier to understand their models.

The study in this dissertation relies on the mathematical optimisation-based approaches of process integration to tackle the problem of integrating water and power distribution networks because they allow detailed handling of difficult optimisation problems.

2.3 Mathematical Optimisation

2.3.1 Definition

Mathematical optimisation is defined as the science of determining the best solutions to mathematically defined problems, which may be models of physical reality, or manufacturing and management systems (Snyman & Wilke, 2018). It is also commonly referred to as mathematical programming. Over the past 70 years, mathematical optimisation has proven to be a powerful problem-solving technology that has been developed and utilised to tackle complex optimisation problems in various disciplines, such as engineering, science, finance and agriculture. Mathematical optimisation is classified under mathematical modelling. It differs from other mathematical models, such as simulation models, econometric models, time series models, etc., due to the presence of an objective function(s) in their model structure (Williams, 2013).

In general, a mathematical optimisation problem is made up of at least one objective function which must be minimised (or maximised), and a set of equality and/or inequality constraints which represent or approximate the reality of the problem. The intersection of all the constraints of a mathematical optimisation model produces a set of points called a feasible region, as shown in Figure 2.1. This feasible region represents all the possible solutions to the mathematical optimisation problem. Within the feasible region, an optimal solution that satisfies all the constraints and the objective function of the optimisation problem

can be found when a suitable optimisation algorithm (solver) is applied to an optimisation problem. Depending on the nature of the mathematical optimisation problem, the optimal solution can be unique or not, and terms such as, local optima and global optima are used to describe the optimal solutions (Edgar & Himmelblau, 2001).

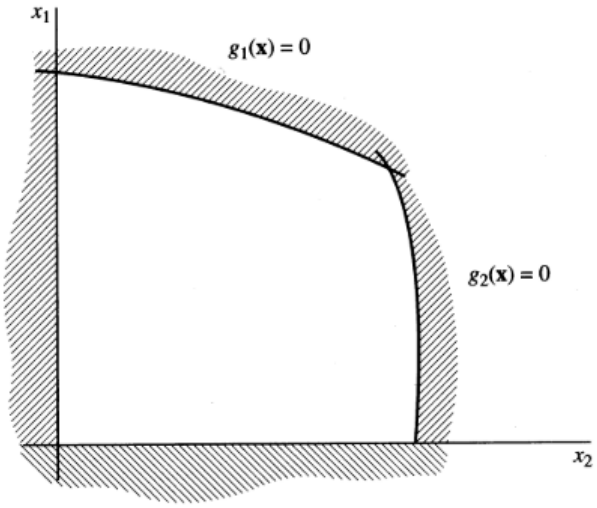


Figure 2.1: Graphical illustration of a feasible region (region within the shaded area) (Edgar & Himmelblau, 2001).

A typical structure of a mathematical optimisation model is given in the following algebraic form:

$$\begin{aligned} &\text{Objective:} && \min Z = f(x,y) \\ &\text{Subject to:} && h(x,y) = 0 \\ & && g(x,y) \leq 0 \\ & && x \in X, y \in \{0,1\} \end{aligned} \tag{2.1}$$

In this mathematical optimisation model, $f(x,y)$ is the objective function to be minimised, subject to the equality constraints $h(x,y)$ and inequality constraints $g(x,y)$. It is important to note that, $f(x,y)$ can also be represented as an objective function for maximising. Depending on the key performance indicators of the given mathematical optimisation problem, the objective func-

tion can be the optimisation of profit, costs, makespan, environmental impact, etc. Constraints $h(x, y)$ and $g(x, y)$ represent the feasible region of variables x and y. The equality constraints $h(x, y)$ describe the physical relationships and systems performance (e.g. material and energy balances, thermodynamic relations), while the inequality constraints $g(x, y)$ express the specifications and boundary conditions of the components in the system (Chen & Grossmann, 2017). Variables x are subject to change during the solution process. They take any real number in a range defined by inequality constraints and are used to represent state or design variables. Binary variables y are a special case of integer or discrete variables which can only take a value of 0 or 1. They indicate the activity or existence of a certain item in a mathematical optimisation problem. Unlike variables, parameters are fixed values given before solving the mathematical optimisation problem.

2.3.2 Classification

Mathematical optimisation models are classified based on the presence of integer variables and nonlinear functions. If any of the functions $f(x, y)$, $h(x, y)$, and $g(x, y)$ are nonlinear, the resultant model is an MINLP; otherwise, it is an mixed-integer linear program (MILP). If there are no integer variables, the model becomes an nonlinear program (NLP) or linear program (LP), on the condition that any of the functions are nonlinear or not, respectively. Figure 2.2 also illustrates different classes of optimisation problems while taking the concepts of convexity and nonconvexity into account.

2.3.3 Convexity and Nonconvexity

The concepts of convexity and nonconvexity (concavity) are both important in the theory and practice of mathematical optimisation, particularly when dealing with mathematical optimisation problems that are intrinsically nonlinear, such as NLP and MINLP (Edgar & Himmelblau, 2001). To understand their importance, it is necessary to define when a set of points (region), function

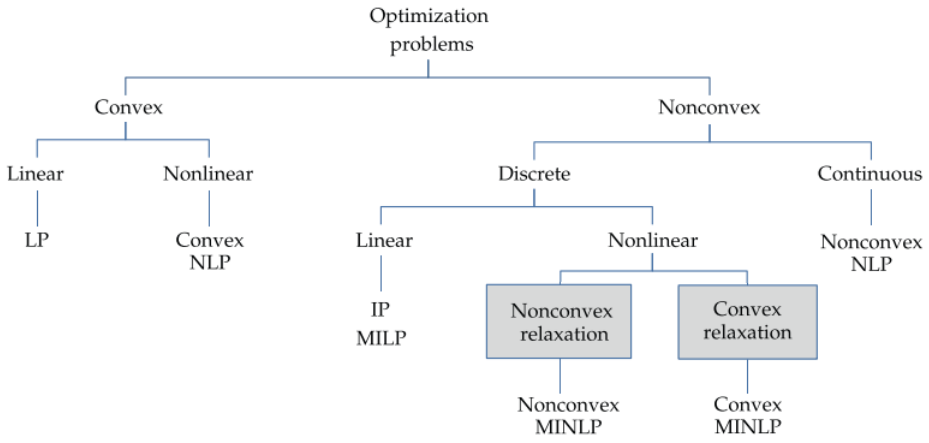


Figure 2.2: Different classes of mathematical optimisation models (Lin et al., 2012).

and mathematical optimisation model is convex or nonconvex.

A set is defined as a convex set if a straight line between any two points inside the set lies entirely within that set. Contrarily, for a nonconvex set, the straight line between any two points inside the set does not entirely lie within that set. Figure 2.3 illustrates the difference between convex and nonconvex sets.

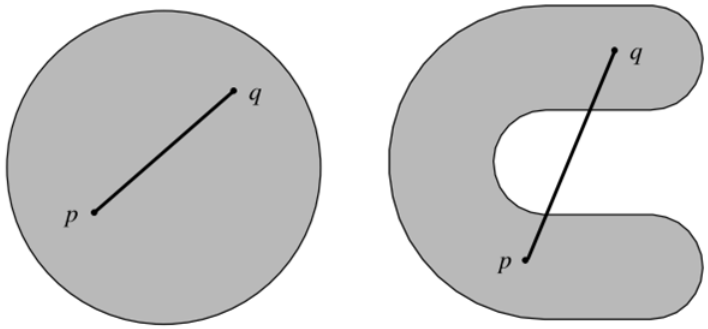


Figure 2.3: Graphical illustrations of convex and nonconvex sets (Hendrix & G.-Toth, 2010).

A function $f(x)$ is referred to as convex, if the chord between the two points (x^1 and x^2) on the function is nowhere below the graph of $f(x)$. On the other hand, for a concave function, the chord between the two points (x^1 and x^2) is below the graph of $f(x)$. Figure 2.4 illustrates the cases for convex and concave functions. It is worth noting that, the definitions of convexity

and nonconvexity are not always reliable for determining if a set or function is convex or otherwise. Edgar and Himmelblau (2001) provides a detailed discussion on the determination of convexity and nonconvexity by checking if the Hessian matrices of a set of points is positive-definite or not.

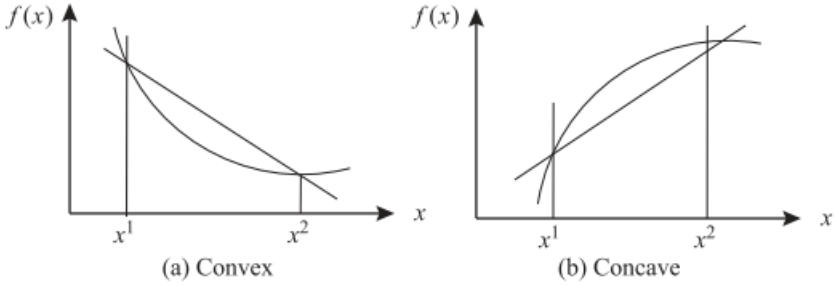


Figure 2.4: Graphical illustrations of convex and nonconvex functions (Grossmann, 2021).

A mathematical optimisation model is convex if it minimises a convex function (or maximises a concave function) over a convex feasible region (Hendrix & G.-Toth, 2010). Such a mathematical optimisation model is often called convex programming model. These models are generally the easiest to solve with optimisation algorithms, such as the simplex method and the interior-points method (Dantzig & Thapa, 2003). LP is a special case of convex programming models. NLPs can also be convex if all their constraints are convex.

On the other hand, if a mathematical optimisation model has at least one nonconvex constraint or objective function (i.e., produces a nonconvex feasible region), the model is nonconvex. Nonconvex programming models are generally very difficult to solve (Burer & Letchford, 2012). This is because they have a possibility of having multiple optimal solutions called local optima in their feasible regions, as shown in Figure 2.5. Local optima are optimal solutions within a restricted part of the feasible region (or neighbourhood) but are not optimal within the entire feasible region (Ambrosio & Lodi, 2013). Unlike convex programming models, where the local optimum is guaranteed to be the global optimum, it is usually difficult to guarantee the globality of a local optimum for nonconvex programming problems. This is particularly the case

when solving nonconvex NLP problems (or NLP subproblems of MINLP) with standard NLP solvers.

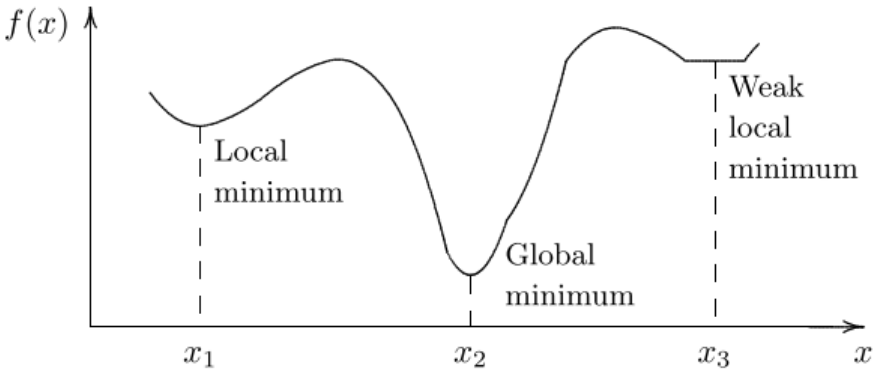


Figure 2.5: Illustration of local minima and global optimum in a minimisation problem (Dantzig & Thapa, 2003).

In NLPs and MINLPs, nonconvexities often arise from bilinear terms (product of a continuous and a binary variable or product of two continuous variables) or nonlinear functions such as: quadratic functions, polynomial functions, signomial functions, absolute value functions and transcendental functions (logarithmic functions, exponential functions, trigonometric functions and hyperbolic functions) (Boukouvala et al., 2016). It is worth noting that, MINLPs are also inherently nonconvex due to the presence of integer variables which produce nonconvex feasible regions (Grossmann, 2021). However, in a slight abuse of terminology, MINLPs are also considered convex if the relaxation of their integer requirement produces an NLP subproblem that is convex (Belotti et al., 2013). Similarly, this is also the case for MILPs.

Many real-world optimisation problems stemming from various disciplines, such as PSE, finance, computational chemistry, biomedical engineering, power systems engineering, etc. are modelled as MINLPs (Lundell & Kronqvist, 2022). This also includes the problem tackled in this dissertation. Since MINLP is a combination of MILP and NLP, it inherits the complexities of these programs, i.e., the combinatorial nature of MILPs and the nonconvex nature of NLPs. Consequently, MINLPs are very challenging to solve. This has resulted in the development of various techniques and optimisation algorithms aimed

at tackling these challenges under the topic of Global Optimisation (Belotti et al., 2013; Boukouvala et al., 2016). Some of these techniques and optimisation algorithms which are relevant to the study in this dissertation are discussed in the following sections.

2.4 Water-Energy Nexus

Water and energy are indispensable resources which are inextricably linked to each other. This mutual interdependency between water and energy is called the water-energy nexus (WEN). The relevance of the WEN stems from the fact that, treating and distributing water requires large amounts of energy, while energy production requires vast amounts of water (Yoon, 2018). Figure 2.6 illustrates various interconnections between water and energy resources. These two resources are tightly interwoven to the extent that acquiring water needs the usage of available energy (Fayiah et al., 2020). In addition, WEN is becoming increasingly relevant due the recent rapid increase in global water and energy demands which are intensifying the interdependencies between water and energy resources. In the future, this nexus will strengthen to the point where water availability will become a limiting factor for meeting energy demands, while energy availability will become a limiting factor when meeting water demands (IEA, 2016; Wu et al., 2020).

Historical evidence shows that the interdependency between water and energy has been well understood and used, for instance, in windmills. However, researchers never showed interest in the interdependencies between water and energy resources until the 1990s (Gleick, 1994). The concept of the WEN only began garnering global attention at the World Economic Forum in 2008 (Ding et al., 2020), and the 2011 Bonn conference in Germany (Hoff, 2011; Fayiah et al., 2020) among various communities. It was clear that, a nexus approach towards the sustainable management of the water and energy systems was necessary to deal with, particularly, the rising global water and energy demands in various sectors (Hoff, 2011). Thereafter, the number of studies in

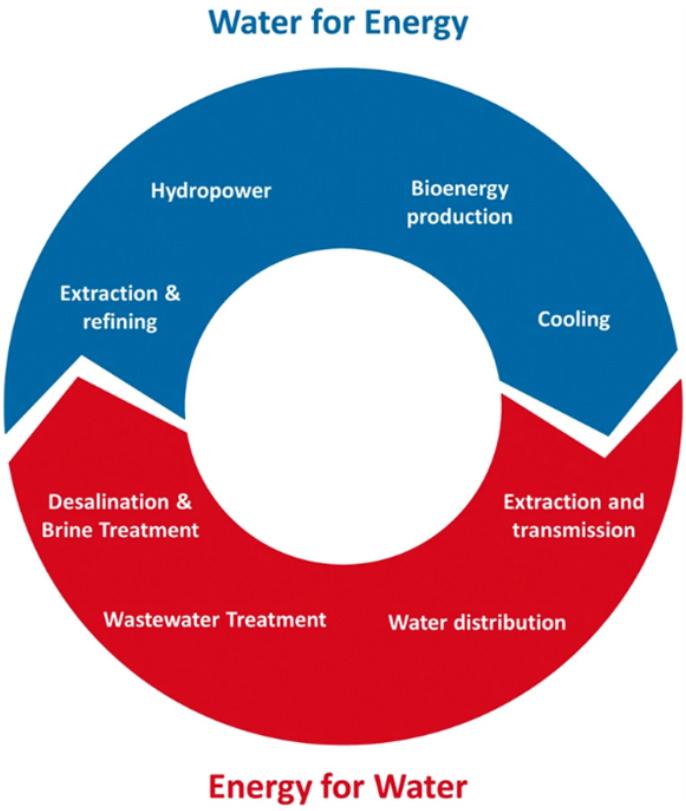


Figure 2.6: Illustration of the water for energy and energy for water concepts (Panagopoulos, 2021).

the scientific community have increased substantially, as shown in Figure 2.7. These studies use different research methods, such as mathematical optimisation models, input and output analysis, life cycle assessment and econometric analysis, with the aim to increase the understanding and implementation of the WEN approach (Ding et al., 2020).

To fully explain the WEN, two key conceptual approaches require analysis and reviewing. These are *water for energy* and *energy for water* concepts (Wu et al., 2020; Yoon, 2018), and both concepts are discussed in the following subsections.

2.4.1 Water for Energy

Water is a key resource in almost all types of energy-related processes, such as fossil fuels extraction and refinery, electric power generation, as well as biofuels cultivation. On a global scale, around 90% of electric power production

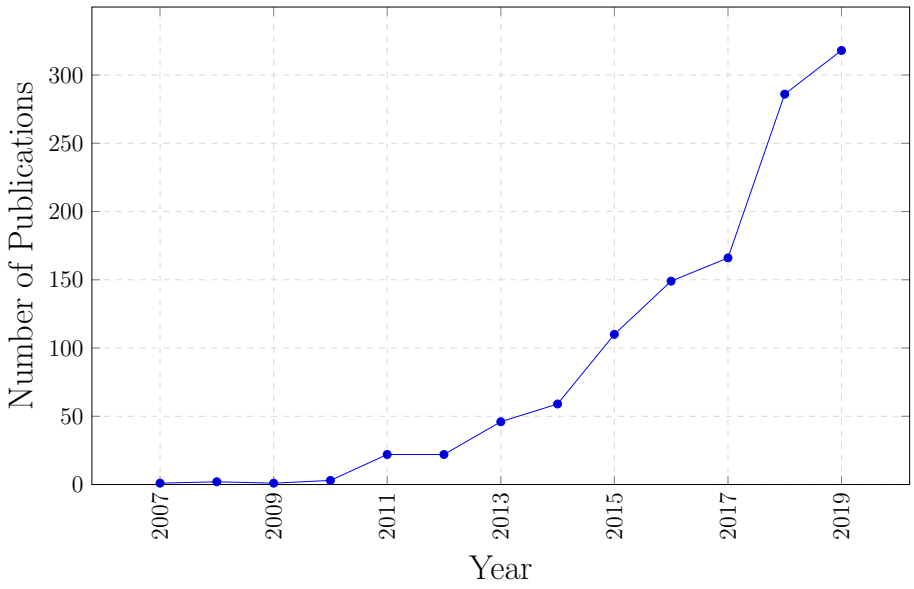


Figure 2.7: Plot showing the increasing number of WEN related publications in literature (Ding et al., 2020).

is water intensive (Smith, 2014). The topic of *water for energy* concept has been well studied because water is tied to energy access, energy security, as well as environmental issues associated with energy production (IEA, 2016). Hydroelectric power generation and biofuel production facilities have been reported to lower output due to water droughts since they rely on water, heavily (Gleick, 1994). Furthermore, in the past decade, there have been various events where low water availability has led to either the shutdown of power generation facilities or reduction in the power generation capacities (Lohrmann et al., 2023).

To understand how much water is used for energy-related processes, water for energy is usually quantified by calculating the water consumed per unit electricity generated (m^3/MWh), either directly or indirectly (Macknick et al., 2012; Yoon, 2018). This calculation of water requirements for energy are commonly based on three concepts: water withdrawal, water consumption and water discharge. Water withdrawal is simply defined as the amount of water removed from a water source (lakes, dams, rivers, and aquifers.), whereas water consumption is a fraction of the water withdrawal that is not returned to the water source. The water lost through water consumption is usually

through evaporation, conversion from a raw material to certain product, or transportation to another location (Mielke et al., 2010). It is important to note that, water withdrawal is always greater than the water consumption. Water discharge is the amount of water returned to the water source despite it being in a different state (Yoon, 2018). These three concepts are linked through the following equation.

$$\text{Water withdrawal} = \text{Water consumption} + \text{Water discharge} \tag{2.2}$$

The International Energy Agency (IEA) estimated that freshwater withdrawal of the global energy sector were around 10%, while the water consumption were roughly 3%, in 2014 (IEA, 2016). Similar statistics for water withdrawals were also published in 2021 (IEA, 2023a). Furthermore, it is estimated that the global energy sector will become thirstier by 2035, with the water withdrawal and water consumption for energy increasing by 20% and 85%, respectively (Smith, 2014). Therefore, it is of utmost importance to understand water requirements of the energy sector.

The energy sector is generally subdivided into (i) power generation, and (ii) primary energy production when analysing water for energy. On one hand, power generation comprises the electric power production operations, such as thermoelectric power plants and hydroelectric power plants. On the other hand, primary energy production consists of the extraction, refinery, and transportation of fossil fuels, as well as cultivation and processing of the biofuels. In 2016, the IEA World Energy Outlook report presented that, in the energy sector, power generation withdraws an immense amount of water with a percentage share of 88%, in terms of water withdrawals, while primary energy production contributes around 64%, in terms of water consumption (IEA, 2016).

Power Generation

Fossil fuel-based power plants Globally, thermal power plants contribute a significant portion of the installed generating capacity, despite the recent rise

in renewable energy sources. In 2022, coal-fired power plants provided around 33%, while natural gas-fired and nuclear power plants supplied approximately 20% and 10% of the global electricity generation, respectively (IEA, 2023b). These power plants have the highest water demands in power generation since they use cooling technologies that require vast amounts of water, primarily for cooling the exhaust steam from turbines. Water is also required for steam generation, washing purposes and other general plant purposes. Furthermore, the introduction of carbon capture and storage technology in fossil fuel-based power plants to reduce CO_2 emissions, has also been known to double the water withdrawal and water consumption of power plants (Hoff, 2011; IEA, 2016).

Water withdrawal and water consumption of thermal power plants are highly dependent on the type of cooling technology installed. They have an influence on the efficiency, capital and operational costs, as well as the environmental impacts of a power plant (Yoon, 2018). The main types of cooling technologies used in thermal plants are dry cooling systems (air-cooled condensing), once-through cooling systems (open loop cooling), open recirculating systems (closed loop cooling/evaporative wet cooling towers), hybrid cooling systems, and pond cooling systems.

Dry cooling uses air as a cooling medium. Despite having the lowest water withdrawal and water consumption ranging between 0.02–0.60 m^3/MWh, it is the least efficient and most expensive cooling technology (Pan et al., 2018). Once-through cooling extracts huge volumes of water from a water source and discharges most of the water back to the water source. It is generally characterised by high water withdrawal and low water consumption values. Among various types of cooling technologies, it is the most efficient and least costly. Wet cooling towers operates based on evaporation cooling, where water is circulated in the cooling systems, and air is forced to pass through the circulated water in a cooling tower. Most of the water is lost through evaporation. The average water withdrawal and water consumption of wet cooling towers range between 0.5–2.6 m^3/MWh and 1–132 m^3/MWh, respectively, depending on

the unit size of the power plants (Pan et al., 2018).

Hydroelectric power plants Hydropower relies on stored water in dams. The water is channelled through turbines to generate electricity. Most of the water withdrawn during the power generation process is returned to the water source. The water consumption for hydropower is usually difficult to quantify because it depends on various factors, such as climate, technology type (runoff or reservoir), and water demands from end users (IEA, 2016). However, for hydropower that utilises reservoir technology, water consumption occurs through evaporation. Depending on the size and the location of the reservoir, the water consumption ranges between 0-540 m^3/MWh (Yoon, 2018).

Other types of power plants Power generation technologies, such as concentrated solar power (CSP) and geothermal power, can also be water intensive. CSP can have water withdrawal and water consumption that are comparable to thermal power plants, depending on the cooling technologies they employ. Additionally, they need water for cleaning mirrors and heliostats (Macknick et al., 2012). Geothermal power plants can have high water consumption due to the water makeup requirements for cooling purposes (IEA, 2016). Water consumption values ranging between 0-15.14 m^3/MWh have been published in several reports (Macknick et al., 2012).

Primary Energy Production

Coal Coal production requires water, primarily for mining activities, such as coal cutting, dust suppression, cooling and lubricating of drilling equipment. In 2006, the United States Department of Energy (US DOE) reported that the coal mining industry in USA use water in the range of approximately 265 000-984 000 m^3/day (US DOE, 2006). However, water demands of coal extraction depends on the type of mine (surface or underground mine), depth, geology and width of coal seam in the mines, as well as the energy content of the coal (IEA, 2016). Furthermore, coal processing requires water for coal washing

to improve its quality, coal transportation through coal slurry pipelines, and revegetation of reclaimed land (Gleick, 1994; US DOE, 2006).

Crude and natural gas Crude oil and natural gas production needs water for exploration and drilling purposes, water injection for improved oil recovery, as well as processing and refining. Water demands associated with the conventional (traditional) methods of extracting oil and natural gas generally depend on the type of technology used for extraction, geology of the oil field, along with the extent of the secondary and tertiary recovery (Gleick, 1994; IEA, 2016). To improve the recovery of oil from drawn down oil wells, oil recovery techniques are employed. Secondary recovery techniques commonly involve flooding the oil wells with water which is highly water intensive, while tertiary recovery techniques (also called enhanced oil recovery) rely on steam injection to increase oil flow and recovery rates (Gleick, 1994).

The extraction of conventional natural gas mainly requires water for drilling in preparation of drilling fluids, therefore far lesser water quantities are used in comparison to the extraction of other fossil fuels (US DOE, 2006). On the other hand, unconventional extraction methods, such as hydraulic fracturing (fracking) are employed for tight oil and shale gas (Hoff, 2011). Water demands for the extraction of unconventional oil and natural gas are usually higher than those of the conventional oil and natural gas (Hoff, 2011; Yoon, 2018). However, water demands for the extraction of conventional and unconventional oil can be comparable when water injection is used for oil recovery in an unconventional oil source, such as tight oils (IEA, 2016).

Following oil extraction, oil is processed and refined to produce various types of liquid fuels. Processing and refining of crude oil typically involves thermal and chemical processes which require water as a process input and a cooling fluid (IEA, 2016).

Biofuels Biofuels are becoming increasingly competitive as a liquid fuel since they are renewable energy sources (IEA, 2016). Examples of biofuels include

biodiesel and bioethanol. Biofuel production contribute the largest share in terms of water consumptions among other primary energy sources. Biomass (biofuel feedstock) is required as an input to produce biofuel. Crop cultivation, which is heavily water intensive, is used to produce biomass. Around 2% of total water used for irrigation is required for cultivating crops for biomass (IEA, 2016). Examples of crops cultivated for biomass include corn, ethanol, soybeans and sugar cane. Other sources of biomass are agricultural, food and municipality waste. Biofuel refineries are also substantially water intensive in comparison to the oil and natural gas refineries (IEA, 2016).

Uranium Uranium is a mineral resource that is used as the main input for electricity generation in nuclear power plants. Its production is dependent on water. Uranium mining relies on water for dust control, ore beneficiation and land reclamation purposes (Gleick, 1994). Water demands for uranium mining are comparable to those of surface mining of coal (Gleick, 1994). Following mining, uranium is passed through refinement, milling and enrichment processes, which are all water consumptive (US DOE, 2006).

2.4.2 Energy for Water

Energy is critical input in water supply systems. Water distribution, transportation, and treatment strongly rely on energy. Energy is needed to meet the water demands of municipality, industrial, and agriculture with clean and pressurised water through various processes found in the water supply system, as shown in Figure 2.8. The energy sector is a larger user of water (approximately 15% of global water) when compared to energy used by the water sector (approximately 8% of global energy) (Tsolas et al., 2018; Yoon, 2018). Nevertheless, understanding the link between water distribution, transportation and treatment with energy is imperative.

Water-related processes have different energy requirements. Energy requirements for water distribution and transportation depend on topography, distance, water losses and inefficiencies, whereas for treatment, energy consump-

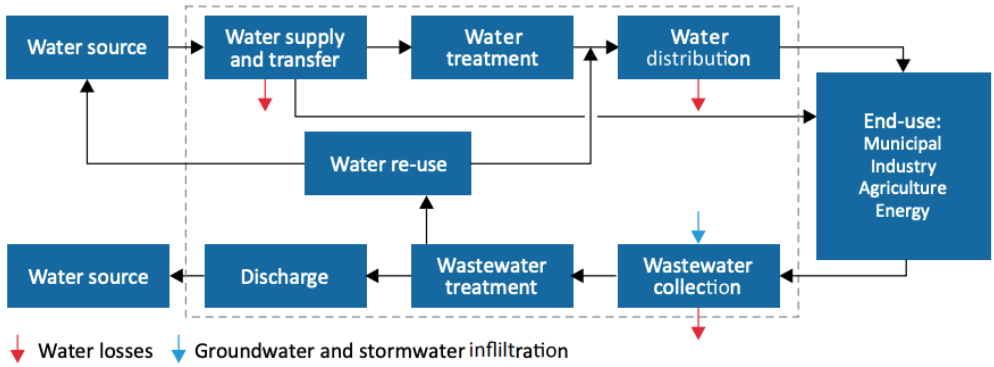


Figure 2.8: Water-related processes in the water supply system (IEA, 2016).

tion is influenced by the treatment level, water treatment technology, and mode of wastewater disposal (IEA, 2016; Yoon, 2018). The energy requirement of water is referred to as energy intensity or energy embeddedness, and is quantified by calculating the energy required per unit volume of water (kWh/m^3) (Yoon, 2018). Figure 2.9 illustrates various water-related processes together with their ranges of energy intensities.

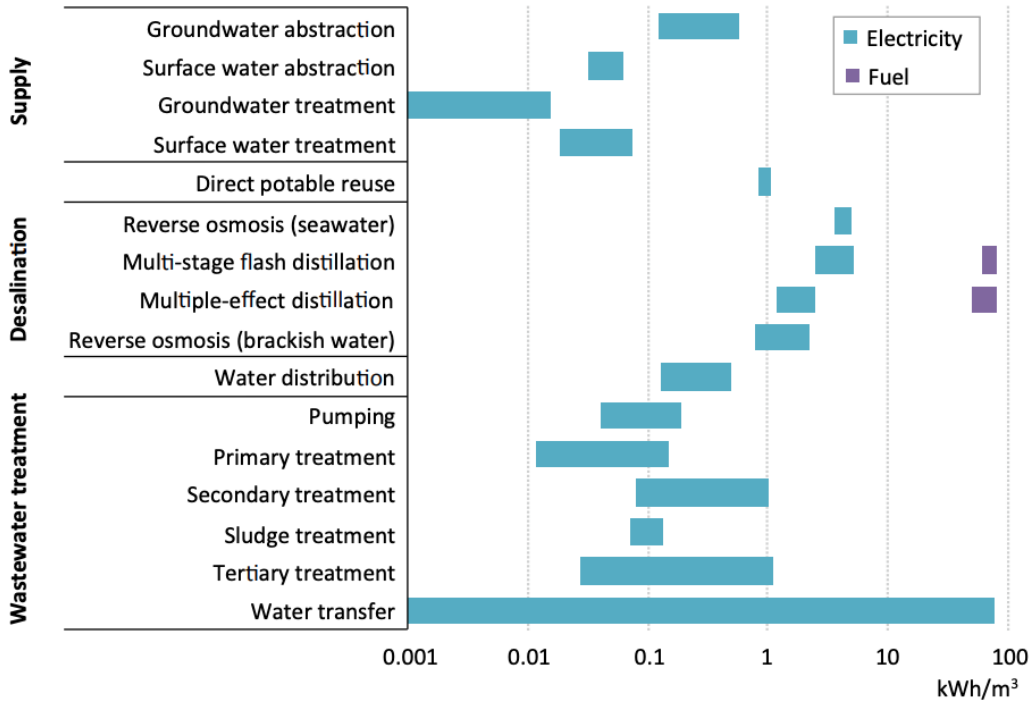


Figure 2.9: Energy use for various water-related processes (IEA, 2016).

Freshwater resources that are available in lakes and rivers are generally un-

evenly distributed. This has resulted in the construction of water supply infrastructure over the history of mankind. Despite the limitation of geographical elevation, ancient civilisations built dams, aqueducts, qanats, canals and brick conduits that relied on gravity as long as the water source was on a high elevation (Gleick, 1994). Modern civilization technology has further improved the conveyance of water through pumps which need energy to move water over long distances and high elevations, such as hills and mountains.

Water supply and transfer Abstraction of water from surface water sources and groundwater sources to water treatment facilities demands energy. This energy is mainly consumed through pumping. It is estimated that, 310 TWh of electricity is consumed through water abstraction. Groundwater abstraction is generally more energy intensive and expensive in comparison to surface water abstraction (Tsolas et al., 2018). Moreover, the energy intensity of groundwater abstraction increases exponentially as the depth of the groundwater source increases (Hoff, 2011). Energy intensities of water abstraction can also vary by sector. For instance, the domestic, commercial, irrigation and livestock sectors are estimated to consume 0.185 kW/m^3 from groundwater sources, whereas from surface water sources, they consume 0.079 kW/m^3 (Yoon, 2018). Energy intensities of channelling water from the source to a water treatment facility depends on the distance and elevational changes.

Countries that are water-stressed or have huge disparities between their water supply and demand, implement large scale water transfer projects to improve water availability (Gleick, 1994). Examples of these projects are South-North Water Transfer Project in China, and State Water Project in California, USA (IEA, 2016). These projects can transfer high volumes of water over long distances, with some projects transferring water over distances of around 1100 km (IEA, 2016). This implies that a substantial amount of energy is used to overcome the elevational changes over these long distances.

Water treatment Water utilities mainly use energy for treating and pumping water. Most of the energy is consumed for pumping water, which uses around 80-85% of the electricity at water treatment facilities (IEA, 2016; Yoon, 2018). Various factors, such as treatment level, type of technology and design flowrates, determine the energy intensity of water utilities (Yoon, 2018). The level of treatment depends on the local regulations that ensure safe and clean water standards of the drinking water or reuse. Despite the energy intensive nature of groundwater sources, energy requirements for treating groundwater are usually a fraction of treating surface water because they are less contaminated.

Wastewater treatment The wastewater discharged by the consumers need energy to be collected, transported, and treated. This is imperative to ensure that wastewater is safely discharged which reduces its environmental and health impact. The energy consumption of wastewater utilities depends on the share of wastewater collected and treated, the level of groundwater infiltration, rainfall into the sewage systems, treatment level and contamination level and the energy efficiency of the treatment operations (IEA, 2016). The treatment of wastewater has three stages: (i) the primary (pretreatment) treatment, (ii) the secondary (biological) treatment, and (iii) the tertiary (advanced/polishing) treatment (Smith, 2005). The primary treatment stage involves the removal of solids, while the secondary treatment removes organic contaminants through biological processes. The tertiary treatment constitutes the final stage of effluent treatment to ensure the disposal of effluent that meets regulatory standards. The secondary treatment stage is known to consume the largest share of energy, contributing between 50% and 60% of the energy consumption of wastewater treatment facilities. It should be mentioned that in various countries, the energy intensity of treating wastewater does not vary significantly, as it ranges between 0.37-0.67 kW/m^3 (Hernández-sancho et al., 2011; Yoon, 2018).

Desalination A process of removing salt from sea or brackish water to produce potable water. It is a relatively new water treatment technology that provides high quality water. However, it has an energy intensity that is at least 5 to 7 times higher than conventional treatment processes (Pabi et al., 2013). There are two types of desalination technologies: thermal-based technologies that require thermal and electrical energy, and membrane-based technologies that need electrical energy (Panagopoulos, 2021). Examples of thermal-based technologies are multi-stage distillation and multi-effect distillation, whereas for membrane-based technologies, there are reverse osmosis (RO), nanofiltration and electrodialysis. RO has lower energy requirements in comparison to thermal-based technologies, and therefore around 70% of desalination plants use RO technology (Panagopoulos, 2021). Most of the thermal-based desalination plants are found in countries that have abundant energy resources and high water scarcity, such as countries in the Arabian Peninsula (Saudi Arabia, United Arab Emirates, Qatar, etc.) (Yoon, 2018).

2.5 Demand-Side Management

The main focus in power systems engineering is to ensure the uninterrupted supply of electric power to electricity consumers (Cho et al., 2022). This means that, despite the varying nature of electricity demands and electricity generation facilities (during a day, season, or year), power system operators must ensure that the power supplied from the generation side of the power grid is equal to power demands of the electricity consumers on the demand side of the power grid at any given time. This is commonly referred to as grid balancing.

Traditionally, power system operators have managed the supply of electricity by ramping up and down electricity production resources on the generation-side of the power grid in response to the fluctuating electricity demands. The demand-side was considered to be relatively inflexible for grid balancing (Paterakis et al., 2017). However, as of recent, the high penetration of re-

newable energy resources into the power grid, as well as emerging deregulated electricity markets (both uncertain in nature) have exacerbated the challenge of grid balancing. This has spurred efforts towards increasing flexibility in power systems from the demand-side. Strategies aimed at leveraging flexible power demands which are referred to as demand-side management (DSM) have been proposed and developed from various disciplines such as, engineering, economics, behaviour science, and public policy (Zhang & Grossmann, 2016). DSM is anticipated to play an important role in improving the reliability and stability of the power grid, as well as provide economic benefits to electricity consumers (Chen et al., 2021). More importantly, DSM offers a cheaper solution to the challenge of grid balancing rather than investing capital in the construction of new power plants or BESSs (Palensky & Dietrich, 2011).

2.5.1 Definition

DSM has been generally defined from the perspective of power system operators since the concept was originally proposed by power utilities in the 1970s (Barakat & Chamberlin Incorporated, 1993). For instance, Gelazanskas and Gamage (2014) defined DSM "as the planning, implementation and monitoring of utility activities that are designed to influence customer use of electricity" (p. 23). Similar definitions can also be found in various literature resources (EIA, 2002; Charles River Associates, 2005; Smith & Parmenter, 2016; Paterakis et al., 2017). These definitions only consider the activities of power utilities as DSM, while the electricity consumers play a passive role in DSM. Consequently, the role of electricity consumers in DSM is understated since they solely carry the capability to change the timing and/or amount of electricity usage. This also lowers the accuracy of electricity market design models of power utilities when assessing the DSM potential of electricity consumers because the perspective of electricity consumer is not considered in detail (Zhang & Grossmann, 2016). Hence, to comprehensively define DSM, it is necessary to view the topic from the perspective of power system operators

and electricity consumers. Figure 2.10 illustrates DSM activities of power system operators and electricity consumers which are linked through the power grid and electricity markets.

Based on Figure 2.10, Zhang and Grossmann (2016) offer a comprehensive definition of DSM that considers both perspectives of the power system operator and electricity consumer as follows:

> DSM encompasses systematic activities at the interplay between system operator and electricity consumer aiming at changing the amount and/or timing of the consumer's use of electricity in order to increase grid performance and consumer benefits. DSM activities on the system operator side involve the assessment of the need for load adjustment and the creation of financial incentives for the consumer, while the consumer reacts to these financial incentives and performs the actual physical load adjustment operations. (p. 118)

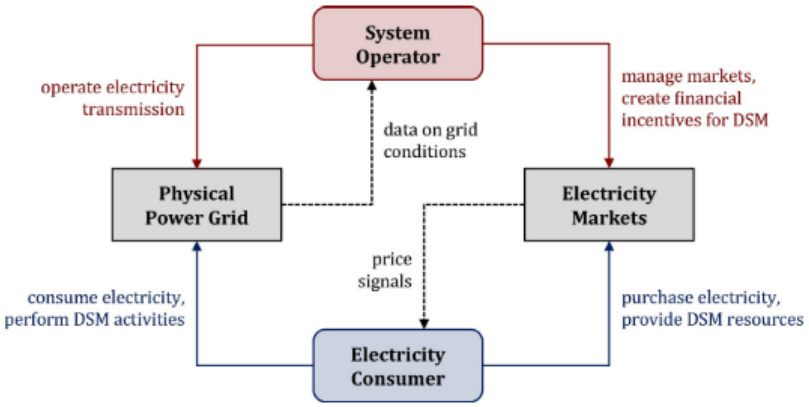


Figure 2.10: Power system operator and electricity consumer perspectives on DSM (Zhang & Grossmann, 2016).

2.5.2 Classification

DSM methods are broadly classified into two categories which are energy efficiency and demand response, as shown in Figure 2.11.

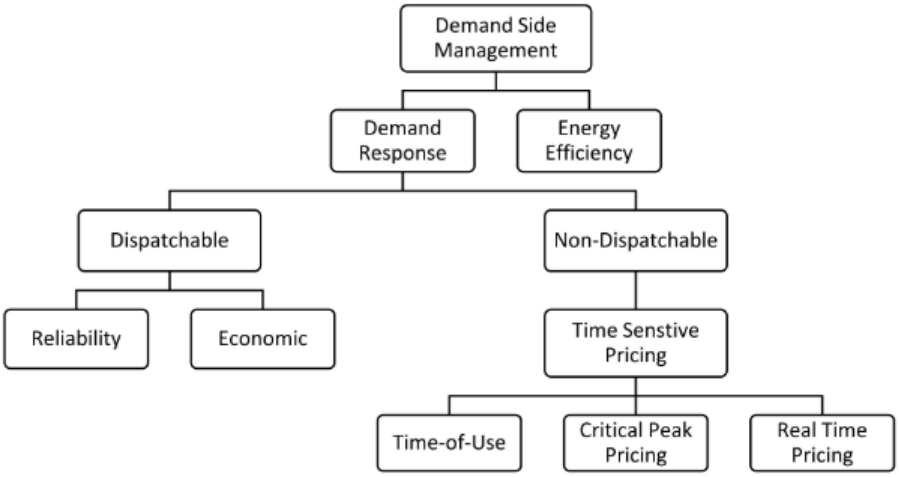


Figure 2.11: Classification of DSM methods (Alotaibi et al., 2020).

Energy Efficiency

Energy efficiency is the usage of an alternative method, process, or equipment in a particular system that lowers the amount of energy used to achieve the same outcome (Smith & Parmenter, 2016). This DSM method is permanent in nature since it involves retrofitting or improving the design of a system. Examples of energy efficiency include, switching to variable-speed air conditioning from standard air conditioning, using optimally designed equipment, and heat integration. (Bakare et al., 2023).

Demand Response

Demand response refers to programs designed to induce lower electricity use by offering incentive payments at times of high market prices or when power grid reliability is threatened (Albadi & El-Saadany, 2008; US DOE, 2006). The goal of demand response is to flatten the power demand pattern either through the reduction of electricity usage during peak hours or shifting the power demands (loads) to off-peak hours (Alotaibi et al., 2020). Electricity consumers can participate in demand response through three ways (Albadi & El-Saadany, 2008; Chen et al., 2021):

(i) by shifting their power demands from peak hours to off-peak hours (load

shifting),

(ii) by reducing the amount of electricity they use during peak hours (load shedding),

(iii) by relying on an onsite generation, such as BESSs.

Demand response is categorised as dispatchable demand response (also called incentive-based demand response) and non-dispatchable demand response (also called price-based demand response). In dispatchable demand response programs power system operators offer payments to electricity users for the reduction of their power demands during certain periods (US DOE, 2006). The power system operator also has either direct control to the consumer power demands or the ability to request the consumer to lower their power demands. Prior the execution of dispatchable demand programs, contracts between power system controllers and electricity consumers are drawn which state the contents (terms and conditions) of the demand response program. The content of the contracts may include, reduction in power demand size, response duration, maximum number of responses accounting standards, advance notice time, compensation or electricity price discount standards, etc. (Chen et al., 2021). Various examples of dispatchable demand response programs are given and briefly explained as follows:

Direct Load Control Power system operators has direct control over electrical appliances of electricity consumers (residential consumers), such as air conditioners, water heating, and pool pumping. Electricity consumers are not given prior notification of disruption; however, they are compensated through discounts or electricity bills credits (Paterakis et al., 2017).

Interruptible/Curtailable Load Electricity consumers (commercial or industrial consumers) respond to calls from power system operators to reduce or interrupt electricity usage (Paterakis et al., 2017; US DOE, 2006). This program is mandatory, therefore, failure to respond to calls may result in penalties towards the consumers (Bakare et al., 2023).

Demand-Side Bidding Electricity consumers bid to reduce specific power demands based on wholesale electricity market prices (US DOE, 2006). If bid is accepted, electricity consumer must reduce their specified power demand; otherwise, they face penalties (Albadi & El-Saadany, 2008).

Capacity Markets Electricity consumer receives incentive payments for reducing their power demands during an emergency event, such as when there is a shortage of reserves (Albadi & El-Saadany, 2008; US DOE, 2006).

Emergency Demand Response Electricity consumers commit to reduce prespecified power demands when system contingencies arise (Albadi & El-Saadany, 2008; US DOE, 2006).

Ancillary Service Markets Electricity consumers bid to curtail their power demands in the spot market as operating reserve (Albadi & El-Saadany, 2008; US DOE, 2006).

Unlike dispatchable demand response programs, in non-dispatchable demand response programs, the electricity consumer voluntarily lower their electricity in response to price signals in the electricity markets (Paterakis et al., 2017). These programs are based on dynamic pricing which follow the real time cost of electricity (Albadi & El-Saadany, 2008). Various examples of non-dispatchable demand response programs are given and briefly explained as follows:

Time of Use Tariffs A stepped rate structure that reflects the average costs of generating and delivering electricity with respect to the time during the day when the electricity is used (Paterakis et al., 2017; US DOE, 2006). Price signals of time of use tariffs are typically broken down into peak, off-peak, and mid-peak times which makes it easier to schedule power demands for electricity consumers (Bakare et al., 2023).

Real Time Pricing A pricing scheme in which the electricity price fluctuates on an hourly basis thereby reflecting the wholesale price of electricity (or utility

price signals) (Bakare et al., 2023; US DOE, 2006).

Critical Peak Pricing This pricing scheme is a hybrid of time of use tariffs and real time pricing. While relying on the time of use tariffs as the basis for its pricing, it replaces the normal peak time prices with much higher prices of the real time pricing scheme (US DOE, 2006).

2.6 Scheduling in PSE

2.6.1 Definition

Scheduling is a decision-making process that plays a vital role in many production and service industries, such as the aviation industry, the construction industry, the hospitality industry, sports industry, etc. (Maravelias, 2012; Pinedo, 2016). Among these industries, the process industry also relies on scheduling to achieve their production goals optimally. In the PSE discipline, scheduling is defined by Maravelias (2012) as a problem that "encompasses the determination of the number of tasks, the assignment of tasks to resources, and the sequencing and/or timing of tasks" (p.1813).

In the process industry, the rise in energy costs, global competition, and stringent environmental regulations motivate research efforts towards the development of optimisation models for scheduling. Objectives of these optimisation models are typically to optimise plant costs and plant performance characteristics. These include maximisation of revenue and throughput, as well as minimisation of operating costs, makespan, tardiness or lateness (Behdani et al., 2007; Harjunkoski et al., 2014; Maravelias, 2012). While objectives can be used to classify the optimisation models for scheduling in the PSE discipline, classification broadly depends on the type of the production facility (batch and continuous processes), time representation and plant topology (sequential and network processes). However, it is important to note that, these classifications are not unique because scheduling problems in process industries have various features, such storage operational policies, changeovers, and demand

patterns. This is also evident in the excellent reviews on scheduling in process industries by Floudas and Lin (2004), Mendez et al. (2006), Maravelias (2012), and Harjunkoski et al. (2014).

2.6.2 Continuous versus Batch Processing

Continuous processing involves the production of high-volume and low-value products in a unit that operate continuously while carrying out a single task over time (Maravelias, 2021). When operating continuous processes, the main challenge is to maintain a near steady state operation which requires advanced process control methods. This steady state nature of continuous processes over time has deemed them to be described as being *frozen in time* (Majozi, 2010). On the contrary, batch processing involves the production of low-volume and high-value products in a unit where discrete tasks follow a predefined sequence (Majozi, 2010). This predefined sequence of tasks is also referred to as the recipe. Batch processes can be classified as: (i) multiproduct batch plants; where products are produced using the same unit(s) and recipe, and (ii) multipurpose batch plants; where products are produced using different units and different recipes.

Scheduling decisions for continuous and batch processes are mostly the same. Batching (size and number of batches) in batch processes is similar to lot-sizing in continuous processes. Also, assignment and sequencing decisions in batch processes are identical to continuous processes, i.e., lots of continuous tasks have to be assigned to a unit and sequenced, exactly as batches of batch tasks (Harjunkoski et al., 2014). However, there are two main differences between the scheduling of batch and continuous processes. These are: (i) the variables that determine the amount of material produced for a batch and continuous tasks, and (ii) the effect of task execution on inventory levels. Firstly, in a schedule for continuous processes, there can be multiple combinations of rates and processing times that can produce the same amount of material during a lot, while in a schedule for batch processes, once the batching decisions are made, the number and duration of batches are fixed, even if the processing

time of a batch is dependent on the batch size (Maravelias, 2021). In other words, the amount of material produced for a batch size in batch processes only depends on the processing time (duration) of the batch, while the amount of material produced for a lot size in continuous processes depends on the rate and processing time of the lot. Secondly, the execution of a batch task leads to a changes in the inventory (filling and drawing) at specified time points, while the execution of a continuous task lead to the depletion (accumulation) of inputs (outputs) throughout the execution of the task (Harjunkoski et al., 2014; Maravelias, 2021) (see Figure 2.12).

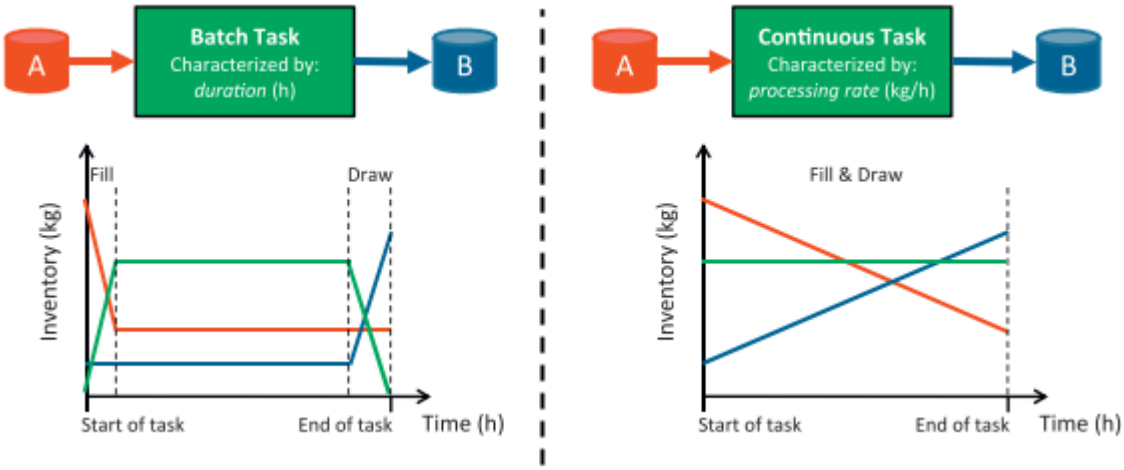


Figure 2.12: Illustration of the differences between batch and continuous tasks (Harjunkoski et al., 2014).

Scheduling problems that arise from batch processes are combinatorial due to the discrete nature of batch processes. From a computational standpoint, this makes solving batch process scheduling problems difficult. The fact that batch tasks are highly time dependent further exacerbates the difficulty of solving batch process scheduling problems. Therefore, solving scheduling problems is a more pertinent issue when dealing with batch processes in comparison to continuous processes (Maravelias, 2012).

2.6.3 Modelling of Time

The issue of capturing time accurately is very important when formulating mathematical optimisation models for scheduling problems. This is particularly the case for batch processes. Time representation is divided into two categories: discrete time representation and continuous time representation.

Discrete-time Representation

Discrete-time representation relies on the discretisation of the time horizon into time intervals of equal length. This forces the starting time and finishing time of tasks in a schedule to be assigned at the boundaries of these time intervals. In terms of structure, models based on the discrete-time representation are generally simpler and easier to solve. This has led to their wide application in many industrial problems (Mendez et al., 2006). However, since time is continuous, discretising the time horizon is an approximate representation of time. Consequently, this can lead to cases where the solution is suboptimal or even infeasible. An attempt to improve the accuracy of time discretisation involves increasing the fineness of the time interval (Majozi, 2010). However, this dramatically increases the combinatorial size of the model thereby increasing the computational burden.

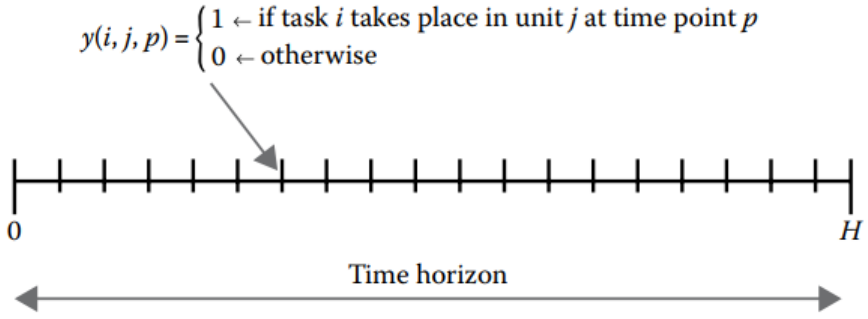


Figure 2.13: Discrete-time representation (Majozi et al., 2017).

Continuous-time Representation

Continuous-time representation captures time in its exact manner by allowing events to occur at any point in a set of continuous variables. Contrary to the case of discrete-time representation, tasks can start or end at any point within the time horizon. Therefore, the models based on the continuous-time representation tends to have lesser variables, as well as more accurate and flexible solutions (Mendez et al., 2006). However, continuous-time models are complex since they need detailed constraints to accurately capture the timing and allocation of tasks. Additionally, the number of time points is initially unknown. Therefore, there is a need for successive manual adaptive refinement to find the optimal number of time points (Perez et al., 2022).

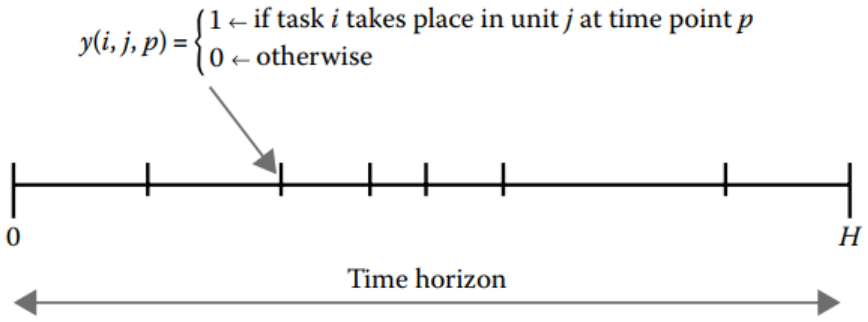


Figure 2.14: Continuous-time representation (Majozi et al., 2017).

2.6.4 Scheduling of the DSM in Process Industries

DSM has proven to be an effective approach for tackling the growing problem of uncertain electricity prices and availability. The approach relies on the participation of electricity consumers through dynamic management of their power demands. Among these electricity consumers, are process industries, which are known to be highly power-intensive. Examples of these processes industries include air separation plants, aluminium production plants, and steel production plants. Since electricity prices are time-sensitive, DSM programs have provided an opportunity for process industries as participants to

improve their profitability through effective planning, scheduling and control (Zhang & Grossmann, 2016). Therefore, since the past decade, researchers and practitioners have proposed detailed scheduling models that consider all the relevant process constraints and interactions with the electricity markets to assess the DSM potential of process industries (Zhang & Grossmann, 2016).

One of the earliest works in the PSE discipline on scheduling while considering energy constraints with relation to varying electricity market prices was that of Castro et al. (2009). Since the issue of time representation is also key in DSM problems, the authors presented both, a continuous-time model, and a discrete-time model with an objective to minimise the total electricity costs while meeting the production demands of the scheduling problem. The results showed that, the discrete-time model performs better when solving problems of industrial significance rather than continuous-time models. It was also shown that, it is easier to model hourly electricity prices, as well as the fixed demands when using discrete-time models. Modelling hourly electricity prices and fixed demands using the continuous-time representation led to an explosive increase in binary variables thereby increasing the complexity of the model. Subsequent research on scheduling frameworks for DSM also substantiated these observations, as indicated in the comprehensive and excellent review on industrial DSM by Zhang and Grossmann (2016). Therefore, most scheduling frameworks for DSM are based on the discrete-time representation.

Another important insight is that the benefit of DSM on industry plant is dependent on level of the utilisation of an industry plant. In cases where industry plants participate in nondispatchable demand response programs, the financial benefits are lesser if the plant has a high level of plant utilisation, viz., has a lower operational flexibility (Mitra et al., 2012; Zhang & Grossmann, 2016). On the contrary, Zhang, Morari, et al. (2016) demonstrated that industry plants can achieve large cost savings when they participate in dispatchable demand response programs, such as interruptible/curtailable load scheme even if their plant utilisation level is high (around 95%).

2.7 Integrated Water and Power Distribution Networks

The integration of water and power distribution networks draws from the concept of WEN and presents an opportunity for a win-win situation between water and energy utilities. The earliest work in literature that tackles the problem of integrating of water and power distribution networks is by Zamzam et al. (2019). However, before providing the state-of-the-art on the mathematical optimisation models of integrated water and power distribution networks, it is necessary to present a brief review of water and power distribution networks, as well as their mathematical optimisation models, separately.

2.7.1 Brief Review of Power Distribution Networks

Power distribution networks are an integral part of power grids (or electric power systems) that deliver electricity to the individual electricity consumer. They receive electricity from the transmission grid through substations and distribute low-medium voltage electricity ranging from 120V to 69kV, depending on the type of consumer (residential, commercial, and industrial consumers) (Cho et al., 2022).

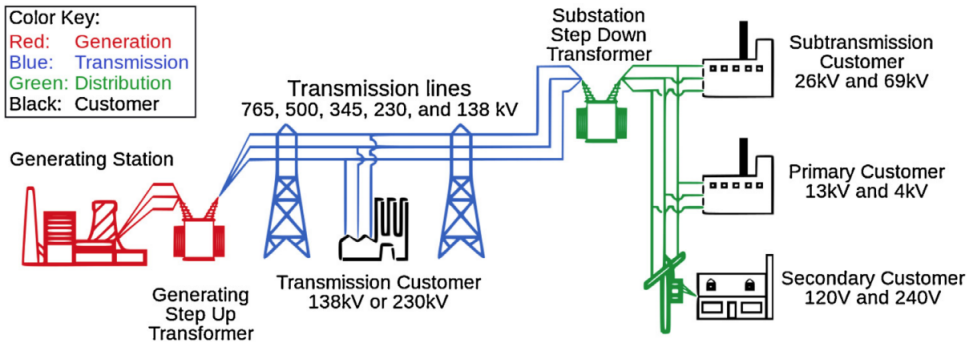


Figure 2.15: Illustration of a power grid (Zhang & Grossmann, 2016).

Typically, a power distribution network comprises various power components that include utility poles, distribution lines (overhead lines and underground cables), distribution transformers, substations, feeders (cables that connects a

substation to the distribution network), and protection devices. As of recent, there has also been an increase in smart grid technologies and distributed generation infrastructure in power distribution networks which include solar and wind power sources, BESSs, inverters and other components of control units (Aybar-Mejía et al., 2021; Marcos et al., 2017).

Power distribution networks can be categorised based on topology and the type of electric current they distribute. On the basis of the type of electric current, there are alternating current power distribution networks and direct current power distribution networks. In practice, alternating current power distribution networks are predominantly implemented as compared to direct current because they are cheaper and easier to operate. Moreover, unlike direct current, alternating current can be easily converted from low to high voltages or vice-versa. In the context of topology, power distribution networks are mainly divided into radial power distribution networks and meshed power distribution networks. The topology of power distribution networks is dependent on the number of their feeders. Power distribution networks that have one feeder have a radial topology, while the ones that have two or more feeders have a meshed topology (Cristian et al., 2013).

2.7.2 Mathematical Optimisation of Power Distribution Networks

To design and operate power distribution networks, power system practitioners and researchers solve various control and optimisation problems (Schneider et al., 2018). These problems include optimal power flow, unit commitment, state estimation, stability and reliability assessment, expansion planning, demand response, and volt/var control, and their underlying constraints are called the power flow equations (Low, 2014; Molzahn & Hiskens, 2019).

Power Flow Equations

Power flow equations are at the core of power system analysis. Their main applications are (i) for solving power flow problems to determine voltage phase and magnitude at all buses, real and reactive power flows in each line, and power losses for specified parameters, and (ii) as the key constraints for optimisation problems in power systems (Elsaiah et al., 2012; Molzahn & Hiskens, 2019). The latter application is also true for the optimisation problem solved in this dissertation. However, power flow equations are inherently quadratic (nonlinear). Consequently, this results in a type of nonconvex programming models called quadratically-constrained quadratic programs (QCQP). These models are difficult to solve. Moreover, most optimisation problems in power systems have a decision-making aspect which requires binary variables, and this produces an MINLP variant called mixed-integer quadratically-constrained quadratic program (MIQCQP) which is very challenging to solve.

A set of power flow equation is referred to as the AC power flow model. To circumvent the nonconvexities of the power equations, researchers have convexified the AC power flow model using linear approximations to give the DC power flow model (Low, 2014; Molzahn & Hiskens, 2019). The DC power flow model has proven to be highly accurate, particularly for circuit branches that have low R/X-ratio (resistance to reactance ratio) (Li et al., 2016). However, feeder(s) of power distribution networks have high R/X-ratio (Li & Vittal, 2017). Hence, this lowers the accuracy of DC power flow models when modelling power distribution networks. This has motivated researchers to opt for nonlinear convex relaxations of the AC power flow model, such as semi-definite programming (SDP), second order cone programming (SOCP), quadratic convex (QC), and moment-based relaxations (Li, 2016). There are two types of AC power flow models which are briefly discussed as follows:

Bus injection model A set of power flow equations with variables that represent the bus voltages, as well as the bus injection of power and current of a distribution network (Subhonmesh et al., 2012). These power flow constraints

are preferred for meshed power distribution networks.

Branch flow model A set of power flow equation with variables that represent the bus voltages, as well as the power and current in branches of a distribution network (Subhonmesh et al., 2012). These power flow constraints are valid for radial power distribution networks (Baran & Wu, 1989; Molzahn & Hiskens, 2019). The model is also called *DistFlow*.

In this dissertation, the branch flow model was used to represent the power flow constraints because power distribution networks are generally radial.

Test Feeders

A test feeder is a distribution network model that replicates the characteristics of an actual power distribution network (Marcos et al., 2017). In power systems engineering, test feeders have proven to be indispensable because they allow practitioners and researchers to test the performance of proposed power flow solution methods for various power systems problems (Schneider et al., 2018). However, obtaining test feeders with recent data is generally difficult because power distribution networks are critical infrastructures that are inherently sensitive. This makes it difficult to acquire real world data of power distribution networks (Babaeinejadsarookolaee et al., 2021). To tackle this issue, the Institute of Electrical and Electronics Engineers Power and Energy Society (IEEE PES) Test Feeders have published a few test feeders on their website since 1992. These test feeders include the 4 Node Test Feeder, 13 Node Test Feeder, 34 Node Test Feeder, 37 Node Test Feeder, 123 Node Test Feeder, Comprehensive Test Feeder, 8500 Node Test Feeder, Neutral-Earth-Voltage Test Feeder, Low Voltage Network Test System and European Low Voltage Test Feeder (Schneider et al., 2018). Figure 2.16 shows a topology of the 13 Node Test Feeder. The black points which connect the lines represent utility poles and are called buses, while the lines represent the distribution lines and are called the branches.

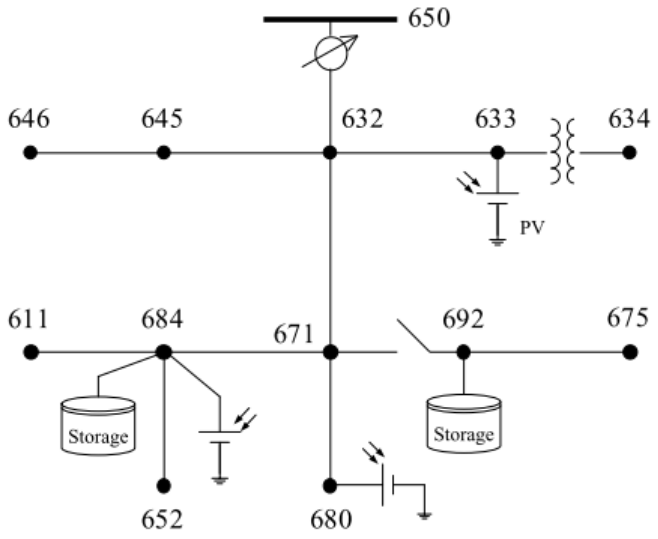


Figure 2.16: An illustration of a 13-Node Test Feeder (Li, 2016).

2.7.3 Brief Review of Water Distribution Networks

Water distribution networks are an indispensable and complex component of water supply systems that connect water sources to the water consumers. They play a crucial role of channeling sufficient and pressurised water over long distances through pipes to several consumption points. At the consumption points, the water is consumed for several purposes that include drinking, washing, cooling, irrigation, and industrial purposes.

The main components of water distribution networks consist of a piping network, pumping stations and distribution storage (Mays, 2010). These components are generally connected in a complex manner that depends on the spatial distribution of water consumption points. The piping network is made up of interconnected pipes and valves. The point of interconnection between two or more pipes is called nodes, while the pipes are referred to as arcs or links. The piping network receives water from the water source (usually a water treatment facility) through a large pipe called feeder and the water subsequently flows through various interconnected pipes that gradually decrease in size until it reaches the consumption points. To ensure that water flows through the entire distribution network, pumps provide energy to the water. The amount of energy provided is sufficient to overcome frictional forces and

elevational changes. Storage tanks play a crucial role of acting as buffers in the water distribution network. They provide flexibility to the water distribution networks by acting as a standby reserve of water that can be readily used when the water demand is high. Valves serve the purpose of regulating the flow or the pressure of the water in distribution networks.

2.7.4 Mathematical Optimisation of Water Distribution Networks

Water distribution networks require effective management to meet their varying water demands reliably. To achieve this goal, analysis and design of water distribution networks is essential in a variety of situations, such as designing new water distribution networks, assessing water quality, analysing system malfunctions, testing for system performance, etc. (Mays, 2010). In literature, a plethora of optimisation models for water distribution networks have been presented, mainly aimed on designing water distribution networks, water quality, and pump scheduling (Mala-Jetmarova et al., 2017).

In general, the core constraints of optimisation models for water distribution networks are mass balance and pressure loss constraints. Mass balance constraints are based on the law of conservation of mass and ensure that net difference between the inflow and the outflow of the distribution network always zero. These constraints are easy to deal with because water is usually the only component that is considered during the formulation process, except for water quality models where other components, such as chlorine are included. Pressure loss constraints are used to account for the pressure drop due to friction along a pipe. There are two common equation that are used for accounting for pressure loss in water distribution network optimisation models:

(i) Darcy-Weisbach equation:

$$h_n - h_{n'} = \frac{8 f_k^2 L_k F_k^f}{\pi^2 g D_k^5} \quad \forall n, n' \in N, \ \ \forall k \in K \tag{2.3}$$

(ii) Hazen-Williams equation:

$$h_n - h_{n'} = \frac{10.7 f_k^{1.852} L_k}{C^{1.852} D_k^{4.87}} \quad \forall n, n' \in N, \ \forall k \in K \tag{2.4}$$

While the Darcy-Weisbach equation is a theoretial equation and the Hazen-William equation is an empirical-based equation, there are no computational results that confirm the accuracy of both equation for water distribution network optimisation models (D'Ambrosio et al., 2015). However, the notable trait of both equations is their nonconvex and nonlinear nature which often leads to nonconvex NLP or MINLP optimisation models that are notoriously difficult to solve. Other features of water distribution networks, i.e., valves, pumps and storage tanks are often modelled with lesser granularity because they are not core constraints of the models.

Solving optimisation problems of water distribution networks is very challenging. Firstly, the problem is combinatorial in nature. For instance, designing a water distribution network involves finding the best combination of pipes, and pump scheduling involves choosing the optimum timing for pumping water. Secondly, as mentioned before, the pressure loss constraints are nonconvex. Finally, parameters of the problem, such as water demands, pipe roughness, and minimum nodal pressure requirements are inherently uncertain (Mala-Jetmarova et al., 2017). Due to these reasons, most researchers and practitioners rely on stochastic approaches over deterministic approaches. Stochastic approaches provide a quicker and practical solution, particularly for real life medium- to large-scale problems (Mawengkang et al., 2023). However, over the past 20 years, deterministic approaches have advanced significantly. This has allowed them to handle water distribution network optimisation problems effectively under reasonable computational times while, guaranteeing accurate results (Bragalli et al., 2012).

2.7.5 State-of-the-Art of Mathematical Optimisation Models for Integrated Water and Power Distribution Networks

Recently, there has been growing interest in the integrated operation of water and power distribution networks that results from DSM programs. This has led to the development of various mathematical optimisation models that address a short-term scheduling problem of the unit operations of integrated water and power distribution networks to minimise the overall operating costs. In mathematical optimisation models proposed in literature, the connection between both networks originates solely from the pumps. These mathematical optimisation models are nonconvex MIQCQP (MINLP variant) that are very difficult to solve because they inherit computational complexities of the water and power distribution that are discussed in the foregoing sections. Therefore, most of the work in literature that tackle this problem generally introduces convexification techniques during the solution process to make the problem more tractable.

Initially, Zamzam et al. (2019) presented a formulation to improve the flexibility in the power grid by optimising pump and storage tank operations in an integrated water and power distribution network. The authors applied a feasible point pursuit-successive convex approximation technique to solve the resultant nonconvex MINLP and achieved a near-optimal solution. Their results showed that the integrated approach enhanced grid flexibility, and consequently lowered operating costs in comparison to the decoupled approach.

Li et al. (2019) developed a mathematical model to explore the demand response capabilities of power-intensive water loads in water networks. They used the quasi-convex hull technique to relax the nonconvex MINLP to a convex MIP. The convexified model demonstrated the demand response capability of the irrigation systems and water storage tanks under a significantly lower computational time.

Stuhlmacher and Mathieu (2020b) presented a chance-constrained formula-

tion that catered for the uncertain nature of power demands in integrated water and power distribution networks. A heuristic scenario-based approach was used to solve the nonconvex problem. Due to the increased complexity of the problem, they introduced the quasi-convex hull technique similar to Li et al. (2019) to the formulation, and managed to obtain feasible results. Subsequently, Stuhlmacher and Mathieu (2020a) extended the work by simultaneously incorporating the water and power uncertainties.

Oikonomou and Parvania (2020) proposed a model that leverages the operational flexibility of water desalination plants concurrently with storage tanks. A piecewise linear approximation was utilised to linearise the nonlinear constraints stemming from pressure loss and water desalination plant constraints. The nonconvex branch flow constraints are relaxed using the SOCP relaxation. After solving the convexified MINLP, the results showed that reduced operating costs are achieved for integrated water and power distribution networks, especially when the recovery ratio of water desalination plants is allowed to vary. The authors also assessed the impact of different tariff schemes on the overall operating cost of integrated water and power distribution networks. Dynamic tariff schemes led to higher operating cost savings as compared to flat and night tariff schemes.

Nguyen et al. (2020) proposed a scheduling framework that aimed to exploit the energy storage potential associated with flexible power-driven water and thermal loads. The authors presented a mathematical optimisation model that has differential equations for capturing the operation of water storage tanks and thermal storages. To ease the solution process of this model, the SOCP relaxation was adapted to transform the branch flow constraints into convex constraints, whereas the quasi-convex hull technique was used to transform the pressure loss constraints into convex constraints. Also, the forward Euler method was used to make it easy to model differential equations through discretisation. Although, these techniques made the problem more tractable, they are also intrinsically inexact. The results of this work showed that water storage tanks offer outstanding flexibility to the power grid, particularly

for longer time horizons, while the thermal storages offered direct support for short-term load-shifting thereby avoiding the risk of price hikes (Nguyen et al., 2020).

Ayyagari et al. (2021) used a novel successive linear approximation-based approach to optimise the resources in a coupled water and power distribution network. They observed an improvement in the operating costs of the water distribution network, as well as the voltage regulation in the power distribution network.

Goodarzi and Li (2022) explored the capability of electricity-driven water facilities of small communities that have a high penetration of photovoltaic (PV) resources to act as virtual energy storage and virtual power plants to the power grid in integrated water and power distribution networks. The authors concluded that it is economically beneficial to operate water facilities as virtual energy storage because BESS are currently expensive.

Alnahhal et al. (2023) presented a formulation that co-optimised water and power distribution networks while incorporating RO desalination tracks for energy flexibility. The authors applied the Glover Transformation technique (an exact convexification technique) to linearise bilinear terms that were occurring in the inflow and outflow constraints of the storage tanks. This helped to reduce the computational burden of their optimisation model. The results of this work showed integrating water and power distribution networks leads to a 4.6% decrease in the operational costs as compared to the case when they operate separately. However, the obtained results have no global optimality guarantee because Knitro (a convex MINLP solver) was used to solve a nonconvex MINLP problem.

Despite the model complexities of the integrated water and power distribution networks optimisation problem, the results of the discussed optimisation models show that there is a benefit of leveraging the demand response capabilities of water distribution networks. Through integration, power distribution networks benefit from the flexibility of the power-intensive operations of the water distribution network ,i.e, pumping and treating water in conjunction

with storage tanks. This is evident through the reduction of the operating costs of both networks. From this, the potential value of using a WEN concept when dealing with water and power distribution networks is ascertained. However, the WEN concept emphasises on the mutual interdependency of water and energy systems. In the discussed optimisation models, only a one-way interdependency is represented through the pumps, where the water distribution network receives energy from the power distribution network. This neglects connections that send water to the power distribution network, such as distributing water to the thermal power plants that require water for cooling. Also, most of the optimisation models do not include the connection of the water treatment facilities (or desalination) which contributes substantially in terms of increasing the flexibility of power distribution networks. Another drawback of these optimisation models is the lack of detail when modelling the storage facilities, i.e., BESSs and water storage tanks of the optimisation problem. Storage facilities of both networks are the main source of flexibility because they allow flexible timing of power-intensive operations without hindering the satisfaction of water and power demands. Hence, a lack of detail in models for storage facilities lowers the accuracy of the optimisation models.

2.8 Global Optimisation Algorithms and Techniques for MINLP Problems

MINLP has proven to have the most versatile modelling capabilities for a plethora of real-world optimisation problems (Kronqvist et al., 2019). This is because it can accommodate both integer or discrete variables (MILP subproblem) and nonlinear constraints (NLP subproblem) of most optimisation problems, including the problem dealt with in this dissertation. However, MINLPs are NP-hard, i.e., they are very difficult problems to solve, even for relatively simple problems (Belotti et al., 2013; Horst & Tuy, 1996). Therefore, over the past 30 years or so, practitioners and researchers (in tandem with the rapid growth in computational capabilities) have developed rigorous optimisa-

tion algorithms and techniques to solve MINLP problems with a guarantee of global optimality under the field of global optimisation (Belotti et al., 2013; Boukouvala et al., 2016; Kronqvist et al., 2019).

Global optimisation algorithms can be classified into two main categories: (i) deterministic approaches, and (ii) stochastic approaches. Convexification techniques have also proven to be pivotal in increasing the solution efficiency of global optimisation algorithms (Tawarmalani & Sahinidis, 2002). In the following sections, convexification techniques, as well as global optimisation algorithms and solver software are discussed.

2.8.1 Convexification Techniques

Convexification techniques (also called relaxation techniques) are at the heart of global optimisation algorithms. They are used to obtain convex relaxations of nonconvex constraints of nonconvex programming problems thereby making them more tractable. In other words, convex constraints that overestimate the feasible region of the nonconvex constraints are used to simplify the solution process (Trespalacios & Grossmann, 2014). Consequently, global optimisation algorithms are typically integrated with convexification techniques to help drive the solution process (Burer & Letchford, 2012). Although most of these techniques are inexact, they have proven to be very useful in solving difficult optimisation problems. For instance, the solution of a relaxed model produced by an inexact convexification technique can be used as a good starting point for solving the original model.

There are various types of convexification techniques in literature. The most prevalent convexification techniques are discussed in this dissertation, and these include Glover transformation, McCormick relaxations, Reformulation-Linearisation techniques, and Piecewise Linearisation techniques.

Glover Transformation

This technique was presented by Glover (1975) with the purpose of linearising bilinear terms that occur as a product of binary and continuous variables. Glover transformation has proven to be very useful in many optimisation problems because its linearisation is exact. Global optimality is guaranteed after using Glover transformation if there are no other nonconvexities in the model (Majozi, 2010).

McCormick Relaxations

McCormick relaxations (also called McCormick envelopes) is a technique presented in the seminal work by McCormick (1976) for linearising bilinear terms formed from the product of two continuous variables. The technique computes polyhedral relaxations called convex and concave envelopes (convex under- and concave over-estimators) which replaces each bilinear term. This results in the addition of a new variable and four sets of linear inequality constraints (Castro, 2014). McCormick relaxations have been applied in many optimisation problems that have bilinear terms because they essentially create a convex solution space in the original space of a problem thereby making it easier to solve a problem. However, due to the inexact nature of McCormick relaxations, methods for *tightening* the convex and concave envelopes are often required to reduce the convex solution space they create (Belotti et al., 2013).

Reformulation-Linearisation Techniques

Sherali and Alameddine (1992) presented the seminal work for Reformulation-Linearisation techniques. The technique generates tight linear relaxations for bilinear terms through a two-step process: (i) reformulation, and (ii) linearisation. The reformulation step involves the automatic generation of certain additional nonlinear valid constraints based on the product of stated inequality constraints or on products of equality constraints with variables (Sherali et al., 2001; Sherali & Liberti, 2009). Subsequently, a linearisation step is

implemented where each product constraint produced from the prior step is replaced with a single continuous variable (Sherali & Liberti, 2009). Although Reformulation-Linearisation techniques were originally designed to deal with bilinear terms of the product of binary and continuous variables, they have also been used to tackle problems with bilinear terms of two or more continuous variables (Sherali & Liberti, 2009). However, the technique is inexact, and this leads to the need for further steps in the solution procedure to achieve global optimality. This is evident in the work of Quesada and Grossmann (1995) and Dippenaar and Majozi (2021).

Piecewise Linearisation Techniques

These techniques are applied broadly in various disciplines. They rely on replacing nonconvex functions of an NLP or MINLP model with piecewise linear functions. For a univariate nonconvex function, piecewise linear approximation involves partitioning the function into several linear segments. The points of partitioning are called break points. The line produced by joining these break points approximates the nonconvex function (see plot in Figure 2.17). The equation representing this line is called the piecewise linear function. Piecewise linear approximation can also be done on multivariate functions. Since these techniques approximate optimisation problems, they are naturally inexact. Hence, the global optimality of a solution obtained from using piecewise linear approximation cannot be guaranteed. Moreover, one needs to be mindful of the number of break points used because it is tied to the accuracy of the model and computational performance of the solution process. More break points give a more accurate model at the expense of computational performance and vice-versa (Belotti et al., 2013).

2.8.2 Deterministic Approaches

Deterministic approaches provide a theoretical guarantee of locating the global optimal solution or at the very least, an approximate global optimal solution to an optimisation problem within a given range of tolerance (Liberti &

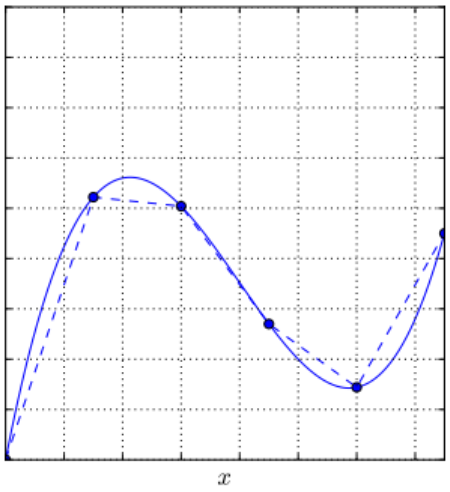


Figure 2.17: Graphical representation of a nonconvex function with its piecewise linear approximation (Belotti et al., 2013).

Kucherenko, 2005). They take advantage of the analytical properties of optimisation problems to generate a sequence of points that converge towards the global solution (Lin et al., 2012). Due to these qualities, deterministic approaches provide highly accurate results in comparison to stochastic approaches. However, deterministic solution methods often fail to deliver solutions in reasonable time when tackling large-scale optimisation problems (Lin et al., 2012). Various deterministic approaches targeted at solving convex and nonconvex MINLP problems have been proposed over the years. These approaches are generally classified as Branch-and-Bound (BB) algorithms and Decomposition algorithms (Grossmann, 2021).

Branch-and-Bound Algorithms

The first BB solution method was presented by Land and Doig (1960) for tackling MILP problems, and after this, Dakin (1965) and Gupta and Ravindran (1985) extended it to convex MINLP problems. Since then, optimisation algorithms based on BB, such as branch-and-cut and branch-and-price have been developed for solving different types of optimisation problems. BB algorithms offer a divide and conquer strategy where the feasible region is relaxed, and subsequently divided into parts (branching) where lower and upper bounds of

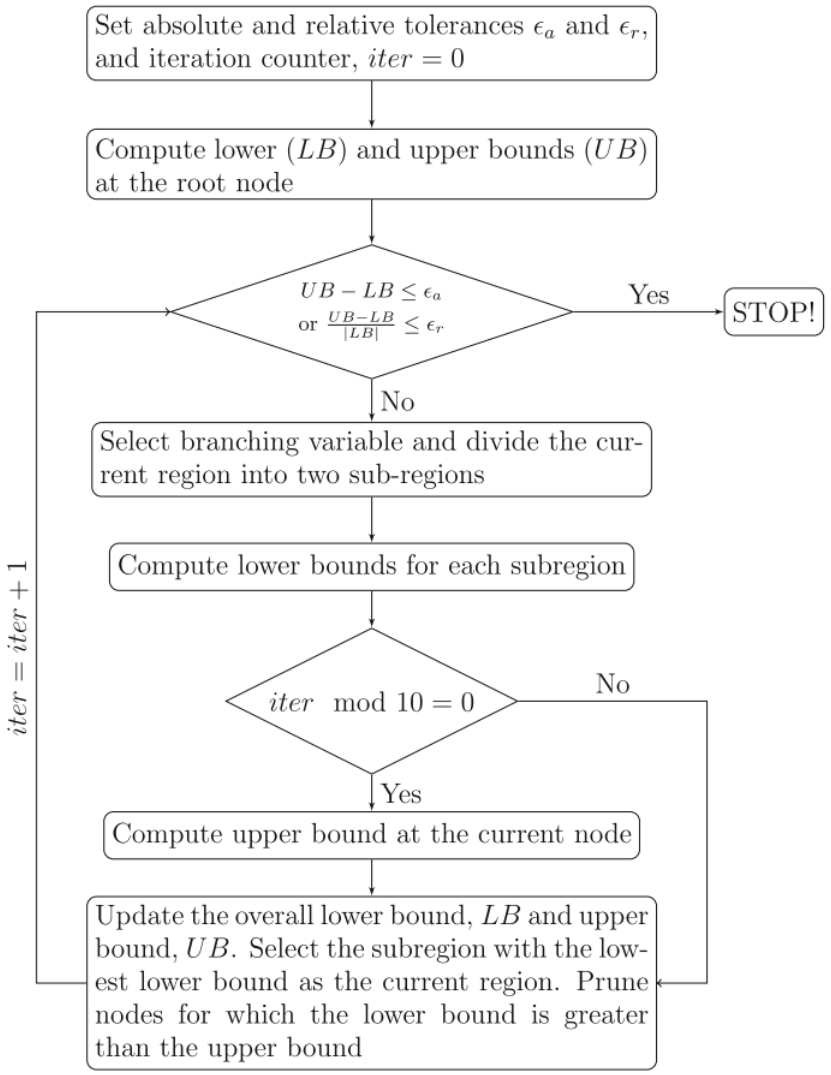


Figure 2.18: Flowchart of a general sBB algorithm (Bajaj & Hasan, 2020).

the objective function are computed (bounding) (Horst & Tuy, 1996). A variant class of BB algorithms called Spatial Branch-and-Bound (sBB) has proven to be the most effective solution method for solving nonconvex MINLPs with a formal guarantee for global optimality (Liberti & Kucherenko, 2005; Belotti et al., 2009, 2013). Examples of solver software based on sBB algorithms are Algorithms for Continuous/Integer Global Optimisation of Nonlinear Equations (ANTIGONE), Branch-and-Reduce Optimisation Navigator (BARON), and Solving Constraint Integer Programs (SCIP). Figure 2.18 provides an overview of the general steps in sBB algorithms.

Decomposition Algorithms

Decomposition algorithms have proven to be very effective exact solution approaches particularly for convex MINLPs (Burer & Letchford, 2012). This is because the relaxation of the integrality condition of convex MINLP leads to a convex NLP subproblem which is usually tractable. While these optimisation algorithms cannot provide a global optimality guarantee for nonconvex optimisation problems, they are very useful as heuristic methods for finding good starting solution points when solving nonconvex MINLPs (Ambrosio & Lodi, 2013).

The solution approach of decomposition algorithms generally involves iterations between the NLP subproblems and MILP master problems. During these iterations, NLP subproblems with fixed binary variables provide upper bounds to the objective function Z^U if there is a feasible solution, while the MILP master problem predicts a lower bound to the objective function Z^L, as well as new values of binary variables (Grossmann, 2021). The iterations continue until a lower bound Z^L that is greater than the current upper bound Z^U is found (by margins within the given tolerance); otherwise, the iterations continue (see Figure 2.19).

The following algorithms rely on the solution approach described above: Outer Approximation (OA) (Duran & Grossmann, 1986), Extended Cutting Plane (ECP) (Westerlund & Pettersson, 1995), Generalised Benders Decomposition (GBD) (Geoffrion, 1972), and LP/NLP-Branch-and-Bound (LP/NLP BB) (Quesada & Grossmann, 1992). These algorithms have been used to construct nonglobal MINLP solver software. Examples of these solvers include Discrete and Continuous Optimiser (DICOPT), Alpha-Extended Cutting Plane (Alpha-ECP), Basic Open-source Nonlinear Mixed Integer Programming (BONMIN), and AIMMS Outer Approximation (AOA).

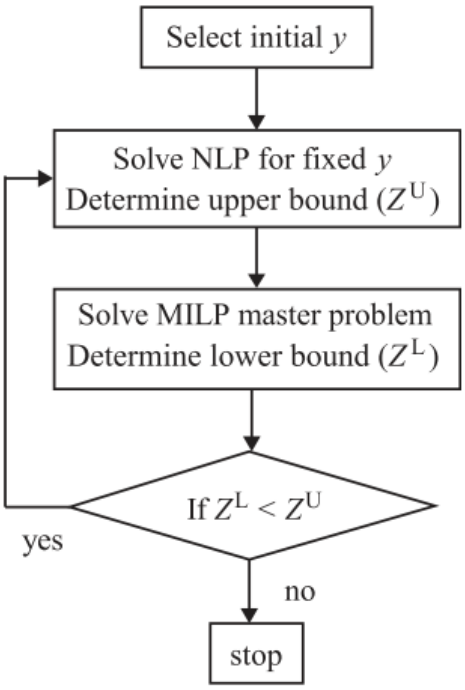


Figure 2.19: Flowchart showing the general steps involved in Decomposition Algorithms (Grossmann, 2021).

2.8.3 Stochastic Approaches

Stochastic approaches (also called probabilistic search approaches) are solution methods that require at each iteration a random choice of a candidate solution or parameters that determine a solution with respect to a given measure of solution quality (Belotti et al., 2013). The random nature of stochastic approaches leads to different solutions for an optimisation problem in different runs, even though each run starts with the same parameters. This characteristic allows one to choose the most suitable solution from a variety of solutions. Also, stochastic approaches are easy to design, and typically arrive at solutions quickly as compared to deterministic approaches. Due to these qualities, stochastic approaches are popular, particularly for real application cases where a quick solution that falls within the feasible region of a problem is needed.

However, stochastic approaches have their own drawbacks. Firstly, it is generally difficult to ascertain the global optimality of solutions because they can only offer a probabilistic guarantee to the solution (Liberti & Kucherenko,

2005). Therefore, the solutions are often suboptimal. This drawback is further exacerbated when solving large optimisation problems which is the case for many real-world optimisation problems (Lin et al., 2012). Secondly, there is a need for tailoring stochastic solution methods to the specific structure of the problem being solved when implementing them (Belotti et al., 2013).

Some of the common examples of stochastic approaches include simulated annealing, tabu search, genetic algorithms, ant colony optimisation, and particle-swarm optimisation.

2.8.4 Global Optimisation Solver Software for MINLP Problems

Since the nineties, various types of global optimisation solver software based on deterministic approaches have been developed for modelling and solving convex and nonconvex MINLP optimisation problems (Alkhalifa, 2022). Optimisation solver software generally relies on the integration of various techniques to improve their performance, such as BB methods, primal heuristics (using local standard solvers to find a good feasible solution), and preprocessing procedures (convexification techniques and bound-tightening techniques) (Kronqvist et al., 2019). Different combinations of mathematical optimisation techniques are used to build global optimisation solvers depending on the type of optimisation problems they are intended to solve. This is the case for global solvers, such as ANTIGONE, BARON, SCIP, GUROBI, Couenne, and LINDO. Therefore, the choice for the most suited global solver is depended on the characteristics of the MINLP problem at hand. In this dissertation, the global solver ANTIGONE is the most suited for tackling the integrated water and power distribution network optimisation problem. This is because the problem at hand is an MIQCQP, and ANTIGONE has been proven to perform strongly when solving MIQCQP in comparison to other global solvers (Misener & Floudas, 2014).

Table 2.1 and Table 2.2 present a list of some common non-global and global

MINLP solvers along with their key characteristics, respectively. Note that, the list solver software presented in the tables are not exhaustive. Detailed reviews of solver software for MINLP optimisation problems are provided by Kronqvist et al. (2019), Belotti et al. (2013), Ambrosio and Lodi (2013), and Bussieck and Vigerske (2011).

2.8.5 Modelling Systems

Modelling systems are complete support systems that are used to solve real-world optimisation problems (Kallrath, 2001). At the heart of a modelling system is a algebraic modelling language which translates the optimisation model developed by the user into a readable form for a solver (Ambrosio & Lodi, 2013). Algebraic modelling languages closely express optimisation models in their algebraic form through the usage of syntax that is similar to mathematical notations, and this makes the modelling process easier (Castillo et al., 2001; Ambrosio & Lodi, 2013). A modelling system also carries various types of solver software and the choice of a solver is supported by the algebraic modelling language. Other key features that characterise modelling systems are their capability to provide hints for dealing with infeasible outputs, as well as import and export data to other software, such as Microsoft Excel and MATLAB.

Examples of the most widely used modelling systems are General Algebraic Modeling System (GAMS), A Mathematical Programming Language (AMPL), and Advanced Interactive Multidimensional Modeling System (AIMMS). These modelling systems are commercial products, and are often used by academics and practitioners. As of recent, various modelling systems that are free (open-source) have been introduced. Examples of these modelling systems include PyOMO and JuMP. An alternative to these modelling systems is the NEOS (Network-Enabled Optimisation System) server which offers access to a plethora of solvers (over 50 solvers) for different types of optimisation problems through the NEOS server website (Dolan et al., 2008). It is important to note that, features of modelling systems are mostly similar (Castillo et al., 2001) and

thus, the choice of a modelling system is usually dictacted by whether a user can afford the product package of a modelling system. In this dissertation, GAMS is utilised as the modelling system.

2.9 Summary

This chapter provides a detailed review of the important subject matter that relates to the optimal operation of integrated water and power distribution networks. The review shows that there is an opportunity to utilise PSE methodologies, such as mathematical optimisation-based process integration techniques to tackle the problem of integrated water and power distribution networks. Opportunities that can improve the flexibility of integrated network are also observed. These include, capturing all the possible mutual interdependencies between both networks, and improving the level of detail when modelling storage facilities. An assessment of the optimisation tools that can provide a guarantee global optimality is also provided. Based on these deductions, the following chapter develops an optimisation model that includes all these opportunities to achieve an optimal operation of integrated water and power distribution networks.

Table 2.1: Non-global solvers for MINLP problems.

Solver	References	Modelling System(s)	Type of Deterministic Algorithm
Alpha-ECP	Westerlund and Pettersson (1995)	GAMS, NEOS	Decomposition (ECP)
AOA	Hunting (2011)	AIMMS	Decomposition (OA)
BONMIN	Bonami et al. (2008)	AMPL, JuMP, GAMS, etc.	Decomposition (OA, GBD)
DICOPT	Grossmann et al. (2002)	GAMS, NEOS	Decomposition (OA)
Juniper	Kroger et al. (2018)	JuMP	Standard Branch-and-Bound
Knitro	Byrd et al. (2006)	AIMMS, AMPL, GAMS, etc.	Standard Branch-and-Bound

Table 2.2: Global solvers for MINLP problems.

Solver	References	Modelling System(s)	Type of Deterministic Algorithm
ANTIGONE	(Misener & Floudas, 2014)	GAMS, NEOS	Branch-and-Cut
BARON	Kılınç and Sahinidis (2018)	AMPL, GAMS, JuMP, etc.	Branch-and-Reduce
GUROBI	(Gurobi, 2020)	AMPL, GAMS, Python, etc.	Branch-and-Cut
Couenne	Belotti et al. (2009)	AMPL, GAMS, JuMP, etc.	Spatial Branch-and-Bound
LINDO	(Lindo, 2003)	LINGO, GAMS, JuMP, etc.	Branch-and-Cut
SCIP	Bestuzheva et al. (2021)	GAMS, AMPL, PyOMO	Branch-and-Cut

Chapter 3

Model Development

In this chapter, the developed optimisation model is presented. The chapter is subdivided into 6 distinct sections. Superstructure and time representation sections presents the basis on which all the formulations of the optimisation model are built upon, while the rest of the sections describe all the formulations of the optimisation model, comprehensively. Sets, parameters, and variables used in the formulations are given at the beginning of the dissertation under the Nomenclature.

3.1 Superstructure

The superstructure is a postulation that includes all the useful unit operations, as well as their relevant interconnections in a particular process (Ryu et al., 2020). This postulation is usually used to explore of all possible combinations when using mathematical optimisation methods to find the optimal structure of a process system (Mencarelli et al., 2020). However, the superstructure in this dissertation is used to build a robust optimisation model that is capable of solving the integrated operation of existing water and power distribution networks while considering all the possible mutual interconnections between both networks. This superstructure (depicted in Figure 3.1) is very helpful as it generalises the model, thereby making it easy to apply on existing water and power distribution networks (Castro et al., 2009).

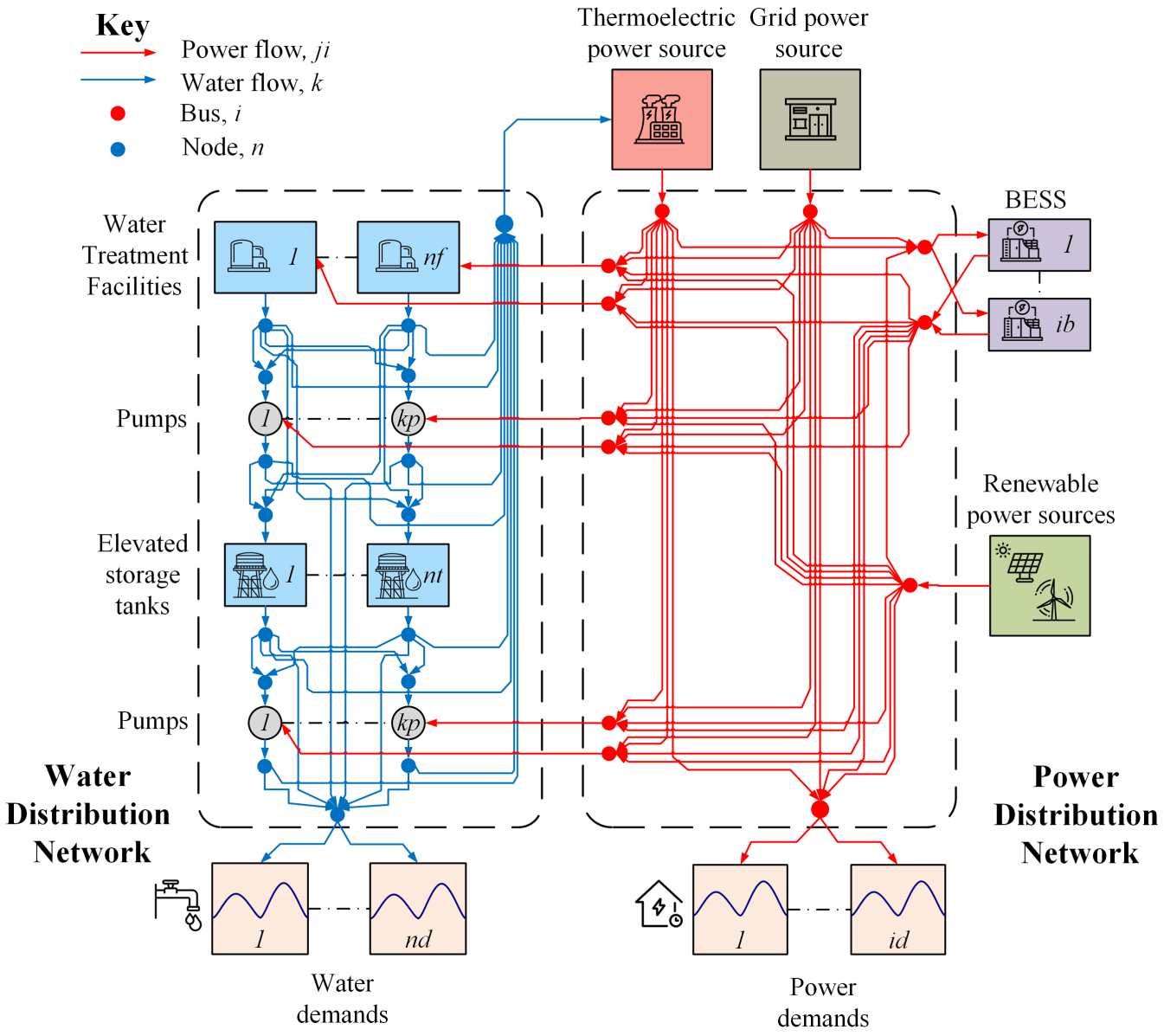


Figure 3.1: Integrated water and power distribution network superstructure for the proposed mathematical optimisation model.

The superstructure comprises two networks: a water distribution network, and a power distribution network. It shows all the possible interconnections that lead to the satisfaction of the sets ND and ID of water and power demands of the consumers, respectively, at time intervals t. The water distribution network is made up of sources, water demands and unit operations which are connected by a set of nodes N and a set of pipes K that represent water flow. On the other hand, the power distribution network consists of a power sources and consumers linked by a set of buses I (points which connect distribution lines and various electrical components, such as utility poles, loads, power sources, etc.) and a set of branches (distribution lines) IJ that represent power flow.

A set of water treatment facilities NF is the main source of water for the water distribution network. The water from the water treatment facilities is pumped through the piping network to the water consumers by a set of pipes with a pump KP. The pumps are active if the water flows through them to provide energy. However, depending on the geographical elevation of a node connected to a water treatment facility and the successive nodes, water may flow from the water treatment facility to the piping network without pumping. As the water flows through the piping network, some of it is collected in elevated storage tanks that belong to the set NT for later usage. The amount of water allocated to the consumers depend on the forecasted water demands. The thermoelectric power plant also receives water for cooling purposes when power generation is occurring.

The power distribution network receives power from the power grid, thermoelectric power plant and distributed renewable energy sources. Power flow occurs in the distribution lines connected through buses until it reaches power consumers. A set of BESS IB is considered for storing energy that is eventually fed back into the power distribution network. The amount of power consumed by power consumers depends on the forecasted power demands. Pumps and water treatment facilities in the water distribution network also rely on the power from the power distribution network to operate.

3.2 Time Representation

The choice of time representation is a critical matter when dealing with optimisation scheduling problems in PSE (Harjunkoski et al., 2014). There are two well-known types of time representation: discrete-time representation which splits the scheduling time horizon into uniform number of time intervals, and continuous-time representation which unevenly discretises the scheduling time horizon (Majozi et al., 2017). Considering the time characteristics of the given hourly electricity prices and demands in the integrated water and power distribution network problem, the discrete-time representation is chosen over the continuous-time representation. The discrete-time representation has been proven to be superior when tackling scheduling problems with hourly changing electricity prices (Basán et al., 2018). Moreover, capturing the hourly fixed parameters with the continuous-time representation leads to highly complex models (Castro et al., 2009). Nevertheless, it is worth mentioning that, the continuous-time representation can become competitive when considering cases where longer time horizons with consecutive periods of the same electricity prices exist (Basán et al., 2018).

In this dissertation, a scheduling time horizon of a day is discretised into a set of time intervals $T = \{1, 2, \ldots, 24\}$, where each time interval represents a period of length 1 hour.

3.3 Water Distribution Network Constraints

3.3.1 Material Balance Constraints

Material balance constraints ensure that incoming and outgoing water flowrates at each node in the water distribution network are always equal. Constraint (3.1) encapsulates the mass balance around every node n in the water distribution network, at any time interval t. It states that the sum of water flowrates that enter into node n from water treatment facilities nf and pipe(s) k are equal to the sum of water flowrates that leaves node n through pipe(s) k' and

water demands *nd*. Note that, pipe k represents the pipe prior to the node n, while pipe k' represents the subsequent pipe that leaves the node n. Constraint (3.2) bounds the water flowrate through pipe k. The upper and lower bounds of water flowrate are calculated based on the maximum velocity of the water flowrate and area of the pipe k (Bragalli et al., 2012).

$$\sum_{nf \in NF} f_{nf,t} + \sum_{k \in K} f_{k,t} = \sum_{nd \in ND} F_{nt,t} + \sum_{k' \in K} f_{k',t} \quad \forall t \in T \tag{3.1}$$

$$-3600 \frac{\pi}{4} v_k^U D_k^2 \leq f_{k,t} \leq 3600 \frac{\pi}{4} v_k^U D_k^2 \quad \forall k \in K \tag{3.2}$$

3.3.2 Pressure Loss Constraints

The pressure difference at connected nodes in the water distribution network induces the flow of water through the pipes. As the water flows in every pipe, hydraulic friction leads to the loss of pressure. This pressure loss is captured by the Darcy-Weisbach constraint (3.3), a theoretical equation that characterises the pressure loss due to friction (D'Ambrosio et al., 2015).

$$h_{n,t} - h_{n',t} + Z_n - Z_{n'} = R_k f_{k,t}^2 \quad \forall t \in T, \ \forall n, n' \in N, \ \forall k \in K \setminus KP \tag{3.3}$$

The head loss coefficient R_k is expressed in constraint (3.4) where F_k^f, D_k and L_k are the frictional factor, diameter, and length of pipe k respectively, and g is the gravitational acceleration. The frictional factor is calculated in constraint (3.5), using a simplified law of Prandtl-Karman for hydraulically rough pipes where *kk* is the material roughness of the pipe k (Verleye & Aghezzaf, 2013).

$$R_k = \frac{8 F_k^f L_k}{\pi^2 g D_k^5} \quad \forall k \in K \tag{3.4}$$

$$F_k^f = \left(2 \log \left(\frac{kk}{3.17 D_k} \right) \right)^{-2} \quad \forall k \in K \tag{3.5}$$

For the pipe that has a pump *kp*, constraints (3.6) and (3.7) ensure that

the head gain imposed by an active pump is added to the Darcy-Weisbach constraint. Constraint (3.8) bounds the pressure head at every node n in the water distribution network.

$$h_{n,t} - h_{n',t} + Z_n - Z_{n'} + h_{kp,t} \geq R_{kp} f_{kp,t}^2 - H_n^U \Big(1 - y_{kp,t}\Big) \quad \forall t \in T, \;\; \forall n, n' \in N, \;\; \forall kp \in KP \tag{3.6}$$

$$h_{n,t} - h_{n',t} + Z_n - Z_{n'} + h_{kp,t} \leq R_{kp} f_{kp,t}^2 - H_n^U \Big(1 - y_{kp,t}\Big) \quad \forall t \in T, \;\; \forall n, n' \in N, \;\; \forall kp \in KP \tag{3.7}$$

$$H_n^L \leq h_{n,t} - Z_n \leq H_n^U \quad \forall t \in T, \;\; \forall n, n' \in N \tag{3.8}$$

Constraint (3.9) bounds the water flowrate pumped through a pipe that has a pump kp, when the pump is active.

$$F_{kp}^L y_{kp,t} \leq f_{kp,t} \leq F_{kp}^U y_{kp,t} \quad \forall t \in T, \;\; \forall kp \in KP \tag{3.9}$$

Constant speed pumps are considered in this work. The head gain imposed by the pump kp is defined by the constraint (3.10). The binary variable $y_{kp,t}$ is added to the third term to ensure that no pressure is added when the pump is inactive.

$$h_{kp,t} = A_{kp} f_{kp,t}^2 + B_{kp} f_{kp,t} + C_{kp} y_{kp,t} \quad \forall t \in T, \;\; \forall kp \in KP \tag{3.10}$$

Constraint (3.11) gives the amount of active power consumed by a pump kp at a time interval t when the pump is active. The pump efficiency is also taken into consideration. The reactive power of the pump is determined in constraint (3.12) by assuming a constant power factor (Sun et al., 2022).

$$\eta_{kp} P_{kp,t} = f_{kp,t} h_{kp,t} \rho g \quad \forall t \in T, \;\; \forall kp \in KP \tag{3.11}$$

$$p_{kp,t} = q_{kp,t} PF_{kp} \quad \forall t \in T, \ \ \forall kp \in KP \tag{3.12}$$

3.3.3 Water Storage Tank Constraints

A detailed model for the operation of an elevated cylindrical storage tank is considered in this dissertation. The model is adapted from the work by Verleye and Aghezzaf (2013). Figure 3.2 illustrates the operation of an elevated water storage tank.

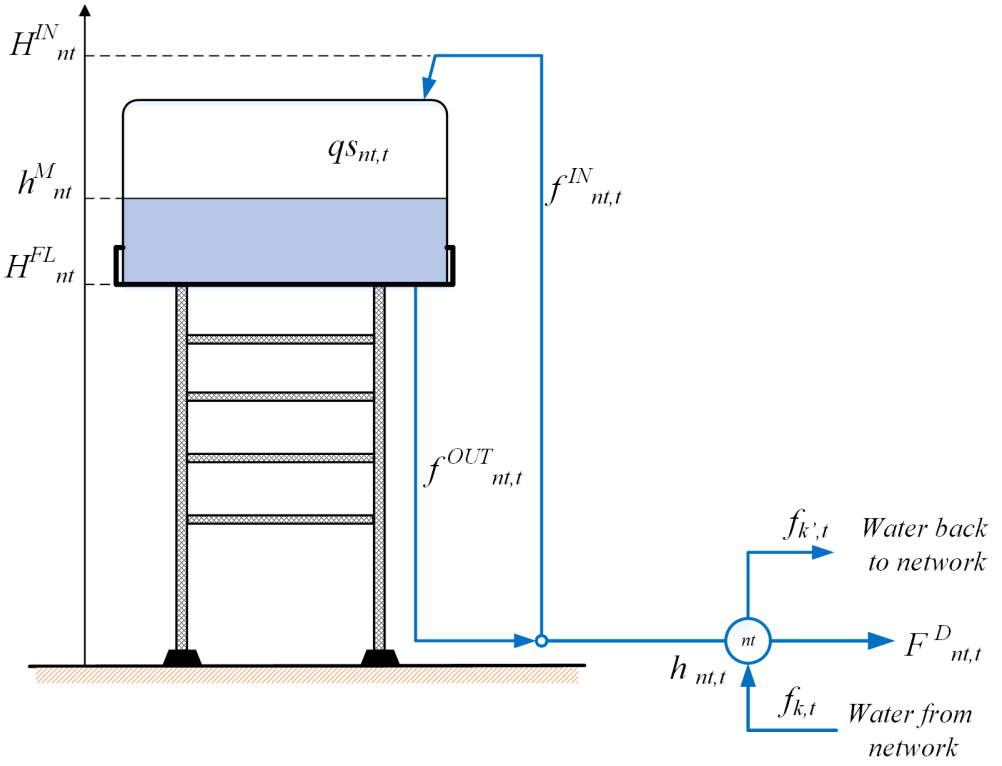


Figure 3.2: Illustration of the operation of a typical elevated storage tank (Verleye & Aghezzaf, 2013).

The water that flows into and out of the storage tank is dependent on the water head at node *nt*. Constraint (3.13) ensures that water flows into the storage tank if the water head at *nt* is larger than the level of inflow at any time interval *t*. Constraint (3.14) stipulates that the water should flow out if the average head of water inside the storage tank is greater than the water

head at node nt at any time interval t.

$$h_{nt,t} - H_{nt}^{IN} \geq \left(Z_{nt} - H_{nt}^{IN}\right)\left(1 - y_{nt,t}^{IN}\right) \quad \forall t \in T, \ \forall nt \in NT \tag{3.13}$$

$$h_{nt,t}^{M} - h_{nt,t} \geq \left(H_{nt}^{FL} - H_{n}^{U} - Z_{nt}\right)\left(1 - y_{nt,t}^{OUT}\right) \quad \forall t \in T, \ \forall nt \in NT \tag{3.14}$$

An allocation constraint (3.15) ensures that only one operation occurs at the storage tank nt, i.e., either water inflow or outflow can occur at a time interval t; otherwise, none of the operations are active.

$$y_{nt,t}^{IN} + y_{nt,t}^{OUT} \leq 1 \quad \forall t \in T, \ \forall nt \in NT \tag{3.15}$$

Constraint (3.16) and (3.17) ensures that water flowrate into or out of a storage tank nt over the duration of the time interval t does not exceed the maximum capacity of the storage tank nt.

$$f_{nt,t}^{IN} \leq \left(\frac{A_{nt} L_{nt}^{U}}{\tau_t}\right) y_{nt,t}^{IN} \quad \forall t \in T, \ \forall nt \in NT \tag{3.16}$$

$$f_{nt,t}^{OUT} \leq \left(\frac{A_{nt} L_{nt}^{U}}{\tau_t}\right) y_{nt,t}^{OUT} \quad \forall t \in T, \ \forall nt \in NT \tag{3.17}$$

Constraint (3.18) defines the average head of water inside the storage tank during a time interval t.

$$h_{nt,t}^{M} = H_{nt}^{FL} + \left(\frac{l_{nt,t} + l_{nt,t-1}}{2}\right) \quad \forall t \in T, \ t \leq t1, \ \forall nt \in NT \tag{3.18}$$

Constraint (3.19) describes the mass balance around the node nt at any time interval t. It states that difference between water flowrate from the water distribution network in pipe k and water flowrate to the water distribution network in pipe k' at node nt is equal to difference between the storage tank

inflow and outflow water flowrates adjusted by the water demand at node *nt*.

$$f_{k,t} - f_{k',t} = f^{IN}_{nt,t} - f^{OUT}_{nt,t} + f^{D}_{nt,t} \quad \forall t \in T, t \leq t1, \;\; \forall nt \in NT, \;\; \forall k, k' \in K \quad (3.19)$$

Constraint (3.20) gives the material balance for the water in the storage tank *nt*. The amount of water in the storage tank at time interval t is made up of the amount of water in the storage tank nt at the previous time interval $t-1$ and the difference between the amount of water inflow and outflow at time interval t.

$$qs_{nt,t} = qs_{nt,t-1} + \left(f^{IN}_{nt,t} - f^{OUT}_{nt,t}\right)\tau_t \quad \forall t \in T, t \leq t1, \;\; \forall nt \in NT \quad (3.20)$$

Constraint (3.21) states that the amount of water inside the storage tank at the first time interval is equal to the product of the initial water level inside the storage tank and its surface area.

$$qs_{nt,t=0} = L^{INI}_{nt} A_{nt} \quad \forall nt \in NT \quad (3.21)$$

Constraint (3.22) ensures that the amount of water inside the storage tank at the end of the scheduling horizon is the same as at the beginning of the schedule. This constraint extends the optimal operation in the current scheduling horizon to the subsequent days assuming that, the water demands and electricity prices remain constant (Verleye & Aghezzaf, 2013).

$$qs_{nt,t=0} = qs_{nt,t=T} \quad \forall nt \in NT \quad (3.22)$$

Constraints (3.23) and (3.24) gives the level of the water inside the storage tank at any time interval t in the scheduling horizon.

$$l_{nt,t=0} = L^{INI}_{nt} \quad \forall nt \in NT \quad (3.23)$$

$$l_{nt,t} = \frac{qs_{nt,t=T}}{A_{nt}} \quad \forall t \in T, t \leq t1, \ \ \forall nt \in NT \tag{3.24}$$

Capacity constraints (3.25) and (3.26) ensure that the level and amount of the water in the storage tank nt are confined within the level and capacity upper bounds of the storage tank nt.

$$L^L_{nt} \leq l_{nt,t} \leq L^U_{nt} \quad \forall nt \in NT \tag{3.25}$$

$$L^L_{nt} A_{nt} \leq qs_{nt,t} \leq L^U_{nt} A_{nt} \quad \forall nt \in NT \tag{3.26}$$

In this dissertation, conditional pressure constraints (3.13)-(3.14), the allocation constraint (3.15), capacity bounding constraints (3.16)-(3.17), and the constraint (3.18) for the average pressure head of water inside the storage tank are included to give a more realistic representation of the storage tank. The storage tank operation constraints from Li et al. (2019) are used to model the black box storage tank (Scenario A in **Chapter 4**).

3.4 Power Distribution Network Constraints

3.4.1 Branch Flow Constraints

Power distribution networks are usually characterised by a radial structure and high R/X ratios in comparison to transmission networks (Li et al., 2019). To represent the power flow in a three-phase balanced radial distribution network, a set of constraints called the branch flow or *DistFlow* model are applied since they are known to produce computationally efficient and robust solution algorithms (Li et al., 2019; Baran & Wu, 1989). In this work, only three-phase balanced cases are considered. Despite the exclusive consideration of three-phase balanced cases, it is worth mentioning that the branch flow model can also be extended to unbalanced three-phase cases by making some approximations (Li et al., 2019; Sun et al., 2022).

The branch flow constraints of the power distribution network defined in con-

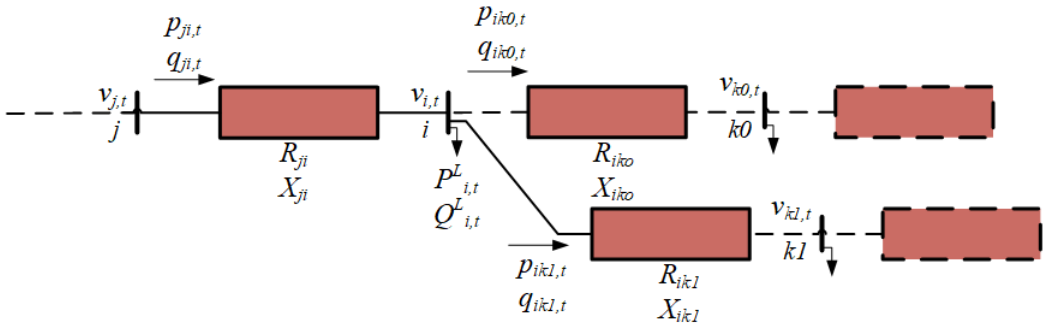


Figure 3.3: A typical radial power distribution network structure.

straints (3.27)-(3.35) are conducted in accordance with Figure 3.3. The active and reactive power balance of branch ji is captured by constraints (3.27) and (3.28), respectively (Li et al., 2019; Baran & Wu, 1989). It states that the amount of power that flows into the branch ji, injected at bus j is equal to summation of the active power lost due to the resistance of the branch ji, the active power consumed by the active power demand at bus i, and the active power that flows out of branch ji at bus i to branches $ik0$ and $ik1$. Similarly, constraint (3.28) also captures the reactive power balance of branch ji. Note that, $\ell_{ji,t}$ represents the square of the current flowing through the branch ji at time interval t.

$$p_{ji,t} = R_{ji}\ell_{ji,t} + P^D_{i,t} + p_{ik0,t} + p_{ik1,t} \qquad \forall t \in T,\ \ i \in I,\ \ ji, ik0, ik1 \in IJ \quad (3.27)$$

$$q_{ji,t} = X_{ji}\ell_{ji,t} + Q^D_{i,t} + q_{ik0,t} + q_{ik1,t} \qquad \forall t \in T,\ \ i \in I,\ \ ji, ik0, ik1 \in IJ \quad (3.28)$$

These two constraints also incorporate other components which are considered in this dissertation in the power distribution network, such as renewable energy sources and BESSs. For instance, injecting power from a renewable power

source at bus j results in the following active power balance of branch ji.

$$p_{ji,t} + P^{RE}_{j,t} = R_{ji}\ell_{ji,t} + P^{D}_{i,t} + p_{ik0,t} + p_{ik1,t} \quad \forall t \in T,\ \ i \in I,\ \ ji, ik0, ik1 \in IJ \tag{3.29}$$

Constraint (3.30) computes the voltage drop due to power losses along a branch ji, while constraint (3.31) expresses the Ohms law along branch ji. Constraint (3.32) bounds the amount of power that flows through branch ji depending on the thermal and power capacity limits of the distribution feeder (Li & Vittal, 2018). Note that, $v_{j,t}$ and $v_{i,t}$ represents the square of the voltages at buses j and i at time interval t.

$$v_{j,t} - v_{i,t} + \Big(R^2_{ji} + X^2_{ji}\Big)\ell_{ji,t} = 2\Big(R_{ji,t}p_{ji,t} + X_{ji,t}q_{ji,t}\Big) \quad \forall t \in T,\ \ j, i \in I,\ \ ji \in IJ \tag{3.30}$$

$$p^2_{ji,t} + q^2_{ji,t} = v_{j,t}\ell_{ji,t} \forall t \in T,\ \ j \in I,\ \ ji \in IJ \tag{3.31}$$

$$p^2_{ji,t} + q^2_{ji,t} = S^2_{ji,t} \forall t \in T,\ \ j \in I,\ \ ji \in IJ \tag{3.32}$$

The following constraints impose a lower and upper bound on the square currents (3.33), square voltages (3.34), and power from the power grid (3.35).

$$IC^L_{ji} \leq \ell_{ji,t} \leq IC^U_{ji} \quad \forall t \in T,\ \ \forall ji \in IJ \tag{3.33}$$

$$V^L_i \leq v_{i,t} \leq V^U_i \quad \forall t \in T,\ \ \forall i \in I \setminus IG \tag{3.34}$$

$$P^L_{ig} \leq p^G_{ig,t} \leq P^U_{ig} \quad \forall t \in T,\ \ \forall ig \in IG \tag{3.35}$$

3.4.2 BESS Constraints

A detailed BESS model is considered in this dissertation. The model is adapted from the work by Mehrjerdi and Hemmati (2019). Figure 3.4 illustrates the operation of a typical BESS.

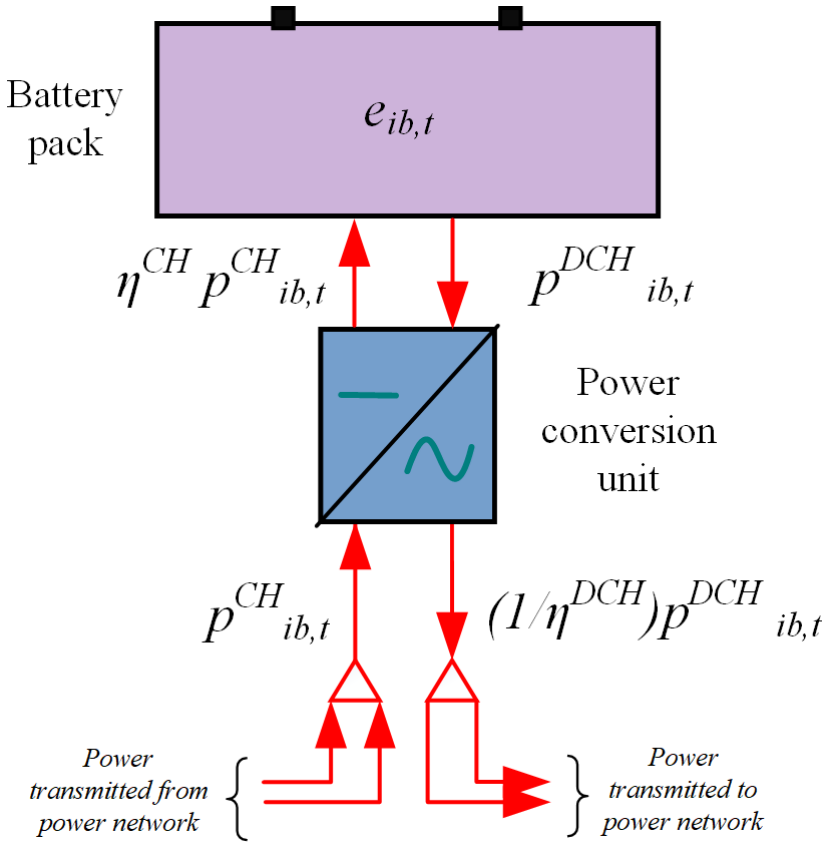


Figure 3.4: Illustration of the operation of a typical BESS.

When the BESS is operating, the allocation constraint (3.36) ensures that active power charging and discharging operations do not occur at the same time, respectively; otherwise, none of the operations are active. Similarly, constraint (3.37) also ensures the reactive power charging and discharging operations do not occur at the same time.

$$y^{PCH}_{ib,t} + y^{PDCH}_{ib,t} \leq 1 \quad \forall t \in T, \;\; \forall ib \in IB \tag{3.36}$$

$$y^{QCH}_{ib,t} + y^{QDCH}_{ib,t} \leq 1 \quad \forall t \in T, \;\; \forall ib \in IB \tag{3.37}$$

Constraints (3.38)-(3.41) limit the amount of active and reactive power charged into or discharged from the BESS based on its rated power capacity.

$$p_{ib,t}^{CH} \leq y_{ib,t}^{PCH} P_{ib}^{U} \quad \forall t \in T, \ \ \forall ib \in IB \tag{3.38}$$

$$p_{ib,t}^{DCH} \leq y_{ib,t}^{PDCH} P_{ib}^{U} \quad \forall t \in T, \ \ \forall ib \in IB \tag{3.39}$$

$$q_{ib,t}^{CH} \leq y_{ib,t}^{QCH} P_{ib}^{U} \quad \forall t \in T, \ \ \forall ib \in IB \tag{3.40}$$

$$q_{ib,t}^{DCH} \leq y_{ib,t}^{QCH} P_{ib}^{U} \quad \forall t \in T, \ \ \forall ib \in IB \tag{3.41}$$

Constraint (3.42) ensures that when the BESS discharges power into the power distribution network over the time interval t, the product of active power $P_{ib,t}^{DCH}$ and duration of τ_t does not exceed the amount of energy stored at time interval t. The power flow limit when charging or discharging the BESS is expressed in constraint (3.43).

$$p_{ib,t}^{DCH} \tau_t \leq e_{ib,t} \eta_{ib}^{DCH} \quad \forall t \in T, \ \ \forall ib \in IB \tag{3.42}$$

$$\left(p_{ib,t}^{CH} + p_{ib,t}^{DCH}\right)^2 + \left(q_{ib,t}^{CH} + q_{ib,t}^{DCH}\right)^2 \leq \left(P_{ib,t}^{U}\right)^2 \quad \forall t \in T, \ \ \forall ib \in IB \tag{3.43}$$

Constraint (3.44) expresses the energy balance around the BESS. It states that the amount of energy stored at the time interval t is equal to the initial amount of energy stored in the BESS at the beginning of the time horizon (i.e., at time interval $t = 1$) or the amount of energy stored at the previous time interval $t-1$ adjusted by the hourly self-discharge rate of the BESS, and the amount of energy charged or discharged from the BESS during the time interval t. Note that, the power losses due to the power conversion unit are captured through the charging and discharging inefficiencies, while the hourly self-discharge rate σ_{ib} is included to account for the hourly loss of energy from

the BESS.

$$e_{ib,t} = \Big(e_{ib,t=1} + e_{ib,t-1,t>1}\Big)\Big(1 - \sigma_{ib}\tau_t\Big) + \left(\eta_{ib}^{CH} p_{ib,t}^{CH} - \left(\frac{1}{\eta_{ib}^{DCH}}\right) p_{ib,t}^{DCH}\right)\tau_t \quad \forall t \in T, \;\; \forall ib \in IB \quad (3.44)$$

Constraint (3.45) and (3.46) ensure that the amount of energy in the BESS at the beginning and end of the scheduling horizon is the same as the given initial amount of energy in BESS. The energy capacity constraint for the BESS is given in the constraint (3.47).

$$e_{ib,t=1} = E_{ib}^{INI} \quad \forall ib \in IB \quad (3.45)$$

$$e_{ib,t=T} = E_{ib}^{INI} \quad \forall ib \in IB \quad (3.46)$$

$$E_{ib}^{L} \leq e_{ib,t} \leq E_{ib}^{U} \quad \forall t \in T, \;\; \forall ib \in IB \quad (3.47)$$

A few studies in literature consider BESS operations despite their key role in improving flexibility in power distribution networks. Moreover, the few studies that consider BESS operations, utilises the black box modelling approach to maintain model simplicity and reduce computational burden at the cost of accuracy (Wu & Ma, 2021). The constraints for the black box model of BESS considered in this work are from Li et al. (2019).

3.5 Linking Constraints

3.5.1 Water Treatment Facility Power Consumption

The amount of active power consumed by a water treatment facility connected to node nf at time interval t is given by constraint (3.48) where PCI_{nf} is a parameter that denotes the power consumption intensity of a water treatment facility nf and $f_{nf,t}$ represents the amount of water flow a water treatment

facility delivers to the water distribution network.

$$p^{WTF}_{nf,t} = PCI_{nf} f_{nf,t} \quad \forall t \in T, \ \ \forall nf \in NF \tag{3.48}$$

It is worth noting, that the current model can be extended to include water regeneration technologies, such as RO, electrodialysis and membrane distillation because they also depend on energy for water treatment.

3.5.2 Thermoelectric Power Plant Water Consumption

The cooling water demand of a thermoelectric power plant it at time interval t is given by constraint (3.49) where $CWCI_{it,t}$ is a parameter that denotes the cooling water consumption intensity of a thermoelectric power plant and $p_{it,t}$ is the amount of power received from the power distribution network.

$$f^{D}_{it,t} = CWCI_{it,t} p_{it,t} \quad \forall t \in T, \ \ \forall it \in IT \tag{3.49}$$

Depending on the type of cooling technology utilised by thermoelectric power plant, as well as the environmental conditions at the location of the thermoelectric power plant the cooling water consumption intensity can vary (Lohrmann et al., 2022). For instance, a power plant that utilises wet cooling towers (open recirculating cooling system), the cooling water consumption intensity parameter accounts for the makeup water required in the cooling system, whereas for once through cooling system, the cooling water consumption intensity parameter represents the water withdrawn from a water source (Pan et al., 2018). The consideration of the type of cooling technology is crucial to accurately capture the amount of power that is required to pump the water from a water source to a power plant.

3.6 Objective Function

The objective function is to minimise the total operating costs associated with meeting the water and power demands of the integrated water and power dis-

tribution network. It comprises the following terms: (i) the cost of purchasing power from the power grid, (ii) the cost of generating power at the power plant, and (iii) the energy costs of the pumps and water treatment facilities, as given in the constraint (3.50).

$$\begin{aligned}\min \Big[Cost^{Total}\Big] = &\sum_{ig\in IG}\sum_{t\in T} CPP_t p^{G}_{ig,t}\tau_t \\ &+ \sum_{it\in IT}\sum_{t\in T} CTP_{it} p_{it,t}\tau_t \\ &+ \sum_{\substack{kp\in KP \\ nf\in NF}}\sum_{t\in T} CPW_t\Big(p_{kp,t} + p^{wtf}_{nf,t}\Big)\tau_t \end{aligned} \quad (3.50)$$

Due to the presence of binary variables, as well as linear and nonlinear constraints, the optimisation model developed in this chapter is rendered as an MINLP. This MINLP is also a special type called MIQCQP because all its nonlinearities are quadratic (Boukouvala et al., 2016). These nonlinearities stem from the pressure loss constraints, branch flow constraints, and BESS constraints.

Chapter 4

Model Application

Chapter 4 demonstrates the applicability of the proposed optimisation model by solving an illustrative example adapted from literature.

4.1 Illustrative Example

An illustrative example comprising two modified networks, an IEEE 13-bus power distribution network and an 8-node water distribution network of a small community is adapted from Li et al. (2019), as shown in Figure 4.1. It is used to illustrate the application of the proposed optimization model. The integrated water and power distribution network in this example aims to meet the daily water and power demands of the water and power consumers within a scheduling horizon of 24 hours. The 13-bus power distribution network is made up of power consumers, two BESS, three PV power sources and a natural gas-fired power plant. The 8-node water distribution network consists of a water treatment facility, pump, elevated water storage tank, and water consumers. The power connection to the water treatment facility *wtf1* and pump *wtf1n2*, and the water connection to the natural gas-fired plant *i632* represent the links between the water and power distribution networks.

Detailed data of the 13-bus power distribution network and 8-node water distribution network is given by Kersting (2001) and Rossman (2000), respectively. Table 4.1 presents parameters for the BESS on buses *i684* and *i692*, whereas

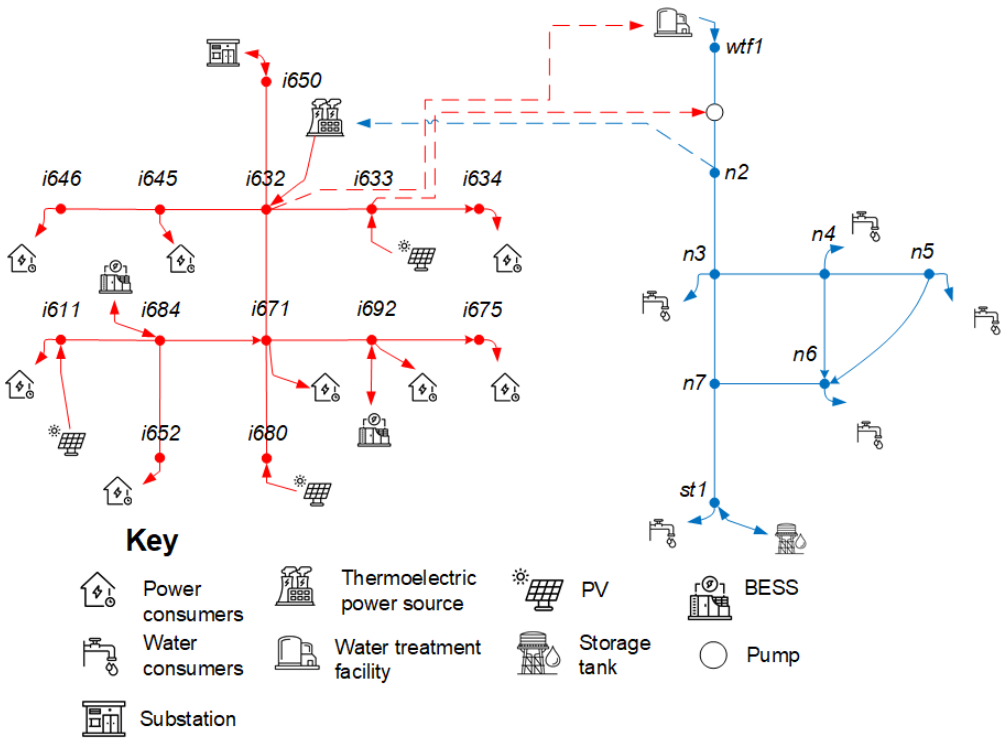


Figure 4.1: Topology of a 13-bus power distribution network integrated with an 8-node water distribution network.

Table 4.2 presents other parameters of the water distribution network components. The natural gas-fired power plant considered has a capacity of 10 MW. It uses an open recirculating system for the cooling technology and relies on the water from the water distribution network for the makeup water required to restore the water lost through evaporation. The cooling water consumption intensity of the power plant accounts for makeup water required per unit of generated energy by the power plant and is 0.0026 m^3/kWh (Macknick et al., 2012). The cost of generating energy from the power plant is \$0.065/kWh. The water treatment facility considered has a capacity of 200 m^3/h, and a power consumption intensity of 0.79 kWh/m^3 (Pan et al., 2018).

Figure 4.2 shows the real time pricing offered by the power utility operators to the power consumers, whereas Figure 4.3 shows the forecasted electricity prices of the energy from the power grid. Detailed data on the forecasted water and power demands of the consumers, as well as the forecasted solar PV power

sources, are given in Table 4.3-Table 4.6.

The following three scenarios were investigated, and the objective function was used to compare and highlight the characteristics of each model.

(i) Scenario A: one-way interdependency with black box modelling of storage facilities,

(ii) Scenario B: one-way interdependency with detailed modelling of storage facilities,

(iii) Scenario C: mutual interdependency with detailed modelling of storage facilities.

The resultant models were solved in GAMS 38.1.0 (GAMS, 2023) using a global optimisation solver called Antigone, that is particularly designed to deal with MIQCQP (MINLP variant) problems (Misener & Floudas, 2014). The computer used to solve these models had the following specifications: Intel ®Core i7-10700, a 2.90GHz processor with an installed RAM capacity of 16.0GB and a 64-bit Windows 10 Operating System.

Table 4.1: BESS parameters (Li et al., 2019)

Bus	i684	i692
Power rating (kW)	1150	1150
Charging/Discharging efficiency(%)	90	90
Self-discharging rate (%)	0.004	0.004
Initial stored energy (kWh)	1000	1000
BESS capacity (kWh)	2500	3200

Table 4.2: Other water distribution network parameters (Verleye & Aghezzaf, 2013).

Parameters	Value
Material dependent pipe roughness (mm)	0.5
Maximum velocity of flow in pipes (m/s)	1.5
Minimum pressure head at any node (m)	20
Maximum pressure head at any node (m)	100
Diameter of storage tank (m)	18.29
Minimum level of storage tank (m)	1.00
Maximum level of storage tank (m)	5.00
Initial level of storage tank (m)	1.08
Level of storage tank floor (m)	60
Level of inflow in tank (m)	65
Area of storage tank (m^2)	262.68
Pump efficiency	0.86
Pump head coefficient A (m^{-5})	-0.0001
Pump head coefficient B (m^{-2})	0.02
Pump head coefficient C (m)	70.318
Pump minimum flowrate (m^3/h)	20
Power factor of the pump	0.85

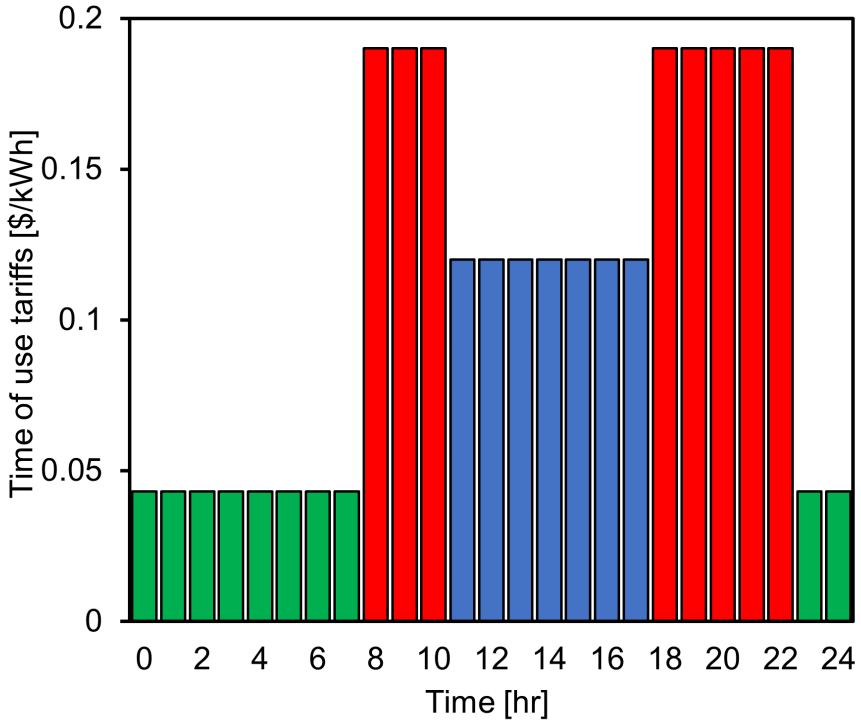


Figure 4.2: Forecasted energy time-of-use tariffs charged by the power utility operators (Xiao et al., 2022).

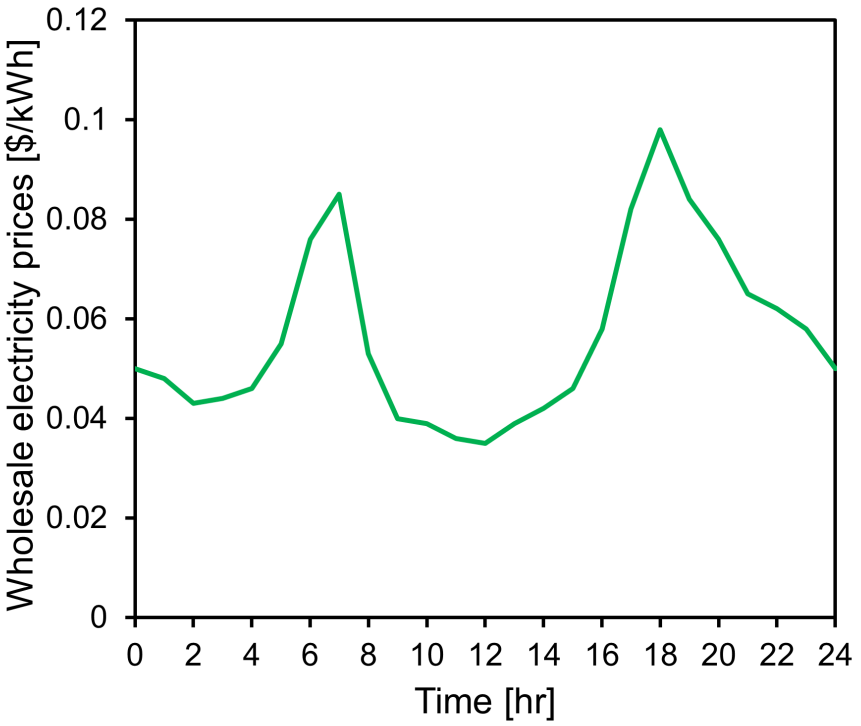


Figure 4.3: Forecasted real time pricing of the electricity from the grid (Oikonomou & Parvania, 2020).

Table 4.3: Forecasted solar power.

Time (h)	Power profile (kW)		
	i611	i680	i633
0-1	0.00	0.00	0.00
1-2	0.00	0.00	0.00
2-3	0.00	0.00	0.00
3-4	0.00	0.00	0.00
4-5	0.00	0.00	0.00
5-6	0.00	0.00	0.00
6-7	93.75	3.35	93.75
7-8	250.00	8.93	250.00
8-9	390.63	13.95	390.63
9-10	500.00	17.86	500.00
10-11	562.50	20.09	562.50
11-12	625.00	22.32	625.00
12-13	562.50	20.09	562.50
13-14	562.50	20.09	562.50
14-15	500.00	17.86	500.00
15-16	375.00	13.39	375.00
16-17	250.00	8.93	250.00
17-18	93.75	3.35	93.75
18-19	0.00	0.00	0.00
19-20	0.00	0.00	0.00
20-21	0.00	0.00	0.00
21-22	0.00	0.00	0.00
22-23	0.00	0.00	0.00
23-24	0.00	0.00	0.00

Table 4.4: Forecasted water demands.

Time (h)	Water demands (m^3/h)				
	n3	n4	n5	n6	st1
0-1	7.30	7.30	9.73	7.30	3.65
1-2	6.08	6.08	8.11	6.08	3.04
2-3	4.87	4.87	6.49	4.87	2.43
3-4	4.87	4.87	6.49	4.87	2.43
4-5	4.87	4.87	6.49	4.87	2.43
5-6	13.38	13.38	17.85	13.38	6.69
6-7	26.77	26.77	35.69	26.77	13.38
7-8	34.07	34.07	45.42	34.07	17.03
8-9	34.07	34.07	45.42	34.07	17.03
9-10	32.85	32.85	43.80	32.85	16.43
10-11	30.42	30.42	40.56	30.42	15.21
11-12	27.98	27.98	37.31	27.98	13.99
12-13	23.12	23.12	30.82	23.12	11.56
13-14	20.68	20.68	27.58	20.68	10.34
14-15	19.47	19.47	25.96	19.47	9.73
15-16	20.68	20.68	27.58	20.68	10.34
16-17	21.90	21.90	29.20	21.90	10.95
17-18	24.33	24.33	32.45	24.33	12.17
18-19	26.77	26.77	35.69	26.77	13.38
19-20	25.55	25.55	34.07	25.55	12.78
20-21	24.33	24.33	32.45	24.33	12.17
21-22	23.12	23.12	30.82	23.12	11.56
22-23	19.47	19.47	25.96	19.47	9.73
23-24	13.38	13.38	17.85	13.38	6.69

Table 4.5: Forecasted active power demands.

Time (h)	Active power demands (kW)							
	i634	i645	i646	i652	i671	i675	i692	i611
0-1	356.21	169.48	229.29	107.22	1035.34	721.89	145.29	145.29
1-2	331.73	157.83	213.53	99.85	964.18	672.28	135.30	135.30
2-3	313.37	149.09	201.71	94.32	910.81	635.07	127.81	127.81
3-4	307.25	146.18	197.77	92.48	893.02	622.66	125.32	125.32
4-5	295.00	140.36	189.89	88.80	857.45	597.86	120.32	120.32
5-6	313.37	149.09	201.71	94.32	910.81	635.07	127.81	127.81
6-7	331.73	157.83	213.53	99.85	964.18	672.28	135.30	135.30
7-8	368.45	175.30	237.17	110.90	1070.92	746.70	150.28	150.28
8-9	399.05	189.86	256.87	120.12	1159.86	808.72	162.76	162.76
9-10	417.41	198.60	268.69	125.64	1213.23	845.93	170.25	170.25
10-11	435.77	207.33	280.51	131.17	1266.60	883.14	177.74	177.74
11-12	454.14	216.07	292.33	136.70	1319.97	920.35	185.23	185.23
12-13	457.20	217.52	294.30	137.62	1328.86	926.55	186.48	186.48
13-14	460.26	218.98	296.27	138.54	1337.76	932.75	187.72	187.72
14-15	466.38	221.89	300.21	140.38	1355.55	945.16	190.22	190.22
15-16	472.50	224.80	304.15	142.22	1373.34	957.56	192.72	192.72
16-17	478.62	227.71	308.08	144.06	1391.13	969.97	195.21	195.21
17-18	484.74	230.63	312.02	145.91	1408.92	982.37	197.71	197.71
18-19	496.98	236.45	319.90	149.59	1444.49	1007.18	202.70	202.70
19-20	503.10	239.36	323.84	151.43	1462.28	1019.58	205.20	205.20
20-21	521.46	248.10	335.66	156.96	1515.65	1056.79	212.69	212.69
21-22	527.58	251.01	339.60	158.80	1533.44	1069.19	215.18	215.18
22-23	484.74	230.63	312.02	145.91	1408.92	982.37	197.71	197.71
23-24	417.41	198.60	268.69	125.64	1213.23	845.93	170.25	170.25

Table 4.6: Forecasted reactive power demands.

Time (h)	Reactive power demands ($kVAr$)							
	i634	i645	i646	i652	i671	i675	i692	i611
0-1	215.98	102.76	139.02	65.01	627.75	437.70	88.09	88.09
1-2	201.13	95.69	129.47	60.54	584.60	407.61	82.04	82.04
2-3	190.00	90.40	122.30	57.19	552.24	385.05	77.49	77.49
3-4	186.29	88.63	119.91	56.07	541.46	377.53	75.98	75.98
4-5	178.87	85.10	115.14	53.84	519.89	362.49	72.95	72.95
5-6	190.00	90.40	122.30	57.19	552.24	385.05	77.49	77.49
6-7	201.13	95.69	129.47	60.54	584.60	407.61	82.04	82.04
7-8	223.40	106.29	143.80	67.24	649.32	452.74	91.12	91.12
8-9	241.95	115.12	155.74	72.83	703.25	490.34	98.68	98.68
9-10	253.09	120.41	162.91	76.18	735.61	512.90	103.23	103.23
10-11	264.22	125.71	170.08	79.53	767.96	535.46	107.77	107.77
11-12	275.35	131.01	177.24	82.88	800.32	558.03	112.31	112.31
12-13	277.21	131.89	178.44	83.44	805.71	561.79	113.06	113.06
13-14	279.06	132.77	179.63	84.00	811.11	565.55	113.82	113.82
14-15	282.77	134.54	182.02	85.11	821.89	573.07	115.33	115.33
15-16	286.48	136.30	184.41	86.23	832.68	580.59	116.85	116.85
16-17	290.19	138.07	186.80	87.35	843.47	588.11	118.36	118.36
17-18	293.91	139.83	189.19	88.47	854.25	595.63	119.87	119.87
18-19	301.33	143.36	193.96	90.70	875.82	610.67	122.90	122.90
19-20	305.04	145.13	196.35	91.82	886.61	618.19	124.42	124.42
20-21	316.17	150.43	203.52	95.17	918.97	640.75	128.96	128.96
21-22	319.88	152.19	205.91	96.28	929.75	648.27	130.47	130.47
22-23	293.91	139.83	189.19	88.47	854.25	595.63	119.87	119.87
23-24	253.09	120.41	162.91	76.18	735.61	512.90	103.23	103.23

4.2 Results and Discussion

Table 4.7 presents the computational solutions and model statistics from the optimisation of Scenarios A, B and C of the given illustration example.

Table 4.7: Results obtained from the illustrative example.

Scenarios	A	B	C
Cost of generating power ($)	2982.81	3395.98	3330.25
Cost of purchasing power from the grid ($)	1297.90	864.63	938.56
Water treatment facility cost ($)	248.69	176.30	190.55
Pumping cost ($)	90.61	49.90	53.91
Operating cost for the water distribution network ($)	339.30	226.20	244.46
Operating cost for the power distribution network ($)	4280.71	4260.61	4268.81
Total operating cost for the integrated network ($)	4620.01	4486.81	4513.27
Cost savings (%)	-	2.88	2.31
Single variables	2761	2425	2449
Single equations	3077	3124	3148
Binary variables	24	264	264
CPU time (s)	17.16	229.58	286.89

In Scenario A, black box modelling constraints for the storage facilities obtained from Li et al. (2019) were used, whereas Scenario B and C used detailed constraints. Table 4.7 shows that costs of treating and pumping water are reduced as more detailed constraints are used for modelling the storage tanks in the water distribution network. Cost savings of 2.88% in the total operating costs is observed in Scenario B when using Scenario A, as a basis. The operating cost of the water distribution network decrease from $339.30 in Scenario A to $226.30 in Scenario B. The integrated network operates under time-varying electricity prices, therefore costs of treating and pumping are influenced by capturing the operation of the storage facilities in the model, accurately. The storage tank model used in Scenario A is not detailed enough to allocate water inflow and outflow operations of the storage tank. For instance, a simplified constraint Equation 4.1 is used to capture the operation of the storage tank in the study by Li et al. (2019) used for Scenario A. The term $f_{nt,t}$ is used to

represent inflow and outflow operations of the storage tank.

$$l^L_{nt} A_{nt} \leq qs_{nt,t=0} + \sum_{t=0}^{t} f_{nt,t} \leq l^L_{nt} A_{nt} \quad \forall t \in T, \quad \forall nt \in NT \tag{4.1}$$

The usage of this simplified model results in the underutilisation of the storage tanks which reduces the flexibility offered by the storage tanks in Scenario A. Consequently, this led to instances where water treatment and pumping occurs during peak hours which are tied to high electricity prices. Thus, the usage of detailed constraints (constraints (3.13)-(3.19)) for storage facilities is necessary to provide accurate cost representation for design and operational purposes. However, it is worth noting that, usage of detailed constraints in Scenario B and C for modelling the storage facilities come with a cost of computational burden.

In Table 4.7, it can be observed that there is an increase in CPU time as the level of detail increase in the model. Scenario A has a CPU time of 17.16s, where as Scenario B and C have a CPU time of 229.58s and 286.89s. This occurs due to the number of binary variables increasing from 24, in Scenario A to 264, in Scenario B and C. These CPU times are fairly higher as compared to the optimisation models that tackle the integrated water and power distribution networks problem by Li et al. (2019) (less than 1s), Oikonomou and Parvania (2020) (5.93s), and Ayyagari et al. (2021) (less than 120s). Although the CPU time of the proposed model in this dissertation is higher, it should be noted that, unlike the solution process in this work where the global solver Antigone is solely used to solve the problem, Li et al. (2019), Oikonomou and Parvania (2020), and Ayyagari et al. (2021) used convex hull relaxations, piecewise relaxation and linear approximations, respectively, to linearize the nonconvex (quadratic) constraints of the problem which simplifies the solution process. These linearization techniques are inexact and therefore, introduce inaccuracies to their results, unlike the study in this dissertation.

Unlike Scenario A and B, Scenario C has a connection that sends water to the power plant for cooling purposes. Table 4.7 shows that the operating cost of the

water distribution network increases from \$226.30 in Scenario C to \$244.46 in Scenario B. The total operating cost of the integrated network also increases upon addition of water connection to the power distribution network. The increase in costs in Scenario C occurs because higher amounts of water need treatment and pumping in comparison to Scenario A and B to cater for the cooling water of the power plant. The addition of the cooling water demand variable in the model for Scenario C (constraint (3.49)), also led to a slight increase in the CPU time.

A trade-off between the cost of purchasing power from the grid and the cost of generating power is observed between Scenario B and C. For instance, in Scenario B, the cost of generating power is \$3395.98 and the cost of purchasing power from the grid is \$864.63. On the other hand, Scenario C has a lower cost of generating power of \$3330.25 and a higher cost of purchasing power from the grid of \$938.56. Clearly, the model opts to use more power from the grid rather than the power generated from the power plant which leads to a lower overall water demand of the power plant, as well as lower water treatment facility and pumping costs.

Figure 4.4 illustrates the power consumption profile of pump *wtf1n2*. It is apparent that the water treatment facility *wtf1* and pump *wtf1ln2* are active almost throughout the entire scheduling horizon. This is due to the continuous requirement to meet the water demands. However, large pumping loads occur during the off-peak hours, to fill up the storage tank for later usage during peak hours.

Figure 4.5 shows the Gantt chart that indicates the timing decisions of the various operations involved in the integrated water and power distribution network for Scenario C. The storage tank *st1* inflow occurs at $t \in [8, 11]$ and $t \in [18, 23]$, and the storage tank *st1* outflow at $t \in [1, 8]$ and $t \in [11, 18]$. Water treatment and pumping power demands are shifted to the off-peak hours to lower energy costs since the peak hours correlate to high electricity prices. A similar timing decision trend is also observed for the charging and discharging operations of the BESS *i684* and *i692*. The BESS

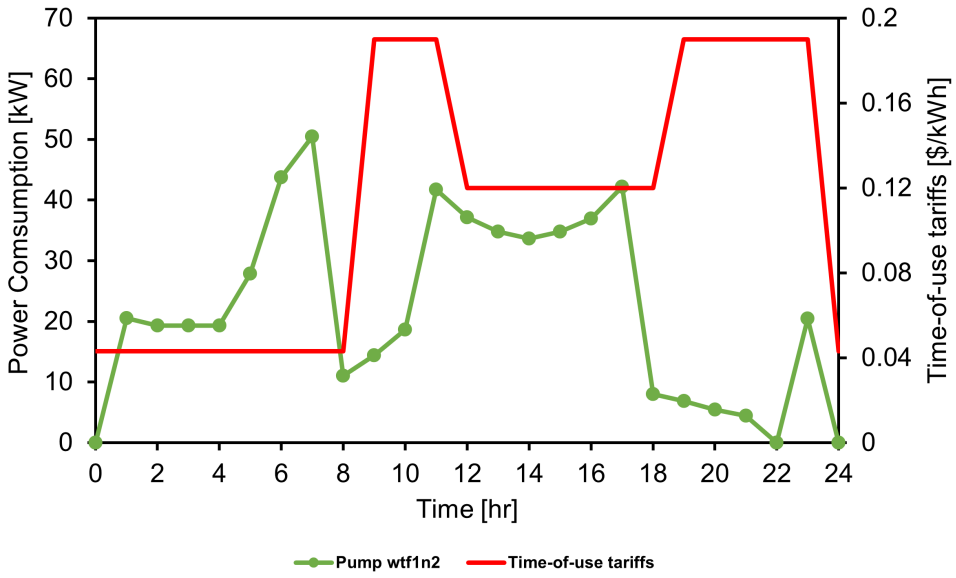


Figure 4.4: Power consumption profile of pump *wtf1n2* for Scenario C.

charge at $t \in [2, 5]$ and $t \in [9, 15]$, and discharge at $t \in [5, 8]$ and $t \in [16, 23]$. This indicates the flexibility offered by BESS, which buttresses their usage in avoiding solar and wind energy curtailment during daytime off-peak hours (Udawalpola et al., 2021), despite their high capital costs (Stecca et al., 2020). The natural gas-fired power plant is active at $t \in [5, 8]$ and $t \in [16, 24]$ which is during peaking hours, a trend similar to peaking power plants. This results in excess power during the peak hours which is transmitted into the power grid. The power distribution network is assumed to participate in a deregulated electricity market; therefore, the power utility operators receive income which lowers the total operating costs.

Figure 4.6-4.11 depicts the optimal integrated water and power distribution networks of Scenario B and C at time intervals associated with the peak and off-peak hours since they are among the critical moments in the scheduling horizon. It is worth mentioning that the active and reactive power losses in the distribution lines that are considered in constraints (3.27) and (3.28) are not shown in the schematic diagrams for brevity.

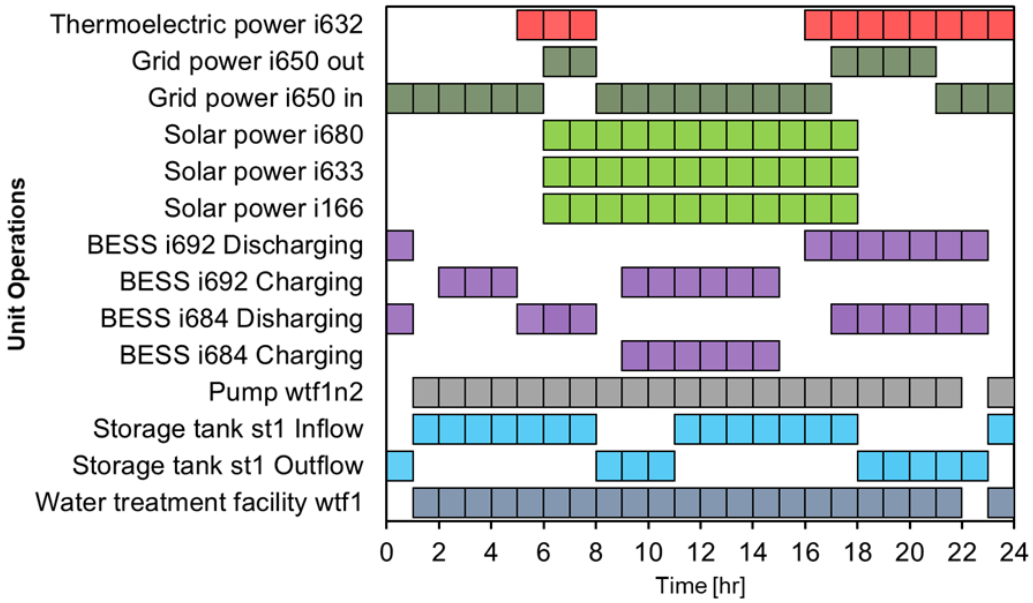


Figure 4.5: Gantt chart for Scenario C.

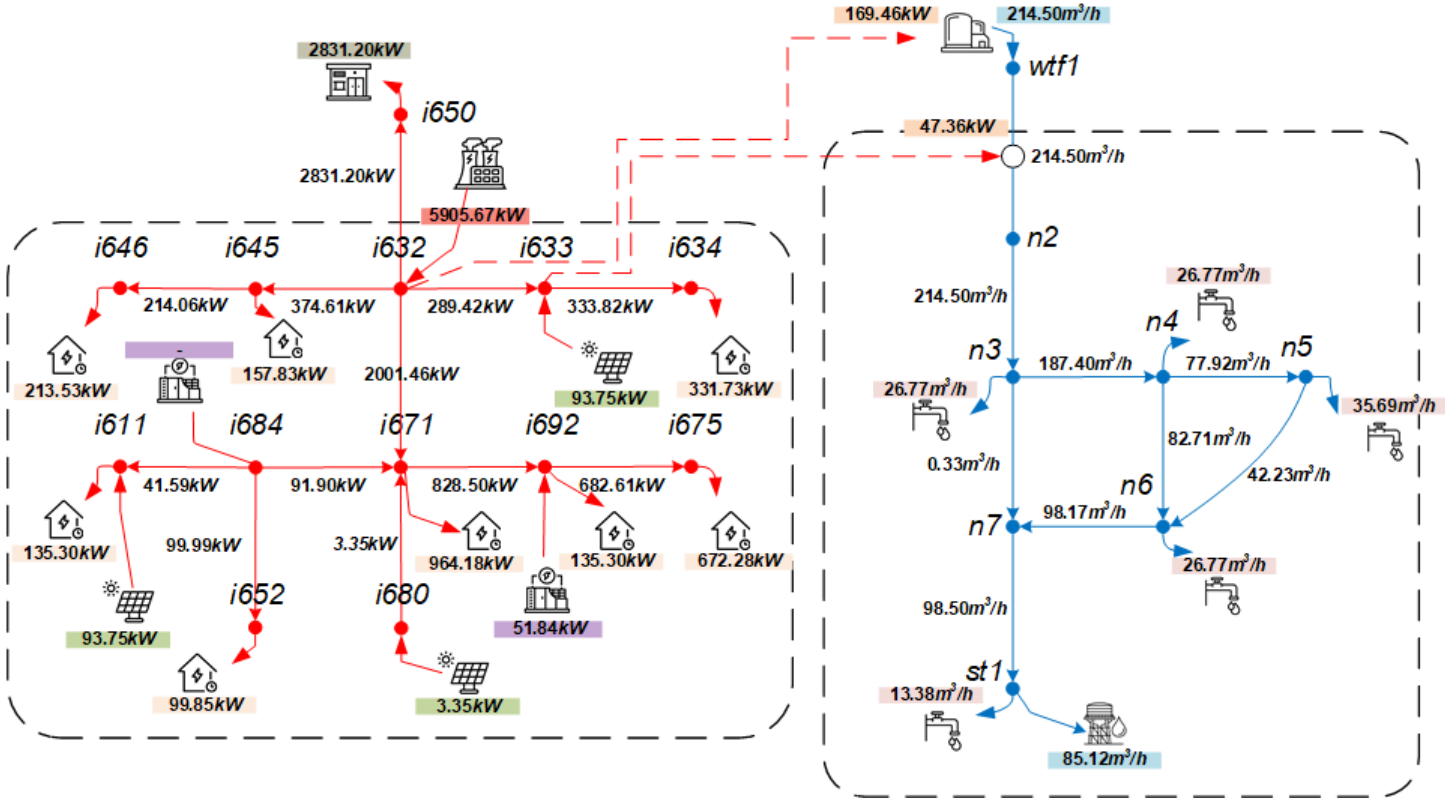


Figure 4.6: Optimal integrated water and power distribution network of the Scenario B at time interval t=6.

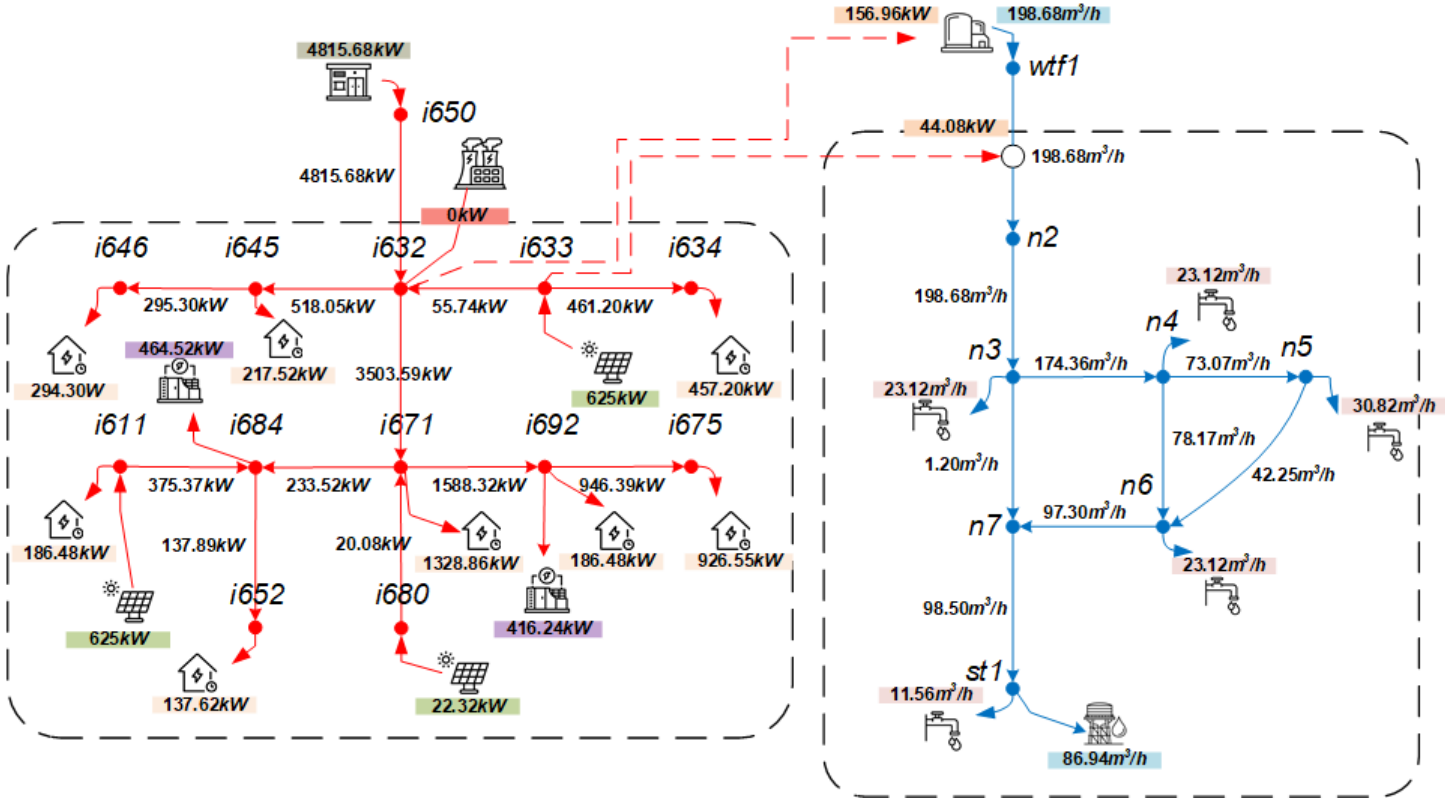


Figure 4.7: Optimal integrated water and power distribution network of the Scenario B at time interval t=13.

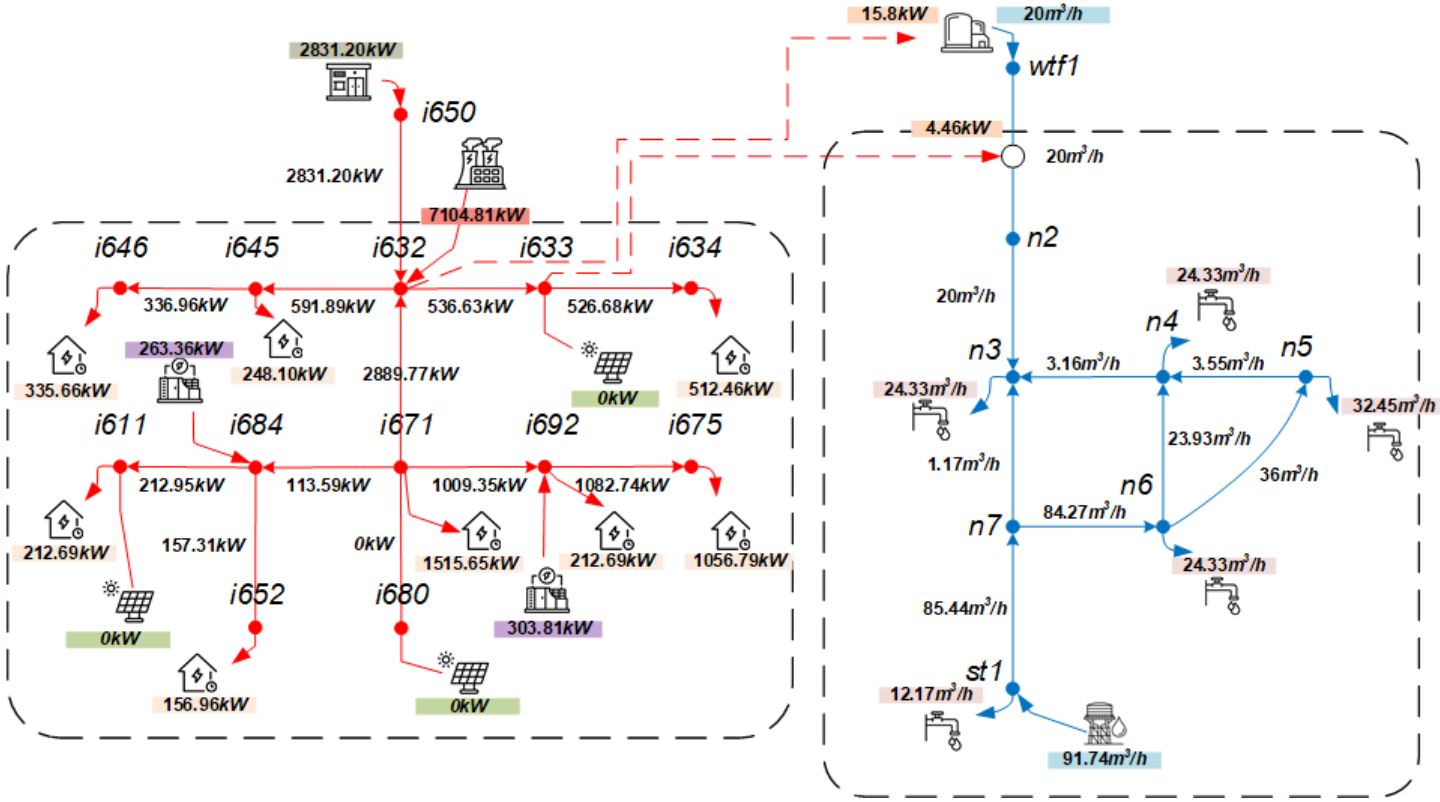


Figure 4.8: Optimal integrated water and power distribution network of the Scenario B at time interval t=20.

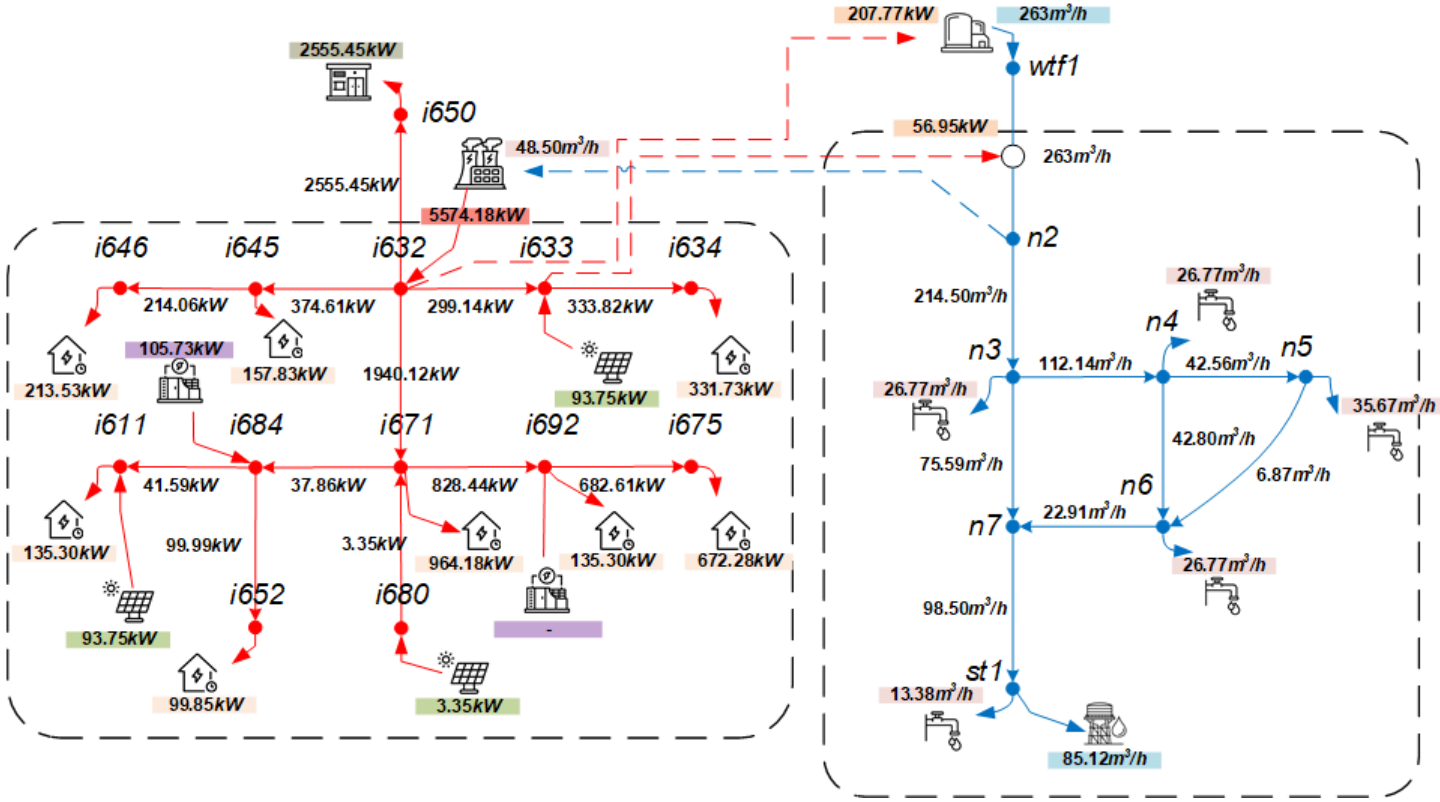


Figure 4.9: Optimal integrated water and power distribution network of the Scenario C at time interval t=6.

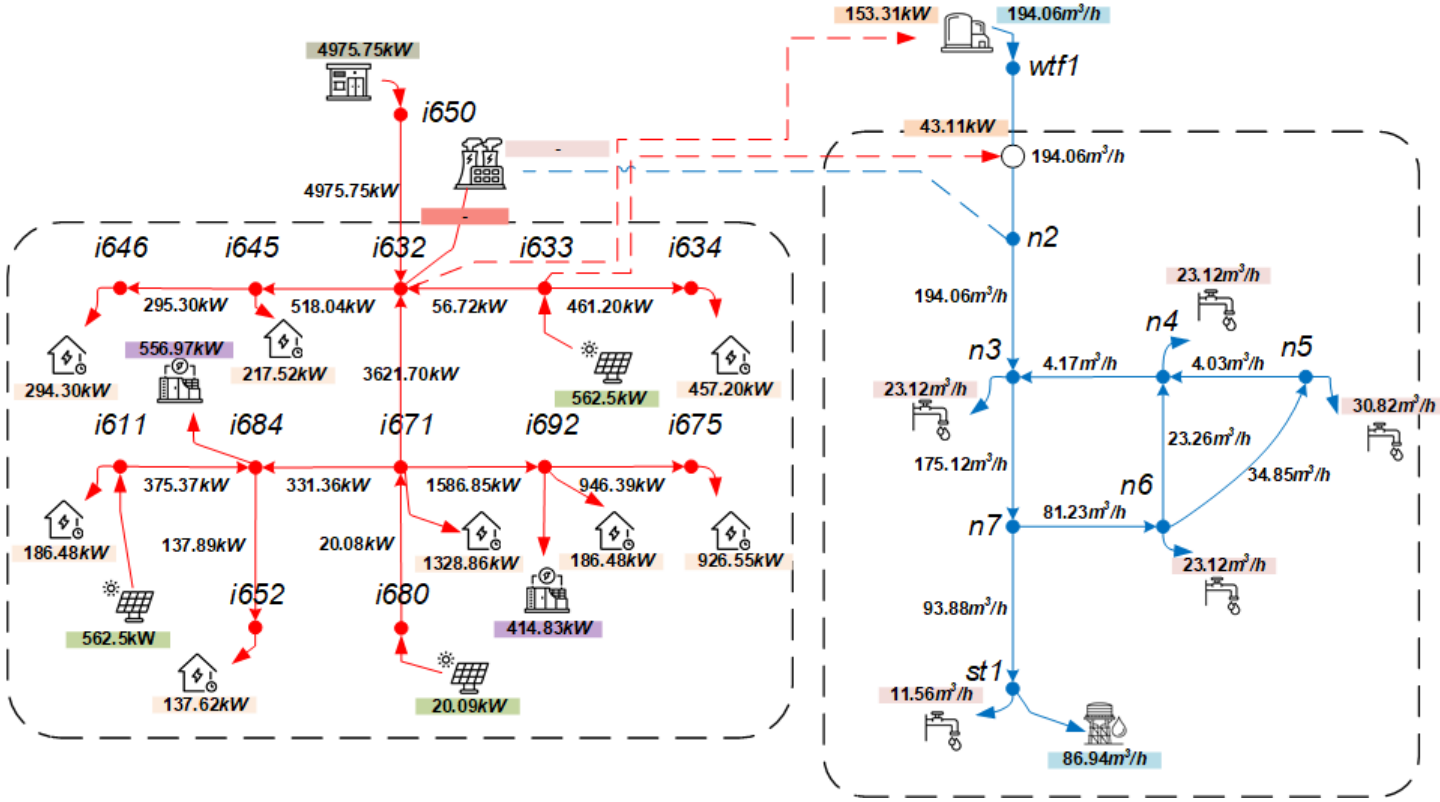


Figure 4.10: Optimal integrated water and power distribution network of the Scenario C at time interval t=13.

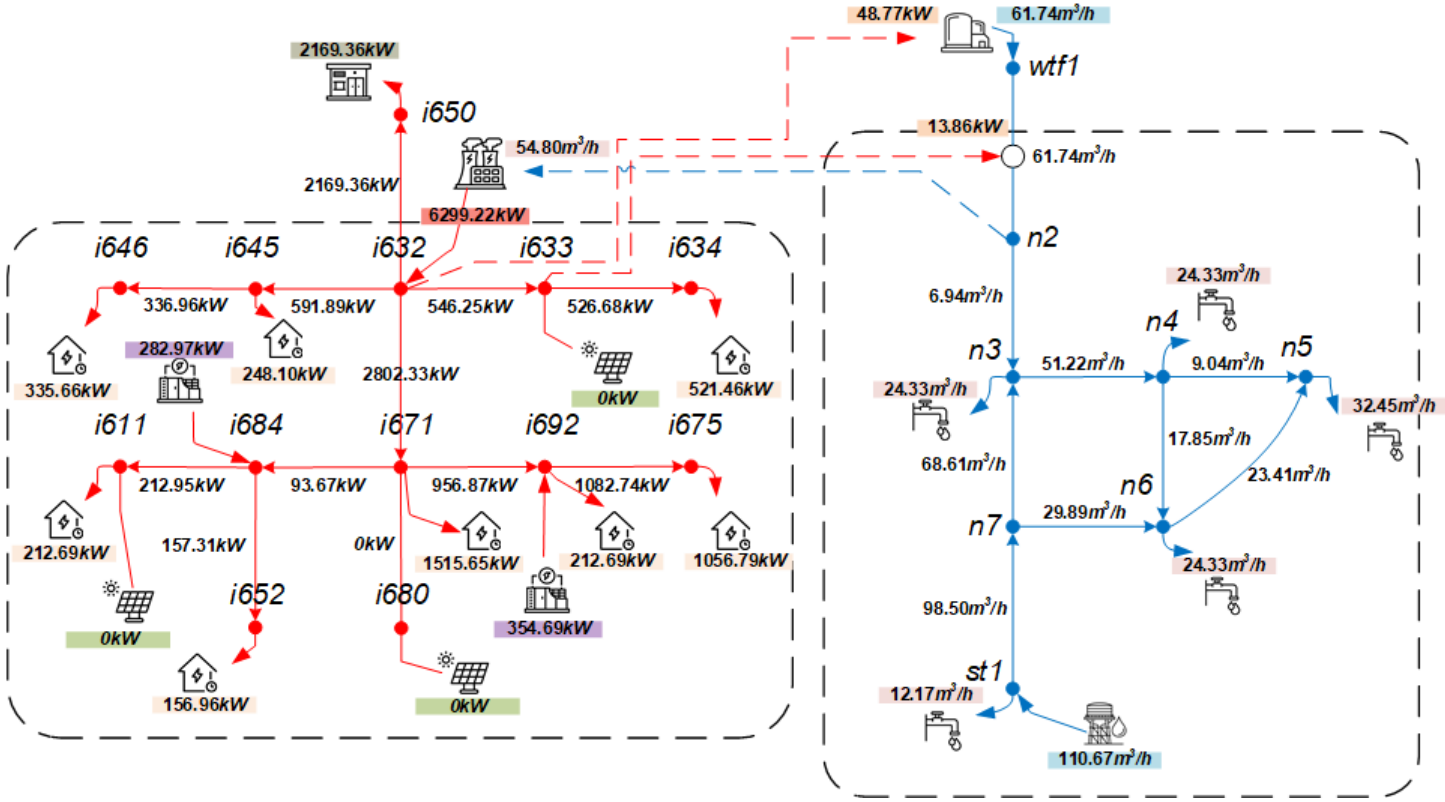


Figure 4.11: Optimal integrated water and power distribution network of the Scenario C at time interval t=20.

Chapter 5

Concluding Remarks

5.1 Conclusions

Water and power distribution networks are mutually interdependent on each other. The integration of both networks have spurred development of mathematical optimisation models that provide a reliable basis for the implementation of DSM schemes. Mathematical optimisation-based process integration techniques have proven to be very powerful tools in the PSE discipline that offer detailed handling of complex process industry problems. A key feature of these techniques is their capability to explore various dimensions which results in robust and optimal solutions.

In this dissertation, an optimisation model for the optimal operation of integrated water and power distribution networks in DSM programs is developed. Since the integration of already existing water and power distribution networks is inspired by the concept of the WEN, a superstructure that considers all the possible interconnections between water and power distribution networks to fully capture the WEN is used to build the optimisation model. The integration of water and power distribution networks emanates a short-term scheduling problem and therefore, the issue of capturing time is important. The proposed optimisation model used a discrete-time representation framework rather than a continuous-time representation framework to capture time because parameters of integrated water and power distributed networks such

as, forecasted demands, forecasted renewable energy sources, and the time-varying electricity costs are fixed on an hourly basis. Also, detailed models of the storage facilities i.e., water storage tanks and BESSs are incorporated into the optimisation model.

The proposed optimisation model is applied to an illustrative example that comprises a 13-bus power distribution network and an 8-node water distribution network of a small community to demonstrate its applicability. The resultant models from the considered scenarios are nonconvex MINLP, and the Antigone (GAMS) solver is used to solve the models with a guarantee of global optimality. The results showed that accurately capturing the operation of storage facilities leads to accurate cost representation which further justifies the potential DSM programs between water and power distribution networks. This is shown through the reduction of the overall operating cost of the integrated networks when detailed models of the storage facilities are used instead of black box models. The addition of a water connection to the thermoelectric power plant to fully capture the WEN of the problem resulted in an increase of the overall operating cost. A tradeoff between the usage of electric power from the power grid and locally generated power is observed. The optimal schedule for the DSM program of the integrated networks while satisfying the water and power demands is found.

5.2 Recommendations for Future Works

There is an opportunity to design the optimal integrated water and power distribution network using the proposed optimisation model as a basis. This can be achieved by the addition of design constraints for the storage tanks and BESS, as well as their capital costs in the objective function to find the optimal flexibility that the integrated water and power distribution network can offer. Although solving this design of storage facilities will lead to a computationally challenging problem, this would lead to more insightful view on the optimal flexibility that can be achieved by the integrated networks.

In terms of practicability, the proposed optimisation model may become unreliable for larger integrated water and power distribution networks as a tool. The problem is intrinsically combinatorial and nonconvex due to the features of pumps, storage tanks, and BESSs. It inherits both the mathematical optimisation challenges from the water and power distribution networks thereby making it highly intractable. This implies that, solving medium to larger scales of the problem will require high CPU times which are generally unfavorable in practice. Therefore, it is recommended that future research should focus on solving medium to large scale problems at reasonable CPU times. Also, mathematical optimisation techniques, such as decomposition methods are worthwhile options to achieve optimal solutions under reasonable CPU times.

The forecasted time-varying electricity prices, water and power demands, and variable renewable energy resources strongly dictate the timing decisions of operations in integrated water and power distribution networks. In practice, these parameters are uncertain due to forecast errors, inaccurate measurements or a lack of information (Li & Grossmann, 2021). Relying solely on deterministic optimisation models may lead to suboptimal or even infeasible schedules due to uncertainties, thereby making it difficult to implement demand-side management schemes between water and power utility operators. Therefore, it is important to develop optimisation models that also assess the feasibility of the operation of integrated water and power distribution networks under uncertainty.

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