

ELECTRIC ENERGY STORAGE FOR HIGH PENETRATION
RENEWABLES

A Dissertation by

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Submitted to the Department of Electrical Engineering and Computer Science
and the faculty of the Graduate School of
Wichita State University
in partial fulfillment of
the requirements for the degree of
Doctor of Philosophy

December 2016

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DEDICATION

To my family, my husband, and my friends

ACKNOWLEDGEMENTS

I would like to express my deepest appreciation to my advisor, Dr. Ward Jewell. I have been receiving his great guidance, instructions, and financial support throughout my Master's and PhD studies. His valuable teaching and inspirations have led me to the deeper field of electrical power systems, and will continuously benefit my future career.

Meanwhile, I am so grateful to have my dissertation committee members, Dr. Edwin Sawan, Dr. Visvakumar Aravinthan, Dr. Chengzong Pang, and Dr. Janet Twomey. I would like to thank them for their valuable suggestions and instructions on my thesis.

In addition to professors, I want to acknowledge my former colleagues, who have also been good friends from the beginning of my graduate studies. I am pleased to thank my colleagues Zhouxing Hu and Trevor Hardy for their helpful suggestions on the research projects. I also thank my other friends and every person who supported me to reach to this level.

I send warm thankfulness to my grandfather's soul who wished to stay alive to see me becoming the person who am I today.

Finally, I especially thank my parents, my sister, my brother, my husband, and my whole family for their great love and support.

ABSTRACT

The future is moving toward increasing the capacity of energy storage technologies in the system to tackle the high ramping requirements from generators due to the expected high penetration level of variable renewable resources, such as wind and solar. Bulk energy storage will play a vital role in the future to meet the electricity market needs. Currently, pumped hydro storage represents the majority of the energy storage capacity. It is planned to bring more pumped hydro storage to the system, with considering the adjustable speed technology. Currently the adjustable speed technology is not utilized in the US. Therefore, there is a need to study the best way of merging it into the electricity markets. This thesis presents the modeling of the adjustable-speed pumped hydro storage in the US electricity markets under different penetration levels of renewables. The thesis is divided into two major studies; operation and planning studies. The operation study goes through the optimization of adjustable-speed pumped hydro storage in the day-ahead and real-time markets. Full- and sub- optimizations were compared under low and high penetration levels of renewables. The planning study utilizes the planning optimization model for 10-year period while considering the adjustable-speed pumped hydro storage and US Environmental Protection Agency emissions standards for existing and new power plants.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
AS	Adjustable-Speed
BSER	Best System of Emission Reduction
CAES	Compressed Air Energy Storage
CAGR	Compound Annual Growth Rate
CCS	Carbon Capture and Storage
CO ₂	Carbon Oxide
DA	Day-ahead
DFIM	Double-fed Induction Motor
DOE	Department of Energy
ED	Economic Dispatch
EPA	Environmental Protection Agency
FERC	Federal Energy Regulatory Commission
GW	Gigawatt
ISO	Independent System Operator
LMP	Locational Marginal Price
MIP	Mixed-Integer Programming
MMBTU	Million British Thermal Unit
MW	Megawatt
MWh	Megawatt Hour
NERC	North American Electric Reliability Corporation
NREL	National Renewable Energy Laboratory
OASIS	Open Access Same Time Information System
O&M	Operation and Maintenance

LIST OF ABBREVIATIONS (continued)

OPF	Optimal Power Flow
PHS	Pumped-hydro Storage
PJM	Pennsylvania New Jersey Maryland Interconnection
PNNL	Pacific Northwest National Laboratory
RMS	Root Mean Square Error
RPS	Renewable Portfolio Standard
RT	Real-time
RTO	Regional Transmission Operator
TEPCO	Tokyo Electric Power Company
TWh	Terawatt Hour
UC	Unit Commitment
US	United States
WECC	Western Electricity Coordinating Council

NOMENCLATURE

Indicies

<i>b</i>	Index for buses
<i>c</i>	Index for cycling
<i>Ch</i>	Index for charging
<i>d</i>	Index for demand
<i>D</i>	Index for discharging
<i>DA</i>	Index for day-ahead market
<i>f</i>	Index for fuel type
<i>g</i>	Index for generation
<i>i</i>	Index for generators
<i>inv</i>	Index for investment
<i>j</i>	Index for invested generators
<i>ret</i>	Index for retirement
<i>RT</i>	Index for real-time market
<i>s</i>	Index for storage
<i>sh</i>	Index for shunt elements
<i>SD</i>	Index for shut-down
<i>SU</i>	Index for start-up
<i>t</i>	Index for time
<i>Sets</i>	
<i>I</i>	Set of generators
<i>S</i>	Set of storage
<i>T</i>	Set for retired generators
<i>V</i>	Index for invested generators

NOMENCLATURE (continued)

Parameters

B	Analogous to the system Y matrix
CF	Capacity factor
E_{max}	Maximum MWh energy capacity
E_{min}	Minimum MWh energy capacity
F_{max}	Vector of branch flow limit
G	Vector of approximated active power consumed by shunt elements
I_{max}	Maximum MW invested capacity
I_{min}	Minimum MW invested capacity
$in.R$	Fraction of energy capacity
P_{max}	Maximum MW active power output
P_{min}	Minimum MW active power output
R_{max}	Maximum MW retired capacity
R_{min}	Minimum MW retired capacity
R_{max_down}	Maximum MW reserve down power output
R_{max_up}	Maximum MW reserve up power output
R_{min_down}	Minimum MW reserve down power output
R_{min_up}	Minimum MW reserve up power output
P_r	MW active power ramping limit

NOMENCLATURE (continued)

θ_{max}	Maximum angle
θ_{min}	Minimum angle
η_{ch}	Charging efficiency
η_D	Discharging efficiency
<i>Variables</i>	
C	cost function
I	Invested MW capacity
P	Active power
P_{shift}	Active power shift
R	Retired MW capacity
r_{down}	Reserve down MW active power
r_{up}	Reserve up MW active power
u	Commitment status
v	Start-up/shut-down status
w	Charging/discharging dispatch status
θ	Vector of branch flow limit

CHAPTER 1

INTRODUCTION

1.1 Background

In 2014, the United States (US) generated about 4,093 billion kilowatthours (kWh) of electricity, in which fossil fuels (represented by coal, natural gas, and petroleum) generated about 67% of the electricity [1]. In addition, renewable resources (represented by wind, solar, geothermal, and biomass) generated about 7% of the 2014 electricity [1]. In the first two quarters (January – June) of 2015, US generated about 1,997 billion kWh, in which around 66% of the electricity generated was from fossil fuels (represented by coal, natural gas, and petroleum) [2]. Renewables (represented by wind, solar, geothermal, and biomass) generated about 7% of the 2015 electricity [2]. Figure 1.1 shows the percentage of generation by energy source in the first two quarters of 2015 in US [2].

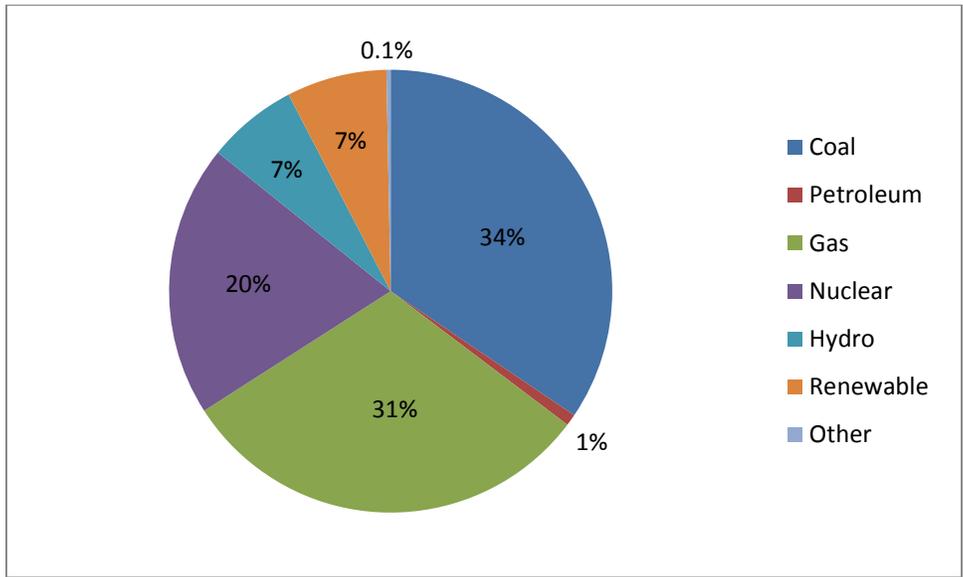


Figure 1.1. Percentage of generation by energy source in the first two quarters of 2015 in US

In Figure 1.1, “Other” includes non-biogenic municipal solid waste, batteries, hydrogen, purchased steam, sulfur, tire-derived fuel, and other miscellaneous energy sources [2].

While hydro includes conventional hydro and pumped hydro storage (PHS).

On June 2, 2014 and September 20, 2013, the US environmental protection agency (EPA) proposed carbon pollution standards for existing and new power plants. These standards, along with renewable portfolio standards (RPS), will result in a significant increase in the penetration level of renewables. As more renewable resources are adopted in the system, the uncertainty and variability issues associated with intermittent renewable resources increase and need to be addressed. The power systems have been relying on conventional generators to address the intermittent renewable resources issues. However, under high penetration levels of renewables, the conventional generators will be operated at lower output levels or be used as backup generators. The lower operating levels will decrease the locational marginal prices (LMP). This decrease in the LMP, beside the zero fuel cost for

wind, will result in a drop in the energy prices. As a result, the profits of conventional generators will decrease and their cost increases. The efficiency of conventional generators will be also affected negatively by the imposed ramping requirement to follow the intermittent renewables. The imposed ramping rate will also increase the emissions level from conventional generators. Therefore, more flexible resources are needed to address all of these issues, such as energy storage.

As of August 2013, the Department of Energy (DOE) database reported 202 storage systems in the US totaling 24.6 gigawatts (GW) storage capacity, in which 95% of this capacity is for PHS [3]. Besides PHS, the storage technologies mix includes compressed air energy storage (CAES), thermal energy storage, various types of batteries, and flywheels [3]. Figures 1.2 shows the 2013 capacity for different energy storage technologies in US [3].

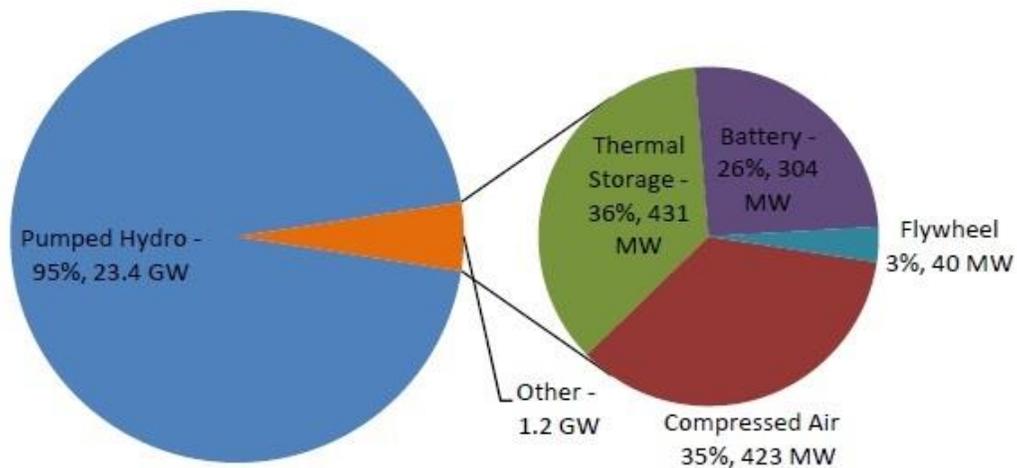


Figure 1.2. 2013 US energy storage capacity

Based on the DOE [3], *“The future for energy storage in the U.S. should address the following issues: energy storage technologies should be cost competitive (unsubsidized)”*

with other technologies providing similar services; energy storage should be recognized for its value in providing multiple benefits simultaneously; and ultimately, storage technology should seamlessly integrate with existing systems and sub-systems leading to its ubiquitous deployment.”

1.2 Summary of Chapters

This section presents the structure of this thesis as follows:

- Chapter 2: presents a literature review about pumped-hydro storage; its history, types based on speed and structure, and current situation in the US market. It also present the previous work related to the research proposed here.
- Chapter 3: presents the objective of the research presented in this thesis. It also introduces the system model and software used. The research studies that this thesis addresses are presented at the end of this Chapter.
- Chapter 4: presents the optimization formulations that model the research problem. It also presents the data and assumptions used to model the test system. The Chapter is divided into 4 sections, in which the first three sections present the optimization models of the three study cases being addressed in this research, and the last section presents the data and assumptions required to implement the models.
- Chapter 5: presents the results of running the optimization models on the test system. The Chapter is divided into three sections, in which each section represent the results of each study presented in Chapter 4.

- Chapter 6: presents conclusions drawn from the thesis chapters, and what still can be done in the research area to improve the problem solution and add new ideas to the existing ones.

CHAPTER 2

LITERATURE REVIEW

In 2013, Zhouxing Hu developed an optimal generation expansion planning with integration of variable renewables and bulk energy storage systems to find out the optimal investments of different energy resources in different locations [11]. The work in this research is built on the top of Zhouxing work to focus on modeling one type of the bulk energy storage, which is PHS.

Hydropower is an energy resource that provides several benefits to the US grid [4]. It is the least expensive source of electricity, does not require fossil fuel for generation, and able to shift loads to provide peaking power without requiring ramp-up time like combustion technologies [4]. PHS is a modified use of the conventional hydropower technology to store and manage energy. As shown in Figure 2.1, PHS stores energy by pumping the water from a lower reservoir to an upper reservoir (converts kinetic energy to potential energy) [4]. During periods of high energy demand, the stored water is released back through turbines (converts potential energy to kinetic energy) and converted back to electricity like a conventional hydro power [4].

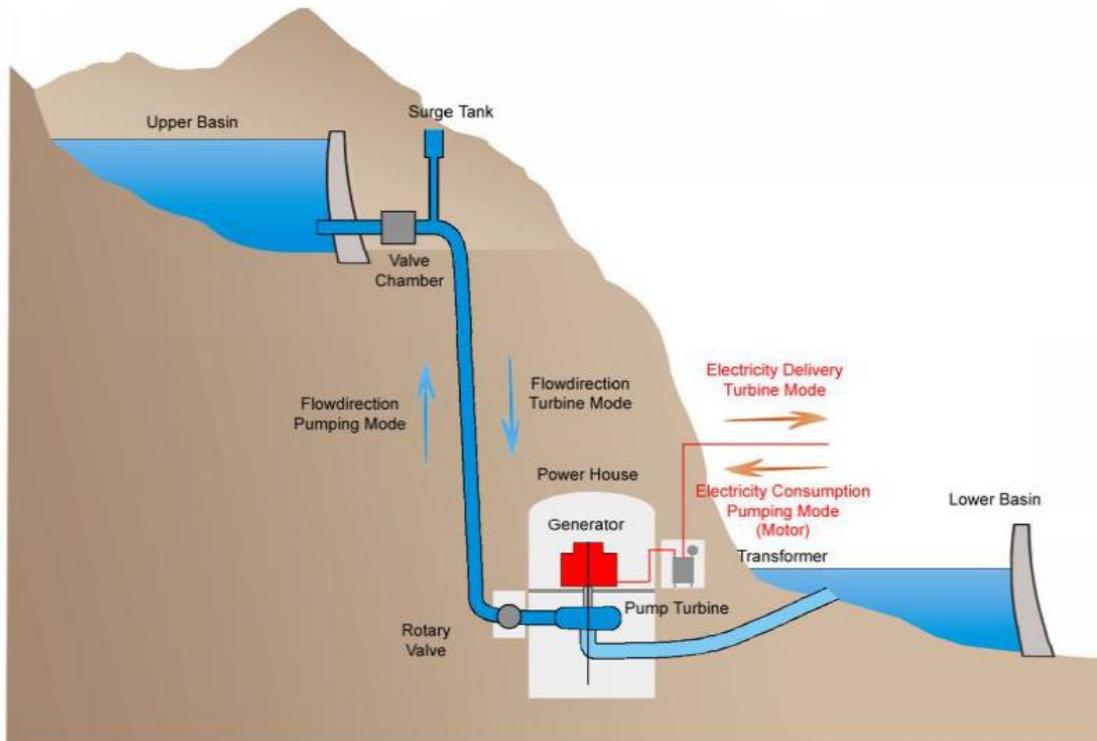


Figure 2.1. PHS principle of operation

The earliest use of PHS was in Switzerland in 1882 [4]. In the early 1900s, several small PHS plants were constructed in Europe, mostly in Germany [4]. In 1929, the Rocky River facility was the first PHS plant constructed in North America on the Housatonic River in Connecticut [4]. Currently, in the US, there are 40 existing PHS projects totaling 22 gigawatt (GW) of storage capacity, with largest projects in Virginia, Michigan, and California (Bath County, Ludington and Helms, respectively) [4]. Additionally, there are 51.310 GW representing over 60 pumped storage waiting for Federal Energy Regulatory Commission (FERC) licensing and permitting. Globally, there are approximately 270 PHS plants either operating or under construction totaling 127 GW of storage capacity [4]. Therefore, PHS is currently considered as a large, mature, and commercial utility-scale technology used at many locations in the US and around the world [3]. PHS is able to provide energy storage, load balancing, frequency control, and reserve peak power

generation services to the grid [4]. Figure 2.2 [5] and 2.3 [4] show the existing and the future PHS projects in the US, respectively.



Figure 2.2. Existing PHS plants in the US

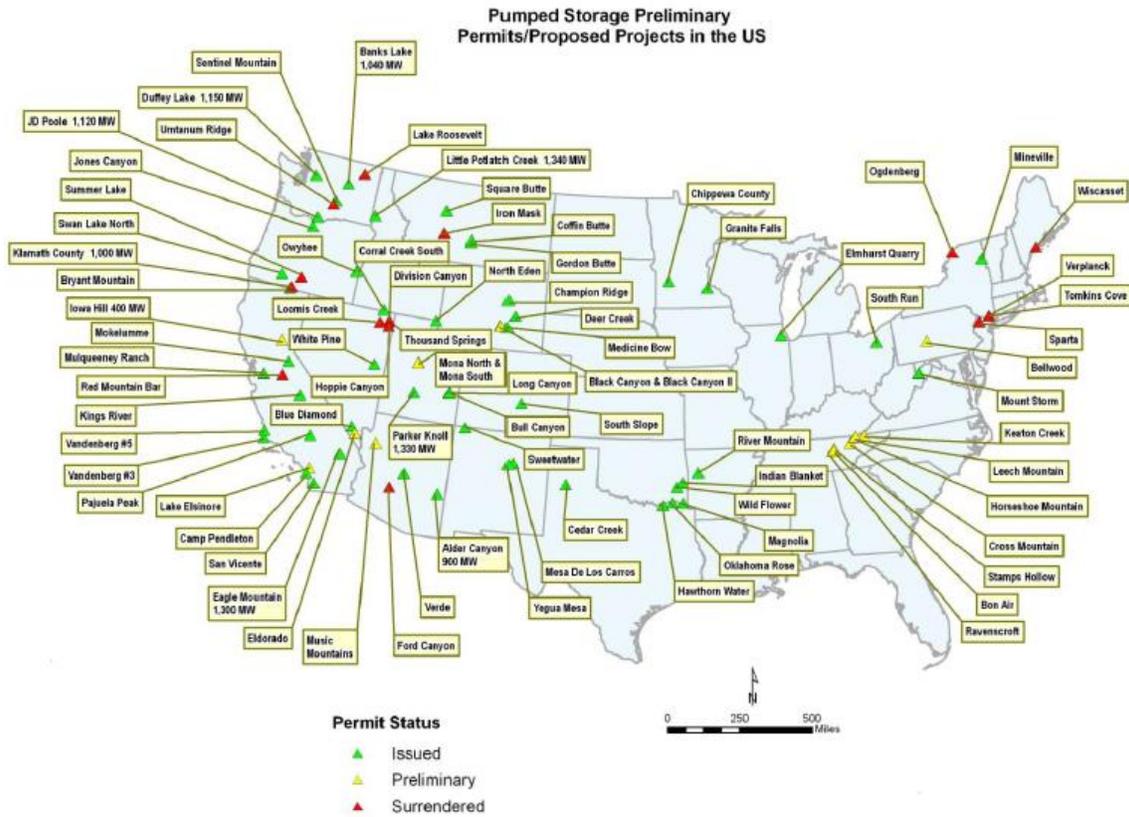


Figure 2.3. PHS preliminary permits/proposed projects in the US

All existing PHS plants in the world are either closed-loop or open-loop surface reservoirs. The closed-loop PHS is not continuously connected to a naturally flowing water source [6]. Therefore, after the initial filling of the reservoirs, the only additional water requirement is to replace the evaporation or seepage losses [4]. All the existing PHS plants in the US are open-loop, in which they are connected to a naturally flowing water source [6]. The current technology that is utilized by the PHS plants in the US is the fixed-speed technology [4]. This technology applies the reversible single-stage Francis pump-turbine design, which acts as a pump in one direction and as a turbine in the other. Although this technology is proven and has worked well for over six decades, there are limitations on its

performance, especially in the pumping mode [4]. The synchronous machines, which are used in the Francis pump-turbine design, are directly connected to the grid and operate at a constant speed and constant input pumping power [4]. In the turbine mode, the energy produced by each unit can vary, but does not operate at peak efficiency during part load [4]. Adjustable-speed (AS) machines, with its double-fed induction motor (DFIM)-generator standard design, have several additional benefits when compared to single-speed machines. AS machines enable input pumping power to be varied over a range of outputs and allows modifying the speed to operate the turbine at peak efficiency over a larger portion of its operating range [4]. Therefore, AS PHS reduces the need for thermal plant cycling that is critical for avoiding greenhouse gas (GHG) emissions and it leads to reduction in the operations and maintenance cost and increases the equipment lifespan [4]. Since the early to mid-1990s and the late 1990s AS machines have been used in Japan and Europe respectively [4]. The first AS PHS, Yagasawa Unit 2, was constructed for the Tokyo Electric Power Company (TEPCO) [4]. *“A main reason that adjustable speed pumped storage was developed in Japan in the early 1990’s was the realization that significant quantities of oil burned in combustion turbines could be reduced by shifting the responsibility for regulation to pumped storage plants” [4].*

The flexibility of PHS, especially with its AS technology, will play an important role in integrating high penetration level of variable renewables due to its fast ramping capability, low operating cost, and the ability of AS technology to vary the power consumed in the pumping and generating modes over a range of values [7]. Many of planned PHS projects are for closed-loop and considering the use of adjustable speed (AS) technology [7].

In the US deregulated markets, except for Pennsylvania New Jersey Maryland Interconnection (PJM), the PHS operation is sub-optimized by the independent system operators (ISOs) [7]. ISOs require that PHS choose the generation and pumping mode periods in advance of the day-ahead (DA) market, and then the ISO decides the commitment status, energy and ancillary services schedules of the plant in that operating mode [7]. Unlike other ISOs, PJM fully optimizes the PHS in its DA market by also deciding generation and pumping periods [7].

Full optimization of PHS is computationally very difficult and requires additional data sets [7]. This could be seen when the solution time of PJM's system optimizer was increased 5 to 10 times by the addition of a single PHS plant [7]. In today's market regions the PHS generation and pumping follow consistent daily patterns (e.g. pumping at night and generation in peak load periods) [7]. The unique characteristics of PHS with full optimization will be more needed when there are higher penetrations of variable generation because at that time, the marginal prices have much more volatility throughout the day [7]. Figure 2.5 [8] and 2.4 [9] show the regional transmission operators (RTOs) and ISOs, and the regional entities that manage and control the RTOs/ISOs operation respectively.



Figure 2.4. The current regional entities in the US

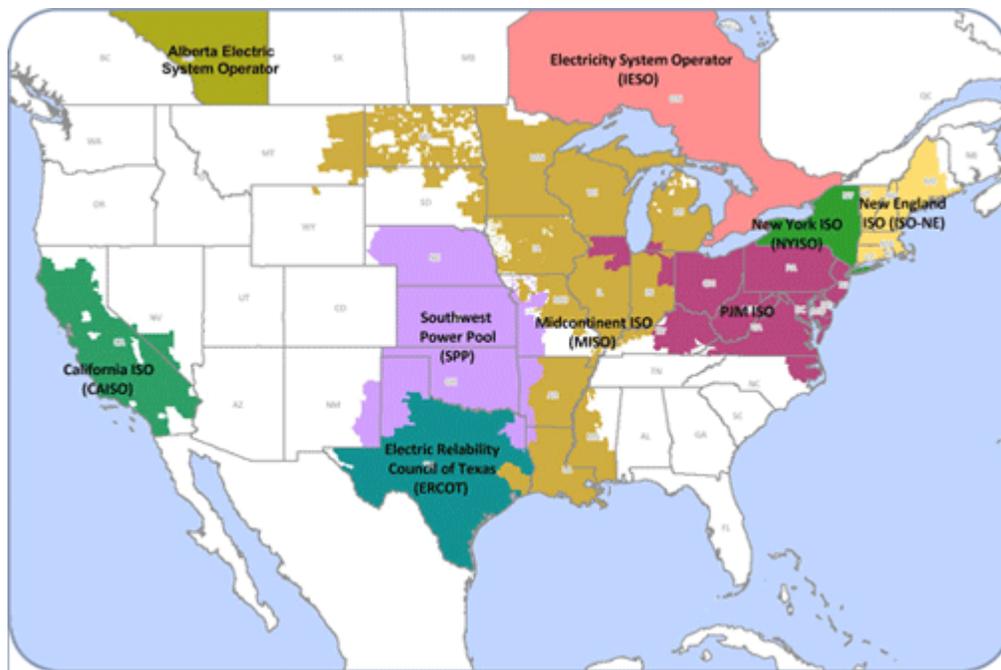


Figure 2.5. The current RTOs and ISOs in the US

Based on Figures 2.4 and 2.5, California ISO is the only ISO that operates in the western electricity coordination council (WECC) region's power grid and its wholesale electric markets. These markets are as follows:

- Energy markets: three – settlement (day ahead, hour ahead, and real time).
- Ancillary services.
- Financial Transmission Rights market.

WECC is geographically the largest and most diverse regional entity with given authority from the North American Electric Reliability Corporation (NERC) and FERC [10]. WECC is responsible for compliance monitoring and enforcement. In addition, WECC provides an environment for the development of reliability standards and the coordination of the operating and planning activities of its members [10]. Figure 2.6 shows the WECC balancing authorities and sub-regions [10].

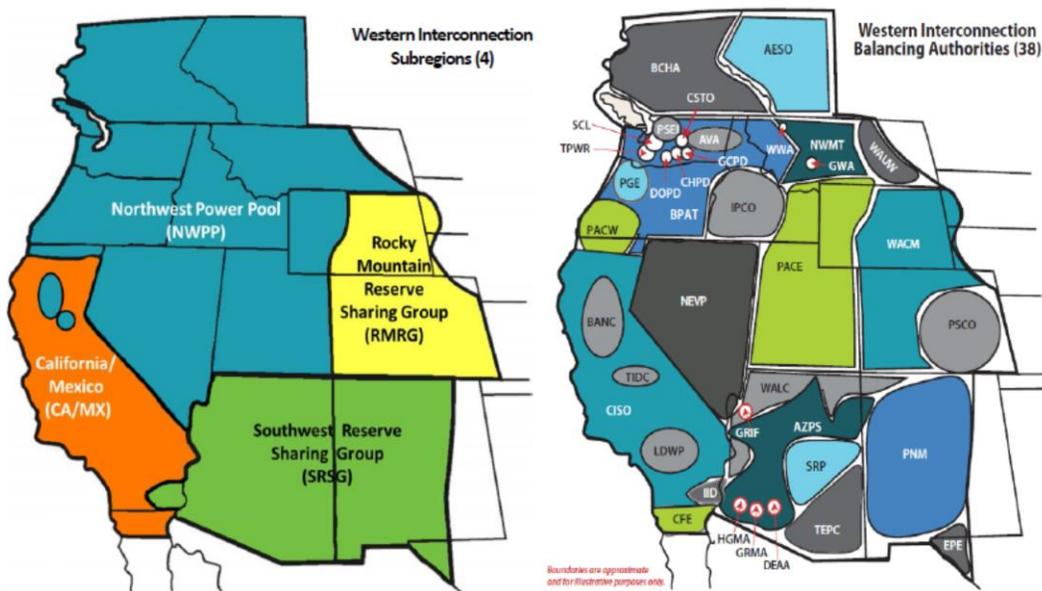


Figure 2.6. The current RTOs and ISOs in the US

As it is an extension to the work done in [11], this research uses the same reduced WECC system that was built on MATPOWER software. However, new optimization model is developed to include the AS technology of PHS in the system in order to explore its operation in the DA and RT markets under different penetration levels of renewables and cycling costs of conventional units. This research also includes planning optimization model to study the effect of AS PHS in the future WECC region under the new EPA emissions standards.

The modeling of PHS has been addressed in several research papers before; In [12], PHS was optimally integrated with a wind farm in Kenya, and the effect of fixed versus dynamic pricing on the wind farm operator was studied. The PHS was only used to balance the wind power variability. PHS stored energy generated by wind during low consumption hours, and released energy during high consumption and low wind hours. A stochastic dynamic programming approach was followed in [12] and implemented in Matpower for a one day simulation horizon with hourly periods. However, [12] did not include a detailed model for the PHS storage operation that describes its pumping and generating modes in addition to its ramping limits. Also, [12] did not study the impact of integrating the storage with the main grid, it only studied the maximization of the wind farm operator revenues (which is basically in this case PHS owner since the PHS was owned by the wind farm operator) without considering the effect of integrating the storage into a market serving consumers.

In [13], PHS was again optimally integrated with a wind farm in Europe; however, the effect on the wind farm operator of coordinated operation versus uncoordinated between the wind farm and PHS dynamic pricing was studied. A two-stage stochastic linear programming approach was followed in [13] and implemented in General Algebraic

Modeling System (GAMS) for the DA market. The study in [13] provided a more detailed model for PHS in pumping and generating modes; however, it did not consider the ramping limits of PHS.

The operation of PHS in conjunction with a wind farm in the Electric Reliability Council of Texas (ERCOT) market was studied in [14]. In [14] deterministic versus the stochastic approaches were compared. Deterministic models simplify the problem and achieve a solution faster than stochastic, but deterministic models underestimate risk from the uncertainty of wind. As in [13], the study in [14] considered a detailed model for PHS operation and restricted the operation in each hour for either pumping or generating; however, ramping was not considered.

In [15] and [16], unit commitment and real-time (RT) models had been developed to represent the operation in the DA and RT markets. [15] provided a stochastic optimization model for operations and planning of an electricity network managed by an ISO. The research papers [12-15] modeled the operation of AS PHS, in which the pumping mode has flexibility in its operation. A limited number of publications, however, address the optimization of AS PHS [4, 7, 29-30]. The National Renewable Energy Laboratory (NREL) provided in [29] an overview about the current status of PHS in the US markets, and the differences in operation between FS and AS. It also suggested potential market changes that can help PHS in today's restructured markets.

A more detailed overview and analysis of PHS in the US was presented in [7] by Argonne National Laboratory (ANL). In [7], dynamic simulation models were developed to study the operation of advanced PHS (AS and ternary) in 2022. The analysis in [7] also examined the benefits and value of advanced PHS plants in both regulated and deregulated electricity

markets in 2022. The study in [7] used four different computer models (PSS®E, FESTIV, CHEERS, and PLEXOS) to simulate system operation and analyze various control issues occurring at different timescales. Although [7] compared the benefits of having FS alone in the system versus having both FS and advanced PHS technologies, it did not compare the market treatment of AS PHS from the optimization points of view (sub versus full optimization).

The National Hydropower Association (NHA) in [4] presented additional detail on historic and current trends in PHS development, and policy changes that are needed to support the timely development of additional grid-scale energy storage. In [30], the research demonstrated and quantified some of the reliability and production cost benefits afforded by FS and AS PHS in the DA and RT markets with high penetration of variable renewables utilizing FESTIV. The model was built in MATLAB and leverages GAMS.

None of these, however, present details of the actual AS PHS optimization models applied because they are industrial models and not available for academic research purposes.

CHAPTER 3

RESEARCH OBJECTIVE

The objective of this research is to study the integration of AS PHS in current and future energy and market management systems using different optimization models. The WECC system with its reduced version presented in [19] is used as the test model for this research. The system is built on MATPOWER software to use its DC optimal power flow (OPF) feature. The research objective is reached by developing the techniques for three studies, which are then implemented on the WECC system:

- Operation study: Develop full- and sub- optimized models for AS PHS in both DA and RT market environments while considering the conventional generators cycling cost and different penetration levels of renewables.
- Planning study: Develop and apply a fully-optimized model for AS PHS while considering the EPA CO₂ emissions standards for existing and new generators in the WECC 2013 10-year plan.

These studies will be explained in Chapter 4 in more detail with their optimization models and required to data to implement them.

CHAPTER 4

PROBLEM STATEMENT

This Chapter provides the operation and planning optimization models, data, and assumptions that were used to accomplish the objective of the research presented in Chapter 3. The optimization models were built in the MATPOWER environment [16] using its standard and extensible OPF structure. MATPOWER is a package of MATLAB M-files for solving power flow and optimal power flow problems [16]. For simplicity, DC OPF formulations were used in the model because of its faster solution time. Many industrial and commercial OPF formulations use the DC equations to get satisfactory results [17]. The techniques developed will also apply to ac OPF, but the use of ac OPF in this research would increase the complexity and solutions times to impractical levels.

Quadratic programming was used to solve the optimization models. Quadratic programming is a special form of nonlinear programming in which the objective function is quadratic and all constraints are linear [17]. The integer variables values were approximated since MATPOWER does not support defining the integer variables that are needed to reflect the commitment, start-up, and shut-down status. The optimization models were built on the reduced 240-bus model of the WECC system

4.1 Day-ahead Market Operation Study

This section presents the optimization model that was used to study the operation of AS PHS in the DA market. A DA unit commitment (UC) and economic dispatch (ED) model was developed and demonstrated to study the operation of open-loop AS technology

under two variable renewable penetrations, 6% and 14%, and two different optimization scenarios. The cycling costs for conventional generation are included in the models.

The optimization model is represented by equations (1) through (23). The objective function developed specifically for this work is shown in equation (1). It includes the conventional quadratic and linear generation cost function C_g^i , and linear start-up cost function C_{SU}^i . It adds to these a linear cycling cost function C_c^i , which is needed because generators are cycling more to follow variable generation as penetrations of variable generation increase. The cycling cost is added to the objective function only when the change in load between two following time periods is more than a set value proposed by NREL in [21]. Equations (2) through (6) represent the standard DC OPF variables and constraints applied in MATPOWER and other DC OPF models such as [15]. This formulation includes angle θ^{bt} , active power P_g^{it} , branch, and bus power limits [16]. Hydro optimization is presented by equation (7). In Equation (7), all hydro units are assumed to have the same capacity factor (CF) value during the simulation horizon. The P_{\max}^{it} is the forecasted hourly hydro generation limit that represents the hourly limit of water capacity. Equations (8) through (16) represent the AS PHS optimization model. The modeling of PHS and hydro generating plants has been addressed in several research papers before; however, the research done in the area of optimizing AS PHS operation in the US is rare since the AS technology is new to the US power system. The AS PHS optimization model applied in the [29, 7, 4, 30] studies was not shown and explained since they are industrial models and not available for academic research purposes. Therefore, based on the operation of the US markets and AS PHS, the AS PHS optimization model is developed by converting theories into equations. In this model, the storage is modeled as dispatchable

load P_{gCh}^{it} (to represent the pumping “charging” mode) and as a generator P_{gD}^{it} (to represent the generating “discharging” mode). The difference between FS and AS PHS is that, the AS PHS can be dispatched over a range of values between its maximum and minimum capacity during its pumping mode, but the FS can only be dispatched at either its maximum or minimum capacity. The operation of AS PHS is translated to equations (8) and (9), in which the AS PHS can be dispatched between its P_{smin} and P_{smax} in both pumping and generating modes. The variables w_{Ch}^{it} and w_D^{it} used in equations (8) and (9), are defined and constrained in equations (10) through (12). Equations (10) through (12) guarantee the fully-optimized operation of the AS PHS, and that the AS PHS operates only in pumping or generating mode during each time period. Regarding the fully-optimized operation, equations (10) through (12) provide the freedom for the market operator to decide which operating mode to commit in each time period. In the case of sub-optimized operation, equations (10) through (12) are not included in the optimization model and the variables w_{Ch}^{it} and w_D^{it} will be binary parameters (0 or 1) provided by the PHS owner. Equation (13) was added to the model to make the initial and final reservoir levels equal. Equations (14) and (15) guarantee that the charged power at the current time period does not exceed maximum available empty capacity in the previous time period. In addition, the discharged power at the current time period does not exceed the available stored capacity in the previous time period. Equations (14) and (15) show that the AS PHS had an initial energy capacity of $in.RE_{smax}^i$ at the beginning of each time period, which is a fraction of the maximum energy capacity. Equation (16) represents the ramping constraint of AS PHS, in which the change in power between time periods should not exceed the ramping limit. The ramping constraint of all other generators in the system is stated in equation (17). This

work also extends the work developed in [11] and [18] by adding the UC commitment and cycling operation of conventional generators. [15] was used to develop the UC optimization model that is presented in equations (18) through (23). The optimization model is as follows:

Objective function:

$$\min_{\theta, P_g, u, v_{SU}, v_{SD}} \sum_t \sum_i C_g^i(P_g^{it}) + \sum_t \sum_i C_c^i(P_g^{i(t-1)} - P_g^{it}) + \sum_t \sum_i C_{SU}^i(v_{SU}^{it}) \quad (1)$$

DC OPF variables and constraints:

$$\theta_{min}^b \leq \theta^{bt} \leq \theta_{max}^b \quad \forall t \quad (2)$$

$$P_{min}^i \leq P_g^{it} \leq P_{max}^i \quad \forall i \in I, \forall t \quad (3)$$

$$B\theta^{bt} + P_{shift}^{bt} - F_{max} \leq 0 \quad \forall t \quad (4)$$

$$-B\theta^{bt} - P_{shift}^{bt} - F_{max} \leq 0 \quad \forall t \quad (5)$$

$$B\theta^{bt} + P_{shift}^{bt} + P_d^{bt} + G_{sh} - P_g^{bt} \leq 0 \quad \forall t \quad (6)$$

Hydro constraint:

$$\sum_t \sum_i P_g^{it} \leq CF \sum_t \sum_i P_{max}^{it} \quad \forall i \in I, \forall t \quad (7)$$

AS PHS variables and constraints:

$$-w_{Ch}^{it} P_{smax}^i \leq P_{gCh}^{it} \leq 0 \quad \forall i \in S, \forall t \quad (8)$$

$$0 \leq P_{gD}^{it} \leq w_D^{it} P_{smax}^i \quad \forall i \in S, \forall t \quad (9)$$

$$0 \leq w_{Ch}^{it} \leq 1 \quad \forall i \in S, \forall t \quad (10)$$

$$0 \leq w_D^{it} \leq 1 \quad \forall i \in S, \forall t \quad (11)$$

$$w_{Ch}^{it} + w_D^{it} \leq 1 \quad \forall i \in S, \forall t \quad (12)$$

$$\sum_t \sum_i \eta_{Ch}^i P_{gCh}^{it} + \sum_t \sum_i \frac{P_{gD}^{it}}{\eta_D^i} = 0 \quad \forall i \in S, \forall t \quad (13)$$

$$0 \leq -P_{gCh}^{i(t-1)} - P_{gCh}^{it} - \frac{P_{gD}^{i(t-1)}}{\eta_{Ch}^i \eta_D^i} \leq \frac{(1 - in.R^i) E_{smax}^i}{\eta_{Ch}^i} \quad \forall i \in S, \forall t \quad (14)$$

$$0 \leq P_{gD}^{i(t-1)} + P_{gD}^{it} + \eta_{Ch}^i \eta_D^i P_{gCh}^{i(t-1)} \leq \eta_D^i in.R^i E_{smax}^i \quad \forall i \in S, \forall t \quad (15)$$

$$-P_{rs}^i \leq [P_{gCh}^{i(t-1)} + P_{gD}^{i(t-1)}] - [P_{gCh}^{it} + P_{gD}^{it}] \leq P_{rs}^i \quad \forall i \in S, \forall t \quad (16)$$

$$-P_r^i \leq P_g^{i(t-1)} - P_g^{it} \leq P_r^i \quad \forall i \in S, \forall t \quad (17)$$

UC variables and constraints:

$$0 \leq u_g^{it} \leq 1 \quad \forall i \in S, \forall t \quad (18)$$

$$0 \leq v_{gSU}^{it} \leq 1 \quad \forall i \in I, \forall t \quad (19)$$

$$0 \leq v_{gSD}^{it} \leq 1 \quad \forall i \in I, \forall t \quad (20)$$

$$u_g^{it} P_{min}^i \leq P_g^{it} \leq u_g^{it} P_{max}^i \quad \forall i \in I, \forall t \quad (21)$$

$$u_g^{it} - u_g^{i(t-1)} = v_{gSU}^{it} - v_{gSD}^{it} \quad \forall i \in I, \forall t \quad (22)$$

$$v_{gSU}^{it} + v_{gSD}^{it} \leq 1 \quad \forall i \in I, \forall t \quad (23)$$

4.2 Real-time Market Operation Study

This section presents the optimization model that was used to study the operation of AS PHS in the RT market. A RT ED model was developed and demonstrated on the reduced 240-bus model of the WECC system to study the operation of open-loop AS technology under two variable renewable penetrations, 6% and 14%, and two different optimization models. For the high renewable case, three scenarios have been studied: wind

is blowing more during the day, at night, and varying during the day. The cycling costs for conventional generation are included in the models. In the RT either the system is intact and has the configuration of the DA market case (with some changes in demand) or a contingency has occurred and the system has faced a transition. The study in this research treats the system in RT as intact system with a slight change from the DA contracted results [22]. In the CAISO market, energy and ancillary services are co-optimized in the DA Market; however, the RT ED market is not co-optimized with ancillary services. Ancillary services are energy products used to help maintain grid stability and reliability [24]. There are four types of ancillary services products: regulation up, regulation down, spinning reserve and non-spinning reserve [24]. The DA market study presented in section 4.1 was an energy market study, in which it did not consider adding the ancillary services constraints to the optimization model. However, part of the generation capacity was reserved for ancillary services and only the energy market capacity was available for the optimization models. This is because the simulation horizon for the problem of section 4.1 was 28 days (672 hours), and considering the ancillary services market would increase the complexity of the problem solving to a non- desired levels. For the study presented in this section, the co-optimization of energy and ancillary services was considered since the optimization horizon was only for one day (24 hours). The ancillary services were divided into two parts; up and down reserves. The energy and reserves quantities are determined and payed for in the DA market. In the RT market, the deviation from the determined DA energy quantities will be met by utilizing the determined DA reserves quantities. The DA optimization models used for the study in this section are represented in section 4.2.1, while the RT optimization models are presented in section 4.2.2.

4.2.1 Day-ahead Market Optimization Model

This section presents the optimization model, equations (1) through (27), that was used to get the committed and dispatched energy and reserves quantities to be used for the RT ED market study. The model presented in this section differs from the one presented in section 4.1 by adding the reserve optimization. The reserve optimization part was reflected in the objective function, generation model, and AS PHS model. In addition, the load, solar, and wind generation data were forecasted using historical and current DA and RT market data provided by CAISO. The tool that was used to forecast the required profiles is called NeuralWare software. More information about the data and software will be provided in section 4.4.

The other parts of this section model do the same job explained in section 4.1. The objective function in equation (1) includes the linear up ($C_{r_{g_{up}}}^i, C_{r_{s_{up}}}^i$) and down ($C_{r_{g_{down}}}^i, C_{r_{s_{down}}}^i$) reserves costs in addition to the energy costs that were presented in section 4.1. The goal is to minimize the total system operating cost. The reserves costs were imposed on the up $r_{s_{up}}^{it}$ and down $r_{s_{down}}^{it}$ reserves variables defined in equations (8) through (9) for storage, and (23) through (24) for other types of generation. For AS PHS, the full and sub optimization equations, (10) through (14) were applied in this section. The reserves variables were added to equations (10) and (11) to ensure that the dispatched (charged or discharged) energy with (down or up) reserves respectively does not exceed the committed storage capacity limits at each time period for each AS PHS plant. Similar concept can be seen in equation (25) for other types of generators. In equation (25), the dispatched energy and reserve at each time period has to be within the limits of the committed generation capacity. The optimization model is as follows:

Objective function:

$$\begin{aligned} \min_{\theta, P_g, r_{g_{up}}, r_{g_{down}}, r_{s_{up}}, r_{s_{down}}, u, v_{SU}, v_{SD}} & \sum_t \sum_i C_g^i (P_g^{it}) + \sum_t \sum_i C_{r_{g_{up}}}^i (r_{g_{up}}^{it}) + \\ & \sum_t \sum_i C_{r_{g_{down}}}^i (r_{g_{down}}^{it}) + \sum_t \sum_i C_{r_{s_{up}}}^i (r_{s_{up}}^{it}) + \sum_t \sum_i C_{r_{s_{down}}}^i (r_{s_{down}}^{it}) + \sum_t \sum_i C_c^i (P_g^{i(t-1)} - \\ & P_g^{it}) + \sum_t \sum_i C_{SU}^i (v_{SU}^{it}) \end{aligned} \quad (1)$$

DC OPF variables and constraints:

$$\theta_{min}^b \leq \theta^{bt} \leq \theta_{max}^b \quad \forall t \quad (2)$$

$$P_{min}^i \leq P_g^{it} \leq P_{max}^i \quad \forall i \in I, \forall t \quad (3)$$

$$B\theta^{bt} + P_{shift}^{bt} - F_{max} \leq 0 \quad \forall t \quad (4)$$

$$-B\theta^{bt} - P_{shift}^{bt} - F_{max} \leq 0 \quad \forall t \quad (5)$$

$$B\theta^{bt} + P_{shift}^{bt} + P_d^{bt} + G_{sh} - P_g^{bt} \leq 0 \quad \forall t \quad (6)$$

Hydro constraint:

$$\sum_t P_g^{it} \leq CF \sum_t P_{max}^{it} \quad \forall i \in I, \forall t \quad (7)$$

AS PHS variables and constraints:

$$R_{s_{min_up}}^i \leq r_{s_{up}}^{it} \leq R_{s_{max_up}}^i \quad \forall i \in S, \forall t \quad (8)$$

$$R_{s_{min_down}}^i \leq r_{s_{down}}^{it} \leq R_{s_{max_down}}^i \quad \forall i \in S, \forall t \quad (9)$$

$$-w_{Ch}^{it} P_{smax}^i \leq P_{gCh}^{it} + r_{s_{down}}^{it} \leq 0 \quad \forall i \in S, \forall t \quad (10)$$

$$0 \leq P_{gD}^{it} + r_{s_{up}}^{it} \leq w_D^{it} P_{smax}^i \quad \forall i \in S, \forall t \quad (11)$$

$$0 \leq w_{Ch}^{it} \leq 1 \quad \forall i \in S, \forall t \quad (12)$$

$$0 \leq w_D^{it} \leq 1 \quad \forall i \in S, \forall t \quad (13)$$

$$w_{Ch}^{it} + w_D^{it} \leq 1 \quad \forall i \in S, \forall t \quad (14)$$

$$\sum_t \sum_i \eta_{Ch}^i P_{gCh}^{it} + \sum_t \sum_i \frac{P_{gD}^{it}}{\eta_D^i} = 0 \quad \forall i \in S, \forall t \quad (15)$$

$$0 \leq -P_{gCh}^{i(t-1)} - P_{gCh}^{it} - \frac{P_{gD}^{i(t-1)}}{\eta_{Ch}^i \eta_D^i} \leq \frac{(1-in.R^i)E_{Smax}^i}{\eta_{Ch}^i} \quad \forall i \in S, \forall t \quad (16)$$

$$0 \leq P_{gD}^{i(t-1)} + P_{gD}^{it} + \eta_{Ch}^i \eta_D^i P_{gCh}^{i(t-1)} \leq \eta_D^i in.R^i E_{Smax}^i \quad \forall i \in S, \forall t \quad (17)$$

$$-P_{rs}^i \leq [P_{gCh}^{i(t-1)} + P_{gD}^{i(t-1)}] - [P_{gCh}^{it} + P_{gD}^{it}] \leq P_{rs}^i \quad \forall i \in S, \forall t \quad (18)$$

$$-P_r^i \leq P_g^{i(t-1)} - P_g^{it} \leq P_r^i \quad \forall i \in S, \forall t \quad (19)$$

UC variables and constraints:

$$0 \leq u_g^{it} \leq 1 \quad \forall i \in S, \forall t \quad (20)$$

$$0 \leq v_{gSU}^{it} \leq 1 \quad \forall i \in I, \forall t \quad (21)$$

$$0 \leq v_{gSD}^{it} \leq 1 \quad \forall i \in I, \forall t \quad (22)$$

$$R_{gmin_up}^i \leq r_{gup}^{it} \leq R_{gmax_up}^i \quad \forall i \in I, \forall t \quad (23)$$

$$R_{gmin_down}^i \leq r_{gdown}^{it} \leq R_{gmax_down}^i \quad \forall i \in I, \forall t \quad (24)$$

$$u_g^{it} P_{min}^i \leq P_g^{it} + r_{gup}^{it} + r_{gdown}^{it} \leq u_g^{it} P_{max}^i \quad \forall i \in I, \forall t \quad (25)$$

$$u_g^{it} - u_g^{i(t-1)} = v_{gSU}^{it} - v_{gSD}^{it} \quad \forall i \in I, \forall t \quad (26)$$

$$v_{gSU}^{it} + v_{gSD}^{it} \leq 1 \quad \forall i \in I, \forall t \quad (27)$$

4.2.2 Real-Time Market Optimization Model

This section presents the RT ED model that deals with the deviations in the demand and generation from the DA market results occurred due to the forecasting errors. The optimization model is represented by equations (1) through (19). This model is similar to the model presented in sections 4.1 and 4.1.1 with some differences. The objective function of the RT market model includes only energy and cycling cost minimization; however, it does not include reserves and start-up costs minimization. The reason is that the reserves were committed and paid for in the DA market, and the RT ED does not include ancillary services optimization. Regarding the start-up costs, the generating units were committed in the DA market and the RT ED only includes economic dispatch part and it does not include unit commitment part. Equation (1) shows the objective function of the model in this section. The reserve variables of the DA market models were turned out to become parameters for the RT ED market models. Equations (8) through (9) show the up and down $(R_{sup}^{it}, R_{sdown}^{it})$ storage reserves parameters, while equations (18) through (19) show the up and down $(R_{pup}^{it}, R_{pdown}^{it})$ other generation reserves parameters. Equations (8) (9), (18), and (19) guarantees that the deviation, covered by the RT dispatch, does not exceed the contracted up or down reserves quantities in the DA market. For AS PHS, as explained in section 4.1, both full- and sub- optimization models are considered in this section to study the RT case of these models. The optimization model is as follows:

Objective function:

$$\min_{\theta, P_g, u, v_{SU}, v_{SD}} \sum_t \sum_i C_g^i(P_g^{it}) + \sum_t \sum_i C_c^i(P_g^{i(t-1)} - P_g^{it}) \quad (1)$$

DC OPF variables and constraints:

$$\theta_{min}^b \leq \theta^{bt} \leq \theta_{max}^b \quad \forall t \quad (2)$$

$$P_{min}^i \leq P_g^{it} \leq P_{max}^i \quad \forall i \in I, \forall t \quad (3)$$

$$B\theta^{bt} + P_{shift}^{bt} - F_{max} \leq 0 \quad \forall t \quad (4)$$

$$-B\theta^{bt} - P_{shift}^{bt} - F_{max} \leq 0 \quad \forall t \quad (5)$$

$$B\theta^{bt} + P_{shift}^{bt} + P_d^{bt} + G_{sh} - P_g^{bt} \leq 0 \quad \forall t \quad (6)$$

Hydro constraint:

$$\sum_t \sum_i P_g^{it} \leq CF \sum_t \sum_i P_{max}^{it} \quad \forall i \in I, \forall t \quad (7)$$

AS PHS variables and constraints:

$$-w_{Ch}^{it} R_{sdown}^{it} \leq P_{gChRT}^{it} + w_{Ch}^{it} P_{gChDA}^{it} \leq 0 \quad \forall i \in S, \forall t \quad (8)$$

$$0 \leq P_{gDRT}^{it} - w_D^{it} P_{gDDA}^{it} \leq w_D^{it} R_{sup}^{it} \quad \forall i \in S, \forall t \quad (9)$$

$$0 \leq w_{Ch}^{it} \leq 1 \quad \forall i \in S, \forall t \quad (10)$$

$$0 \leq w_D^{it} \leq 1 \quad \forall i \in S, \forall t \quad (11)$$

$$w_{Ch}^{it} + w_D^{it} \leq 1 \quad \forall i \in S, \forall t \quad (12)$$

$$\sum_t \sum_i \eta_{Ch}^i P_{gCh}^{it} + \sum_t \sum_i \frac{P_{gD}^{it}}{\eta_D^i} = 0 \quad \forall i \in S, \forall t \quad (13)$$

$$0 \leq -P_{gCh}^{i(t-1)} - P_{gCh}^{it} - \frac{P_{gD}^{i(t-1)}}{\eta_{Ch}^i \eta_D^i} \leq \frac{(1 - in.R^i) E_{smax}^i}{\eta_{Ch}^i} \quad \forall i \in S, \forall t \quad (14)$$

$$0 \leq P_{gD}^{i(t-1)} + P_{gD}^{it} + \eta_{Ch}^i \eta_D^i P_{gCh}^{i(t-1)} \leq \eta_D^i in.R^i E_{smax}^i \quad \forall i \in S, \forall t \quad (15)$$

$$-P_{rs}^i \leq [P_{gCh}^{i(t-1)} + P_{gD}^{i(t-1)}] - [P_{gCh}^{it} + P_{gD}^{it}] \leq P_{rs}^i \quad \forall i \in S, \forall t \quad (16)$$

ED variables and constraints:

$$-P_r^i \leq P_g^{i(t-1)} - P_g^{it} \leq P_r^i \quad \forall i \in S, \forall t \quad (17)$$

$$P_{min}^i \leq P_{gRT}^{it} - P_{gDA}^{it} \leq R_{gDA_{up}}^{it} \quad \forall i \in I, \forall t \quad (18)$$

$$P_{min}^i \leq P_{gDA}^{it} - P_{gRT}^{it} \leq R_{gDA_{down}}^{it} \quad \forall i \in I, \forall t \quad (19)$$

4.3 Planning Study

As was mentioned in section 1.1, the EPA proposed Carbon pollution standards for new and existing power plants under Section 111(b) and Section 111(d) of the Clean Air Act respectively. The Clean Air Act was designed by the Congress in 1970, and made major revisions in 1977 and 1990, to protect public health and welfare from different types of air pollution caused by a diverse base of pollution sources [25].

The proposed Carbon Pollution Standard for New Power Plants was released on September 20, 2013 to replace an earlier proposal released by EPA in March, in which it proposed rules to limit the lbs CO₂/MWh emitted by the new natural gas and coal power plants [27]. The new power plants' standard is intended through 2022, and it is possible with the latest combined cycle technology, and by employing carbon capture and storage (CCS) technology to the new coal plants [27].

On June 2, 2014, the EPA released its proposed Carbon Pollution Standards for Existing Power Plants, also known as the Clean Power Plan, to establish different lb CO₂/MWh target for each state due to varying opportunities for emission reduction, current state programs and measures, and characteristics of the electricity system [26]. The proposed emission rates will be achievable by applying the Best System of Emission Reduction

(BSER) that considers the energy requirements, cost of achieving this reduction, and health and environmental impacts [26]. The BSER has the following building blocks [26]:

- Heat rate improvements.
- Replacing coal with natural gas generation.
- Substituting coal and natural gas generation with expanded renewable energy generation.
- Applying demand-side energy efficiency programs.

These blocks can be applied in two different options as follows [26]:

- Option 1: involves higher deployment of the four blocks but longer time frame through 2030.
- Option 2: involves lower deployment of the four blocks over a shorter time frame through 2025.

Under each option, there are two approaches as follows [26]:

- State compliance approach: the average of emission rate from affected generators within the state comply the proposed standards.
- Regional compliance approach: group of states comply the proposed standards.

States have the right to choose between a state or regional compliance approaches [26].

The EPA standards for new power plants vest more authority in EPA, and are more straightforward. EPA is required to find emission reduction technology that has been adequately demonstrated and use it to meet the standards for the new power plants [27].

The EPA standards for new power plants are implemented by the states, but states do not have much flexibility to alter the standards set by EPA [27]. On the other hand, under EPA standards for existing power plants, states have greater flexibility in how they

implement the EPA standard. In addition, it allows for the possibility of market to reduce emissions systemwide, rather than focusing on individual power plants [27].

In 2013, the Western Electricity Coordinating Council (WECC) issued a plan for the coming 10 and 20 years (2022 through 2032). This plan is intended to guide stakeholders on where and when to build new transmission or generation or to take other related actions that ensure reliability, low-cost, efficiency in the WECC region [28].

This section provides a planning study that utilizes the 2013 WECC 10- year plan and the EPA's option 2 regional compliance approach for existing and new power plants. The goal of this study is to test the ability of the 2013 WECC 10- year plan in meeting the EPA standards while considering the fully-optimized AS PHS in the BSER mix. The optimization model presented in this section is similar to the one presented before but with adding the investment optimization model and considering the EPA emissions limit. The investment optimization model is presented in equations (1) and (18) through (24). Equation (1) shows the objective function that minimizes the operating and investment costs $C_{inv}^j(I^j)$, while maximizing the retirement cost $C_{ret}^i(R^i)$. Equations 18 and 19 reflect the limits on the retired and invested MW capacity. Equations 20 and 21 are constraints of the power output from retired and invested generators respectively. Equation 22 indicates that the sum of invested generator j of fuel type f should not exceed the maximum investment allowed for that fuel type. Same for equation 23, the sum of invested generator j of fuel type f should not exceed the maximum retirement allowed for that fuel type. Equation 24 indicates that new invested capacity should cover the retired capacity. Each generator has its own capacity factor Δ based on the fuel type. Equation 24 shows the CO₂ emissions regional constraint. This constraint was imposed onto the existing coal and gas

units in the WECC region since the EPA regional approach was followed in this research. The fully-optimized AS PHS was modeled in equations (8) through (16). The planning optimization model is as follows:

Objective function:

$$\min_{\theta, P_g, I, R} \sum_t \sum_i C_g^i(P_g^{it}) + \sum_t \sum_i C_c^i(P_g^{i(t-1)} - P_g^{it}) + \sum_j C_{inv}^j(I^j) - \sum_i C_{ret}^i(R^i) \quad (1)$$

DC OPF variables and constraints:

$$\theta_{min}^b \leq \theta^{bt} \leq \theta_{max}^b \quad \forall t \quad (2)$$

$$P_{min}^i \leq P_g^{it} \leq P_{max}^i \quad \forall i \in I, \forall t \quad (3)$$

$$B\theta^{bt} + P_{shift}^{bt} - F_{max} \leq 0 \quad \forall t \quad (4)$$

$$-B\theta^{bt} - P_{shift}^{bt} - F_{max} \leq 0 \quad \forall t \quad (5)$$

$$B\theta^{bt} + P_{shift}^{bt} + P_d^{bt} + G_{sh} - P_g^{bt} \leq 0 \quad \forall t \quad (6)$$

Hydro constraint:

$$\sum_t \sum_i P_g^{it} \leq CF \sum_t \sum_i P_{max}^{it} \quad \forall i \in I, \forall t \quad (7)$$

AS PHS variables and constraints:

$$-w_{Ch}^{it} P_{smax}^i \leq P_{gCh}^{it} \leq 0 \quad \forall i \in S, \forall t \quad (8)$$

$$0 \leq P_{gD}^{it} \leq w_D^{it} P_{smax}^i \quad \forall i \in S, \forall t \quad (9)$$

$$0 \leq w_{Ch}^{it} \leq 1 \quad \forall i \in S, \forall t \quad (10)$$

$$0 \leq w_D^{it} \leq 1 \quad \forall i \in S, \forall t \quad (11)$$

$$w_{Ch}^{it} + w_D^{it} \leq 1 \quad \forall i \in S, \forall t \quad (12)$$

$$\sum_t \sum_i \eta_{Ch}^i P_{gCh}^{it} + \sum_t \sum_i \frac{P_{gD}^{it}}{\eta_D^i} = 0 \quad \forall i \in S, \forall t \quad (13)$$

$$0 \leq -P_{gCh}^{i(t-1)} - P_{gCh}^{it} - \frac{P_{gD}^{i(t-1)}}{\eta_{Ch}^i \eta_D^i} \leq \frac{(1-in.R^i)E_{smax}^i}{\eta_{Ch}^i} \quad \forall i \in S, \forall t \quad (14)$$

$$0 \leq P_{gD}^{i(t-1)} + P_{gD}^{it} + \eta_{Ch}^i \eta_D^i P_{gCh}^{i(t-1)} \leq \eta_D^i in.R^i E_{smax}^i \quad \forall i \in S, \forall t \quad (15)$$

$$-P_{rs}^i \leq [P_{gCh}^{i(t-1)} + P_{gD}^{i(t-1)}] - [P_{gCh}^{it} + P_{gD}^{it}] \leq P_{rs}^i \quad \forall i \in S, \forall t \quad (16)$$

$$-P_r^i \leq P_g^{i(t-1)} - P_g^{it} \leq P_r^i \quad \forall i \in S, \forall t \quad (17)$$

Planning variables and constraints:

$$R_{min}^i \leq R^i \leq R_{max}^i \quad \forall i \in T \quad (18)$$

$$I_{max}^j \leq I^j \leq I_{max}^j \quad \forall j \in V \quad (19)$$

$$P_{min}^i \leq P_g^{it} + R^i \leq P_{max}^i \quad \forall i \in S, \forall t \quad (20)$$

$$P_g^{it} \leq I^j \quad \forall i \in S, \forall t \quad (21)$$

$$\sum_j I^{jj} \leq I_{max}^f \quad \forall j \in V \quad (22)$$

$$\sum_i R^{if} \leq R_{max}^f \quad \forall i \in T \quad (23)$$

$$\sum_i \Delta i R^i \leq \sum_j \Delta j I^j \quad \forall i \in T, \forall j \in V \quad (24)$$

Emissions constraint:

$$\sum_t \sum_i CO_{2(\frac{tons}{MWh})} P_g^{it} \leq CO_{2(region\ tons)} \quad \forall i \in S, \forall t \quad (25)$$

4.4 WECC System and Data Assumptions

The WECC 240-bus model is a realistic test system for the WECC market [19]. The WECC model was reduced to 240-buses by aggregating the bulk transmission system and generators, and estimating the transmission line parameters [19]. Figure 4.1 shows the generation mix in the reduced WECC model [19].

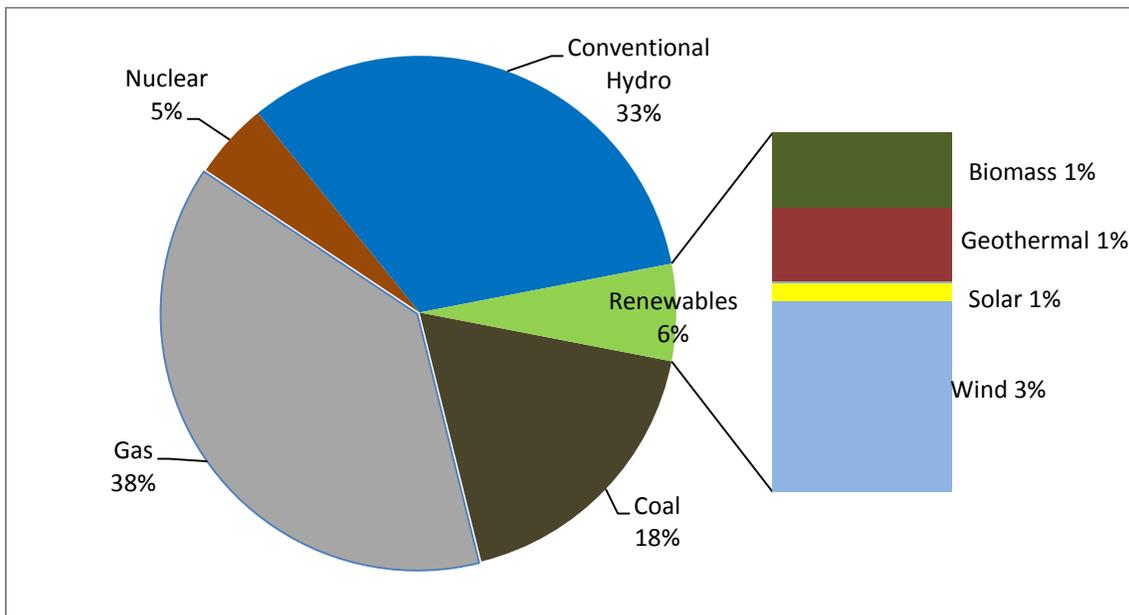


Figure 4.1. WECC model generation mix

The system was used to implement the studies modeled in sections 4.1 through 4.3 as follows:

- DA market operation study: 28 days simulation horizon (hourly periods).
These represent one typical week in each of the spring, summer, fall, and winter seasons.

- RT market operation study: This study is divided into two parts; 1 day simulation horizon (hourly periods) for the DA market, and 1 day simulation horizon (5 minutes periods) for the RT market.
- Planning study: 28 days simulation horizon (hourly periods). These represent one typical week in each of the spring, summer, fall, and winter seasons in 2022.

4.4.1 Operation Studies Data

The reduced WECC system includes four PHS plants aggregated at buses 2638, 3432, 7031, and 7032. Bus 7031 is also connected to a wind plant with 597 MW capacity [19]. These PHS plants were treated as AS PHS plants in all the studies conducted in this research. Table 4.1 shows the data for the PHS plants. The original model [19] included the data shown in columns 2, 3, and 5 of Table 4.1, but did not include variable O&M costs and the provided round-trip efficiency in Table 4.1. Variable O&M costs are needed in this research to allow accurate representations of the ramping capability of AS PHS in the optimization models. The variable O&M costs and the round-trip efficiency of PHS in Table 4.1 are based on a Pacific Northwest National Laboratory (PNNL) report [20].

TABLE 4.1

WECC PHS Plant Specifications

PHS Plant	Max Capacity (MW)	Storage Volume (GWh)	Round-trip Efficiency (%)	Ramp Rate (MW/min)	Variable O&M Cost (\$/MWh)
CASTAI4G	1272	12.72	81	10.6	4
COLOEAST	333	1.332	81	2.78	4
CRAIG	200	1	81	1.67	4
HELMS	1218	186.354	81	10.15	4

Startup costs for generators were not included in the original model [19] because the model was not originally used for UC. They are needed for this work because units will be committed and de-committed. To calculate startup costs, the conventional coal and gas generators from the original model [19] were divided into the following types [21]:

- Large coal- sub-critical steam (300-900 MW).
- Large coal- supercritical steam (500-1300 MW).
- Gas- combined cycle
- Gas- simple cycle large frame combustion turbine
- Gas-fired steam (50-700 MW)

All the generators were assumed to be in hot start-up status. The total start-up cost of the conventional generators, shown in Table 3.2, includes the cost of starting auxiliary power and operations (chemicals, water, additives, etc.) and cost of startup fuel [21].

TABLE 4.2

WECC CONVENTIONAL GENERATOR COSTS

Generator Type	Start-up Cost (\$)	Cycling Cost (\$/MWcap)
Large coal- sub-critical steam	56.16	1.99
Large coal- supercritical steam	59.36	1.72
Gas- combined cycle	31.95	0.33
Gas- simple cycle large frame combustion turbine	23.85	0.88
Gas-fired steam	48.34	1.56

As the penetrations of variable generation have increased, aging fossil units that were originally designed for base load operation [21] have at times been forced to cycle. Cycling refers to the operation of power plants at varying load levels, including on/off, load following, and minimum load operation, in response to changes in system load requirements [21]. When a power plant is turned off and on, the boiler, steam lines, turbine, and auxiliary components face large thermal and pressure stresses, which cause damage [21]. This damage is expected to increase with the increased cycling as future penetration levels of variable renewables continue to increase. AS PHS plants can help in reducing the cycling from conventional generators, but considering the cycling costs of conventional generators will allow more accurate optimization. But cycling cost estimates are needed for this, and were not included in the original model [19]. To address this issue, WECC has

been working with software vendors to allow for the consideration of cycling costs, but commercial software is not yet available. A recent NREL report [21] provided the data for generation cycling costs that are needed to implement the optimization developed in Section 4.1. Flexible conventional generators are built for quick start and fast ramping capabilities, but they are not inexpensive to cycle. The cycling costs used are presented in Table 4.2, in which they were chosen depending on the conventional generation type presented previously in this section.

All generators are assumed to have first order cost functions except gas generators, which were considered to have second order cost functions. The generators' variable costs, which include variable O&M costs and fuel costs, are shown in Table 4.3 [11]. All coal generators are assumed to have the same 10.414 (MMBTU/MWh) heat rate as in [11], while it differs from one gas generator to another based on the data provided by J. E. Price, and J. Goodin in [19].

TABLE 4.3

WECC Generator Variable Costs

Generator Type	Variable Cost (\$/MWh)
Coal	25.24
* Gas	5 (\$/MMBTU)
Nuclear	21.94
Hydro	10
Wind	8.08
Solar	5.76
Geothermal	23
Biomass	49.08

Figure 4.2 shows, for the 28 days DA market operation study, the hourly renewable generation profiles for low and high penetration levels based on [19]. For the low penetration case 6% of the annual load energy is provided by renewables. The high penetration is 14%. The renewable generation includes wind, solar, biomass, and geothermal generation. Figure 4.2 also shows the hourly load profiles for the four weeks based on [19].

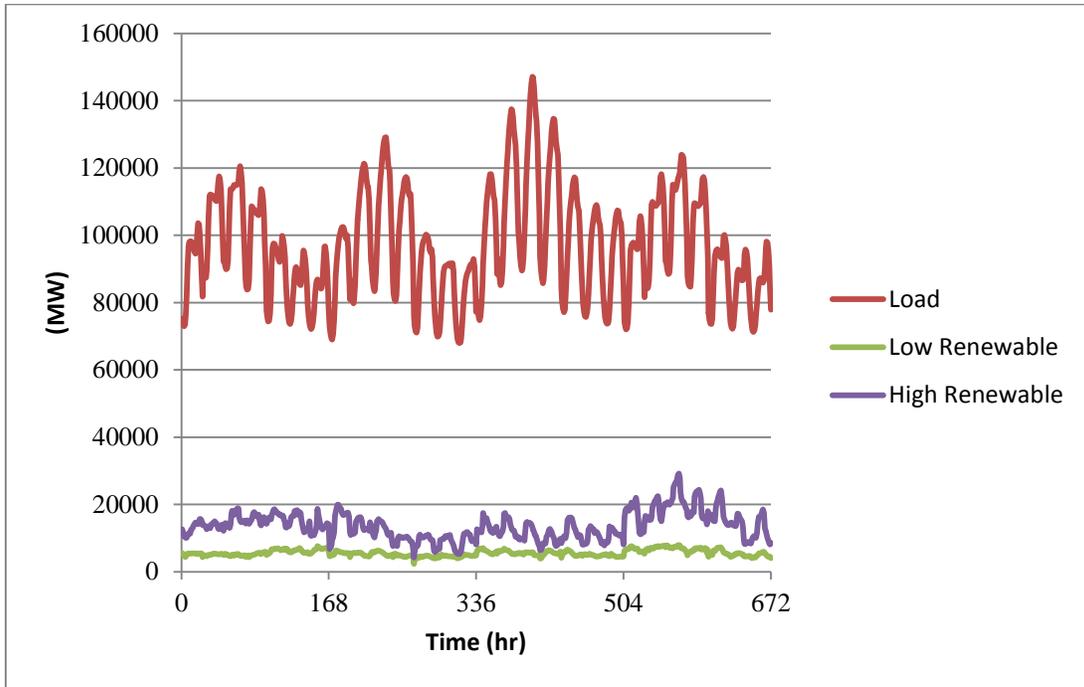


Figure 4.2. Renewables and load generation within the 672-hour simulation horizon.

In Figure 4.2, the first 24 hours data (first quarter, winter) was used as RT data for the RT market operation study. This data was interpolated in MATLAB to get the 5 minutes intervals required for the RT ED simulation. In addition, historical data from CAISO Open Access Same-Time Information System (OASIS) for load, wind, and solar generation was used along with the data in Figure 4.2 to forecast the 24 hours data for DA market demand and variable generation in the RT market operation study. Figure 4.3 shows the load data for 2010 in the RT and DA markets. Figure 4.4 shows the variable renewable (wind and solar) data for 2014 in the RT and DA markets.

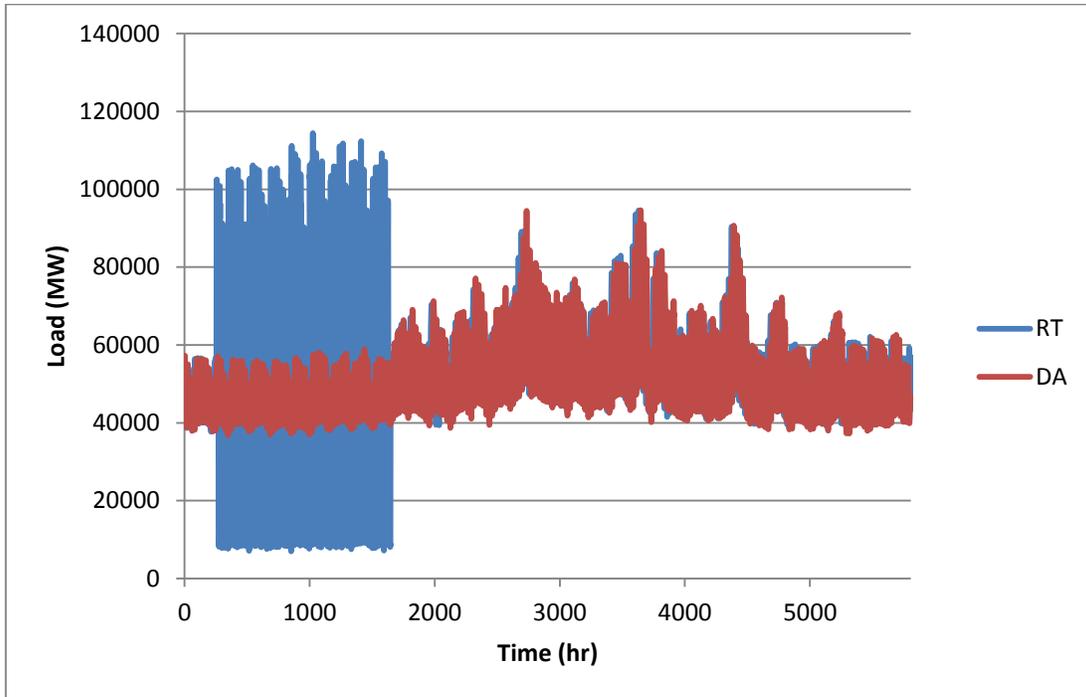


Figure 4.3. The CAISO historical load data in the 2010 RT and DA markets.

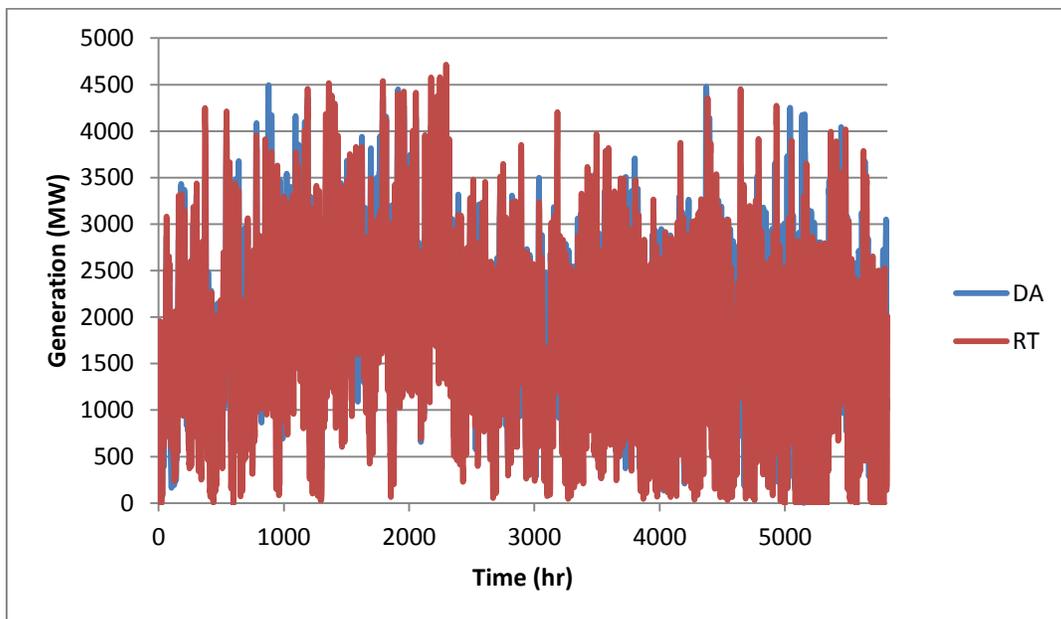


Figure 4.4. The CAISO historical renewable data (wind and solar) in the 2014 RT and DA markets.

The forecasting of hourly data for one day to week ahead is usually referred to as short-term load forecasting [31]. The artificial neural network technique (ANN) is becoming so popular for short term forecasting since it is able to automatically map the relationship between input and output. Moreover, it has the ability to handle nonlinear relationships between data and the factors affecting it directly from the historical data [32, 33]. Therefore, ANN was used to forecast the required DA market data. In this research, NeuralWare software has been used to compute the ANN. NeuralWare is developing and deploying empirical modeling solutions based on neural networks [33]. It is mainly used for prediction, classification, or pattern recognition. The ANN computes system parameters while learning the input variables, which is called training. The best number of hidden layers was ascertained by a trial and error process to find the minimum root mean square (RMS) error [32]. Back Propagation learning is most common and general neural network currently in use. As shown in Figure 4.5, numbers of neurons are arrayed to form a layer. Input layer is where the input from external world is connected, hidden layer is not connected to the external world and the output layer gives output to the external world [32]. Figure 4.5 shows the ANN architecture for this research [32].

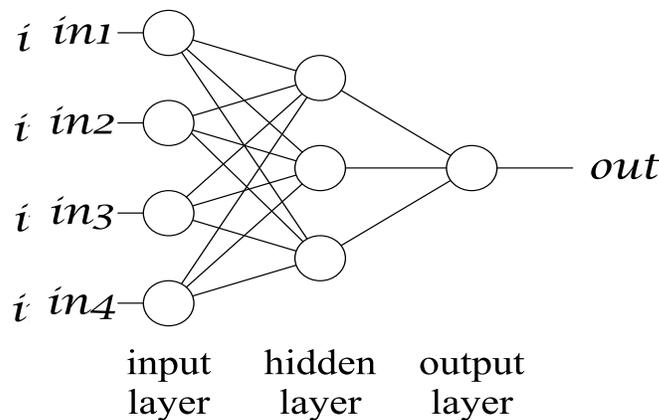


Figure 4.5. Basic Multi-layer Feed Forward Network with Back Propagation Learning.

After using trial and error method, the best ANN architecture inputs were as follows for load forecasting:

- # of hidden layers = 1
- # of hidden neurons = 5
- Learning method = backpropagation
- Learning rule = delta rule
- Learning function = sigmoid
- # of inputs = 1 (RT data)
- # of outputs = 1 (DA data)
- Training data = 70 % historical (DA and RT) data
- Testing data = 30% historical (DA and RT) data and the 24 hours data from Figure 4.2

and as follows for low and high renewables penetration forecasting:

- # of hidden layers = 1
- # of hidden neurons = 10
- Learning method = backpropagation
- Learning rule = delta rule
- Learning function = sigmoid
- # of inputs = 1 (RT data)
- # of outputs = 1 (DA data)
- Training data = 70 % historical (DA and RT) data
- Testing data = 30% historical (DA and RT) data and the 24 hours data from Figure 4.2

The best RMS error achieved for load was:

RMS training=0.0771, RMS testing= 0.0306

The best RMS error achieved for renewables was:

RMS training=0.1593, RMS testing= 0.0951

Figure 4.6 shows the DA ANN forecasted data versus RT data obtained from Figure 4.2.

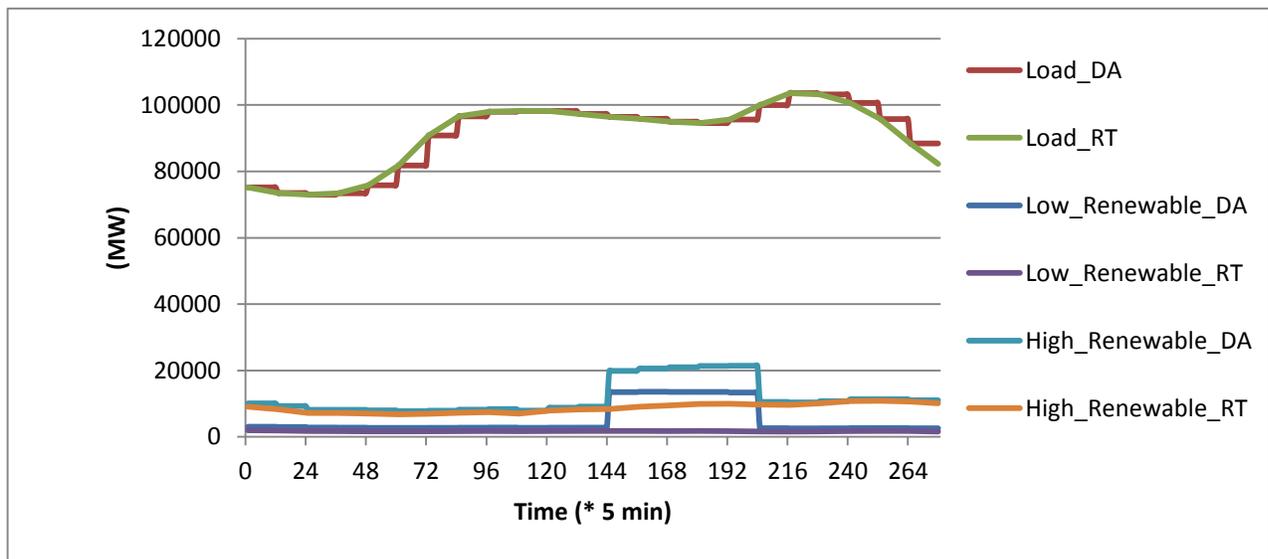


Figure 4.6. DA and RT market (load and renewables) data for the RT operation study.

In contrast to the cost of energy, which can be known from fuel prices and power plant performance characteristics, the cost of operating reserves in a real system is inherently a function of the interaction of multiple power plants. The incremental and total cost of reserves in any hour is entirely a function of which generators are online, which generators can provide reserves, and sometimes complicated market rules for procuring and pricing operating reserves [34]. Table 4.4 shows the reserves costs imposed on generators in the WECC model [34].

TABLE 4.4
RESERVES COST

Generator Type	Reserve Cost (\$/MW-h)
Large coal- sub-critical steam	10
Large coal- supercritical steam	15
Gas- combined cycle	6
Gas-fired steam	4
Hydro	2
PHS	2

4.4.2 Planning Study Data

This section presents the data and assumptions used for setting the reduced WECC model for the planning study. The second column in Table 4.5 shows the MW investment capacity limit for gas, wind, solar, and other renewables by 2022 [35,36]. Based on the 2013 10-year WECC plan, the coal and nuclear generators are not in the WECC investment generation plan for the next 10 years. The third column in Table 4.5 also shows the 2015 capacity factor of each of the generators [37,38].

TABLE 4.5
MW INVESTED CAPACITY LIMIT AND CAPACITY FACTOR

Type	Added Capacity by 2022 (MW)	Capacity Factor (%)
Gas	20,000	58.5
Wind	18,500	37
Solar	12,000	22.5
Geothermal	1,500	92
Biomass	989	83
Conventional Hydro	2,500	54

The total MW retirement capacity limit by 2022 is 14,044, in which 10,562 MW is coal and 3,482 MW from gas [36,37]. Figure 4.7 shows the 2010-2022 compound annual

growth rate (CAGR) for the WECC balancing authorities (BA) [35]. Based on [39], “CAGR is a useful measure of growth over multiple time periods. It can be thought of as the growth rate that gets you from the initial investment value to the ending investment value if you assume that the investment has been compounding over the time period”. Therefore, an average CAGR value was obtained for the BAs in each WECC sub-region. These average values were used in equation to get the expected hourly load profile in 2022.

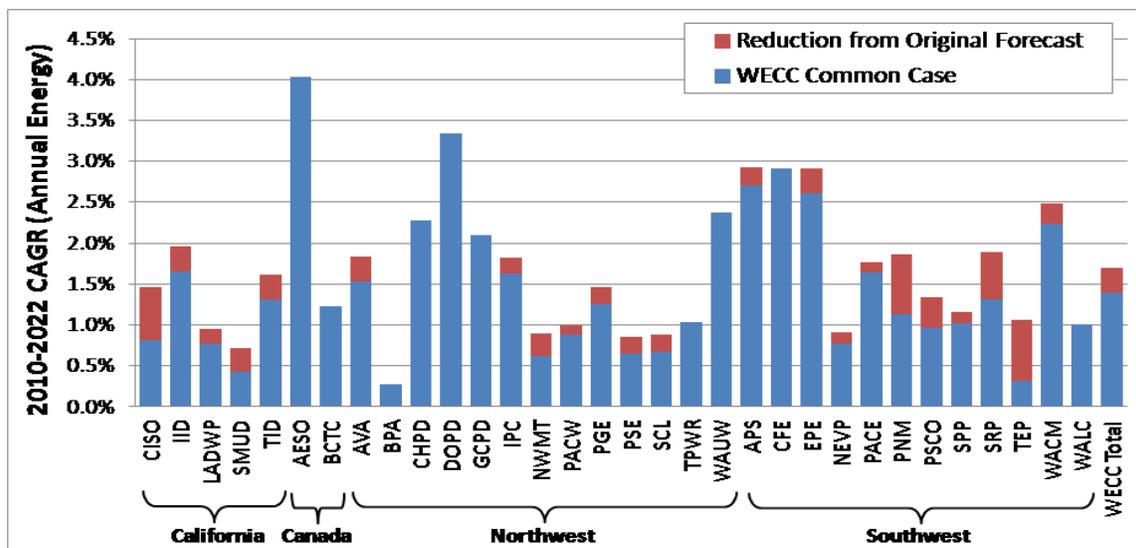


Figure 4.7. 2010-2022 CAGR (annual energy) for the WECC BAs and sub-regions.

The average CAGR values used in this study included the expected energy efficiency (EE) reduction that is shown in Figure 4.7.

Table 4.6 shows the average levelized cost of electricity (LCOE) for generators entering service in 2020 [37]. These costs include the capital cost, fixed operation and maintenance (O&M) cost, variable O&M cost, and subsidy.

TABLE 4.6

LCOE FOR GENERATORS ENTERING SERVICE IN 2020

Type	LCOE Capital Cost (\$/MWh)	LCOE Fixed O&M Cost (\$/MW)	LCOE Variable O&M Cost (\$/MWh)	LCOE Subsidy (\$/MWh)
Coal	60.4	4.2	29.4	0
Gas	27.55	2.25	76.2	0
Nuclear	70.1	11.8	12.2	0
Wind	113.2	17.65	0	0
Solar	150.7	26.75	0	15.1
Geothermal	34.1	12.3	0	3.4
Biomass	47.1	14.5	37.6	0
Conventional Hydro	70.7	3.9	7	0

In [35], capacity factors are given for wind and solar profiles in 2022 for each WECC state. In this research, the average capacity factor for each WECC sub-region was calculated and assigned to the current hourly wind and solar profiles to get the expected 2022 profiles. Table 4.7 shows the 2022 average capacity factors for wind and solar in each reduced WECC sub-region.

TABLE 4.7

2022 WIND AND SOLAR CAPACITY FACTORS

WECC Sub-region	Wind Capacity Factor (%)	Solar Capacity Factor (%)
California	26.6	20.7
Northwest	26.8	22.3
Southwest	33.4	24.2
Rocky	35.6	31.7

Based on [11], the CO₂ price was considered to be 36 \$/ton, and this price was imposed on the current and future coal and gas generators. For gas generators, an average 8.004 \$/MMBtu fuel price was considered of the expected gas prices in 2022 based on [35]. The heat rates were provided for the current coal and gas generators in [19]; however, the coal generators' heat rates were improved based on [40] by taking the average of heat rate reductions that can be achieved by applying several capital and maintenance projects. Based on the EPA standards for new power plants, new gas generators (roughly 100 MW or larger) could emit no more than 1,000 lb/MWh of electricity produced, which is achievable with the latest combined cycle technology. The latest combined cycle technology will result in heat rate improvement for gas generators. This improvement was translated to a \$/MWh cost imposed onto the investment model by using the average \$/MMBtu fuel price and the information in [41]. The cost of improving the heat rate of new gas generators equals to 68.43 \$/MWh.

CHAPTER 5

RESULTS

The optimization models for different case studies presented with the data and assumptions presented in Chapter 4 were utilized to get the results of this Chapter. This Chapter is divided into 3 sections, in which each section presents and analyzes the results of each case study.

5.1 DA Operation Study Results

This section presents the results of the DA market operating study. The optimization models presented in section 4.1 and the data in section 4.4 were utilized. Different study cases for the AS PHS full- and sub- optimization models, with and without cycling costs, and at the two renewable penetration levels (low and high). Results are compared with the base case, which has no AS PHS.

5.1.1 Conventional Generator Cycling Costs Included

Tables 5.1 and 5.2 show the results of the cases when cycling costs were considered for high and low renewables penetration levels respectively. The sub-optimized case uses equations (8) and (9), in which the pumping and generating time periods (represented by w_{Ch}^{it} and w_D^{it} parameters) are provided by the AS PHS owner, but the ISO decides the dispatch level of AS PHS within those time periods. The fully-optimized case uses equations (8) through (12), in which the AS PHS operating mode is both committed and dispatched by the ISO.

TABLE 5.1

HIGH RENEWABLE WITH CYCLING COST RELATIVE TO NO PHS MODEL
CASE IN DA

Renewables Penetration Level (%)	PHS Model	Cycling Cost	Total System Cost (\$)	AS PHS Value (\$)
14 %	-----	Considered	1,054,871,478	-----
	Sub-optimized	Considered	1,054,867,000	4,478
	Fully-optimized	Considered	1,054,850,000	21,478

The results shown in Table 5.1 show a significant AS PHS value (the difference between the operating cost and the cost without AS PHS) in the sub- and fully-optimized operating. The value of AS PHS is especially significant since the total amount of storage, 2.7 GW/201 GWh, is low relative to the maximum total renewable penetration of 29.14 GW based on Figure 4.2. The value of AS PHS fully optimized case is much higher than its value in the sub-optimized case because PHS commitment is optimized in addition to PHS dispatch. The energy costs for each case were also calculated by dividing the system operating cost by the 65.3 TWh energy demand. The energy costs are \$16.1638/MWh for the case with no AS PHS, \$16.1542/MWh for the sub-optimized case, and \$16.1539/MWh for the fully- optimized case.

TABLE 5.2

LOW RENEWABLE WITH CYCLING COST RELATIVE TO NO PHS MODEL
CASE IN DA

Renewables Penetration Level (%)	PHS Model	Cycling Cost	Total System Cost (\$)	AS PHS Value (\$)
6 %	-----	Considered	1,143,760,347	-----
	Sub-optimized	Considered	1,143,740,000	20,347
	Fully-optimized	Considered	1,143,679,000	81,347

The lower renewable penetration results shown in Table 5.2 again show significant AS PHS value in the sub- and fully-optimized. In this case, the maximum total renewable generation was 7.9 GW based on Figure 4.2. Table 5.2 shows that the AS PHS value in the fully optimized case is again much higher than its value in the sub-optimized case. The energy costs are 17.5258 \$/MWh for the case with no AS PHS, 17.5151 \$/MWh for the sub-optimized case, and 17.5142 \$/MWh for the fully- optimized case. The total system costs are higher in Table 5.2 when compared to Table 5.1, because of the lower penetration of renewables considered in Table 5.2, which have low operating costs. Tables 5.1 and 5.2 showed that full- and sub- optimization of AS PHS provided more operating cost savings in the low renewable than the high renewables cases. The reason is that when we have high penetration of renewables, the volatility is higher as shown in Figure 4.2, thus the ramping expectations from storage is going to be higher too. However, there is a ramping constraint

imposed on the AS PHS beside its low capacity when compared to the high penetration level of renewables. All of this resulted in the need for higher storage capacity to address the increased volatility in the generation due to renewables since we cannot change the ramping limits of the generation. However, the AS PHS value in the full-optimization case is much higher than the sub-optimization case. Therefore, A larger capacity from the fully-optimized AS PHS is needed in the future when higher penetration of renewables are presented in the system to increase the value of having this kind of storage in the system.

5.1.2 Conventional Generator Cycling Costs Not Included

Tables 5.3 and 5.4 show the results of the cases when cycling costs were not considered for high and low renewables penetration level respectively. Costs in each case are lower than or equal to the comparable Table 5.1 and 5.2 cases because cycling costs are not included. This comparison is discussed further in Tables 5.5 and 5.6. Tables 5.3 and 5.4 show that both the sub- and fully-optimized cases resulted in a significant AS value, with full-optimization providing significantly higher AS PHS value for high and low renewable penetrations. These results demonstrate the benefits of fully-optimizing AS PHS.

TABLE 5.3

HIGH RENEWABLE WITH NO CYCLING COST RELATIVE TO NO PHS MODEL
CASE IN DA

Renewables Penetration Level (%)	PHS Model	Cycling Cost	Total System Cost (\$)	AS PHS Value (\$)
14 %	-----	Not Considered	1,054,871,373	-----
	Sub-optimized	Not Considered	1,054,867,000	4,373
	Fully-optimized	Not Considered	1,054,850,000	21,373

TABLE 5.4

LOW RENEWABLE WITH NO CYCLING COST RELATIVE TO NO PHS MODEL
CASE IN DA

Renewables Penetration Level (%)	PHS Model	Cycling Cost	Total System Cost (\$)	AS PHS Value (\$)
6 %	-----	Not Considered	1,143,760,261	-----
	Sub-optimized	Not Considered	1,143,740,000	20,261
	Fully-optimized	Not Considered	1,143,679,000	81,261

5.1.3 Effects of Including Conventional Generator Cycling Costs

Tables 5.5 and 5.6 detail the effects of considering cycling costs in scheduling generation with and without AS PHS. The last column in Tables 5.5 and 5.6 shows that the difference in operating cost (cycling case subtracted from the no cycling case) is negative (cycling costs increase the total operating costs) when there is no AS PHS in the system, zero (cycling cost did not affect the total system cost when there is AS PHS in the system). It can be noticed that the value of AS PHS is higher when cycling cost is included in all cases. This is because the cycling cost imposed on conventional generators increases the utilization of AS PHS in the system by shifting part of the cycling role from conventional generators to AS PHS.

TABLE 5.5

HIGH RENEWABLE, EFFECTS OF CONSIDERING CYCLING COSTS IN DA

Renewables Penetration Level (%)	PHS Model	Total System Cost (\$), cycling cost considered	Total System Cost (\$), cycling cost not considered	Difference in Cost (\$)
14 %	-----	1,054,871,478	1,054,871,373	-105
	Sub-optimized	1,054,867,000	1,054,867,000	0
	Fully-optimized	1,054,850,000	1,054,850,000	0

TABLE 5.6

LOW RENEWABLE, EFFECTS OF CONSIDERING CYCLING COSTS IN DA

Renewables Penetration Level (%)	PHS Model	Total System Cost (\$), cycling cost considered	Total System Cost (\$), cycling cost not considered	Difference in Cost (\$)
6 %	-----	1,143,760,347	1,143,760,261	-86
	Sub-optimized	1,143,740,000	1,143,740,000	0
	Fully-optimized	1,143,679,000	1,143,679,000	0

5.1.4 Solution Time and PHS Revenues

Table 5.7 presents the solving time and the AS PHS revenues for different cases. Table 5.7 shows that adding four AS PHS units with either sub- or full- optimization to the system increases the solving time between 74 and 247 percent. The full-optimization solution time has decreased when a higher penetration of renewables presented in the system. The opposite happened with the sub-optimized solution time. This highlights the solving capability of the fully-optimized model in the future of high renewables. In addition, considering the cycling cost in both renewable level cases has reduced the solving time when compared to the no cycling case.

AS PHS revenue was calculated by subtracting the pumping cost from the generation profit. As shown in Table 5.7, the AS PHS broke even in all high renewable cases. The AS PHS revenues were higher in all low renewable cases when compared to high renewable cases, again because the capacity of AS PHS was more effective in the low renewables cases. This indicates that considering the DA ancillary services market and other incentives

for AS PHS may be needed in future studies, especially as renewable penetrations increase. The revenues in all fully-optimized cases were much higher than the sub- optimized cases. This all highlights the market benefit of deploying the full- optimization of AS PHS in the future while considering the cycling cost of conventional generators.

Figure 5.1 shows the coal and gas generation under high penetration level of renewables and while fully-optimizing the AS PHS operation. Based on the Figure 5.1, most of the load and variable generation following is done by gas-fired generation, but in times of high load and high variability, coal-fired generation is also cycled. This again underscores the importance of considering cycling costs in dispatch calculations. Considering the cycling costs in the optimization model resulted in a slight but considerable decrease in the cycling of coal and mainly gas generators since gas generation was the dominant in following the load and renewables variations. It is expected that the effect of cycling costs will appear more when more storage is added to the system. Figures 5.2 and 5.3 show that optimal dispatch of AS PHS also provides some of load and variable generation following that is needed, reducing the need for such cycling of conventional generation. In Figure 5.2 the AS PHS capability was more utilized in the fully-optimized case than the sub-optimized case to follow the variations in load and the high penetration level of renewables. The fully-optimized AS PHS was noticeably dispatched seven times, in which during these times the system encountered large variations in load and renewables, especially wind generation. Figure 5.3 highlights the importance of AS PHS under high renewable penetrations. Under high renewables, the AS PHS was dispatched in a larger MW amount and periods of time.

TABLE 5.7

SOLVING TIME AND PHS REVENUES IN DA

Renewables Penetration Level (%)	PHS Model	Cycling Cost	Solving Time (sec)	PHS Revenue (\$)
14 %	-----	Considered	2638	-----
	Sub-optimized	Considered	5140	2,635
	Fully-optimized	Considered	5347	15,325
6 %	-----	Considered	2352	-----
	Sub-optimized	Considered	4097	15,168
	Fully-optimized	Considered	6114	47,026
14 %	-----	Not Considered	2792	-----
	Sub-optimized	Not Considered	5390	2,620
	Fully-optimized	Not Considered	5951	15,313
6 %	-----	Not Considered	2259	-----
	Sub-optimized	Not Considered	4395	15,158
	Fully-optimized	Not Considered	7848	47,034

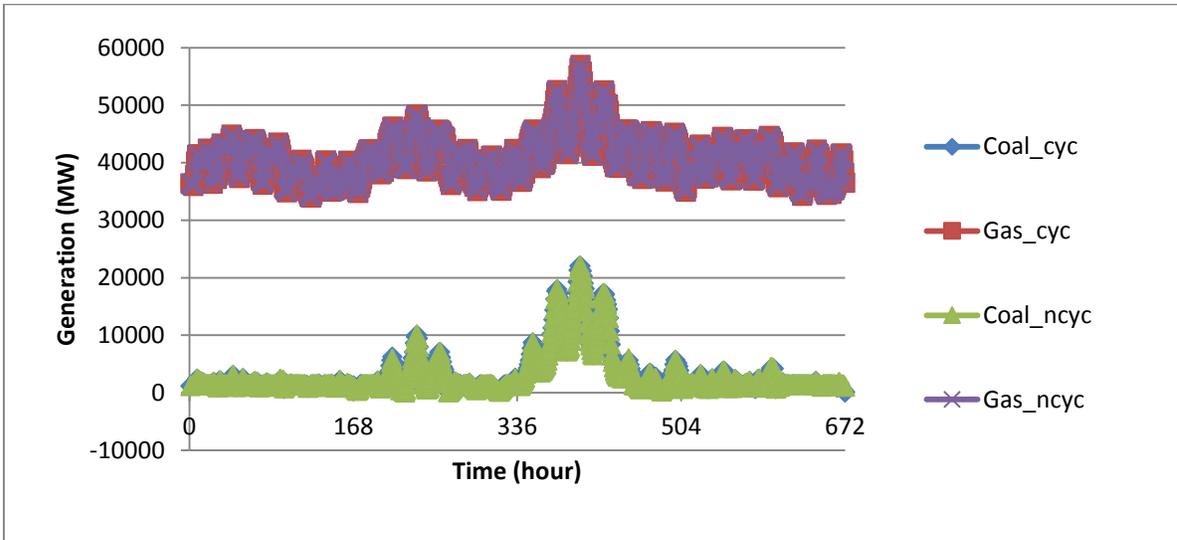


Figure 5.1. Coal and gas generation with cycling and without cycling costs, while fully-optimizing AS PHS and considering high renewables penetration level.

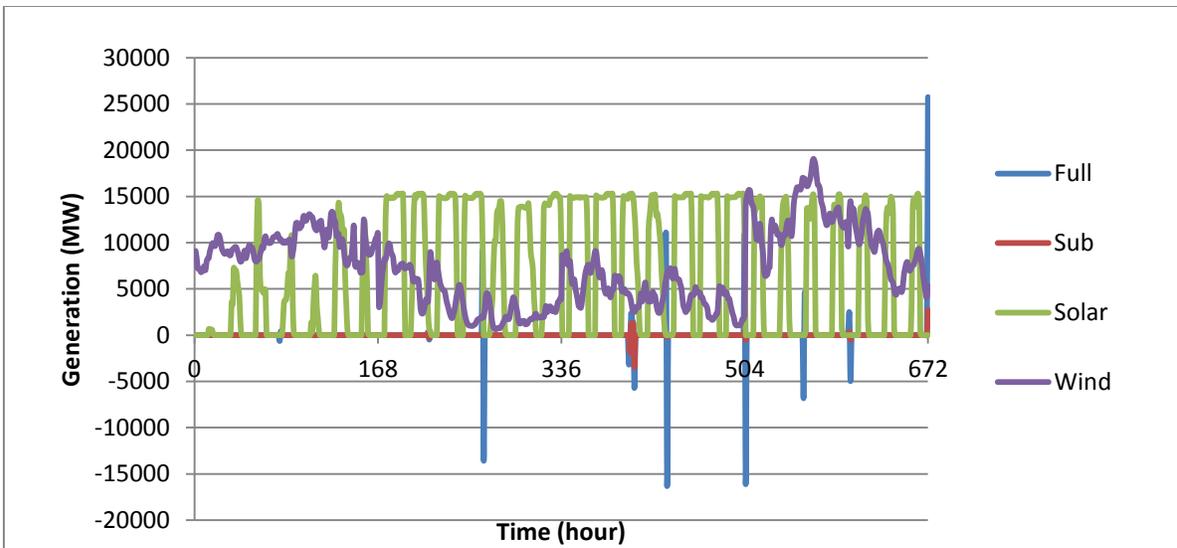


Figure 5.2. AS PHS operation under full- and sub- optimized cases, while considering conventional generators cycling cost and high penetration level of renewables while AS PHS output is scaled by 10.

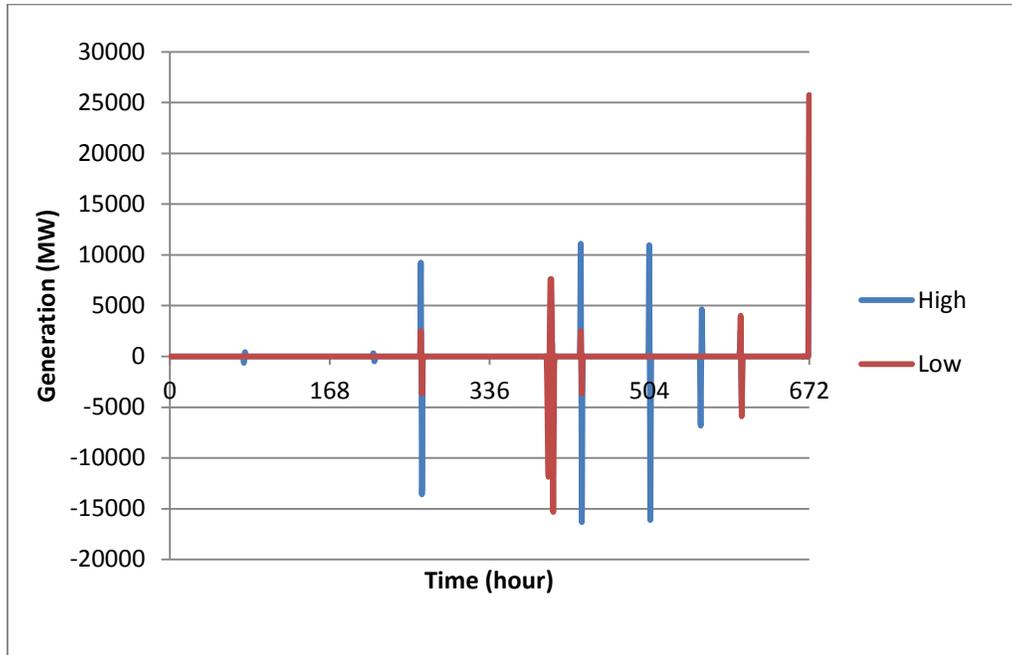


Figure 5.3. AS PHS operation under high and low penetration level of renewables, while fully-optimizing the AS PHS operation and considering conventional generators cycling and scaled by 10.

5.2 RT Operation Study Results

This section presents the results of the RT market operating study. The optimization models presented in section 4.2 and the data in section 4.4 were utilized. As for the DA operation study, different study cases for the AS PHS sub- and full- optimization models, with and without cycling costs, and at the two renewable penetration levels (low and high) in the RT market study. In addition to the high renewable profile provided in section 4.4, two new high renewable profiles were considered for extended studies in this section. Results are compared with the base case, which has no AS PHS.

5.2.1 Conventional Generator Cycling Costs Included

Tables 5.8 and 5.9 show the results of the full- and sub- optimized models when cycling costs were considered for high and low renewables penetration levels respectively.

The DA optimization model of section 4.2.1 was used to get the one day commitment and dispatch results for energy and reserves to feed it in the RT optimization model of section 4.2.2. The optimization model of section 4.2.2 did the required adjustments on the generation dispatch every 5 minutes for the RT market while considering the capacity limits, and the contracted reserves and energy from the DA market.

TABLE 5.8

HIGH RENEWABLE WITH CYCLING COST RELATIVE TO NO PHS MODEL CASE IN RT

Renewables Penetration Level (%)	PHS Model	Cycling Cost	Total System Cost (\$)	AS PHS Value (\$)
14 %	-----	Considered	393,082,150.8	-----
	Sub-optimized	Considered	397,985,006	-4,902,855
	Fully-optimized	Considered	393,082,474.1	-323.33

The results in Table 5.8 show that the value of AS PHS in both sub- and fully optimized cases was negative, in which the total system operating cost was higher for the sub- and fully optimized AS PHS case when compared to the no AS PHS case. However, the value was better in the fully-optimized case. The energy costs for each case were also calculated by dividing the system operating cost by the 25.25 TWh energy demand. The energy costs are 15.57 \$/MWh for the case with no AS PHS and fully-optimized case, 15.76 \$/MWh for

the sub-optimized case. This again emphasizes the importance of full-optimization over sub-optimization of AS PHS in high renewables RT market.

TABLE 5.9

LOW RENEWABLE WITH CYCLING COST RELATIVE TO NO PHS MODEL CASE IN RT

Renewables Penetration Level (%)	PHS Model	Cycling Cost	Total System Cost (\$)	AS PHS Value (\$)
6 %	-----	Considered	428,377,149.4	-----
	Sub-optimized	Considered	432,774,682	-4,397,533
	Fully-optimized	Considered	428,369,089	8,060.33

The lower renewable penetration results are shown in Table 5.9. In Table 5.9, the sub-optimized case received a higher value when compared to the one in Table 5.8; however, it is still negative. For the fully-optimized case, the value of AS PHS was significantly positive. This indicates that more capacity of AS PHS is needed when high renewables are presented in the system to increase its RT market value. The energy costs are 16.97 \$/MWh for the case with no AS PHS and the fully-optimized case, and 17.14 \$/MWh for the sub- optimized case. The total system costs are higher in Table 5.9 when compared to Table 5.8, because of the lower penetration of renewables considered in Table 5.9, which have low operating costs.

5.2.2 Conventional Generator Cycling Costs Not Included

Tables 5.10 and 5.11 show the results of the cases when cycling costs were not considered for high and low renewables penetration level respectively. Tables 5.10 shows that the AS PHS value is negative in both sub- and full optimization, with a better value in full optimization. For Table 5.11, when low renewables are presented in the system, the sub- optimization lead to negative AS PHS value, while the value was significantly positive in the full optimization.

TABLE 5.10

HIGH RENEWABLE WITH NO CYCLING COST RELATIVE TO NO PHS MODEL CASE IN RT

Renewables Penetration Level (%)	PHS Model	Cycling Cost	Total System Cost (\$)	AS PHS Value (\$)
14 %	-----	Not Considered	393,082,513.1	-----
	Sub-optimized	Not Considered	397,985,296	-4,902,783
	Fully-optimized	Not Considered	393,082,649.2	- 136.06

TABLE 5.11

LOW RENEWABLE WITH NO CYCLING COST RELATIVE TO NO PHS MODEL
CASE IN RT

Renewables Penetration Level (%)	PHS Model	Cycling Cost	Total System Cost (\$)	AS PHS Value (\$)
6 %	-----	Not Considered	428,378,249.7	-----
	Sub-optimized	Not Considered	432,775,096	-4,396,847
	Fully-optimized	Not Considered	428,369,590	8,659.72

5.2.3 Effects of Including Conventional Generator Cycling Costs

When comparing the sub-optimized cases in Tables 5.8 and 5.10, the AS PHS value in Table 5.10 has improved; however, it is still negative. On the other hand, comparing the fully-optimized cases in Tables 5.8 and 5.10, the AS PHS value is lower in Table 5.10. This shows that considering the cycling cost in the full optimization model, increases the utilization of AS PHS and therefore its value. For Tables 5.9 and 5.11, the AS PHS value has improved in Table 5.11 in the sub-optimized case; however, it is still negative. The AS PHS value in the fully-optimized case was higher in Table 5.11 when compared to Table 5.9. Therefore, the effect of cycling cost is considerable when high renewables are presented in the system with fully optimizing the AS PHS operation.

5.2.4 Solution Time and PHS Revenues

Table 5.12 presents the total solving time for the one day 5 minutes periods and the AS PHS revenues for different cases.

The AS PHS revenues were higher in all low renewable cases when compared to high renewable cases because the capacity of AS PHS was more effective in the low renewables cases. The revenues in all fully-optimized cases were much higher than the sub-optimized cases. In addition, the AS PHS revenue was higher when cycling cost was considered when compared to the no cycling case in full optimization and both renewable cases. The solving time was higher for all high renewable cases when compared with low renewable cases. Same for all cycling cases when compared to no cycling cases. This is normal since when high renewables and cycling are considered in short time periods, the complexity of the system increases; however, the solving time was less for all fully-optimized cases. This all highlights the market benefit of deploying the full- optimization of AS PHS in the future while considering the cycling cost of conventional generators.

TABLE 5.12

SOLVING TIME AND PHS REVENUES IN RT

Renewables Penetration Level (%)	PHS Model	Cycling Cost	Solving Time (sec)	PHS Revenue (\$)
14 %	-----	Considered	281.39	-----
	Sub-optimized	Considered	824.15	191.85
	Fully-optimized	Considered	556.48	317.66
6 %	-----	Considered	250.09	-----
	Sub-optimized	Considered	766.97	369.41
	Fully-optimized	Considered	440.19	929.04
14 %	-----	Not Considered	284.78	-----
	Sub-optimized	Not Considered	746.81	193.07
	Fully-optimized	Not Considered	517.33	316.59
6 %	-----	Not Considered	263.73	-----
	Sub-optimized	Not Considered	729.27	373.01
	Fully-optimized	Not Considered	483.98	927.90

Figure 5.4 shows the total generation in the WECC system in one day in the DA and RT markets for fully-optimized AS PHS and while considering the cycling cost. Figure 5.5 shows the AS PHS following high renewables (wind and solar) in the fully- and sub-optimized cases while considering the cycling cost. It can be noticed that AS PHS was more utilized and cycled in short time periods (minutes) in the fully-optimized case to follow the drop in wind generation during the first period of the day, when compared to the sub-optimized case. This confirms the high value and revenues for the AS PHS in the fully-optimized case. Same conclusion can be drawn from Figure 5.6 for the high renewable case versus the low renewable one in the fully-optimized AS PHS when cycling cost was considered. In Figure 5.6, the AS PHS was cycled and utilized more when high renewables were on the system. This highlights the importance of fully-optimized AS PHS when high renewables are on the system while considering the cycling cost.

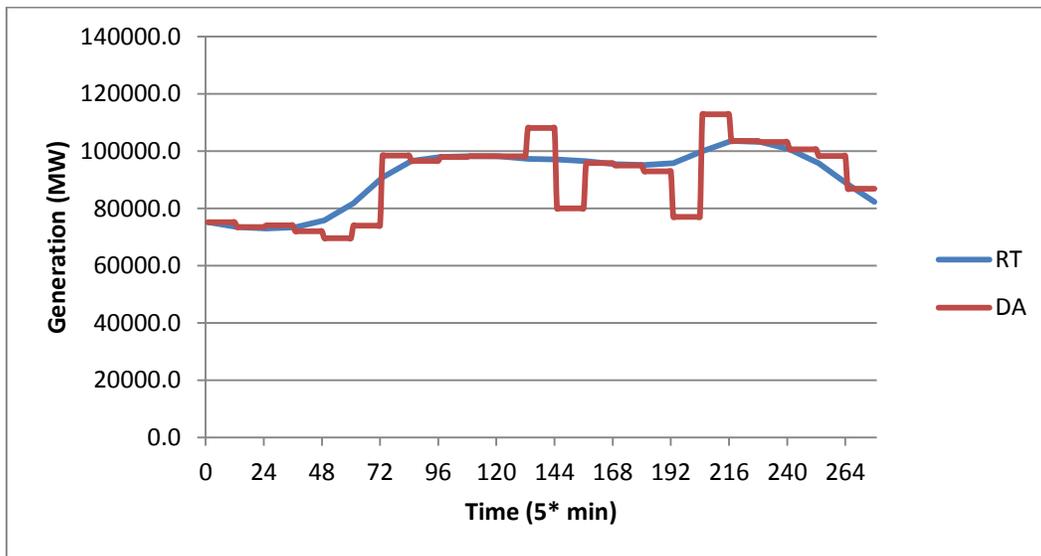


Figure 5.4. Total RT and DA markets generation for the fully-optimized, high renewable, and cycling cost considered case.

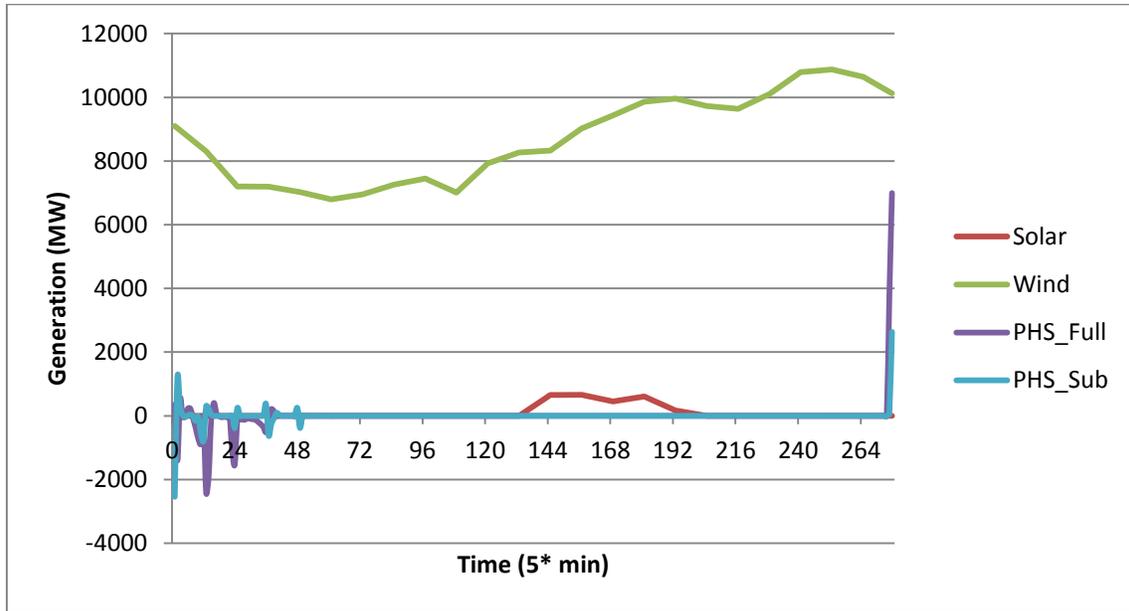


Figure 5.5. AS PHS and high renewables generation in the RT market when cycling cost was considered.

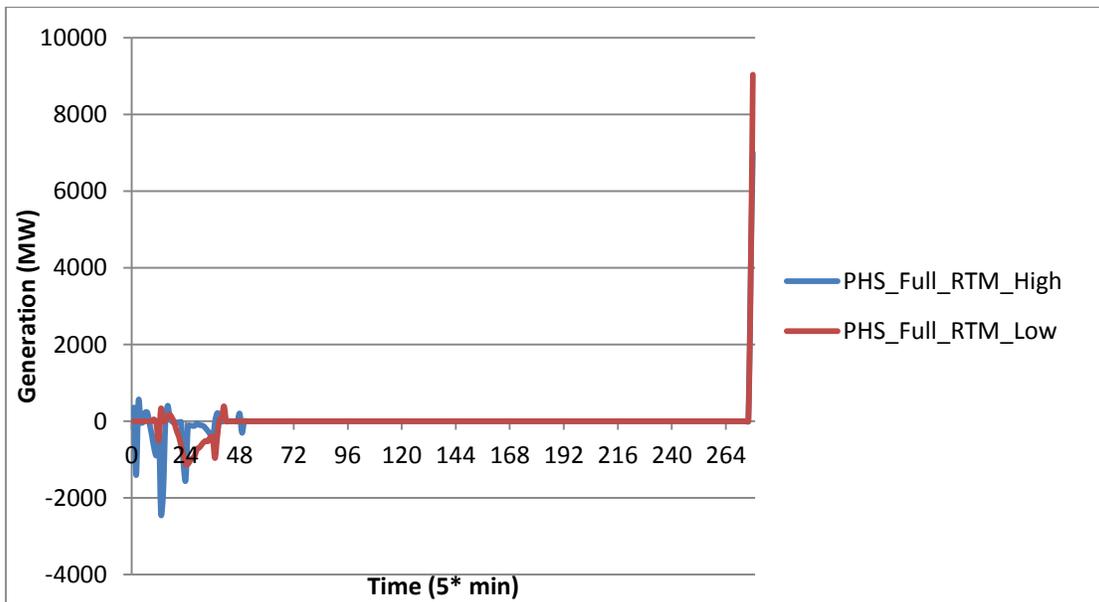


Figure 5.6. Fully-optimized AS PHS generation under low and high renewables penetration while considering cycling cost in the RT market.

5.2.5 Additional Study Cases

This section presents the results of considering two additional high renewable profiles. The high renewable profile considered in sections 5.2.1 through 5.2.4 included low wind generation during night times and high during day. The profiles considered in this section considered high wind generation during night and low during day, and variable wind generation during day. The renewable profiles in this section were chosen for different days than the one considered in sections 5.2.1 through 5.2.4. Therefore, the load profiles for the new renewable profiles were different. The total demand for the two new renewable profiles was around 23 TWh.

5.2.5.1 Night Penetration Wind Profile

This section presents the results of providing a high wind generation profile during night time.

TABLE 5.13
CYCLING COST RELATIVE TO NO PHS MODEL CASE IN RT
-WIND AT NIGHT

PHS Model	Cycling Cost	Total System Cost (\$)	AS PHS Value (\$)
-----	Considered	339,496,773.6	-----
Sub-optimized	Considered	343,672,087	-4,175,314
Fully-optimized	Considered	339,500,491.2	-3,717.65

Table 5.13 shows the results when cycling cost was considered in the model. Both sub- and full- optimization cases provided a negative value for AS PHS; however the situation was

better in the fully optimized case. The energy costs are 14.46 \$/MWh for the case with no AS PHS and fully optimized case, and 14.64 \$/MWh for the sub- optimized. This shows that the energy cost was cheaper in the fully optimized case when compared to the sub- optimized case.

TABLE 5.14

NO CYCLING COST RELATIVE TO NO PHS MODEL CASE IN RT
 – WIND AT NIGHT

PHS Model	Cycling Cost	Total System Cost (\$)	AS PHS Value (\$)
-----	Not Considered	350,741,886.3	-----
Sub-optimized	Not Considered	343,672,483	7,069,404
Fully-optimized	Not Considered	339,500,478.6	11,241,407.7

Table 5.14 shows the results when cycling cost of conventional generators was not considered. Both sub- and full optimization provided positive AS PHS value; however, the AS PHS value was much higher in the fully-optimized case. The energy costs are 14.94 \$/MWh for the case with no AS PHS, 14.64 \$/MWh for the sub- optimized case, and 14.46 \$/MWh for fully optimized case. This shows that the energy cost was cheaper in the fully optimized case when compared to the sub- optimized and base cases.

5.2.5.2 Variable Wind Profile

This section shows the results a high wind generation profile that varies during the day.

TABLE 5.15

CYCLING COST RELATIVE TO NO PHS MODEL CASE IN RT
- VARIABLE WIND

PHS Model	Cycling Cost	Total System Cost (\$)	AS PHS Value (\$)
-----	Considered	338,214,820.8	-----
Sub-optimized	Considered	342,401,057	-4,186,236
Fully-optimized	Considered	338,175,350.7	39,470.06

The cycling cost results are shown in Table 5.15. The AS PHS value was high in the fully optimized case; however, a negative value was noticed in the sub-optimized case. The energy costs are 14.67 \$/MWh for the case with no AS PHS and the fully optimized case, and 14.86 \$/MWh for sub-optimized case. This shows that the energy cost was cheaper in the fully optimized case when compared to the sub- optimized case.

TABLE 5.16

NO CYCLING COST RELATIVE TO NO PHS MODEL CASE IN RT
- VARIABLE WIND

PHS Model	Cycling Cost	Total System Cost (\$)	AS PHS Value (\$)
-----	Not Considered	338,215,246.9	-----
Sub-optimized	Not Considered	342,401,140	-4,185,893
Fully-optimized	Not Considered	338,175,221.8	40,025.15

The results when cycling costs were not considered are presented in Table 5.16. Sub- and optimization resulted in negative AS PHS value; however, full optimization resulted in significant positive AS PHS value. The energy costs are 14.67 \$/MWh for the case with no AS PHS and full optimization, and 14.86 \$/MWh for sub-optimized case. This shows that the energy cost was cheaper in the fully optimized case when compared to the sub- optimized case.

The results presented in this section and all the previous sections of the RT operation study showed that the AS PHS value was the highest in the variable profile among the other two profiles of high renewable penetration when fully-optimizing AS PHS and cycling cost was considered. This highlights the value of AS PHS to follow the variations in renewable generation in short time periods. Table 5.17 and 5.18 present the AS PHS revenues and total solving time for the one day 5 minutes' periods for the renewable profiles presented in sections 5.2.5.1 and 5.2.5.2 respectively.

TABLE 5.17

SOLVING TIME AND PHS REVENUES IN RT
 – WIND AT NIGHT

PHS Model	Cycling Cost	Solving Time (sec)	PHS Revenue (\$)
-----	Considered	611.12	-----
Sub-optimized	Considered	1014.78	-79.04
Fully-optimized	Considered	516.28	609.36
-----	Not Considered	616.75	-----
Sub-optimized	Not Considered	12,933	-81.10
Fully-optimized	Not Considered	589.16	-1251.84

TABLE 5.18

SOLVING TIME AND PHS REVENUES IN RT
 – VARIABLE WIND

PHS Model	Cycling Cost	Solving Time (sec)	PHS Revenue (\$)
-----	Considered	789.79	-----
Sub-optimized	Considered	3100.24	6.80
Fully-optimized	Considered	685.99	5.03
-----	Not Considered	708.68	-----
Sub-optimized	Not Considered	2693.45	-107.945484
Fully-optimized	Not Considered	517.33	4.4897

Table 5.17 shows that full optimization provided revenues for AS PHS; however, the revenues were negative in the sub optimized case when cycling cost was considered. Revenues were also negative when cycling cost was not considered in both sub- and full optimization cases. In Table 5.18, both sub- and full optimization provided AS PHS revenues; however, it was slightly higher in the sub- optimization case when cycling cost was considered. When cycling cost was not considered, full optimization provided revenues for AS PHS while sub- optimization provided negative revenues. Full optimization did not provide positive revenues in all the cases because the objective

function did not include AS PHS revenues maximization. Both Tables 5.17 and 5.18 showed that the solving time in the full optimization case was the lowest. This highlights the importance of AS PHS in the short-period RT market environment. In addition, considering the cycling cost resulted in higher revenues for AS PHS when compared to the no cycling cost cases. This highlights the importance of cycling cost in increasing the utilization of AS PHS. Figures 5.7 and 5.8 show the fully- optimized cases while considering the cycling cost for the two new renewables profiles presented in this section. It can be noticed that AS PHS was more utilized with the variable renewable profile in Figure 5.8. Both figures showed that AS PHS was dispatched when wind was decreasing, because all wind capacity was used when it was generating high amount of energy. The large discharge at the end of the simulation period in both figures was due to constraint 15 presented in section 4.2.2.

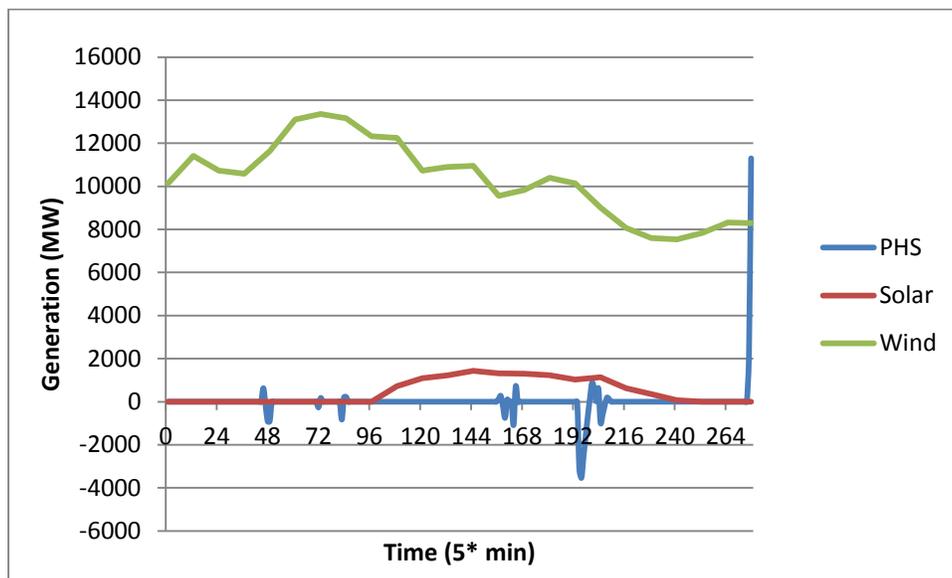


Figure 5.7. Fully-optimized AS PHS generation (scaled by 10) with high penetration of renewables at night while considering cycling cost in the RT market.

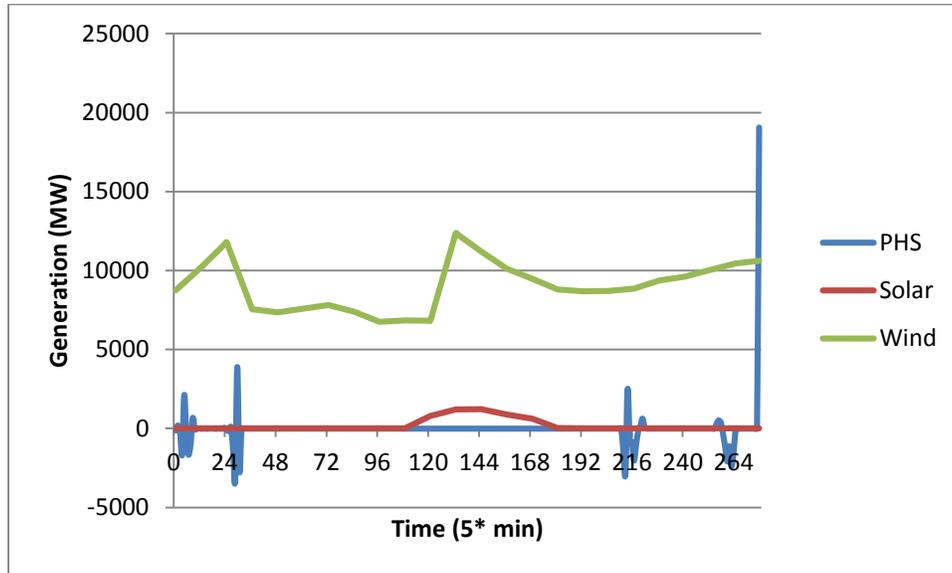


Figure 5.8. Fully-optimized AS PHS generation (scaled by 10) with high penetration of renewables that varies during the day while considering cycling cost in the RT market.

5.3 Planning Study Results

This section presents the results of utilizing the planning optimization model presented in section 4.3 and the data in section 4.4.2 to study the effect of applying the EPA emissions standards for existing and new power plants on the 2013 10-year WECC plan while considering the AS PHS as one of the building blocks of the EPA standards. The total renewables penetration (wind, solar, geothermal, biomass) was 13% in the WECC region. Based on Figure 5.7 the coal and nuclear generators were working as base load generators. Gas, conventional hydro, and AS PHS were cycling to follow the load and variations in renewable generation.

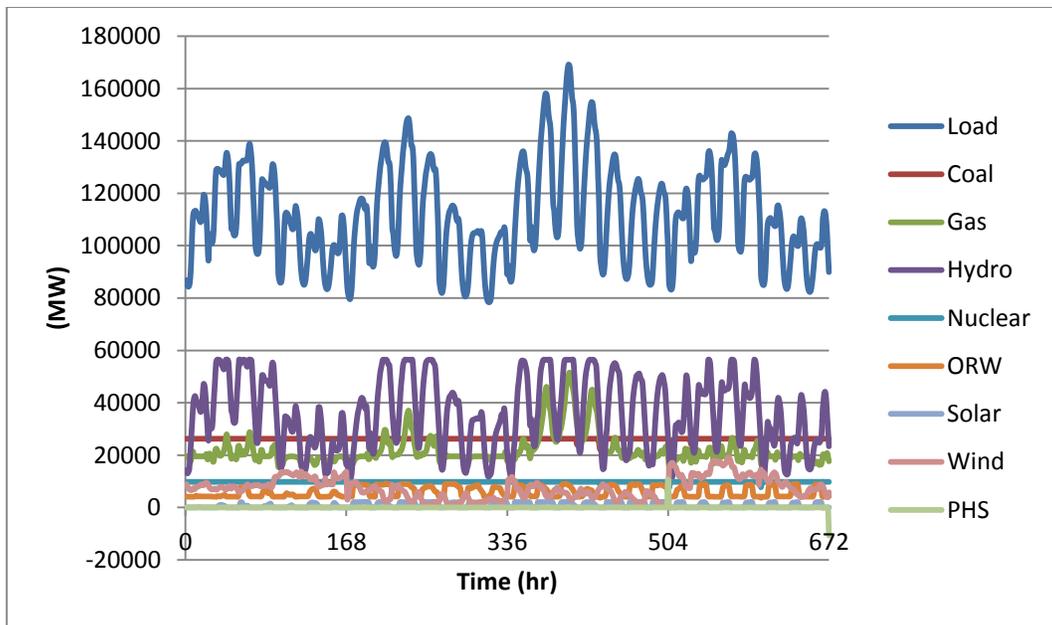


Figure 5.9. The 2022 hourly generation with considering AS PHS in the reduced WECC system.

Table 5.13 shows additional results related to the reduction in gas generation, savings in the total system operating cost, and CO₂ emissions reduction before and after considering AS PHS in the WECC system.

TABLE 5.19

AS PHS PLANNING RESULTS

	Without AS PHS	With AS PHS	Difference
Gas (MW)	14,605,328.8	14,602,286.5	3042.33
Total Operating Cost (\$)	2,417,893,612	2,417,822,052	71559.4
CO ₂ Emissions (tons)	28,706,808.4	28,705,655.71	1152.7

Column 4 in Table 5.13 shows the AS PHS subtracted from those in column 2 (no AS PHS case). The results in column 4 shows that considering AS PHS resulted in a significant reduction in gas generation, total system operating cost, and CO₂ emissions. Therefore, AS PHS played part of the cycling role of gas generators to follow the wind and load variations. This helped in reducing the system operating cost since PHS variable cost is much cheaper than the gas one, and reducing the CO₂ emissions produced by cycling gas generators. The 2,052,503,660 tons EPA emission standard was met in both without and with AS PHS cases; however, the result was better with AS PHS. Therefore, the 2013 WECC plan was able to meet the regional EPA emissions standard for both existing and new power plants in the reduced WECC model.

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

The expected high penetration level of renewable energy resources in the future is putting more ramping requirements on the conventional generators such as coal and gas to follow the variable nature of some types of renewable resources. The increased ramping requirements will lead to decreasing the conventional generation profits and increasing the total system costs. Due to the many benefits that energy storage can provide to the grid in solving this issue, the interest in increasing the capacity of energy storage has grown. Pumped hydro storage is one of the large scale storage technologies that can provide the services that the grid needs in the future of high renewables. Adjustable speed pumped hydro storage (AS PHS) has been a proven technology in Japan and Europe for a long time, and it is planned to have it in the near future of US grid. Since AS PHS is going to be a new technology for the US grid, its operation in the US energy and market management systems should be studied.

The research study in this thesis developed techniques for sub- and full- optimization of AS PHS. The techniques were demonstrated on the Western Electricity Coordinating Council (WECC) day ahead (DA) and the real-time (RT) markets while considering the conventional generation cycling costs and different penetration levels of renewables in addition to different renewable profiles. The study covered the AS PHS operation from the

market, PHS owner, and consumer prospective to provide an overall picture of the expected behavior of this technology in the future.

Based on the results presented in section 5.1, the fully-optimized AS PHS provided the highest DA market value and storage owner revenues for both renewable cases, and for the cases in which cycling costs were included and not included. In addition, the consumer energy cost was the lowest in the fully-optimized case among all cases. The AS PHS value was higher when cycling cost was considered. Considering the cycling costs in the optimization model resulted in a slight but considerable decrease in the cycling of coal and mainly gas generators. The AS PHS revenues were higher in the low renewable case when compared to high renewable one due to the small AS PHS capacity considered for the study.

For the results presented in section 5.2, the sub-optimized case provided negative AS PHS RT market value for all renewable and cycling cases. AS PHS value was positive and significant in the low renewable case of both cycling and no cycling. AS PHS value was the best in the fully optimized case with high renewables and cycling costs included. The AS PHS owner revenues in all fully-optimized cases were much higher than the sub-optimized cases. AS PHS revenue was higher when cycling cost was considered when compared to the no cycling case in full optimization and both renewable cases. Additional case studies were also presented in section 5.2. These studies considered two new high penetration renewables profiles that included high penetration of wind generation at night, and variable wind generation during the day. The results showed that full optimization resulted in the best AS PHS value in all cases. The AS PHS revenue was higher when cycling costs were considered. The variable renewable profile resulted in better utilization

AS PHS and better revenues. Full optimization had the lowest solving time among all cases.

In section 5.3, the results showed that considering AS PHS led to a significant reduction in gas generation, total system operating cost, and CO₂ emissions. The 2013 WECC plan was able to meet the regional EPA emissions standard for both existing and new power plants in the reduced WECC model.

The common conclusion that can be drawn from all of the above is that fully-optimizing the AS PHS while considering the cycling costs of conventional generators in the future of high renewables reduces the system operating cost, increases the PHS owner revenues, decreases the consumer energy cost, reduces the CO₂ emissions in the DA market, RT market, and future WECC system.

6.2 Future Work

- PHS, especially with its AS capability will have other applications in the future, such as voltage control. [29] suggests a pricing structure will be developed to show the benefit of AS PHS in controlling voltage.
- Since it is planned to have higher penetrations of AS PHS in the system, comparing modeling the AS PHS commitment at the unit level (as it is modeled today) and the plant level will be important to obtain the fastest possible converging times when solving a mixed-integer programming (MIP) problem for unit commitment in the DA market. MIP problems involve the optimization of a linear objective function, subject to linear equality and inequality constraints. Some or all of the variables are required to be integer. One of the main factors that affect the performance of MIP is the number of binary variables and the constraints associated with them [42].

Therefore reducing the computation time and memory size allows more complexity to be added into UC in the future, such as increasing the number of AS PHS plants [42]. This idea was based on [42], which provided a new plant level commitment model for FS and AS PHS.

- The minimum up and down times of generators, including AS PHS, will be considered to see their effects on the optimization model and its results.
- The study presented in this thesis is deterministic, in which forecasted data for load and renewables were used. Future work will include the stochastic behavior of load and renewables.
- The planning problem studied in this thesis is large scale. A decomposition method could be employed in this case to convert the problem into a set of smaller and easier to solve subproblems to invest in a higher AS PHS capacity. A suggestion for the proposed planning problem would include a long term investment master problem, a short term operation sub-problem such as the one presented in [43].

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