

May 2014

Understanding the Electricity-Water-Climate Change Nexus Using a Stochastic Optimization Approach

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UNDERSTANDING THE ELECTRICITY-WATER-CLIMATE CHANGE
NEXUS USING A STOCHASTIC OPTIMIZATION APPROACH

by

Ivan Saavedra-Antolínez

A dissertation submitted in
partial fulfillment of the
requirements for the degree of

Doctor of Philosophy

in Engineering

at

The University of Wisconsin-Milwaukee

May 2014

ABSTRACT

UNDERSTANDING THE ELECTRICITY-WATER-CLIMATE CHANGE NEXUS USING A STOCHASTIC OPTIMIZATION APPROACH

by

Ivan Saavedra-Antolínez

The University of Wisconsin-Milwaukee, 2014

Under the Supervision of Professor Vishnuteja Nanduri Ph.D.

Climate change has been shown to cause droughts (among other catastrophic weather events) and it is shown to be exacerbated by the increasing levels of greenhouse gas emissions on our planet. In May 2013, CO_2 daily average concentration over the Pacific Ocean at Mauna Loa Observatory reached a dangerous milestone of ≈ 400 ppm, which has not been experienced in thousands of years in the earth's climate. These levels were attributed to the ever-increasing human activity over the last 5-6 decades. Electric power generators are documented by the U.S. Department of Energy to be the largest users of ground and surface water and also to be the largest emitters of carbon dioxide and other greenhouse gases. Water shortages and droughts in some parts of the U.S. and around the world are becoming a serious concern to independent system operators in wholesale electricity markets. Water shortages can cause significant challenges in electricity production having a direct socioeconomic impact on surrounding regions. Several researchers and institutes around the world have

highlighted the fact that there exists an inextricable nexus between electricity, water, and climate change. However, there are no existing quantitative models that study this nexus. This dissertation aims to fill this vacuum.

This research presents a new comprehensive quantitative model that studies the electricity-water-climate change nexus. The first two parts of the dissertation focuses on investigating the impact of a joint CO_2 emissions and H_2O usage tax on a sample electric power network. The latter part of the dissertation presents a model that can be used to study the impact of a joint CO_2 and H_2O cap-and-trade program on a power grid. We adopt a competitive Markov decision process (CMDP) approach to model the dynamic daily competition in wholesale electricity markets, and solve the resulting model using a reinforcement learning approach.

In the first part, we study the impacts of different tax mechanisms using exogenous tax rate values found in the literature. We consider the complexities of a electricity power network by using a standard direct-current optimal power flow formulation. In the second part, we use a response surface optimization approach to calculate optimal tax rates for CO_2 emissions and H_2O usage, and then we examine the impacts of implementing this optimal tax on a power grid. In this part, we use a multi-objective variant of the optimal power flow formulation and solve it using a strength Pareto evolutionary algorithm. We use a 30-bus IEEE power network to perform our detailed simulations and analyses. We study

the impacts of implementing the tax policies under several realistic scenarios such as the integration of wind energy, stochastic nature of wind energy, integration of PV energy, water supply disruptions, adoption of water saving technologies, tax credits to generators investing in water saving technologies, and integration of Hydro power generation. The third part, presents a variation of our stochastic optimization framework to model a joint CO_2 and H_2O cap-and-trade program in wholesale electricity markets for future research.

Results from the research show that for the 30-bus power grid, transition from coal generation to wind power could reduce CO_2 emissions by 60% and water usage about 40% over a 10-year horizon. Electricity prices increase with the adoption of water and carbon taxes; likewise, capacity disruptions also cause electricity prices to increase.

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To
God and all my family,
especially my wife Blanca Rosa and
my daughter Emma Sofia
for their support, love and motivation
throughout every day of this study

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Chapter 1

Introduction

The security and prosperity of all nations in the twenty-first century are directly connected with smart and sustainable management of both energy and water resources. In the United States, it is well known that the electricity industry is the single largest contributor of greenhouse gases (GHGs) causing climate change and is also one of the largest consumers of ground and surface water. Climate change is known to drastically affect water availability, which in turn affects the operation of new power plants undermining the energy security goals of the nation. Clearly, electricity, water, and climate change are inextricably linked to each other. This relationship, however, has not been considered by the policymakers who continue to tackle energy, water, and climate change management policies as disjointed issues. This approach could be myopic and could have severe consequences in the future.

Climate change has been shown to have a negative effect on the daily

lives of humans, since it impacts the availability and quality of basic natural resources that are essential for a healthy life such as air and water. In the U.S., records for high temperatures have been broken in past two years with 2012 being the hottest year on record. Over the last two years, the U.S. population has faced catastrophic climate-related disasters with some regions experiencing strong hurricanes and tropical storms (e.g., Super Storm Sandy in October of 2012, causing blackouts, floods, deaths and economic losses across the region); while others experiencing large wildfires due to extreme heat and dry weather (e.g., Waldo Canyon Wild Fire in 2012 is the most expensive in history, destroying thousands of homes and businesses). Furthermore, other ecosystem impacts due to climate change such as droughts leading to challenges in irrigation for farmers and other socioeconomic damages for the general public have been reported [2].

In large countries like China and India, population at the middle income level is increasing rapidly leading to a dramatic increase in demand for more electricity. Even at the domestic level, demand for electricity is on the rise albeit not at the same rate. As a consequence of this increasing demand, electricity production from dominant technologies (coal, gas, nuclear) is also increasing, thereby releasing large amounts of greenhouse gas emissions, using up large quantities of water and also causing negative impacts on the climate.

In May 2013, CO_2 daily average concentration over the Pacific Ocean at Mauna Loa Observatory reached a dangerous milestone of ≈ 400 ppm, which has not been experienced in thousands of years in the earth's climate. Similar

significant increases in CO_2 concentrations in the air have also been detected by many observatories around the world, reigniting the discussions of climate change and the role of greenhouse gas emissions.

In 2012, Nebraska experienced power outages because demand exceeded records of electricity usage. It is very likely that there will be more water-stressed regions in the U.S. as the temperatures are expected to increase between two to four degrees Celsius over the next decade. It was noted in [3] that on the one hand power plants experienced water shortages, while on the other hand some power generators faced the challenge of hotter than usual water which affected the efficiency of their cooling systems.

Similarly, records of low precipitation in the Midwest have also been broken in 2012 due to dry conditions and high pressures, affecting thermoelectric generation given their high water consumption. In the case of the thermoelectric power plants, dry conditions could result in a decrease in power generation. As noted in [2] in 2011, Texas thermoelectric power plants were affected due to droughts and were under a high risk of being shutdown. Other similar cases of electricity generation reduction due to droughts were experienced in California and Missouri hydropower plants.

Some federal and individual state-level environmental initiatives have been introduced to increase greener power production, increase energy efficiency, and reduce carbon emissions. Some of these plans include carbon cap-and-trade (in California and RGGI regions) and renewable portfolio standards (in over two dozen states). Cap-and-trade programs for controlling

GHG emissions and their impact on wholesale electricity markets have been studied extensively in the literature. Carbon taxation is a command-and-control approach to reduce GHGs. The fundamental difference between a cap-and-trade program and a tax program is that a tax fixes the price on CO_2 emissions and expects that the emissions would adjust as a result. On the other hand, a cap-and-trade program controls the quantity of emissions and expects prices to follow suit [4]. Proponents of a tax scheme argue that it is a much more stable mechanism since entities subject to taxes have a direct price signal without unnecessary volatility. Given the current aversion of businesses to price and regulatory uncertainties, perhaps, a tax mechanism is a plausible alternative.

The debate as to which carbon reducing mechanism (tax or cap-and-trade) is better is an ongoing one and there is no unanimous agreement among researchers or policy makers. While world leaders are taking some actions about the climate change issues related to energy, the electricity-water-climate change nexus has not been studied in great detail and is starting to become a serious concern. Since there are no existing quantitative models that examine this nexus, the goal of this research is to study this nexus under a joint CO_2 emissions and H_2O usage tax for both water usage and carbon emissions, and then present the directions needed to use this model to study a joint CO_2 emissions and H_2O usage cap-and-trade program.

1.1 Electricity-Water-Climate Change Nexus

As noted in [5, 6], electricity production requires water, and water supply, transport, and purification requires electricity. As such, the growing demand for more energy will drive the demand for more water and vice-versa. Electricity production generates a tremendous amount of carbon dioxide (and other greenhouse gases), leading to climate change. On the other hand, climate change has been shown to cause severe water shortages, in turn affecting the electricity generation ([7]). Extremely high usage of water is ubiquitous in every facet of the energy sector, including extraction, refining, processing, electric power generation, storage, and transport. It also has a devastating impact on downstream water quality because of waste streams, runoff from mining operations, and noxious emissions. [5] have done some of the pioneering work in shining the spotlight on the electricity-water nexus. It is noted in ([8–10]) that on average, thermoelectric generators use more water than the entire U.S agricultural and horticultural industry. A tremendous amount of water is required for thermoelectric power plants to support electricity generation, the highest demand coming from cooling water for condensing steam.

While power generators return a significant percentage of water back to the source, the returned water is at a higher temperature causing heat pollution, which affects the surrounding ecosystem. The returned water is also of much lower quality, thereby requiring significant further energy expenditure

on purification for any future human use. Furthermore, water withdrawal for energy production causes a significant strain to the amount of water available for simultaneous use in the ecosystem and human consumption. It is to be emphasized that up to 3.3 billion gallons of water is consumed each day by power plants. [5] note that due to increasing population, rising energy demands, and water shortages, the U.S. could have close to two dozen water crisis areas in the next decade. These areas include some of the nation's most populous metropolitan centers that may have to trade-off between water-usage for human consumption and electricity production. Clearly, such trade-offs can have devastating impacts on the economy; hence, a coherent electricity-water-climate change policy is needed to avert a national crisis. It is unfortunate that given the importance of this area of research, there are no model-based quantitative studies that comprehensively examine the electricity-water-climate change nexus. This research is targeted at remedying this situation. Some other qualitative reports discussing the electricity-water nexus include ([11–16]) and a quantitative tool for water use estimation was developed by Argonne National Lab ([10]).

It can be seen from Figure 1.1a that the electricity sector is the largest emitter of CO_2 followed by transportation, industry, and residential users. Also note in Figure 1.1b, that thermoelectric power plants are the largest users of ground and surface water in the U.S., followed by irrigation, public usage, and industry. In this research we focus our attention solely on the electricity generation sector.

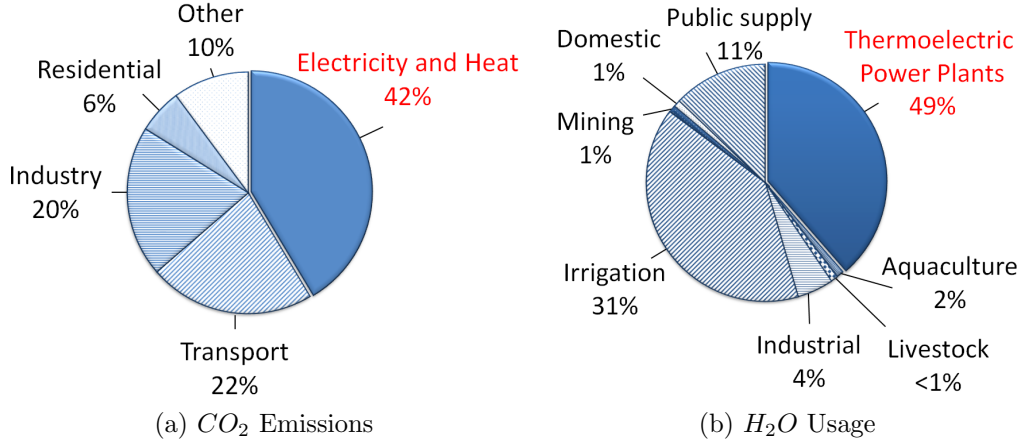


Figure 1.1: Emissions and water usage by sector

1.2 Big Picture

The fundamental contribution of this research is to develop a comprehensive stochastic optimization and simulation framework that connects three important components: electric power generation, CO_2 emissions, and water usage. We investigate the impact of a potential tax policy prescription on electric power markets with the goals of reducing CO_2 emissions and reducing water usage. To ensure realism in the model, this research considers all the intricacies that can manifest in a real life power grid: transmission constraints, power balance constraints, bus angle constraints, supply, and demand constraints.

This research studies the impact of a fixed CO_2 and H_2O tax combination and a calculated optimal CO_2 and H_2O tax policy by imposing it on a power market. The power market model we adopt in this research is a wholesale

independent system operator-based one that is used in over two dozen states in the U.S. The wholesale power market operation is discussed in detail in the Literature Review section of this dissertation. We also model the complex dynamic daily bidding behavior of power generators using a stochastic game setting. Our model captures most of the realistic elements of how power markets operate and how market participants (e.g., generators) interact with it on a daily basis. This dissertation also examines several realistic scenarios such as wind energy integration, impact of stochasticity of wind, long-term water supply disruptions, adoption of water saving technologies, inclusion of clean coal technologies, tax credits, and integration of hydro power generation. We finally present directions needed to use our model to study the impacts of a joint CO_2 and H_2O cap-and-trade program on wholesale electricity markets.

1.3 Outline

The relevant literature review and concepts for this research are discussed in Chapter 2. We present an overview of the wholesale electricity markets to understand the essence of the market competition and the role of independent system operators in the day-ahead operations on wholesale electric power markets. Subsequently, we present an overview of tax policies, we discuss the current mechanisms proposed by policy makers and their actual U.S. environmental policies to mitigate CO_2 emissions. We also discuss the optimal power flow problem which is used by the independent system opera-

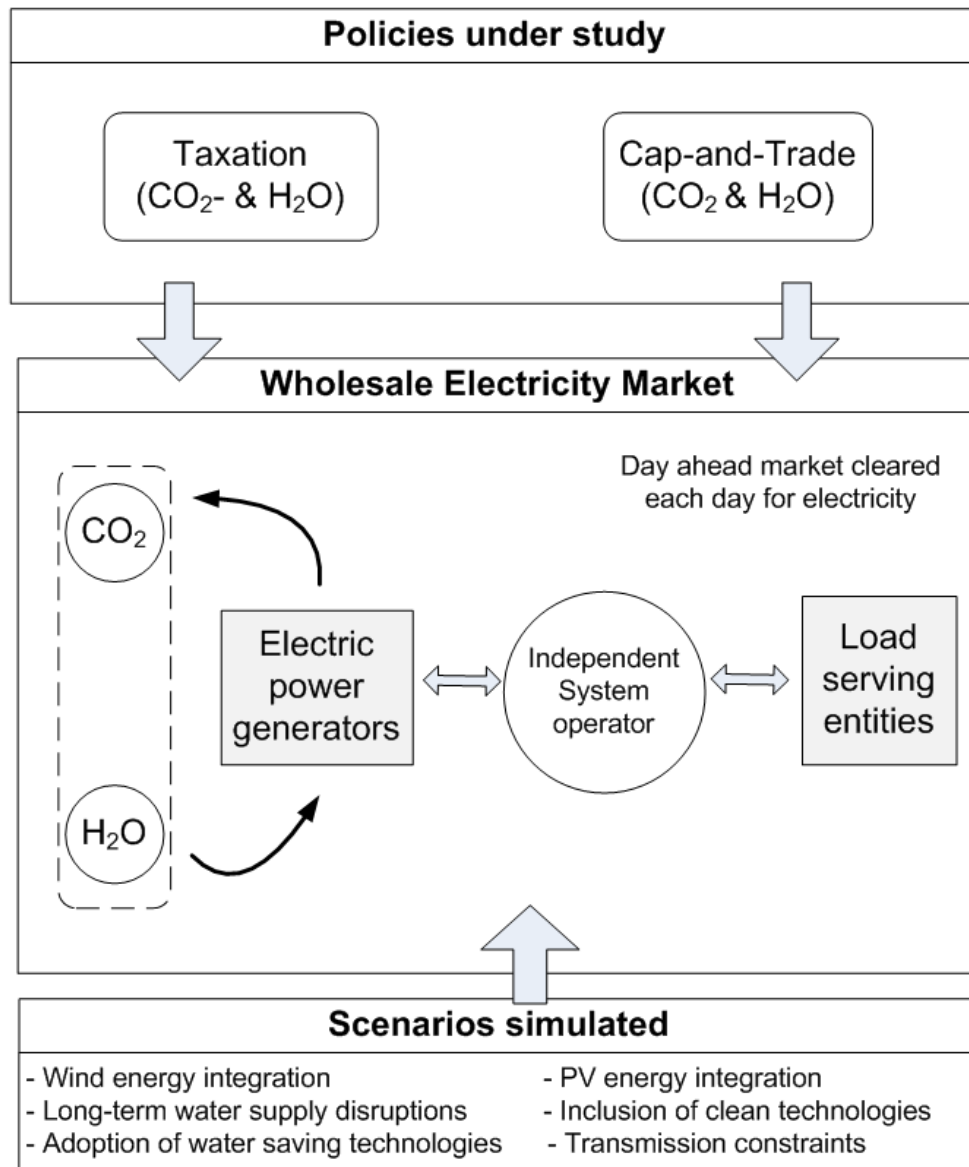


Figure 1.2: Stochastic optimization and simulation framework

tor to determine dispatch quantities and locational marginal prices under the real complexities of a power grid, followed by a summary of the optimization approaches commonly used to solve this problem and a multi-objective variant of the optimal power flow problem. In addition, we present a review of the climate policy models found in the literature in which it can be seen that there is no other model that consider the dynamic behavior of the electricity market participants and the electricity-water-climate change nexus as we are do in this research. In Chapter 3, we introduce the mathematical formulations and the solution approaches used to model the generator's competing behavior in wholesale markets and the intricacies of a real power grid. A competitive Markov decision process is presented to model the generator's bidding problem in competitive wholesale electricity markets and the reinforcement learning approach used as the solution approach to this model is also presented. A standard direct-current optimal power flow formulation is presented to represent the real properties of a power grid, as well as the interior point method used to solve this problem. Similarly, we also present a multi-objective variant of the direct-current optimal power flow formulation which is solved using a evolutionary strength Pareto algorithm. In Chapter 4, we present the comprehensive numerical analysis and conclusions of the impacts of implementing tax policies in wholesale electricity markets. Finally in Chapter 5, we present an overview of cap-and-trade programs, basic concepts, and directions to be followed in our model in order to study the impacts of a joint CO_2 and H_2O cap-and-trade program on wholesale electricity

markets.

Chapter 2

Literature Review

2.1 Review of Relevant Literature and Concepts

This chapter discusses the key concepts of the dissertation and the state of the literature in this area. We discuss the operation of wholesale electricity markets, cap-and-trade programs, carbon taxation, optimal power flow, competitive Markov decision processes, and reinforcement learning.

2.2 Wholesale Electricity Markets

A wholesale electricity market is a system where a set of power companies compete with one another with the interest of supplying electricity to meet the system's demand from large wholesale customers. The U.S. electricity industry has been evolving from regulated markets with vertically integrated monopolies where power systems are regulated by a government agency,

which sets the prices for the electricity; to deregulated wholesale markets with a more diverse industry that promotes competition by allowing power generators to make supply offers, resulting in a variety of purchase options for large electricity retailers or load serving entities [17]. These restructured wholesale markets are typically administered by an independent system operator (ISO), which is a non-profit entity. Readers are referred to [17–19] for detailed description of restructured markets and other terminology.

The transactions in a wholesale electricity market occur in two types of markets: the day-ahead (DA) energy markets and the real-time (RT) energy markets. First, the day-ahead energy market calculates an hourly electricity price for the next day, as well as the dispatch quantities to be assigned to every supplier based on generation offers from suppliers and demands bids from wholesale customers (transactions are settled daily); and second, the real-time market which is a spot market, balances the deviations between the day-ahead scheduled electricity dispatch quantities and the actual real-time operational requirements in the system, given that the demand, the generation capacities, and the system conditions can vary (transactions are settled hourly or even as often as every 5 minutes).

In DA energy markets as shown in figure 2.1, on day D both generators and consumers, submit price-quantity supply offers in \$/MWH and demand bids in MWH respectively to an Independent System Operator (ISO) before the operating day $D+1$. The ISO is the entity that coordinates all the transactions in a power grid, responsible for solving a complex network flow model

(presented in detail in Section 2.4) that accounts for constraints related to transmission, generation capacities, and demands, and returns the respective dispatch quantities scheduled for every generator in the system and the locational prices for the next operating day. In the U.S., currently, there are seven independent system operators providing two-thirds of the electricity demanded: California independent system operator (CAISO), electric reliability council of Texas (ERCOT), Midwest independent transmission system operator (MISO), ISO New England (ISO-NE), New York independent system operator (NYISO), PJM interconnection (PJM), and southwest power pool (SPP). In this research we focus our attention on the day ahead segment of wholesale electricity markets.

2.3 Carbon Taxes

It has been noted in the literature that the purpose of a tax policy is to change a particular consumer behavior associated with a specific good. Furthermore, in the context of non-fiscal taxation, the purpose is to produce a certain economic or social effect and alter private sector choices independently of the revenue in order to meet specific government goals [20, 21]. Policy makers have proposed carbon taxes as an environmental policy instrument to reduce the amount of carbon emissions due to electricity generation [22, 23] by directly taxing the quantities of carbon emissions produced by the sources (coal, oil, gas generators). The revenue obtained from taxes is expected to

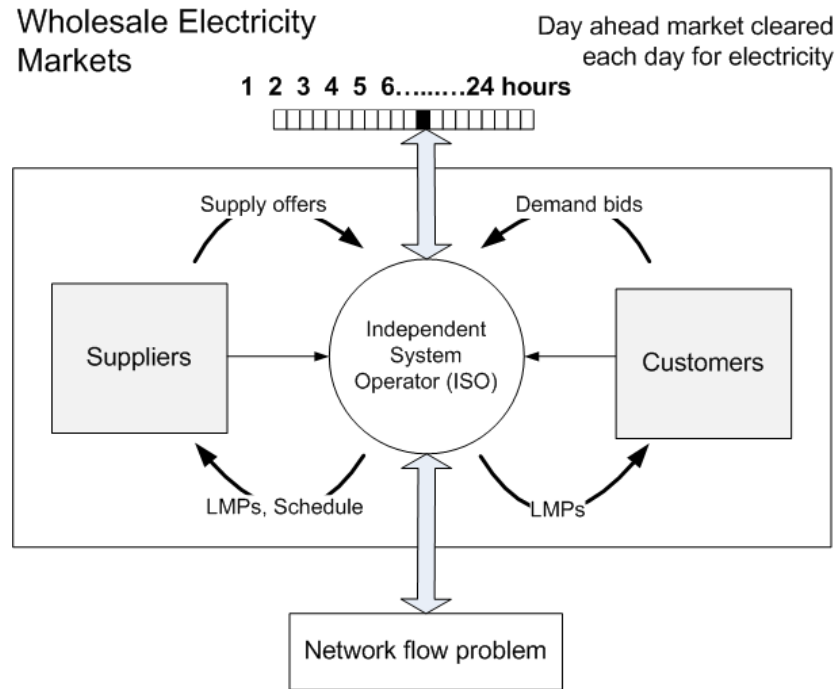


Figure 2.1: Energy market model

be invested in green and efficient energy related projects. There are several goals of implementing a tax policy [24]: to raise revenues, to provide economic stimulus, to achieve social objectives, and to correct market failures. In this research, one of our goals is to examine the effects of imposing such taxes on both CO_2 emissions and water usage in wholesale electricity markets. What implications do different tax rates have on electricity prices? What implications do tax rates have on power generator profits, consumer welfare, and supply shares. These are some of the fundamental questions we examine via this dissertation.

Current U.S. energy tax incentives and rebate policies are described well

in the 2012 CRS report to congress [24]; some of the measures include: credits for investing in clean coal facilities, credits for electricity production and investment in renewable sources, and credits for energy efficiency. Similarly, tax incentives are being used in the European Union (EU) in order to stimulate the use of green energy technologies. In [23], it was noted that most of the countries with the highest increases in green electricity generation in the EU were those where a tax incentive was implemented. Similar findings are reported from simulations of the impacts of a carbon tax on economies like China [25] and South Africa [26].

Carbon tax proposals have been presented to the U.S. Congress (H.R. 594 by Stark [27], H.R. 1337 by Larson [28], H.R. 2380 by Inglis [29], and H.R. 1683 by McDermott [30]), however, they have not been considered as the principal tool for energy and climate change legislations because of particular design elements. Proponents of carbon taxes note that they provide cost certainty given that the tax rate is known ahead of time, but it does not present certainty in benefits (i.e., desired reductions of carbon emissions). However, there is no a clear agreement about whether is better to have cost certainty or benefit certainty [31], since sometimes the tax rate can be adjusted in order to correct this uncertainty. Metcalf and Weisbach [32] noted that an appropriate CO_2 tax should be equal to the social marginal damages from producing an additional unit of carbon dioxide emissions. However, computing social marginal damages is an extremely complex challenge as noted in the Stern Review [33]. It is noted in [33] that estimating the social

cost of carbon is a complex multi-stage process involving the assessment of effects of greenhouse gases on temperature, regional impacts assessment, rates of technical progress, potential abatement investments, and so on.

In this research, we investigate the three different tax schemes proposed for carbon-dioxide emissions by Metcalf and Weisbach [32]: We use our model as a vehicle for understanding the impacts of such tax mechanisms on complex wholesale electricity market operations.

2.4 Optimal Power Flow

Optimal power flow (OPF) problems have been used by independent system operators to minimize cost of electricity production subject to electric power network constraints, to identify dispatch quantities and locational marginal prices. However, several formulations have been studied for about 50 years in the literature making specific assumptions and varying the objective function, constraints, or both. The standard OPF problem seeks to minimize the total generation cost subject to balance power injection constraints, branch flow limits, bus angles limits, and power injection limits. The real-world practical formulation of the OPF problem is known as the alternating current optimal power flow (ACOPF) problem. The ACOPF was first formulated by Carpentier in 1962. It has been shown to be a very difficult problem to solve [34] due to the nonlinearities in the objective function and constraints and because it considers both active and reactive power at the same time,

notwithstanding the large size of real wholesale electricity markets. Given this complexity, a simplified linearized version, the direct current optimal power flow (DCOPF) problem is mostly used in the electricity market literature to study OPF problems. In some DCOPF formulations the objective function is nonlinear but with a linear set of constraints, and it only considers active power injections.

Several methods have been studied to solve the OPF problem as noted in [35], most of which can be subdivided into the following three basic categories: deterministic methods for solving the OPF, stochastic methods for solving the OPF, and hybrid methods.

[36] presents an excellent survey about deterministic optimization methods to solve the OPF problems, including gradient methods (RG), Newton methods, simplex method, sequential linear programming (SLP), sequential quadratic programming (SQP), and interior point methods (IPMs) for non-linear or quadratic formulations. It is also noted by [37] that several non-deterministic methods have been applied to the OPF problem. They include Ant colony optimization (ACO), artificial neural networks (ANN), bacterial foraging algorithms (BFA), chaos optimization algorithms (COA), variety of evolutionary algorithms (EAs), particle swarm optimization (PSO), simulated annealing (SA), and Tabu search (TS). For details readers are referred to [36] and [37]. Both deterministic and non-deterministic methods have their own advantages and disadvantages. For instance, most deterministic methods can not easily handle discrete variables, non-convex, and complex

formulations, while non-deterministic methods can handle these effectively; however, they are usually computationally intensive and sensitive to parameters chosen.

2.4.1 Multi-objective Optimization

There are several papers in the literature that have solved the optimal power flow problem with multiple objectives using non-deterministic/artificial intelligence methods. In our research, for one of the cases we studied, we adopted a multi-objective approach for tackling the optimal power flow problem. There are several variants of the OPF problem from a multi-objective standpoint including multi-objective economic dispatch problem (MOEDP) and variants of the multi-objective optimal power flow problem (MOOPF). For the sake of brevity, we have summarized these contributions in the table below.

2.5 Climate Policy Modeling

Climate Policy Modeling: Research in the area of climate policy modeling and analysis with respect to electricity markets (without any water policy component) has progressed along two distinct lines. The first is **large-scale simulation-based models** ([4, 54–62]) and the second is **mathematical programming based (theoretical) models** ([63–68]). However, none of these papers consider the dynamic gaming behavior, adaptive learning be-

Table 2.1: Multi-objective techniques to solve MOOPF

| <i>Technique</i> | <i>Minimize</i> | <i>Source</i> |
|--|--|---------------|
| Strength Pareto Evolutionary Algorithms (SPEA) | 1. Fuel cost | [38] |
| | 2. Emissions | |
| | 1. Real power cost | [39] |
| | 2. Voltage stability index | |
| Enhanced Genetic Algorithm (EGA) | 1. Fuel cost 2. Real power losses 3. Voltage stability index | [40] |
| Particle Swarm Algorithms (PSA) | 1. Fuel cost | [41] |
| | 2. Emissions | |
| | 1. Generation cost | [42] |
| | 2. Emissions 3. Transmission losses 4. Voltage stability index | |
| Simulated Annealing (SA) | 1. Power losses 2. Emissions 3. Severity index | [43] |
| Bees Algorithms (BA) | 1. Fuel cost 2. Emissions 3. Real power losses | [44] |
| Non-dominated Sorting Genetic Algorithm (NSGA) | 1. Fuel cost | [45] |
| | 2. Emissions | [46] |
| | 1. Real power losses | |
| | 2. Voltage stability index | |
| Gravitational Search Algorithms (GSA) | 1. Fuel cost 2. Transmission losses 3. Voltage deviation | [47] |
| Differential Evolution Algorithms (DEA) | 1. Fuel cost 2. Emissions 3. Real power losses | [48] |
| | 1. Fuel cost | |
| | 2. Emissions | [49] |
| | 1. Fuel cost | |
| Harmony Search Algorithm (HSA) | 2. Emissions | [50] |
| | 1. Fuel cost | [51] |
| | 2. Emissions | |
| Bacterial Foraging Algorithm (BFA) | 1. Fuel cost | [52] |
| | 2. Emissions | |
| | 1. Fuel cost | [53] |
| | 2. Emissions | |

havior, and repeated interactions of electricity market participants. This dissertation, on the other hand, develops a comprehensive CMDP model that considers the dynamic gaming behavior. The proposed reinforcement learning based solution approach incorporates the realistic adaptive learning behavior of numerous market participants.

Solution Approaches for Dynamic Stochastic Games: A critical aspect in the study of dynamic stochastic games (such as CMDPs) is the reward mechanism, common forms of which are discounted reward, average reward, and total reward. In the repeated game environment of a day-ahead

market, the rewards from the bids are realized within a day, and, hence, average reward appears to be the most appropriate reward criterion. The reward criterion significantly impacts the existence of equilibria of stochastic games. For example, discounted reward non-zero sum CMDPs are guaranteed to have at least one mixed strategy Nash equilibrium. But, the question whether, with respect to the average reward criterion, equilibrium solutions always exist for non-zero sum games is still open ([69]).

No exact computational method exists for obtaining the Nash equilibria of a non-zero sum average reward stochastic game. The difficulty of computation arises from the complex nature of interactions among the competing decisions of the participants, probabilities of state transitions, and the reward structure. In the recent years, algorithms based on a stochastic approximation method (known as reinforcement learning) have been presented in literature to solve stochastic games.

2.5.1 Brief background about Reinforcement Learning (RL)

The theory of RL is founded on two important principles: Bellman’s equation and the theory of stochastic approximation ([70, 71]). Any learning model contains four basic elements: system environment (*simulation model*), learning agents (*market participants*), set of actions for each agent (*action spaces*), and system response (*participant rewards*).

Consider a system with three competing market participants. At a decision-

making epoch when the system is in state s , the three learning agents that mimic the market participants select an action vector ($a = (a^1, a^2, a^3) \in \mathcal{A}$). These actions and the system environment (model) collectively lead the system to the next decision-making state (say s'). As a consequence of the action vector (a) and the resulting state transition from s to s' , the agents get their rewards ($r^1(s, a, s')$, $r^2(s, a, s')$, and $r^3(s, a, s')$) from the system environment. Using these rewards, the learning agents update their knowledge base (R-values, also called reinforcement value) for the most recent state-action combination encountered (s, a). The updating of the R-values is carried out slowly using a small value for the *learning rate*, which completes a learning step. At this time the agents select their next actions based on the R-values for the current state s' and the corresponding action choices. The policy of selecting an action based on the R-values is often violated by adopting a random choice, which is known as *exploration*, since this allows the agents to explore other possibilities. The probability of taking an exploratory action is called the *exploration rate*. Both learning and exploration rates are decayed during the iterative learning process. This process repeats and the agent performances continue to improve. In the proposed RL algorithm, the current average reward values are also learned to avoid large fluctuations. After continuing learning for a large number of steps, if the R-values for all state-action combinations converge, the learning process is said to be complete. The converged R-values are then used to find a stable policy for each of the agents. A rationale for the above R-value updating scheme can be

found in the reinforcement learning literature ([72], [73]).

Chapter 3

Mathematical Formulation and Solution Framework

3.1 Problem Statement

This research aims to understand the electricity-water-climate change nexus by first studying the impact of taxation policy in wholesale electric power markets with the goals of reducing carbon dioxide emissions and water usage by electric power generators, and second by proposing a comprehensive framework to study the impact of a cap-and-trade policy in wholesale electric markets to also reduce CO_2 emissions and H_2O usage. For this purpose, we model the electric power generator's bidding problem as a competitive Markov decision process (CMDP) and we solve it using a reinforcement learning approach (RL). This dissertation is subdivided into two main thrust

areas: 1) implications of carbon and water tax policies on electric power markets and 2) a model to study the potential implications of a joint water and carbon cap-and-trade policy on electric power markets.

The first area is further examined in two separate studies:

1. In the first study, we impose exogenous tax rates (from literature) for both water and CO_2 on electric power markets and study their impact in detail. In order to consider the intricacies of a power grid, we use the standard DCOPF formulation as shown in Section 3.2. The objective function of this problem consists of minimizing costs related to: power generation, CO_2 emissions, and water usage. The mathematical model and solution approach are presented in sections 3.2 and 3.5 respectively.
2. In the second study, we calculate the optimal tax rates using a response surface methodology and then study the impact of these optimal tax rates in electric power markets. The OPF formulation we use in this study is a multi-objective one that includes the minimization of three separate objective functions: the generation cost, the cost related to CO_2 emissions, and the cost related to water usage. The mathematical model and the multi-objective OPF's solution approach are presented in sections 3.3 and 3.6 respectively.

The overall research objectives of this dissertation are as follows:

1. Develop a stochastic optimization framework to evaluate the energy-water-climate change nexus.

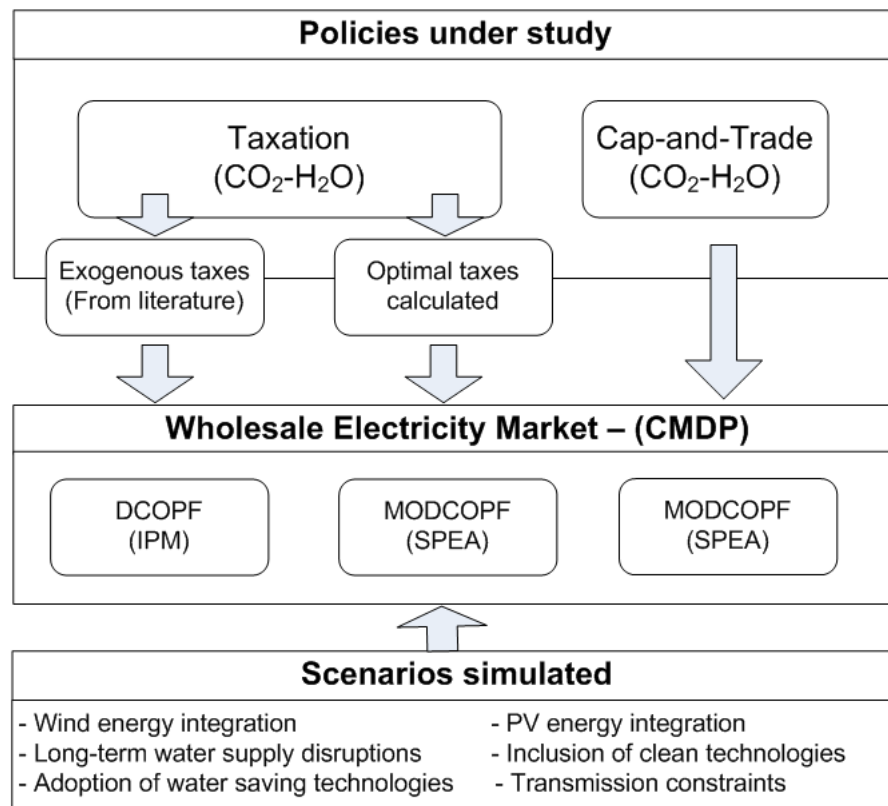


Figure 3.1: Core components under study

2. Perform a detailed study of the impacts of a new joint water and carbon tax mechanism on electric power generators to limit water usage and control CO_2 emissions.
 - exogenous tax rates
 - calculation of optimal tax rates for a given power grid
3. Under taxation policies, investigate several real world scenarios encompassing wind energy integration, stochasticity of wind energy, long-term water supply disruptions, adaptation of water saving technologies, inclusion of clean coal technologies, tax credits, and integration of hydro power generation.
4. Propose a model to study the impacts of a cap-and-trade program on electric power generators to limit H_2O usage and CO_2 emissions.

In the following sections we present the mathematical formulations used to model the traditional optimal power flow problem, the multi-objective optimal power flow problem, the electric power generator's bidding problem; followed by the individual solution approaches for each of them.

3.2 Mathematical Formulation of the DC-Optimal Power Flow

As mentioned in Section 2.4, the optimal power flow problem can be formulated as an alternating current optimal power flow (ACOPF) problem or

as an direct current optimal power flow (DCOPF) problem. Because the difficulties of solving an ACOPF described in Section 2.4, the DCOPF formulation is mostly used in the electricity market literature to study OPF problems. The DCOPF problem consists of a set of linear constraints and seeks the minimization of the total cost of meeting the active power demand of the system. The general formulation is presented below.

$$\min_{\Theta, P_g} \sum_{i=1}^{n_g} f_P^i(p_g^i) \quad (3.1)$$

subject to

$$g_P(\Theta, P_g) = B_{bus}\Theta + P_{bus,shift} + P_d + G_{sh} - C_g P_g = 0 \quad (3.2)$$

$$h_f(\Theta) = B_f\Theta + P_{f,shift} - F_{max} \leq 0 \quad (3.3)$$

$$h_t(\Theta) = -B_f\Theta - P_{f,shift} - F_{max} \leq 0 \quad (3.4)$$

$$\Theta_i^{ref} \leq \Theta_i \leq \Theta_i^{ref}, i \in I_{ref} \quad (3.5)$$

$$p_g^{i,min} \leq p_g^i \leq p_g^{i,max}, i = 1...n_g \quad (3.6)$$

- Equation (3.1) minimizes the total cost of meeting active power demands, where Θ are the voltage angles, P_g denotes the real power injections, n_g is the number of generators, and f_P^i is a piecewise linear cost function of generator i .
- Equation (3.2) balances the real power injections in the system, where $g_P(\Theta, P_g)$ are the load injections, B_{bus} are the bus voltage angles,

$P_{bus,shift}$ is the shift injection vector, P_d is the real power demand, G_{sh} are the generation shift factors, and C_g is a binary variable that identifies the location of a generator.

- Equations (3.3) and (3.4) represent the branch flow limits, where h_f is the branch flow *from* a specific bus, h_t is the branch flow *to* a specific bus, B_f are the shunt susceptance values, $P_{f,shift}$ is the shift injection vector for the *from* bus, and F_{max} is the vector of flow limits.
- Equation 3.5 maintains the bus angles Θ_i within the bounds Θ_i^{ref} , where I_{ref} is the set of bus indices for the reference buses.
- Equation 3.6 controls the real power injections (p_g^i) within lower and upper limits $p_g^{i,min}$ and $p_g^{i,max}$ respectively.

In this research, we assess the performance of power generators in a wholesale electricity market under different CO_2 and H_2O tax mechanisms. We, therefore, introduce two new terms in the objective function described above. Hence, the modified objective function can be written as follows.

$$\min_{\Theta, P_g} \sum_{i=1}^{n_g} f_P^i(p_g^i) + f_{CO_2}^i(p_g^i) + f_{H_2O}^i(p_g^i), \quad (3.7)$$

where $f_{CO_2}^i$ represents the preset tax on CO_2 emissions and $f_{H_2O}^i$ denotes the preset tax on water usage. The solution approach used to solve the DCOPF problem is presented in Section 3.5.

3.3 Mathematical Formulation of the Multi-objective DC-Optimal Power Flow Model

The multi-objective DC-optimal power flow problem (MODCOPF) is a modification of the DCOPF problem presented in the previous section 3.2, which has a linear set of constraints and minimizes the total cost of meeting the active power demand in the system. In this section, we modify the DCOPF formulation by adding two additional objective functions: 1) minimize the total cost of CO_2 emissions and 2) minimize the total cost of water used. Then the MODCOPF formulation is as follows:

Optimize:

$$\min_{\Theta, P_g} \sum_{i=1}^{n_g} f_P^i(p_g^i) \quad (3.8)$$

$$\min \sum_{i=1}^{n_g} f_{CO_2}^i(e^i)(p_g^i) \quad (3.9)$$

$$\min \sum_{i=1}^{n_g} f_{H_2O}^i(w^i)(p_g^i) \quad (3.10)$$

subject to the same set of constraints (3.2-3.6) presented in 3.2.

- Equation (3.8) minimizes the total cost of meeting active power demands, where Θ are the voltage angles, P_g denotes the real power injections, n_g is the number of generators, and f_P^i is the cost function of generator i .

- Equation (3.9) minimizes the total cost of CO_2 emissions, where $f_{CO_2}^i$ is the tax set for CO_2 emissions, e^i is the emission factor of generator i , and p_g^i are the load injections of all generators.
- Equation (3.10) minimizes the total cost of water used, where $f_{H_2O}^i$ is the tax set for water used, and w^i is the water usage factor of generator i .

The solution approach used to solve the MODCOPF problem is presented in Section 3.6.

3.4 Mathematical Formulation of the Competitive Markov Decision Process

In this section, the notation for the electricity generator's bidding problem is presented and we show how it can be model as a competitive Markov decision process (CMDP).

We develop a model similar to the one in [74]. Let \mathcal{B} denote the set of buses in the network, and $\mathcal{B}_s \subset \mathcal{B}$ denotes the subset of supply buses (nodes). Let the number of generators be denoted by N , and M denote the number of loads in the network. Let $\mathcal{G} = \{1, 2, \dots, N\}$ and $\mathcal{L} = \{1, 2, \dots, M\}$ denote the set of generators and the set of loads in the network respectively.

System State: We define the system state for the t^{th} day X^t as the total demand of the most recently completed day. Since demand is a random variable, it is necessary to discretize it to develop a discrete stochastic model.

Let the range of possible values for network demand be discretized in U steps. Our model allows the level of discretization to be as refined as necessary for the desired modeling accuracy.

Stochastic Process: The random process for the state transition of the day-ahead market can be defined as $\mathcal{X} = \{X^t : t \in \mathbf{Z}\}$, where \mathbf{Z} is the set of integers. The value of X^t along with the bid submitted on the t^{th} day dictate the system state of $(t + 1)^{th}$ day, X^{t+1} . Clearly, the \mathcal{X} process satisfies the Markov property. This along with other characteristics such as discrete and finite system states and time homogeneity assumption for the stochastic load realization process (within a demand season), make the \mathcal{X} process a Markov chain.

CMDP Notation: Let the bid decision vector at the t^{th} day be given by $D^t = \{\mathcal{D}_l^t : l \in \mathcal{G}\}$, where \mathcal{D}_l^t is the decision vector of generator l and is given as $\mathcal{D}_l^t = (S_l^t)$. The element S_l^t denotes the vector of bid parameters for each of the 24 hours. The stochastic bidding decision process involves daily selection of bid parameters by the generators. This stochastic process is referred to as the *decision process*, denoted by $\mathcal{D} = \{D^t : t \in \mathbf{Z}\}$, where D^t is the decision vector chosen on the t^{th} day. Since the decision vectors \mathcal{D}_l^t are chosen by the generators in a non-cooperative manner, the bidding scenario characterized by the joint process \mathcal{X} and \mathcal{D} is a competitive Markov decision process (CMDP-[69]).

The rewards for the bidding decisions made by the electric power generators are obtained by solving the DCOPF model presented in Section 3.2 if

mono-objective setting is applied, or the MODCOPF model presented in 3.3 if multi-objective setting. The solution approach used to solve the CMDP model is presented in Section 3.7.

3.5 Solution Approach for the DCOPF Model

In order to solve the DCOPF model presented in the Section 3.2, we implement the primal-dual interior point method described in [75] in C++. A general formulation of an optimization problem is presented below and the primal-dual interior point method is then explained in relation to the DCOPF problem.

$$\min_x \frac{1}{2} x^T H x + c^T x \quad (3.11)$$

subject to:

$$l \leq A x \leq u \quad (3.12)$$

$$x_{min} \leq x \leq x_{max} \quad (3.13)$$

The objective function (Equation 3.11) is quadratic in nature. However, it can also be used to represent the linear objective function as described in the DCOPF problem (Equation 3.7). H is the matrix with the quadratic cost coefficients (this is a matrix of zeros in the DCOPF), c is the vector of linear cost coefficients (related to each generator's piecewise linear cost function). Equation 3.12 describes the linear constraints and Equation 3.13 represents the bounds on the decision variables (Θ, P_g). A , l , and u denote the matrices

of coefficients of x , lower, and upper bounds of the linear constraints (related to real power balancing and branch flow limit equations (3.2, 3.3, 3.4) from the DCOPF), x_{min} and x_{max} in Equation (3.13) are the lower and upper bounds of the x variables (related to bus angles and real power injection equations (3.5, 3.6) of the DCOPF). Very briefly, the interior point algorithm works as follows.

1. The original problem is modified by converting the inequality constraints to equality constraints by adding slack variables, and then by introducing a barrier function to the objective with a parameter value of γ . When γ converges to zero at the end of the algorithm, the solution to this modified problem is the same as that of the original.
2. The Lagrangian for this modified equality constrained problem is computed.
3. All the partial derivatives of the Lagrangian are then set to zero in order to satisfy the first order optimality conditions (Karush-Kuhn-Tucker conditions).
4. Finally, the Newton's method [76] is used to solve the KKT conditions while updating the x variables in each iteration until γ converges to zero.

3.6 Solution Approach for the MODCOPF

The multi-objective optimization approach adopted to solve the MODCOPF described in Section 3.3 was the strength Pareto evolutionary algorithm (SPEA). In our previous work [77], the SPEA was used successfully for solving large multi-objective optimization problems in scheduling operations. In this research, we adopt a similar approach and also utilize the procedure presented by Zitsler and Thiele [78] for solving the multi-objective OPF. The SPEA, makes use of the Pareto optimality concept to find the final set of optimal solutions. This is achieved by performing an iterative evolution process making use of the Pareto dominance concept and by performing genetic operations to create new solutions in every generation until the front set of solutions cannot be improved any more. The steps of the algorithm are presented in the following table (Algorithm 1) and we subsequently describe it in detail.

Step 0) Initialize parameters: Denote MaxGenerations as the maximum number of generations in the algorithm, numGenerations as the counter of generations, and $MaxP_{nd}$ as the maximum number of solutions in the non-dominated set.

Step 1) Generate the initial population:

To create each member of the initial population P , random dispatch quantities are assigned to all generators, and constraints (3.2) - (3.6) from

Algorithm 1: SPEA: MultiObjective DCOPF

```

1  $P \leftarrow \text{GenerateInitialPopulation}()$ 
2 while  $\text{numGenerations} \leq \text{MaxGenerations}$  do
3    $F \leftarrow \text{CalculateObjectiveFunctions}(P)$ 
4    $P_{nd} \leftarrow \text{SelectNonDominated}(P)$ 
5   if  $(\text{size}(P_{nd}) > \text{Max}P_{nd})$  then
6      $P_{nd} \leftarrow \text{Clustering}(P_{nd})$ 
7    $\text{fitness} \leftarrow \text{CalculateFitness}(P, P_{nd})$ 
8    $P_s \leftarrow \text{SelectionSet}(P, P_{nd}, \text{fitness})$ 
9    $P_c \leftarrow \text{CrossOver}(P_s)$ 
10   $P_m \leftarrow \text{Mutation}(P_s)$ 
11   $P \leftarrow \text{UpdatePopulation}(P_{nd}, P_c, P_m)$ 
12   $\text{numGenerations} = \text{numGenerations} + 1$ 
13  $P_{best} \leftarrow \text{FindBestCompromiseSolution}(P_{nd})$ 
14  $LMP \leftarrow \text{CalculateLMP}(P_{best})$ 

```

the MO-DCOPF formulation are checked to ensure the feasibility of each member that is generated.

Step 2) Evaluate the objective functions: Define $A = \{< A_1 >, < A_2 >, \dots, < A_n >\}$ such that each member is a tuple containing all three objective function values based on the dispatch quantities for every member in P . Recall that the objective functions are: 1) minimize the production cost (equation 3.8), 2) minimize the CO_2 emissions cost (equation 3.9), and 3) minimize the H_2O usage cost (equation 3.10).

Step 3) Select the non-dominated solutions: Find $P_{nd} : A_i \preceq A_j$, where $i \neq j$

Step 4) Clustering: If $|P_{nd}| > \bar{P}_{nd}$ (where \bar{P}_{nd} is a predefined constant) reduce P_{nd} by clustering. First, calculate the Euclidean distance for all com-

binations of pairs of solutions in P_{nd} . Second, for the pair of solutions with the minimal distance, select the solution closest to the centroid and remove the farthest one. Repeat these steps until $|P_{nd}| = \bar{P}_{nd}$.

Step 5) Fitness calculation: The fitness is obtained by finding the strength of every solution in P and P_{nd} as described in [79]. For each element of P_{nd} , $f_i = S_i$, $S_i = n_i / (\text{size}(P) + 1)$, where n_i is the number of solutions from P that are dominated by solution i in P_{nd} ; and for every solution j in P , calculate $f_j = 1 + \sum_{i, i \preceq j} S_i$.

Step 6) Selection set: Create a new set $P_s : \{P_{nd}, P_{rws}\}$, where $P_{rws} \subset P$ and is selected by the commonly used Roulette-Wheel Selection (RWS) method ([80]) based on the fitness values (f_i, f_j) calculated in the previous step.

Step 7) Crossover operator: To explore the entire solution space we then perform a crossover operation as follows. For each pair of consecutive solutions we apply one of the two commonly used crossover procedures. Draw a uniform random number between zero and one; if the random number is less than a pre-defined crossover probability use an arithmetic blended crossover operation as shown below [81]:

$$x_i^{new1} = \alpha * x_i + (1 - \alpha) * y_i \quad (3.14)$$

$$x_i^{new2} = (1 - \alpha) * x_i + \alpha * y_i, \quad (3.15)$$

else if, apply a heuristic crossover operation [81]:

$$x_i^{new1} = x_i + (y_i - x_i) * \alpha \quad (3.16)$$

$$x_i^{new2} = x_i - (y_i - x_i) * \alpha, \quad (3.17)$$

else, do nothing.

Where x_i and y_i are the parent solutions and $\alpha = Unif(0, 1)$. All x^{new1} and x^{new2} are elements of a new crossover solution set P_c .

Step 8) Mutation operator: Perform a mutation on the solution set P_s to create a new set P_m .

Step 9) Update population: Concatenate sets P_{nd} , P_c , and P_m to create the updated set P . If generations $<$ MaxGen, return to Step2, otherwise set P becomes the Pareto optimal set of solutions, and then proceed to Step 10.

Step 10) Select the best compromise solution: The fuzzy-based method presented in [38] is applied to select the best compromise solution from the optimal Pareto set found in the previous step. For each objective function of every member in the optimal set, find:

$$\mu_i = \begin{cases} 1, & A_i \leq A_i^{min} \\ \frac{A_i^{max} - A_i}{A_i^{max} - A_i^{min}}, & A_i^{min} < A_i < A_i^{max} \\ 0, & A_i > A_i^{max} \end{cases} \quad (3.18)$$

where A_i is the tuple of objective function values, A_i^{min} is the minimum of the objective function values across all solutions for objective i , and A_i^{max} is the

maximum of the objective function values across all solutions for objective i . Then this membership function is normalized using:

$$\mu^k = \frac{\sum_{i=1}^{N_{obj}} \mu_i^k}{\sum_{j=1}^{N_{sol}} \sum_{i=1}^{N_{obj}} \mu_i^j}, \quad (3.19)$$

where N_{obj} is the number of objective functions in the problem, N_{sol} is the number of solutions in the final set, and k is the index for each solution in the set. The best compromise solution is that solution k for which μ is the maximum.

Step 11) Calculate the Locational Marginal Prices (LMPs): Using the best compromise solution, the LMPs for each bus are calculated as the cost of supplying an additional MW into the system while satisfying all the transmission constraints and supply capacity constraints.

3.7 RL Solution Approach for the CMDP Model

Consider that at a decision making epoch, players make decisions which are sent to the system environment that provides feedback leading the system collectively to the next decision making state. As a consequence of the decisions and the resulting state transition, players get their rewards from the system environment. Using these rewards, the players update their knowledge base. The updating of the knowledge is carried out slowly while players explore other possibilities in their decision space. This process repeats and the players' decision making ability continues to improve and ultimately converges to

lead to equilibrium decisions. We next present an RL-based algorithm along the lines of one of our previous papers [74] for solving the CMDP model.

Learning Phase:

1. Initialize the following components of the algorithm:
 - Iteration count $m = 1$.
 - For all generators $k \in \mathcal{G}$, reinforcement values (R -values) $R^k(s) = 0$ for all states $s \in \mathcal{E}$
 - Average reward values $\rho^k = 0$.
 - Visit counter for each state-action combination (s, a^k) : $n(s, a^k) = 0$, where a^k is an element of the set of all actions $A^k(s)$ available to generator k in state s .
 - Learning rates (α_m, β_m) and the exploration rate (γ_m) .
 - *MaxSteps*, a large value, is designated as the termination criterion.
2. Start the system simulation in an arbitrary state s .
3. For each player $k \in \mathcal{N}$, with probability $(1 - \gamma_m)$, choose an action $a^k \in A^k(s)$ for which $R^k(s, a^k)$ is maximum. With a probability of γ_m choose a random (exploratory) action from the set $A^k(s) \setminus a^k$. At $m = 1$ (i.e., in the first step), choose an action randomly since all the R -values are zeros.

4. Send the generator bids to the DCOPF/MODCOPF program (Section 3.2 or 3.3).
5. Solve the DCOPF problem using the primal-dual interior point method explained earlier (Section 3.5) or the MODCOPF problem using the strength Pareto evolutionary algorithm presented earlier (Section 3.6).
6. Use the stochastic demands from the DCOPF/MODCOPF to determine the system state for the next decision epoch. Let the system state at that epoch be s' .
7. Calculate $r^k(s, s', a^k)$, the reward for k^{th} generator resulting from the actions (a^1, \dots, a^N) chosen by the generators 1 through N in state s (obtained from the DCOPF/MODCOPF problem).
8. Update $\forall k \in \mathcal{G}$ the R-values ($R^k(s, a^k)$) and the average reward (ρ^k) as follows.

$$R_{new}^k(s, a^k) \leftarrow (1 - \alpha_m)R_{old}^k(s, a^k) + \alpha_m(r^k(s, s', a^k) - \rho_m^k + R_{exp}^k(s')), \quad (3.20)$$

where

$$R_{exp}^k(s') = \sum_{a^k \in A^k(s')} p^k(s', a^k) R^k(s', a^k), \quad (3.21)$$

and

$$p^k(s', a^k) = \begin{cases} (1 - \gamma_m) & \text{if } a^k = \text{greedy action} \\ \frac{\gamma_m}{A^k(s') - 1} & \text{for other actions.} \end{cases} \quad (3.22)$$

$$\rho_{m+1}^j = (1 - \beta_m)\rho_m^k + \beta_m \left[\frac{m\rho_m^k + r^k(s, s', a^k)}{(m+1)} \right]. \quad (3.23)$$

9. Set $s \leftarrow s'$ and $m \leftarrow m + 1$.

10. Update the learning parameters α_m and β_m and exploration parameter γ_m following the DCM [82] scheme given below:

$$\Theta_m = \left(\frac{\Theta_0}{1 + u} \right), \quad \text{where } u = \left(\frac{m^2}{\Theta_\tau + m} \right), \quad (3.24)$$

where Θ_0 denotes the initial value of a learning/exploration rate, and Θ_τ is a large value (e.g., 10^4) chosen to obtain a suitable decay rate for the learning/exploration parameters. Exploration rate generally has a large starting value and a quicker decay, whereas learning rates have small starting value and very slow decay rates.

11. If $m < \text{MaxSteps}$, go to Step 3, else go to Step 12.

Learned Phase for Profit Calculation:

12. Simulate the system with the final R-values, $\{R^k(s, a^k) : \forall a^k \in A^k(s), k \in$

$\mathcal{G}, s \in \mathcal{E}\}$, and estimate the average profit for each generator. Profits are computed as the product of locational marginal prices and quantities supplied less the taxes paid for H_2O and CO_2 . These are assumed to be stable rewards (profits) realized by the generators in the day-ahead energy market.

Chapter 4

Numerical Analysis

This section is divided into two subsections. The first section, present the detailed numerical analysis about the impacts on a wholesale electricity market when a fixed tax for CO_2 emissions and water usage is imposed using different tax mechanisms. The second section provides the numerical analysis related to the calculation of an optimal tax rate for a given wholesale electricity market and the evaluation of the impacts of this optimal tax combination.

4.1 Implementation of a fixed tax rate under different tax mechanisms

The objective of this section is to assess the impacts of various carbon and water tax mechanisms, wind energy integration issues, and water supply disruptions on a wholesale electric power market. To accomplish this task

we use a 30-bus IEEE power network [83] as a testbed.

4.1.1 Network Details, Generation Costs, and Tax Assumptions

We selected a standard 30-bus IEEE power network from [83] and modified it slightly to suit our problem needs. Extensive details of the power network are not presented here for the sake of brevity. Interested readers, however, can find these details in the MATPOWER software package [83]. The 30-bus IEEE power network showed in figure 4.1 has 6 generators, 24 consumers, and 41 transmission lines. We assume that out of these six generators there are multiple fuel types, which allows us to assess the impacts of taxes on different generation technologies. We assume that there are three coal generators (100 MW each), two natural gas generators (100 MW each), and one nuclear generator (250 MW).

Based on literature, we made appropriate assumptions about the generator cost function characteristics (e.g., fixed cost of nuclear being higher than the others while its operational cost is lower; natural gas has a low fixed cost and a higher operational cost than the rest). The (X_i, Y_i) coordinates of the 3-part piecewise linear cost functions (base bids) of each of the six generators are presented in Table 4.1 (Y_i represents the price in \$/hr and X_i represents the quantity in MW). Generators are assumed to bid above the piecewise-linear marginal costs presented in Table 4.1. Each generator

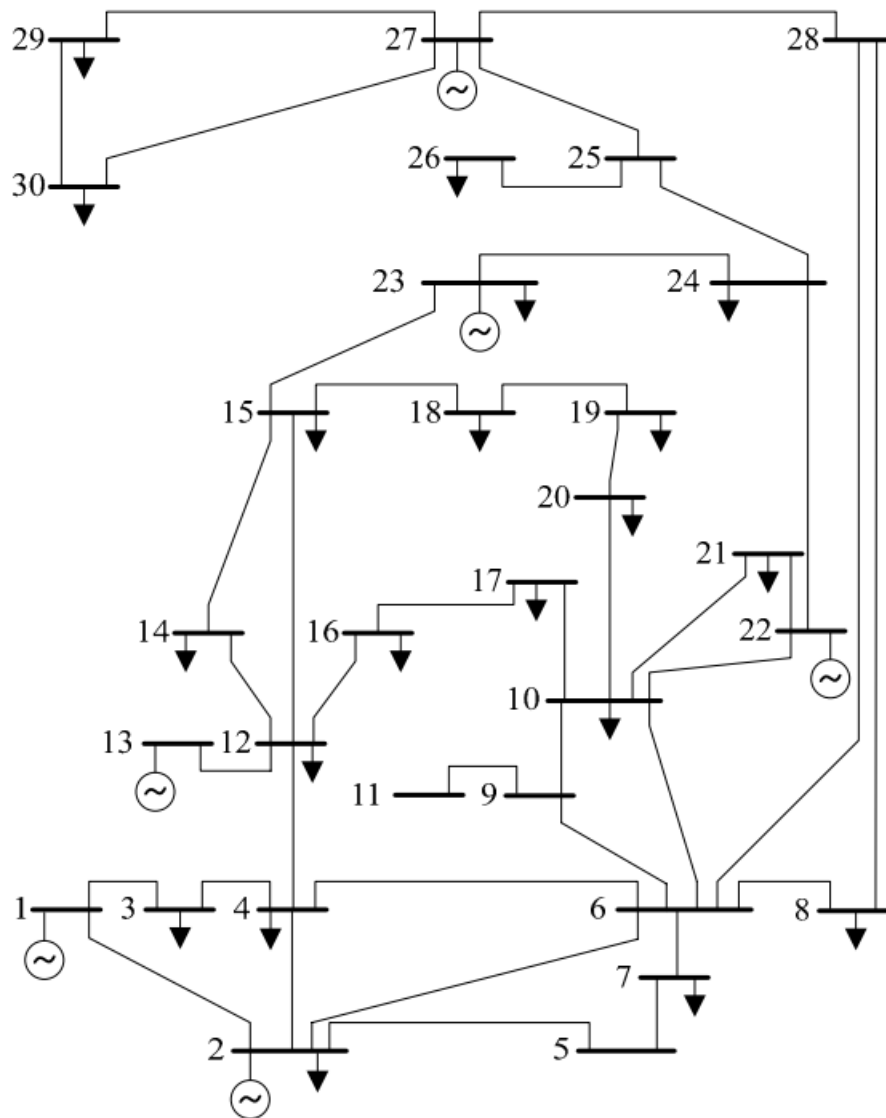


Figure 4.1: Single line diagram of the IEEE 30-bus test system [1]

is assumed to have a total of 30 action choices where each bid is 0.5\$/hr over the last bid. For example, the set of actions available for Coal1 are: $\{(0, 80.5), (12, 130.5), (36, 900.5), (60, 3200.5)\}; \{(0, 81), (12, 131), (36, 901), (60, 3201)\}; \dots; \{(0, 95), (12, 145), (36, 915), (60, 3215)\}$. Therefore, each generator has 30 different piecewise linear functions as action choices. This number can be increased or decreased as needed by the decision makers.

Consumer demand is assumed to be a normal random variable with the mean value as shown in Table 4.2 and standard deviation of 5MW for all consumers. Demand is assumed to increase at the rate of 5% each year. Transmission line capacity is assumed to be 1300MW throughout the power network, thereby removing any potential for transmission congestion. We do this to focus only on the impact of CO_2 and H_2O taxes. Impact of reduced transmission capacity that creates congestion can also be studied quite easily using our stochastic optimization model. Other network parameters of the IEEE 30-bus network are exactly as provided in the MATPOWER software package. The CO_2 emissions factors based on data from U.S. DOE and water usage factors from [84], are shown in Table 4.3.

Tax rate values for both CO_2 and H_2O are obtained from literature and have a wide variability (e.g., $\$5/KgCO_2 - \$95/KgCO_2$). Tax rates for H_2O have been obtained from research reports of the Australian Water Commission, which performed an economic valuation of water for electricity generation [85]. In this section, we used a value of $\$13/TonCO_2$ and $\$500/ML$ for carbon-dioxide emissions and water usage respectively. The planning horizon

Table 4.1: Piecewise linear cost functions of generators

| | (X0,Y0) | (X1,Y1) | (X2,Y2) | (X3,Y3) |
|----------------|---------|----------|-----------|-----------|
| Coal1 | (0,80) | (12,130) | (36,900) | (60,3200) |
| Coal2 | (0,80) | (12,130) | (36,900) | (60,3200) |
| Coal3 | (0,80) | (12,130) | (36,900) | (60,3200) |
| Gas1 | (0,50) | (12,170) | (36,1000) | (60,3400) |
| Gas2 | (0,50) | (12,170) | (36,1000) | (60,3400) |
| Nuclear | (0,120) | (12,260) | (36,800) | (60,3100) |

Table 4.2: Demands at each of the 30 buses

| Bus | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|-------------|------|------|------|------|------|------|------|------|------|------|------|------|-----|------|------|
| Demand (MW) | 0.0 | 31.7 | 12.4 | 17.6 | 0.0 | 0.0 | 32.8 | 40.0 | 0.0 | 15.8 | 0.0 | 21.2 | 0.0 | 16.2 | 18.2 |
| Bus | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 |
| Demand (MW) | 13.5 | 19.0 | 13.2 | 19.5 | 12.2 | 27.5 | 0.0 | 13.2 | 18.7 | 0.0 | 13.5 | 0.0 | 0.0 | 12.4 | 20.6 |

we consider is ten years. Longer planning horizons will need the examination of generation and transmission expansion planning issues, which are beyond the scope of this research.

In this subsection, we examine four main issues:

1. Impact of different tax schemes (for both water and CO_2)

Table 4.3: Emissions and water usage factors

| Generator Fuel Type | KgCO ₂ /MWh | MLH ₂ O/MWh |
|---------------------|------------------------|------------------------|
| Coal | 318.00 | 0.01325 |
| Gas | 184.64 | 0.00189 |
| Nuclear | 0.00 | 0.01512 |
| Wind | 0.00 | 0.00 |

2. Investment in new wind energy by existing generators (replacement)
3. Integration of additional stochastic clean energy resources (capacity additions)
4. Long-term disruptions/shortages of water supply (e.g., due to drought)

Figure 4.2 presents the complete step-by-step procedure we adopted for evaluating each of the four main scenarios presented above.

4.1.2 Impact of Different Tax Schemes (for both water and CO_2)

In this section we analyze the impact of three different tax schemes proposed for carbon-dioxide emissions by Metcalf and Weisbach [32]. Additionally, in this section we also impose a new water tax based on the amount of water used for generating electricity. Such analysis for a joint water and carbon tax scenario has not been presented in literature before. The three different tax scenarios we examine are the ones described in Section 2.3: 1) ramping up, 2) grandfathering, and 3) uniform adoption.

In Figure 4.3, the quantities supplied by each of the six generators are shown under no-tax (NT), ramping-up (RU), grandfathering (GF), and uniform adoption (UN) approaches over a ten-year horizon. In this case the CO_2 and H_2O taxes are assumed to increase by $\$5/KgCO_2$ each year and 5% each year, respectively.

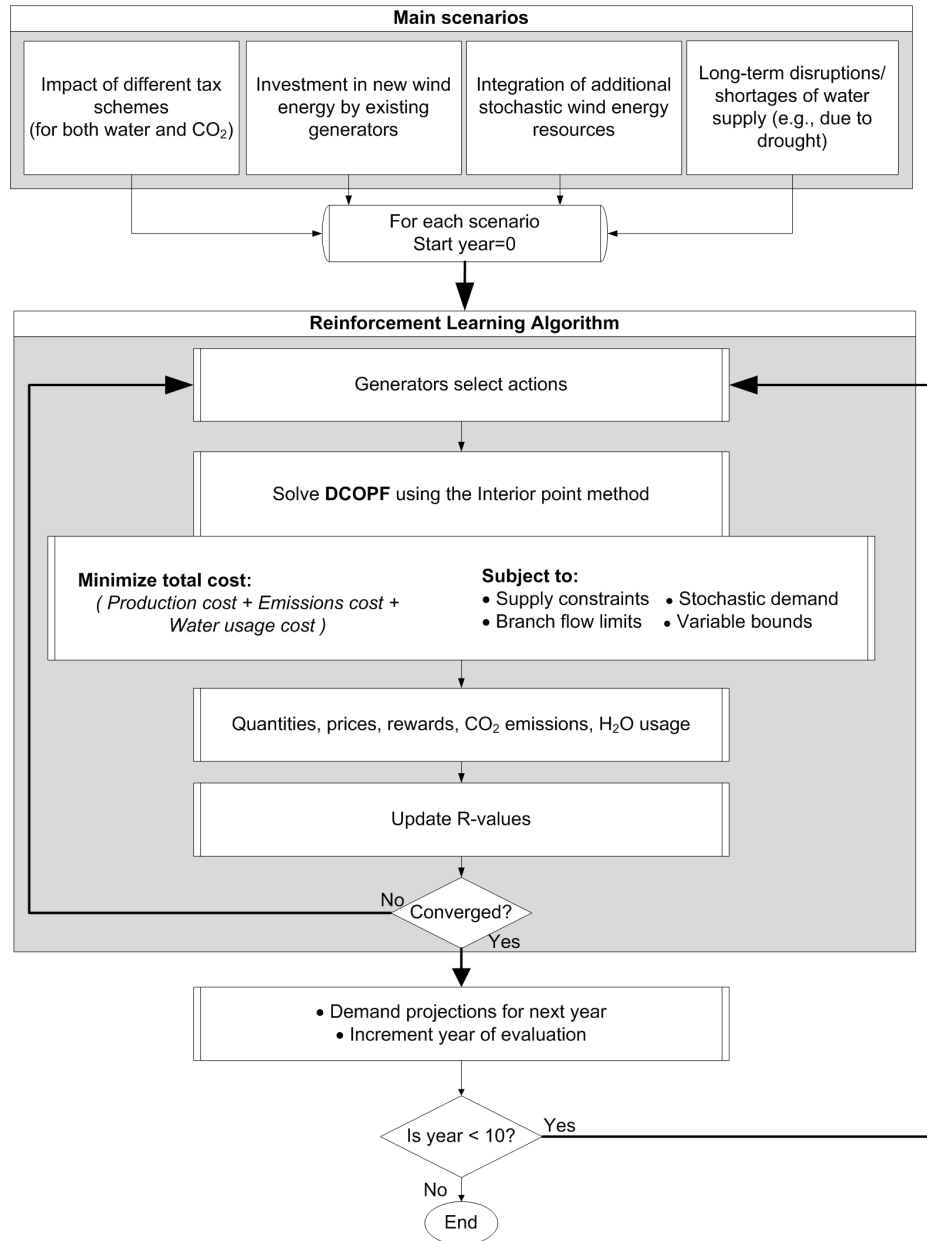


Figure 4.2: Flowchart of the solution procedure for all scenarios

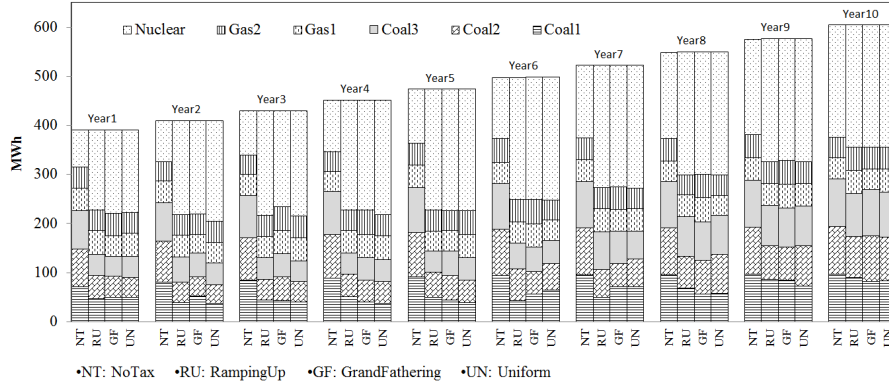


Figure 4.3: Quantities supplied by the six generators under different tax mechanisms over a 10-year horizon

It can be seen in the NT case that the average quantities supplied by each of the generators are directly related to their cost functions and maximum capacities. For instance, all the three coal generators supply up to their maximum capacity (100MW) as demand increases, given that they have the cheapest production cost; followed by the nuclear generator and then the gas generators. As expected, under the RU strategy, the average quantities supplied by coal generators are much smaller than the NT case due to the taxes on CO_2 and H_2O . Even though the nuclear generator does not emit any CO_2 , it uses higher quantities of water than the other generators, however, nuclear generators are still cheaper than gas generators. Hence, in the RU case, after the nuclear generator reaches its maximum capacity (250MW), the coal generators absorb the residual demand in the power network before gas generators are dispatched. In the GF case one would expect that coal generation would be higher than that of either RU or UA. However, in

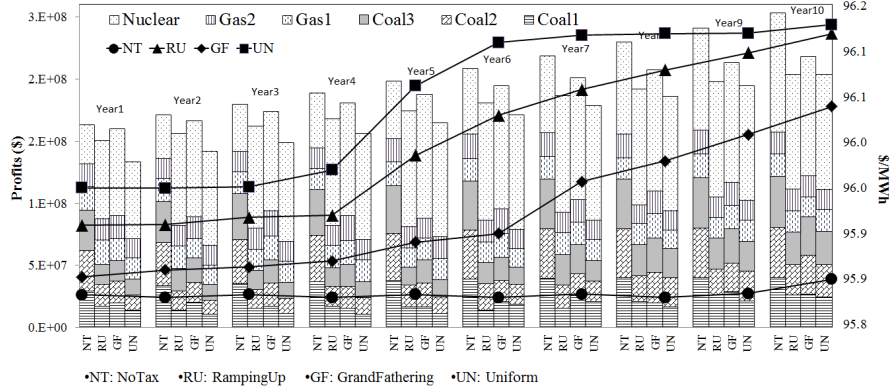


Figure 4.4: Average Locational Marginal Prices and Average Profits for the Various Tax Mechanisms over a 10-year Horizon

this specific case study the monetary values between the taxes are not that different and hence the lack of perceivable variations in quantities supplied. The differences in profits of coal generators between the tax schemes are nevertheless clearly visible in Figure 4.4. Under the UN case (Figure 4.3), the nuclear generator supplies more than under other mechanisms until Year 4, after which its supply quantities are almost the same under all three tax schemes.

In Figure 4.4 the average locational marginal prices (secondary Y-axis) under the three different tax mechanisms are shown. The NT scenario serves as the lower bound on the average LMP, with UN mechanism serving as the upper bound. These prices could potentially vary a lot more if transmission capacity becomes insufficient. As expected the prices are in the order of severity of the tax mechanism. Figure 4.4 also shows the average yearly profits obtained by all generators across the ten year horizon (primary X-

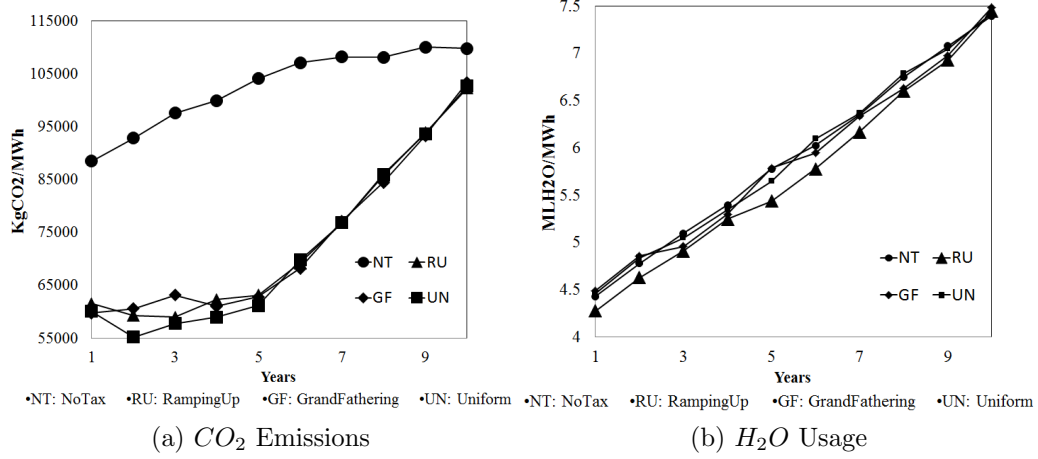


Figure 4.5: Emissions and Water usage Trends under Different Tax Mechanisms

axis). The UN mechanism appears to have the most negative impact on the profits of coal generators and vice-versa for nuclear generators. The profits of most generators from the GF scheme, as expected, are higher than RU and UN but lower than the NT scenario.

From Figure 4.5a, notice that by implementing the UN mechanism, lowest CO_2 emissions are produced by the system, followed by the RU, GF, and NT mechanisms. However, the reductions in CO_2 emissions in this particular network come at the cost of higher water usage due to the increased dispatch of nuclear generators. Therefore, in highly water-stressed areas, system operators may be better off encouraging investments in renewable energy technologies rather than ramping up production from nuclear generators. It can be seen from Figure 4.5b that in most cases the NT scenario acts as the upper bound for the water usage. While the difference in trends of CO_2

emissions between the tax mechanisms was clear, the water usage trends are not as clear. We believe this could be due to the relatively lower rate of water usage tax for each MWh of power generated as compared to CO_2 taxes. In the next section we examine the issue of replacing coal generators with wind generators.

Note: From this point forward within this section, for the ease of exposition, all model simulations are performed assuming that the uniform adoption (UN) tax mechanism is used.

4.1.3 Investment in New Wind Energy by Existing Generators

In this portion of the study, we assume that the coal generators are replaced by wind generators of equal capacity (one at a time). As noted in [86], we assume that the cost characteristics of the wind farm are similar to that of a nuclear generator (high fixed cost and very low operational cost). A zero cost can also be assumed in our model as noted in some literature. Figure 4.6 shows the individual supply shares across a ten year horizon when the coal plants are replaced by wind farms of the same capacity. We perform this analysis by replacing one coal plant at a time (1Cby1W-refers to replacing one coal plant by one wind farm; 2Cby2W refers to replacing two coal plants by two wind farms). Across all the 10 years, in both 1Cby1W and 2Cby2W cases the wind generators supply to their maximum capacities (100MW)

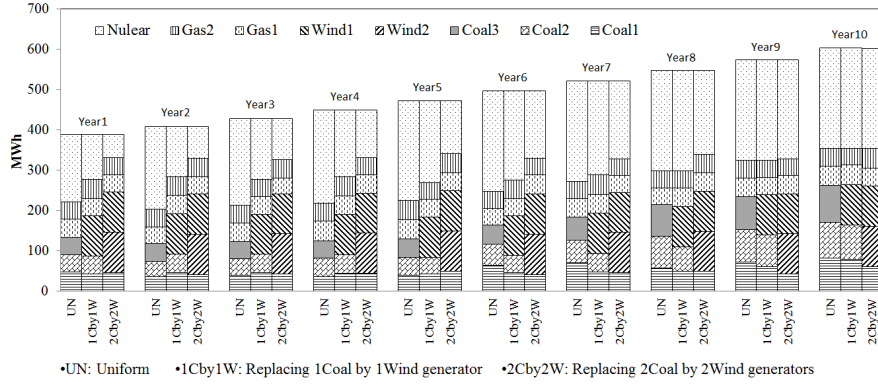


Figure 4.6: Supply Shares when Replacing Coal with Wind

immediately. It can be seen that the supply share of the nuclear generator is reduced significantly as the number of wind generators increases from one to two. Coal generators begin to see their supply shares rise only when the demand increases cannot be met by the wind and nuclear generators.

4.1.4 Integration of Additional Stochastic Wind Generators

The goal of this subsection is to study the system performance due to integration of additional wind energy resources into the existing power network (unlike the previous replacement case). We also extend the analysis by studying the impact of stochastic and intermittent nature of wind energy availability as well as the imposition of a penalty by the system operator on wind generators if the promised generation capacity is not available. Both these extensions make the study much more realistic. Wind energy avail-

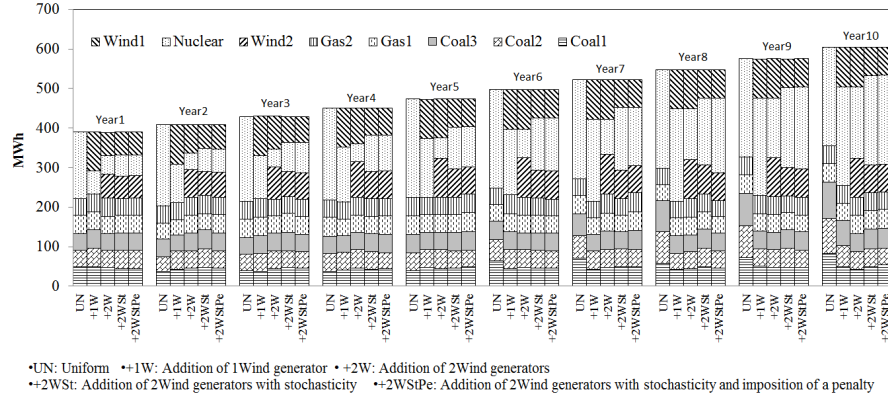


Figure 4.7: Integration of Wind Energy in the Power Network

ability is a random variable with overall capacity factors ranging between 20%-40% (with on-site storage, this can be increased further). Therefore, studying the stochastic nature of wind generation is critical. As in some papers in the literature [87], we also impose penalties on wind generators who do not meet their obligations. In Figure 4.7 +1W refers to the addition of one wind generator (100MW), +2W refers to the addition of two wind generators (100MW each), +2WSt refers to the addition of two wind generators with stochasticity, and +2WStPe refers to the addition of two wind generators with stochastic availability and the imposition of an exogenous penalty for not being able to meet promised generation.

In the +1W case, the addition of a new wind generator causes a marked decrease in the amount of nuclear generation. In all the ten years in the +1W case the wind generator supplies up to its maximum capacity. In the +2W case also, both wind generators are almost dispatched to their full capacities

(100MW each) in lieu of nuclear generation, which also prevents any increase in supply by the coal or natural gas generators.

Modeling the Stochastic Nature of Wind

We incorporated the stochasticity in wind energy availability as follows. Thirty percent of the time the wind generators are assumed to be fully available and the rest of the time, the generators are said to be partially available between 30% – 90% of their maximum capacities. While we understand that the capacity factors in most cases are between 20-40%, these wind generators could be thought of as those with on-site storage devices. We do not model wind speed forecasting considerations. For each run (hour) of the simulation we generated random numbers to first determine their initial state of availability. If the generators are partially available, then the percentage of partial availability is also determined by drawing random numbers from a uniform distribution. In the $+2WSt$ case, it can be seen (Figure 4.7) that the stochastic nature of wind generators has a negative impact on their supply shares when compared to the $+1W$ and $+2W$ cases. As the demand increases the wind energy unavailable due to stochasticities is filled in by the nuclear generator. Coal and natural gas generation, however, remain relatively stable in all the ten years of the study horizon.

Imposition of a Penalty Factor due to Unavailability of Promised Wind Generation

We also investigated the impact of potential penalties imposed by system operators on wind generators if promised capacity is not available after bidding

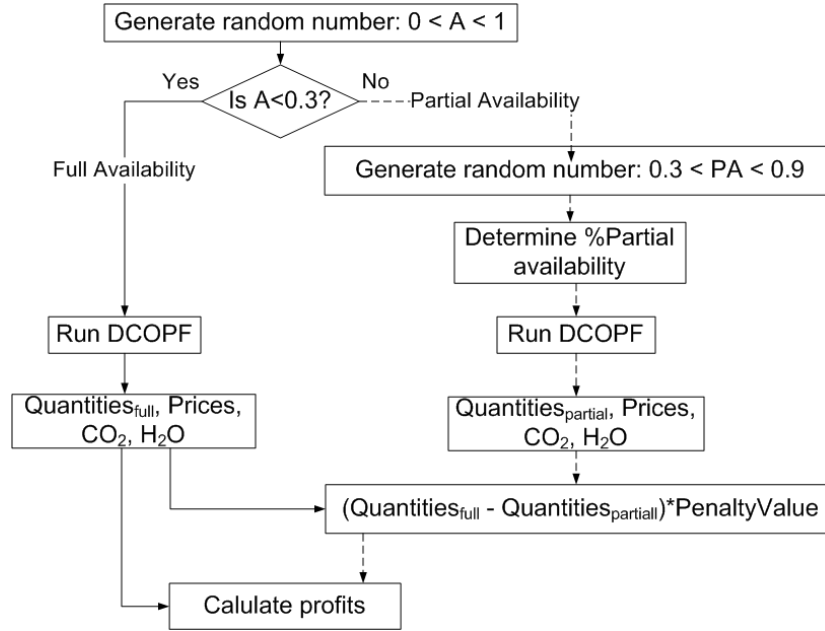


Figure 4.8: Steps in Modeling the Penalty for Stochasticity of Wind Generators

in the power market. We incorporated this in our stochastic optimization model as shown in Figure 4.8. The penalty value we considered is $\$5/MWh$. This value can be modified as needed. It was noticed that the behavior of all generators in the $+2WStPe$ case was very similar to the $+2WSt$ case. We believe that this is due to the low value of penalty that was used for testing in our sample problem.

In the $+1W$ case (see Figure 4.9a), when the new wind generation displaces the nuclear generation, CO_2 emissions remain practically unchanged. The CO_2 emissions remain almost the same even with the addition of another wind generator, since the additional wind generation replaces the nuclear gen-

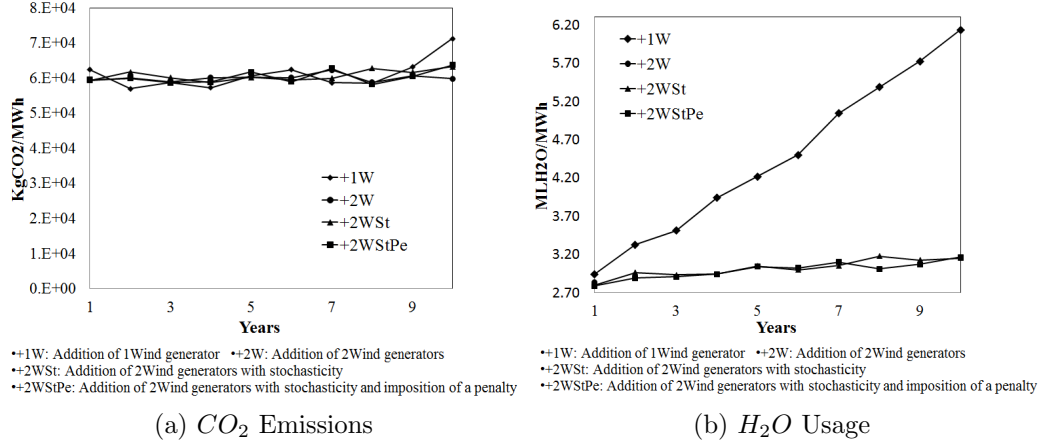


Figure 4.9: Emissions and Water usage Trends due to Integration of Wind Energy

eration. In Figure 4.9b we can see that for water usage, +1W serves as the upper bound while +2WStPe serves as the lower bound.

4.1.5 Long-term Disruptions/Shortages of Water Supply

Disruptions in water supply are becoming increasingly frequent due to drought and other climate-change induced conditions. Power production depends on water and its shortage has been shown in the literature to cause shutdowns or reductions in electricity generation capacities ([88, 89]). In this section we examine the impact of reduction in capacities of power generators due to long-term water supply shortages as a result of prolonged drought or similar events. Since nuclear and coal generators are the largest consumers of water, we first study the impact of water shortages on these generators. We then

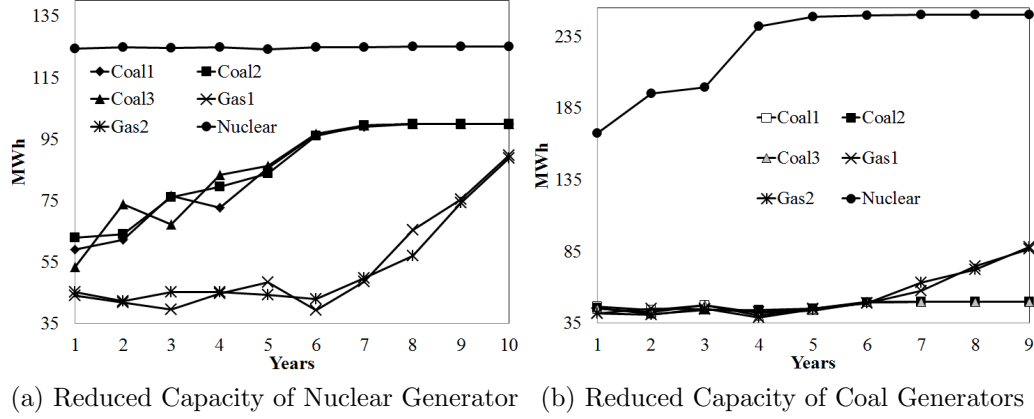


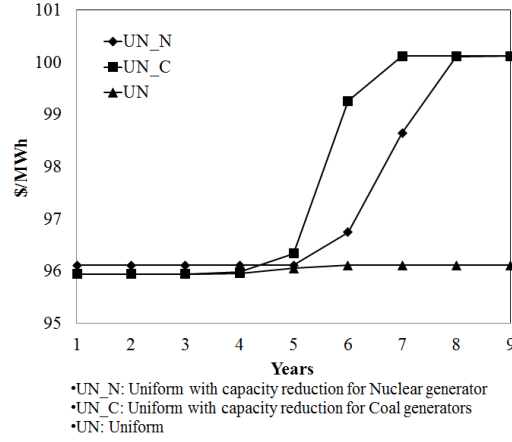
Figure 4.10: Supply Shares under Reduced Capacities due to Water Shortages

studied the impact of addition of stochastic wind energy resources in addition to long-term water supply disruptions.

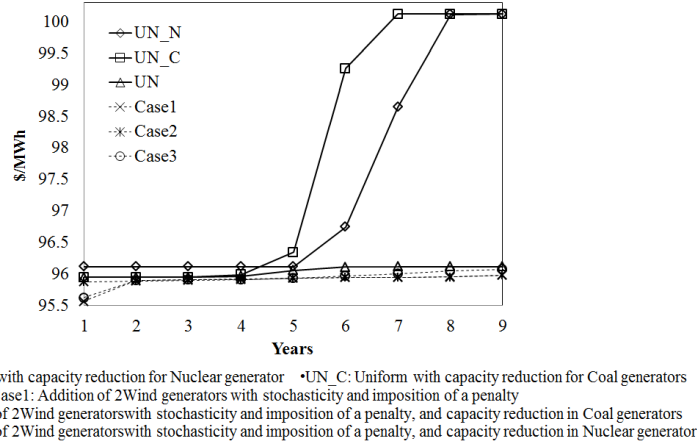
Impact of Water Shortages on Coal and Nuclear Generators

In this case we assumed that due to prolonged water shortages, capacities of all the coal generators and the nuclear generator are reduced by half (one generation technology at a time). In Figure 4.10a, it can be seen that the nuclear generator with its capacity reduced from 250MW to 125MW, supplies up to its new maximum capacity for all ten years. The residual demand is then first absorbed by coal plants followed by the natural gas plants starting Year six. In Figure 4.10b, where the capacity of coal generators is reduced by half (50MW each), the nuclear generator supplies up to its maximum capacity starting Year five. Natural gas generators are only dispatched starting Year seven. This reordering of dispatch involving gas generation is also reflected

in increased prices as shown in Figure 4.11a. In this figure, UN_N refers to capacity reduction for nuclear generator, UN_C refers to capacity reduction for coal generators, and UN is the uniform adoption case from Section 4.1.2.



(a) Reduced Capacity of Nuclear Generator



(b) Reduced Capacity of Coal Generators

Figure 4.11: LMPs under Reduced Capacities due to Water Shortages

Joint Impact of Water Shortages and Integration of Stochastic Wind Energy Resources

We also extended the case examined in Section 4.1.5 by integrating stochastic wind energy resources (as in Section 4.1.4) and the imposition of penalties (as in Section 4.1.4). These extensions make the model as close to a realistic power network as possible. This analysis involves all types of generation technologies, stochastic demands, stochastic availability of wind power generators, and water shortages. For the sake of brevity, we present the results for average prices for the three different cases superimposed over the price graph from the previous section (see Figures 4.11b and 4.11a). In Figure 4.11b, Case1 refers to $+2WStPe$ scenario from Section 4.1.4, Case2 refers to both $+2WStPe$ conditions and capacity reductions in coal generation (down to 70MW each from 100MW) due to water shortages, and Case3 refers to $+2WStPe$ conditions and capacity reduction in nuclear generation (down to 175MW from 250MW) due to water shortages. It can be observed that in the case of additional wind generation becoming available, the price increases that were observed earlier are now prevented. The prices in all three cases remain below the reference UN case. This can be attributed to the large amount of wind generation that is included as part of the dispatch, which does not involve either a water or CO_2 tax. Under drought-like conditions, system operators could prevent price spikes by encouraging investments in wind or other green technologies.

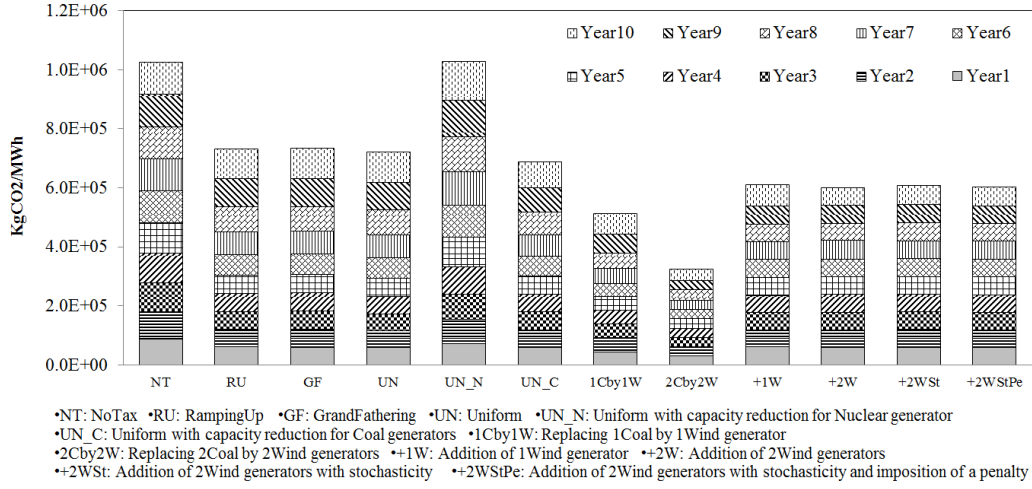
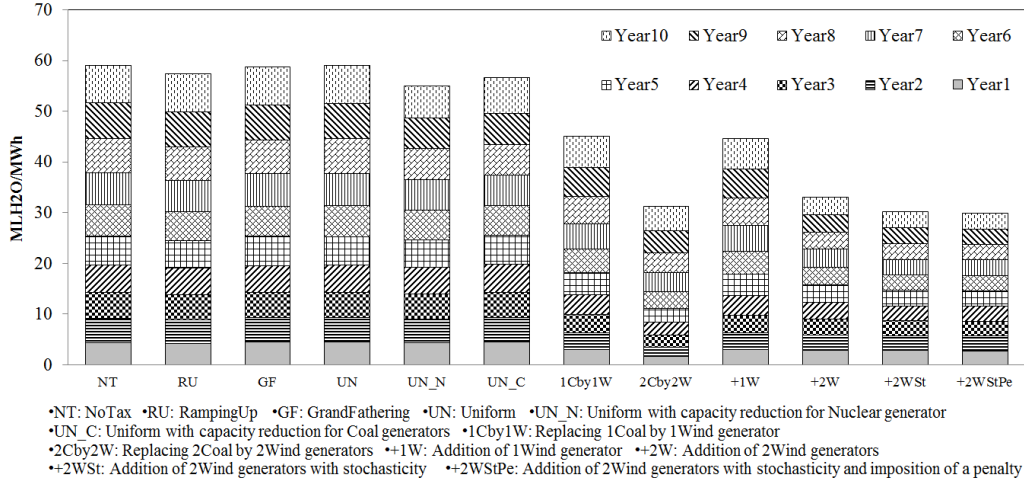


Figure 4.12: Total CO_2 Emissions across all Scenarios

4.1.6 Overall Scenario Analysis

In this section we present the summary of all the twelve comprehensive scenarios we studied in this section with respect to CO_2 emissions and H_2O usage (see Figures 4.12 and 4.13). It can be seen that the UN_N case acts as the upper bound on CO_2 emissions while the NT case serves as the upper bound for H_2O usage. We believe that if the goal of the system operator is to minimize both the overall CO_2 emissions and H_2O usage, the $2CBy2W$ (replacing two coal by two wind generators) setting would be ideal. Addition of wind energy resources has been noted by the Department of Energy as a comprehensive solution for preventing excessive water withdrawals, especially in drought prone areas. There is approximately a 60% reduction in 10-year CO_2 emissions and 40% reduction in water usage between the NT

Figure 4.13: Total H_2O Usage across all Scenarios

case and the $2CBy2W$ case.

However, the $2CBy2W$ setting is not entirely realistic, since it does not consider stochasticity of wind or penalties due to non-availability. The $+2WStPe$ case is a good representation of reality, albeit without consideration of water supply disruptions. The UN_N case (extension of UN case) which considers water supply disruptions to the nuclear generator gives an idea of the negative impact that water shortages could have if there are prolonged droughts in a region without any wind/green energy. In the UN_C case (extension of UN case) which considers water supply disruptions to the three coal generators, the ten year CO_2 emissions drops, but the water usage increases significantly. This is due to the nuclear generator (the largest user of water) and natural gas generators supplying the residual demand.

4.1.7 A Note on Computational Time and Resources

The RL-based solution approach is computationally intense. We developed the code for the RL algorithm as well as the DCOPF problem in $C++$. We executed the code on research computing clusters at University of Wisconsin-Milwaukee. The cluster has 142 compute nodes (1136 cores), each node is a Dell PowerEdge R410 rack-mount server with two quad-core 2.67 GHz, Intel Xeon X5550 processors, and 24GB of system memory. All the cases were simulated for 5000 runs. The base case with six generators took a total of 3 minutes while the largest case with 8 generators with stochastic wind energy scenario took a total of 9.6 minutes.

4.1.8 Concluding Remarks

In this research we developed a first-of-its-kind quantitative model to study the electricity-water-climate change nexus. We examine this nexus by imposing H_2O usage and CO_2 emissions taxes on power generators in a wholesale electricity market. We adopt a CMDP approach to model the competitive behavior of power generators who bid daily into a wholesale market under stochastic demand conditions as well as under carbon-dioxide and water taxes. The CMDP model is solved using a stochastic approximation based reinforcement learning mechanism. The outputs of the RL algorithm are stable bidding strategies for all generators which are used to obtain the average rewards over a demand season.

This section examined four main scenarios including different tax schemes proposed in literature, replacement of coal generation by wind, integration of additional stochastic wind energy resources, and water supply disruptions. We found that if the goal is to minimize both CO_2 emissions and H_2O usage, new green generation should replace coal and nuclear generation. This is also prescribed by Sovacool and Sovacool in [5]. However, given the political and practical difficulties in achieving this goal, we also studied the impact of integration of new wind energy resources which are intermittent and stochastic but have begun to bid into daily electricity markets. Further the case of water droughts impacting coal and nuclear generation was also examined.

In this section we used exogenous tax rate values from literature. In the section 4.2 we conduct a detailed analysis to obtain optimal tax rates for both carbon and water for a given regional power network. While this has been noted as an extremely challenging task by Stern Review [33], our model could be used as a viable tool for such analysis.

4.2 Calculation and implementation of optimal tax rates

The objective of this section is to show the use of our model in obtaining optimal tax rates for carbon emissions and water usage of a given wholesale electricity market. Based on a Central Composite Design, different scenarios of tax rates were created to be simulated. The impositions of all the tax combinations were simulated by solving the multi-objective DCOPF presented

in Section 3.3. The response variable values for each tax combination were obtained. By response optimizer, the optimal tax rates were identified for both CO_2 and water usage. In addition, we also study the impact of the imposition of this optimal tax combination on different scenarios of electricity power networks to analyze the behavior of the energy market.

4.2.1 The Model

Our overall model is developed in two phases as shown in figure 4.14. The first phase involves the calculation of optimal tax rates using a response surface method, and the second phase involves the imposition of these taxes on a wholesale power market, which is modeled using a CMDP approach and solved using the reinforcement learning approach presented in Section 3.7.

4.2.1.1 Calculation of optimal tax rates

In order to find the optimal combination of tax rates for CO_2 emissions and H_2O usage, a three-step procedure was used.

1. A Central Composite Design (CCD) framework of response surface method (RSM, [90]) was used to design the experiment.
2. Response variables for each treatment of the CCD were calculated using a simulation model of the electric power network. The electric power

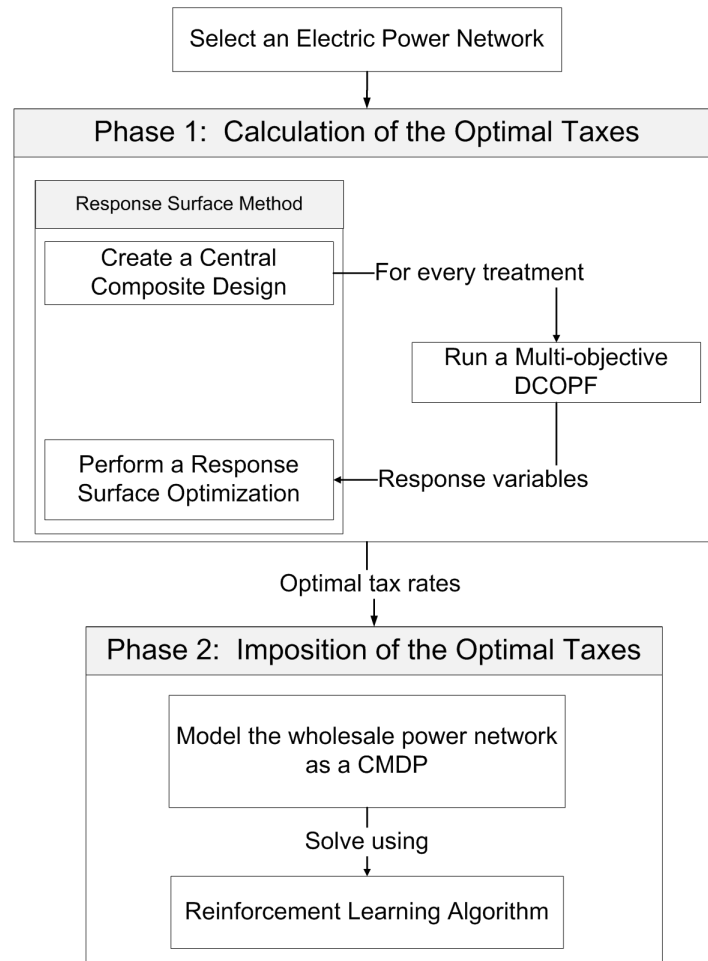


Figure 4.14: Optimal tax rates calculation and evaluation Model

grid operations were optimized using a multi-objective DCOPF model (described in detail in Section 3.3).

3. The optimal tax rate treatment combination was calculated using a response surface optimizer.

4.2.1.2 Response Surface Method

A RSM was used to obtain the optimal combination of CO_2 emissions and H_2O usage tax rates that minimize: 1) the total power generation cost, 2) the total CO_2 emissions cost, and 3) the total H_2O usage cost. A full CCD with two factors (CO_2 and H_2O tax rates) was created to identify the treatments to be simulated on the sample power network. These simulations were performed by solving a multi-objective optimization model for every treatment combination in order to obtain the following responses variables: 1) total cost of generation, 2) total CO_2 emissions, and 3) total H_2O usage. Finally, a response surface optimization was carried out to obtain the optimal tax rate combination for the given electric power network.

The Minitab© response optimizer tool was used to perform the response surface optimization. This tool implements the common desirability approach presented in [90] and [91] to optimize multiple responses variables at the same time. This method uses desirability functions to transform each response variable into a non-measured individual desirability value; then a weighted combined desirability function is calculated; and finally a reduced gradient algorithm is implemented to find the maximum composite desirabil-

ity for a specific tax rate combination, which is considered to be optimal.

4.2.2 Network Details, Generation Costs, and Tax Assumptions

As in Section 4.1.1, we selected the 30-bus IEEE power network found in Matpower package [92]. This power network has 30 buses, six generators (2-coal, 2-gas, and 1-nuclear), and 41 transmission lines. We assumed a maximum electricity generation capacity of 100MW for each coal generator, 100MW for each gas generator, and 250MW for the nuclear generator. The complete power network details can be found in [92], the one-line diagram is shown in Figure 4.1. Table 4.4 shows the emissions and water usage factors for every generation technology simulated. The CO_2 emissions tax and H_2O usage tax are the two factors in the response surface analysis. The low values for each factor were $\$0/TonCO_2$ and $\$0/MLH_2O$, and high values were $\$85/TonCO_2$ and $\$900/MLH_2O$ respectively. Our motivation for choosing these ranges of values for CO_2 and H_2O taxes was based on openly available literature about carbon and water tax rates [32, 85]. The advantage of using a simulation-based optimization model is that one can modify these ranges as needed to understand their implications.

The complete experimental framework based on a CCD is presented in Table 4.5 with the respective response variables obtained from solving the MO-DCOPF. For instance, in Table 4.5 row 4, for the combination of tax rates of

\$0.085/ $TonCO_2$ and \$900/ MLH_2O we solved the MO-DCOPF problem and obtained the response variables shown in corresponding columns. Minitab© statistical software was used to perform the response surface optimization, and Minitab response optimizer tool was used to obtain the optimal tax rate combination for the sample electricity network.

Table 4.4: Emissions and water usage factors

| <i>GeneratorFuelType</i> | <i>KgCO₂/MWh</i> | <i>MLH₂O/MWh</i> |
|--------------------------|-----------------------------|-----------------------------|
| Coal | 318.00 | 0.01325 |
| Gas | 184.64 | 0.00189 |
| Nuclear | 0.00 | 0.001512 |

Table 4.5: Central Composite Design

| <i>Run</i> | <i>Factors</i> | | <i>Response variables</i> | | |
|------------|--------------------------|--------------------------|---------------------------|-------------------------------------|---------------------------------|
| | <i>TaxCO₂</i> | <i>TaxH₂O</i> | <i>TotalProdCost</i> | <i>TotalCO₂Emissions</i> | <i>TotalH₂OUsage</i> |
| 1 | 0 | 0 | 22098.7 | 91022.6 | 4.47 |
| 2 | 0.085 | 0 | 22148.1 | 48123.4 | 4.71 |
| 3 | 0 | 900 | 22657.3 | 84646.5 | 2.98 |
| 4 | 0.085 | 900 | 22965.8 | 67606.7 | 3.36 |
| 5 | 0 | 450 | 22711.7 | 85347.5 | 2.97 |
| 6 | 0.1026 | 450 | 23376.4 | 67538.5 | 3.39 |
| 7 | 0.0425 | 0 | 22196.7 | 48647.1 | 4.70 |
| 8 | 0.0425 | 1086.4 | 23355.1 | 66173.2 | 3.36 |
| 9 | 0.0425 | 450 | 23569.7 | 65166.5 | 3.41 |
| 10 | 0.0425 | 450 | 24166.5 | 64261.2 | 3.36 |
| 11 | 0.0425 | 450 | 23499.7 | 64993.1 | 3.48 |
| 12 | 0.0425 | 450 | 23303.1 | 65944.3 | 3.47 |
| 13 | 0.0425 | 450 | 23386.9 | 65734.5 | 3.45 |

4.2.3 Finding the optimal tax rates

From Figure 4.15a, notice that the lowest value of the total production cost is obtained when there is no tax in the system, meaning that coal generators are the ones supplying most of the electricity demanded in the system. The highest values of the total production cost are found in the center part of

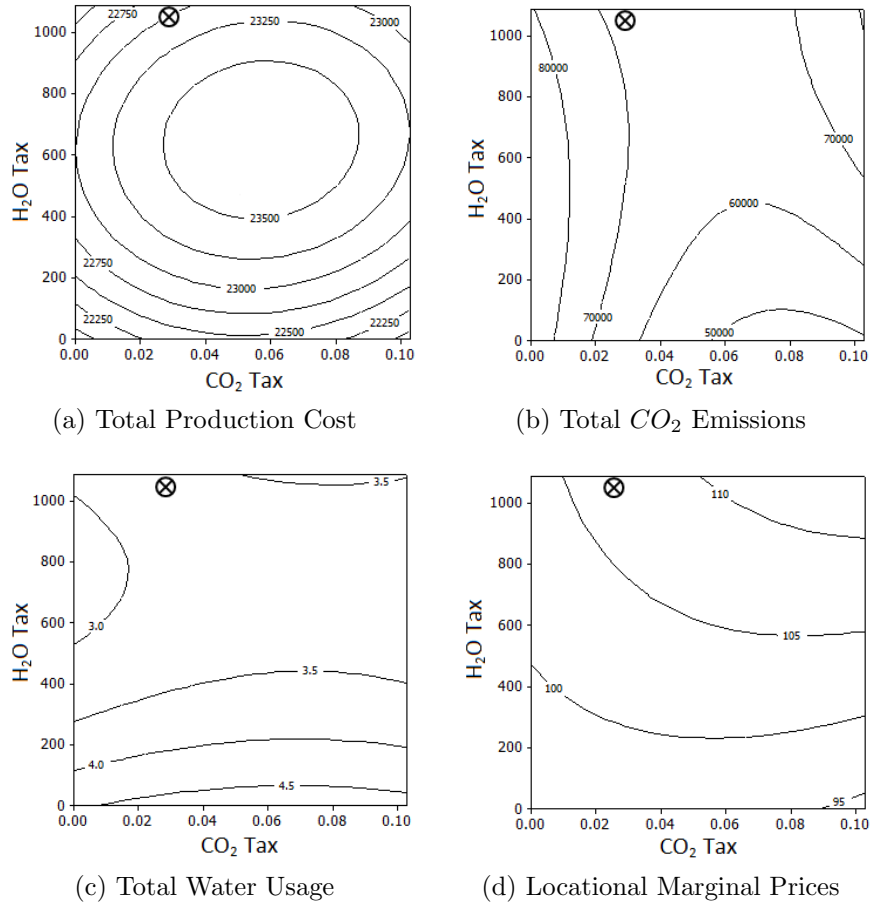


Figure 4.15: Contour plots

the Figure 4.15a where gas generators and nuclear generator are the ones supplying most of the total demand (see Figure 4.16 Combs. 9-13).

From Figure 4.15b, notice that when there are no taxes in the system, the highest value of CO_2 emissions are obtained. This is because coal generators supply most of the demand as seen in Figure 4.16 (Comb. 1). The same results are obtained when there is no CO_2 tax but H_2O tax, in these cases

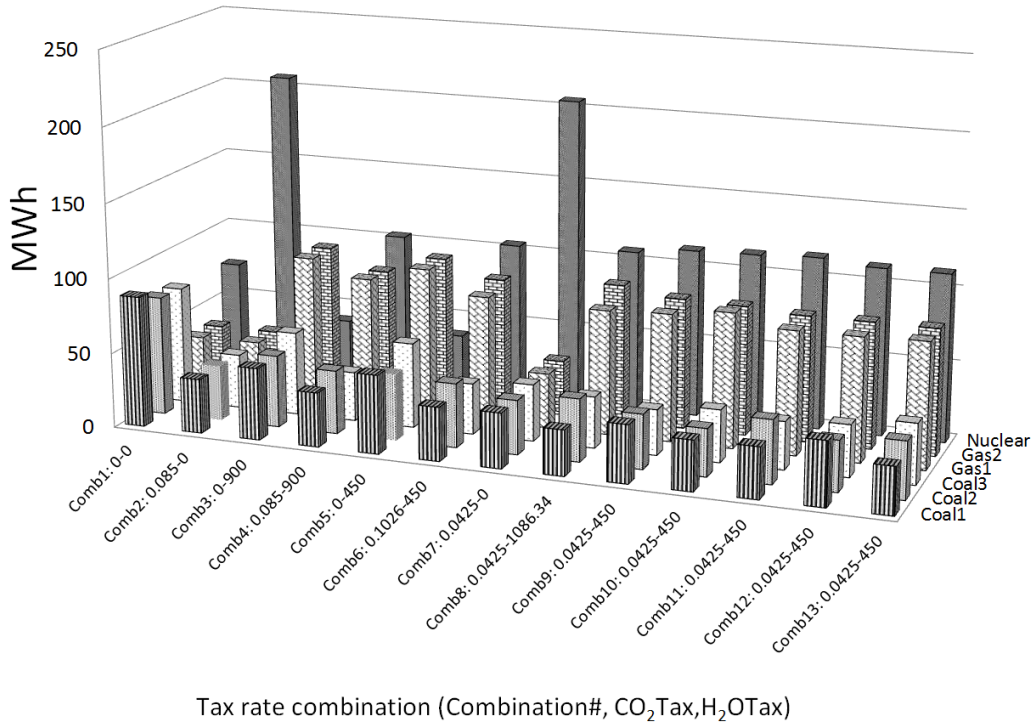


Figure 4.16: Supply Shares for the CCD treatments

coal and gas generators supply most of the demand, and the nuclear generator only supply a small quantity of electricity into the system, (see Figure 4.16 Combs 3 and 5). In contrast, notice that lowest values of CO_2 emissions are found when higher values of CO_2 tax are imposed into the system, this is because nuclear generator becomes the largest supplier of electricity in the system given that it has the lowest CO_2 emission factor, see Figure 4.16 combination 2 and 7.

From Figure 4.15c, notice that with low values of both taxes, high values of H_2O usage are observed, this is because coal generators and nuclear

generator are the biggest suppliers (see Figure 4.16 Comb. 1). The highest values of H_2O usage are obtained when there is no H_2O tax but high CO_2 tax, in this case the nuclear generator is the one supplying the larger share of electricity into the system (see Figure 4.16 Combs. 2 and 7). The lowest values of H_2O usage are obtained when highest values of H_2O tax are imposed, then gas generators becomes the largest producers of electricity (see Figure 4.16 Combs. 3 and 5).

When we consider locational marginal prices in Figure 4.15d, notice that lowest values are observed when both CO_2 and H_2O taxes are low, while highest values are observed when tax rates for CO_2 and H_2O are increased.

After applying the Desirability Method mentioned in Section 4.2.1.2 by using the Minitab response optimizer tool, it was found that the combination of \$0.0269 for CO_2 tax and \$1086.39 for H_2O usage tax represents the optimal combination. This tax combination happens to be optimal for the given sample network when the goal is to minimize all the three objective functions presented in Section 3.3.

4.2.4 Implementation of optimal tax rates under different tax mechanisms

In this section we present the detailed numerical analysis that were performed to demonstrate the applicability of our multi-objective optimization and RL framework to understand the implications of a joint carbon and water tax

scenario. We study four main cases in this paper:

1. Imposition of the optimal tax rates on a sample power network
2. Adoption of water saving technologies by power generators
3. Impact of tax credits for generators who have invested in water saving technologies
4. Integration of Hydro power generation

4.2.4.1 Imposition of the Optimal Tax Rates

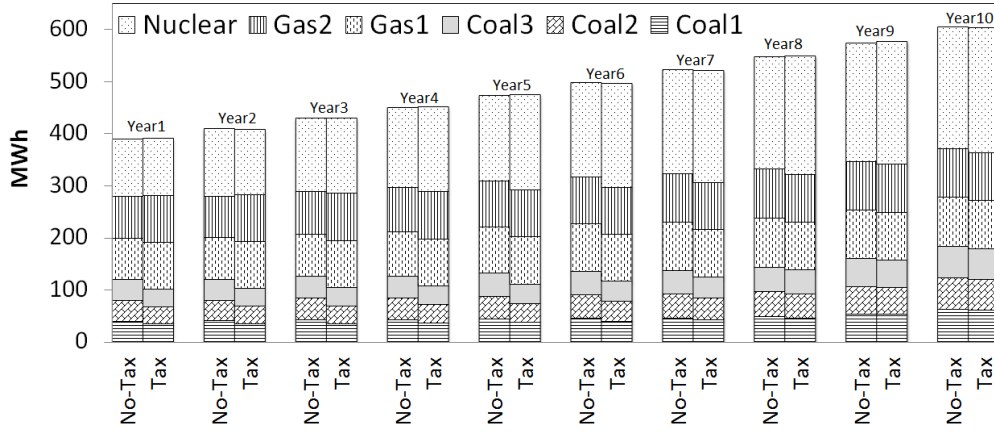


Figure 4.17: Supply Shares under Optimal Tax Imposition

The goal of this section is to evaluate the impact of the imposition of the optimal taxes found in the previous section for CO_2 emission and H_2O usage. Tax case (Tax) refers to the scenario where the optimal taxes are

imposed, and is compared against the scenario with no tax (No-Tax). Figure 4.17 shows that natural gas generation behaves as the dominant electricity supplier for both cases until year 5 when these generators reach their maximal capacity. After this, nuclear generation increases rapidly. Notice that after imposing the optimal CO_2 and H_2O taxes, coal generation is negatively impacted and its electricity generation is reduced. Gas generators absorb the amount of the demand that is not longer fulfilled by the coal generators. In this scenario, gas generators seems to be a moderate option under the three objective functions evaluated and presented in Section 3.3.

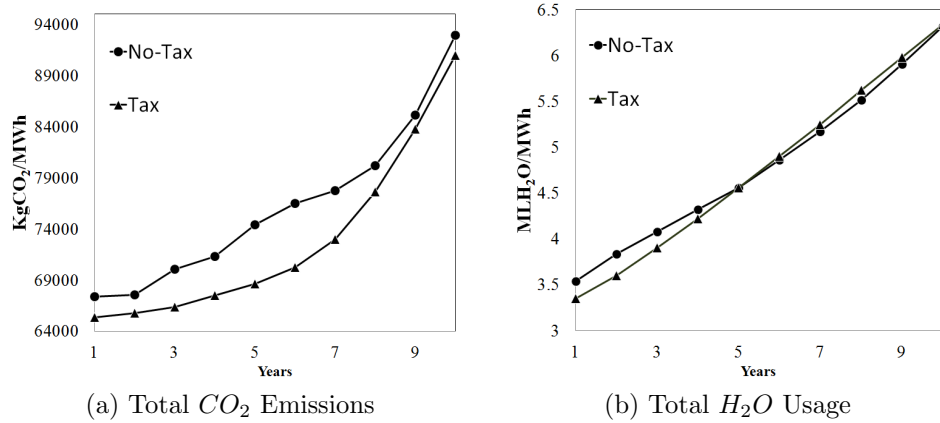


Figure 4.18: Emissions and Water Usage under Optimal Tax Imposition

From Figure 4.18a, it is clear that under the imposition of the optimal taxes, lower CO_2 emissions are produced. Similarly, from Figure 4.18b, we can see that the lower quantities of H_2O are used from year 1 to 5. This is because at year 5, the gas generators reach their maximal capacity of electricity production, and the new demand is absorbed by the nuclear generator

which has a higher H_2O usage factor than gas generators, but lower than the coal generator.

4.2.4.2 Adoption of Water Saving Technologies (WST)

In this section, we study the scenario where all electricity generators are assumed to incorporate water saving technologies in their cooling systems by using wet-recirculating or closed-loop technologies. For this section and for the following cases presented in this paper, all cases use the optimal taxes in the simulations. The water usage factors used for this section are presented in the Table 4.6 as noted in [93]. Notice that by using water saving technologies the usage factors are reduced.

Table 4.6: Water Usage Factors under Closed-Loop Technology

| <i>Technology</i> | <i>MLH₂O/MWh</i> | |
|-------------------|-----------------------------|-------------------|
| | <i>No – WST</i> | <i>With – WST</i> |
| Coal | 0.0132 | 0.0038 |
| Nuclear | 0.0151 | 0.0042 |
| Gas | 0.0019 | 0.001 |

From Figure 4.19, notice that under water saving technologies (Tax-WST case), coal generation increases slightly in comparison to the optimal tax scenario (Tax case) showing that by improving their H_2O usage, coal generators are rewarded. However, see that coal generation is still lower than the No-Tax scenario.

In Figure 4.20a, we can see an increase in CO_2 emissions due to the slight increase in coal generation after investing in WSTs. Figure 4.20b, shows a

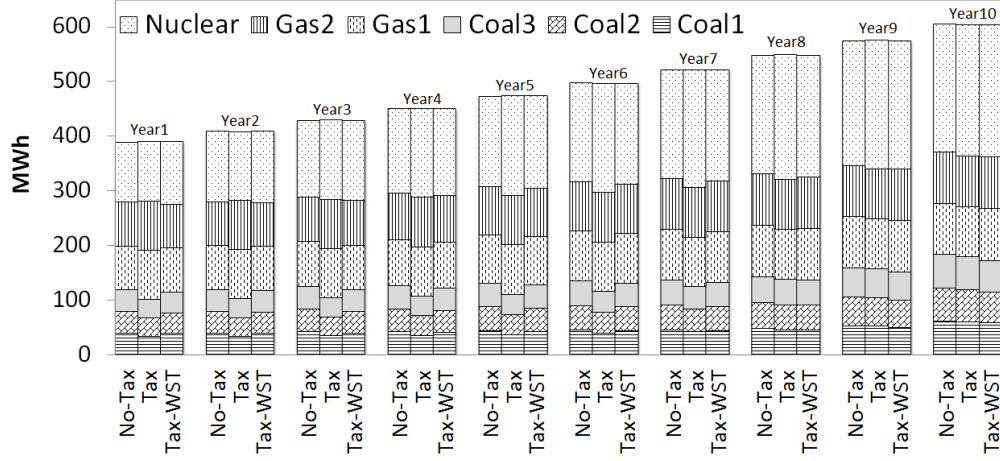


Figure 4.19: Supply Shares using Water Saving Technologies

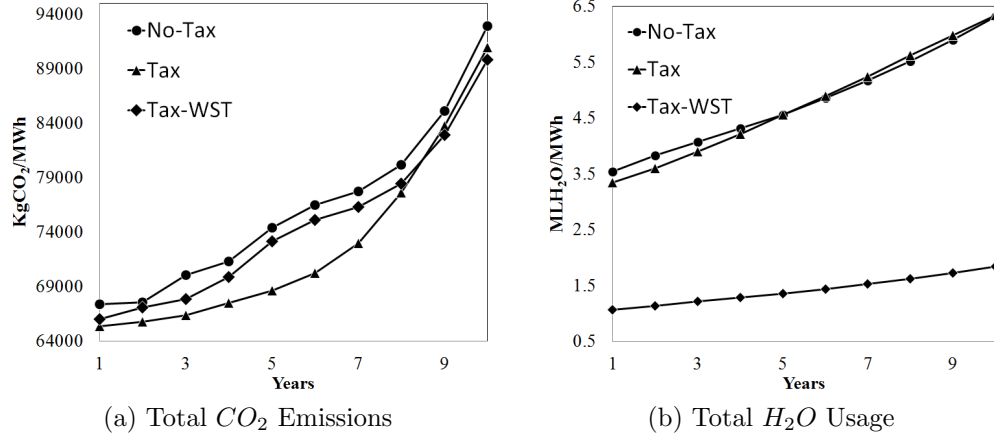


Figure 4.20: Emissions and Water Usage using Water Saving Technologies

marked decrease in H_2O usage when using WSTs as expected. In addition, Figure 4.21 illustrates the tax savings due to the investment in WSTs. It also shows that on average there is a 49% savings on CO_2 and H_2O taxes due to the implementation of close-loop technologies.

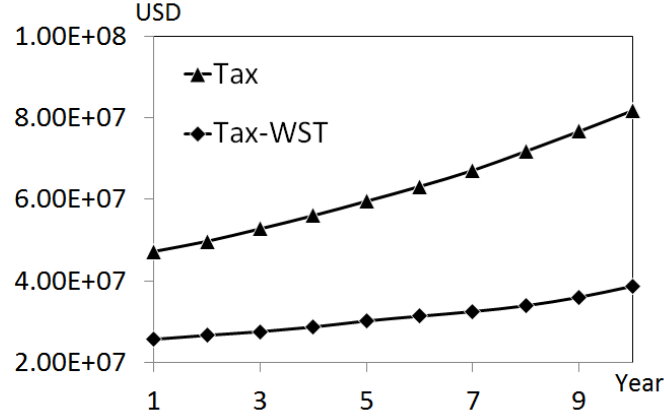


Figure 4.21: Tax Savings

4.2.4.3 Issuing Tax Credits to Generators investing in Water Saving Technologies

In this section, we analyze the scenario where not all electricity generators use water saving technologies. We assume that those electricity generators using WSTs, receive tax credits to reward their investment in these technologies. For this study, we adopted a tax credit of 15% over the total H_2O tax mentioned earlier. We adopted this value based on the tax incentive values presented in the Energy Tax Policy report [24]. Electricity generators using WSTs are assumed to be: Coal2, Coal3, Gas2, and Nuclear generator. Therefore, electricity generators Coal1 and Gas1 do not invest in WSTs.

From Figure 4.22, we can see that under the tax credit scenario, electricity generation from the coal generator with no WSTs is reduced, and the difference is now absorbed by the nuclear generator. Notice that even

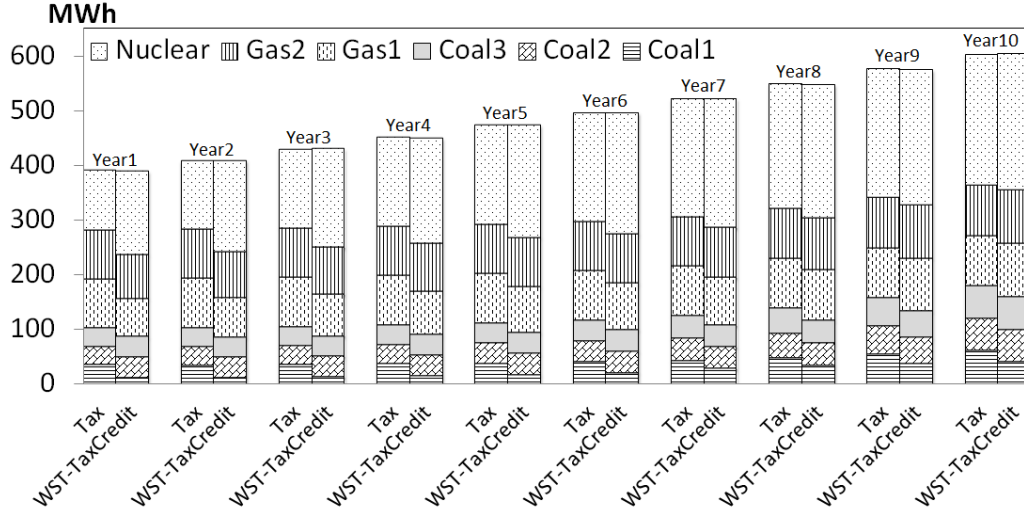


Figure 4.22: Supply Shares under Tax-Credit

though Gas1 does not have WSTs, it continues to produce as much electricity as generator Gas2 that uses WSTs. This is possible since gas generators do not consume as much water as coal generators. Figure 4.23a shows that under tax credits, lower CO_2 emissions are observed due to the reduction in electricity generation from the coal generator with no WST. Similarly, Figure 4.23b shows that the lower H_2O usage is observed since a subset of electricity generators start investing in WSTs.

4.2.4.4 Hydro Power Generation Integration

In this section, we study the integration of a hydro power generator in the grid. In this scenario, we assume to have one coal generator, one wind generator, one hydro generator, two gas generators, and one nuclear generator.

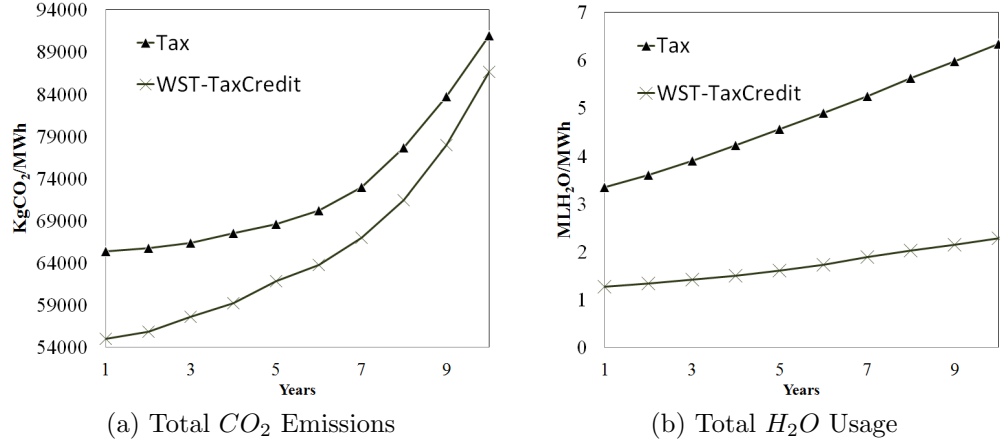


Figure 4.23: Emissions and Water Usage under Tax Credit to Generators investing in WST

In this case, all generators have an electricity generation capacity of 100MW each except the nuclear generator which has a 200MW capacity. The H_2O usage factor used for the hydro generator was $0.017MLH_2O/MWh$ as presented in [93]. Given that water availability depends on the season of the year, we have developed four different scenarios as shown in Table 4.7 ([94]). In order to simulate the availability of water for the hydro generator in each season, we reduced its maximum electricity production capacity depending on the respective water availability percentage of the season under study.

Table 4.7: Water Availability by Season of the Year

| <i>Season</i> | <i>Available</i> | <i>Impact</i> |
|-------------------------|------------------|----------------------------------|
| Winter (January-March) | $\sim 100\%$ | Above normal flows |
| Spring (April-June) | $\sim 80\%$ | Below normal flows |
| Summer (July-September) | $\sim 50\%$ | Below or much-below normal flows |

Figure 4.24 shows the supply shares after a hydro power generator is introduced for every season presented in Table 4.7 (Winter: Hydro-High,

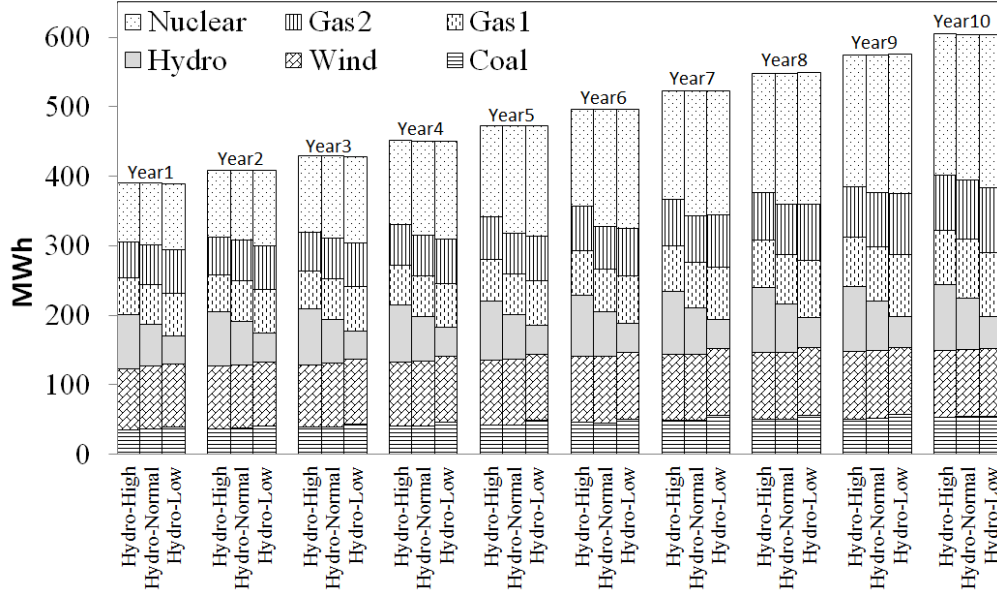


Figure 4.24: Supply Shares with Hydro Generation Integration

spring: Hydro:Normal, and summer: Hydro-Low). The hydro generator does not produce up to its maximum capacity due to its high water usage factor. Notice that in all cases, wind generator produces close to its maximum capacity because it is the best solution for two of the three objective functions (CO_2 emissions and H_2O usage). Coal generator produces a small amount of electricity due to the high CO_2 emission and the high H_2O usage factor. Gas generators seem to be a moderate solution and their electricity production increases through the years. By the end of the time horizon, gas generators produce up to their maximum capacity. Nuclear generation also increases through the time horizon, supplying most of the increasing demand each

year.

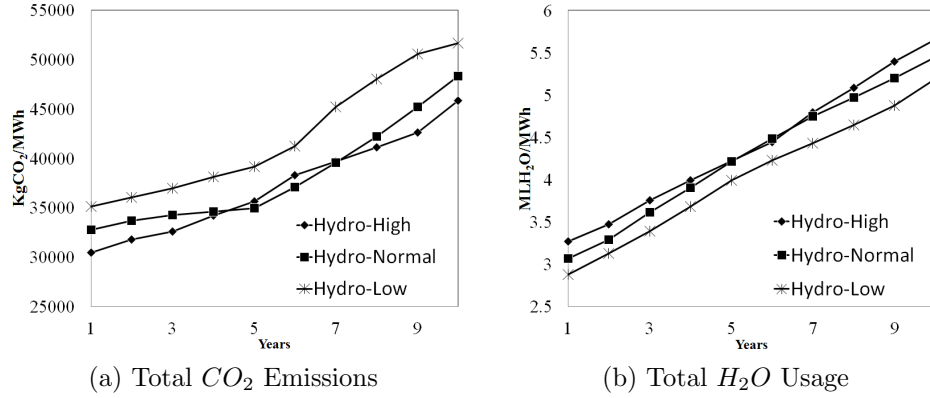


Figure 4.25: Emissions and Water Usage with Hydro Generation Integration

From Figure 4.25a and Figure 4.25b, we can see that during dry seasons (Hydro-Low case) higher CO_2 emissions and lower H_2O usage are observed. This happens because in dry seasons, the supply share from the hydro power generator, which is the generator with the higher H_2O usage factor, is reduced. Therefore all remaining generators increase their supply share including the coal generator which has a high CO_2 emissions factor. Additionally, notice that in seasons with high water availability (Hydro-High case), lower CO_2 emissions and higher H_2O usage are observed. In this case, the hydro power generator's supply share increases.

4.2.5 Conclusions and Policy Implications

While climate change has driven law makers and leaders in some countries to devise policies to reduce CO_2 emissions produced by electricity generation,

so far, only research studies like this one and some research agencies are discussing the need to include H_2O usage policies to address the electricity-water-climate change nexus. To our knowledge, no concrete policies have been proposed to address this critical issue by lawmakers around the world. This paper presented a first-of-its-kind simulation-optimization approach to obtain optimal tax rate combinations (for both CO_2 emissions and H_2O usage) for a given power network and then simulated some realistic scenarios to study the impact of these tax rates.

While studying this nexus, different trade-offs between minimization of electricity generation costs, minimization of CO_2 emissions, and minimization of H_2O usage need to be addressed. Additionally, these trade-offs may vary across regions depending on power network characteristics and water resource conditions, making this decision a very complex one. Therefore, we believe that calculation of tax rates, especially for water usage, needs to be a regional decision since water availability varies significantly across regions. This implies that the opportunity cost for reducing water usage also varies significantly between regions. While CO_2 prices can be uniformized across a country or perhaps even globally, once they are considered in concert with water, they need to be jointly recomputed as generation technologies often have conflicting CO_2 emission and H_2O usage factors. We address this issue in this paper by first calculating an optimal tax rate combination for a given power network and then performing our simulation study.

Results, as expected, show that both CO_2 emissions and H_2O usage are

reduced significantly under a joint tax policy. This indicates the importance of implementing a joint environmental policy for both CO_2 emissions and H_2O usage. It was also seen that investing in WSTs is not only a good option to reduce H_2O usage but also to keep non-renewable energy competitive in the market. WSTs also reduce the risk of possible power plant shutdowns due to droughts or water shortages that may occur. We believe that WSTs also provide a smoother transition route to a low water usage future for critical power generators.

Chapter 5

Future Research

Some federal and individual state-level environmental initiatives have been introduced to increase greener power production, increase energy efficiency, and reduce carbon emissions. Some of these plans include carbon cap-and-trade (California cap-and-trade program [95], RGGI [96], and EU-ETS [97]) and renewable portfolio standards (in over two dozen states of the U.S.). However, researchers, policy makers, and world leaders continue arguing about which carbon reducing mechanism (tax or cap-and-trade) gives better economic and environmental results. So far, Cap-and-trade has been widely discussed as the most effective market-based mechanism to control emissions and mitigate climate change. In fact, the U.S. Environmental Protection Agency had developed a very successful cap-and-trade program in the early 90's for SO_x emissions under the aegis of the Acid Rain Program. The program is said to have achieved its goals within cost and ahead of time [4].

However, no federal or state level green energy policy or program includes water-usage reduction goals even though it has been shown by several researchers that electricity generation, water, and climate change are related to one another [98, 99]. This research, in the previous chapters, contributes to this ongoing debate by studying the impacts of implementing a Tax policy for CO_2 emissions and H_2O usage on wholesale electricity markets to address the electricity-water-climate change nexus. In this Chapter, we propose the use of our stochastic multi-objective optimization framework as a tool to understand the implications of implementing a cap-and-trade program on wholesale electricity markets for future research.

5.0.6 Cap-and-Trade basics for CO_2 emissions

In a cap-and-trade system that reduces CO_2 emissions, a cap for the total amount of carbon emissions that can be emitted in a time period is fixed and it is equivalent to a limited amount of CO_2 allowances. Each ton of CO_2 emissions is equivalent to one allowance. A correct cap on CO_2 emissions is desirable in order to provide certainty and to achieve the emissions reductions goals in the long term. This cap is expected to decrease annually until it reaches the CO_2 emissions target.

Allowances can be assigned to entities interested by giving them for free (grandfathering), by selling them through auctions, or by using a hybrid mechanism where a percentage are given for free and the rest are auctioned. Allowance allocation is a critical component of a CO_2 emissions trading sys-

tem due to the impact it will cause in the performance of wholesale electricity markets. Hence, policy makers have to make decisions regarding the mechanism to be used for the allowances distribution, the percentage of allowances given for free and the percentage that is auctioned, and the type of the auction to be used. Potential effects of allowance allocations in cap-and-trade systems, such as impacts on: the overall cost, social cost, environmental effects, prices, market power, among others, are discussed in [100–103].

Entities that are subject to the cap (e.g., power generators) are then required to surrender allowances for their CO_2 emissions. Those entities that have additional allowances after meeting their requirement, can sell them to those entities in need if permitted. Penalties are imposed on those entities that exceed the limit of CO_2 emissions given by the allowances surrendered.

Cap-and-trade programs provide a market flexibility to their participants that allow them to manage the cost of compliance such as offsets, banking, borrowing, and trading. Offsets are the processes where power generators can compensate a portion of their CO_2 emissions by surrendering certificates of CO_2 emissions reduction from elsewhere outside the cap-and-trade program. Banking is the process that allows power generators to hold unused allowances for future use. Borrowing is the process that allows power generators to surrender allowance from future time periods. Trading is the process where power generators are allowed to sell/purchase allowances from other entities. For a comprehensive review of all these parameters, the readers are referred to [4].

5.1 Proposal for a Cap-and-Trade system

In this section, we explain the procedure that could be adopted in order to model a cap-and-trade program to mitigate both CO_2 emissions and H_2O usage based on the multi-objective stochastic optimization framework presented in this research. The overall procedure is shown in Figure 5.1.

Initially, the auction operator fixes caps for both CO_2 emissions and H_2O usage for the first time period of the program implementation as well as the rates to be used to reduced these caps annually. Subsequently, the allowance allocation process begins by making a decision regarding the methodology to use for the allowances distribution. In order to provide a smooth implementation of the cap-and-trade system, it is safe to start by given away for free all allowances available in the market (grandfathering) in the first period of implementation. This would help to introduce the cap-and-trade system into the market and help entities interested in getting allowances to get used to it. For the following time periods, a transition between grandfathering and a 100% auctioned market should take place by gradually decreasing the number of allowances given for free while the number of allowances auctioned increases at the same time in a fixed rate. For the sake of simplicity, power generators are assume to be the only entities interested in bidding for these allowances. As soon as the CO_2 and H_2O allowances begin to be auctioned, power generators will have a bid decision vector for buying CO_2 emissions and H_2O usage allowances. It is expected that power generators with higher cost

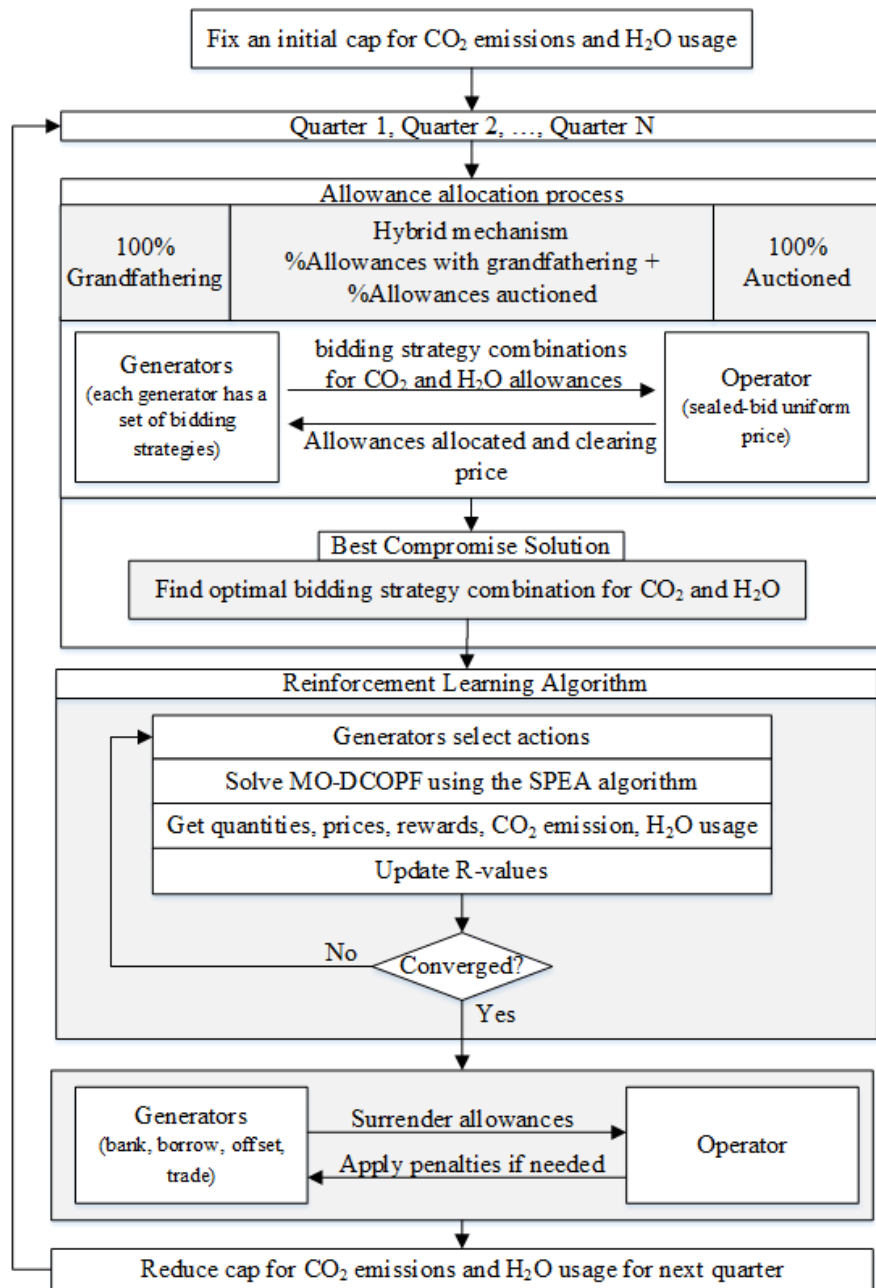


Figure 5.1: Cap-and-Trade model

of reducing CO_2 emissions and H_2O usage will bid higher to get the amount of allowances needed, while generators with lower or no cost of reducing CO_2 emissions and H_2O usage will bid lower.

The allowance distribution could be assume to be a quarterly and single round process as implemented in the California cap-and-trade system [104]. Thereafter, we define $E_g = \{< e_g^1 >, < e_g^2 >, \dots, < e_g^n >\}$ as the set of bidding strategies for CO_2 allowances for every generator $g \in G$ such that each member is a combination of the number of allowances requested Q and the respective bidding price P . For instance, $< e_g^1 > = \{Q_g^1, P_g^1\}$. Therefore, there will be $m = n^g$ possible bidding strategy combinations ($C = c_1, c_2, \dots, c_m$) of quantities of allowances requested and bidding prices. For instance, $c_1 = < e_1^1 >, < e_2^1 >, \dots, < e_G^1 >$. For each bidding strategy combination c_i ($i : 1$ to m), use the sealed-bid uniform method to allocate allowances and to find the clearing price as it is used by RGGI cap-and-trade program [105]. Based on the assumption that each generator wants to obtain as much allowances as requested, we can define the amount of allowances allocated to each generator as an objective function that have to be maximized. Hence, there will as many objective functions as number of generators in the system. Because of this, we can make use of the Best Compromise Solution (BCS) technique used in Section 3.6 to find the optimal bidding strategy combination which will be the solution that maximizes all objective functions. In case of finding a Pareto front of solutions, choose the one that minimizes the total cost of allowances using the clearing price. This process

happens to be the same for H_2O allowance allocation. The optimal bidding strategy combination for both CO_2 emissions and H_2O usage is obtained as a result of the allowance allocation process.

In order to evaluate the effects of the allowance distribution on the wholesale electricity market, we can make use of the CMDP model presented in Section 3.4 to simulate the generators' competitive bidding behavior in wholesale electricity markets, and solve it using the RL algorithm presented in Section 3.7 considering the respective caps for CO_2 emissions and H_2O usage, and to represent the intricacies of a real power grid we can use the multi-objective DCOPF formulation presented in Section 3.3 and solve it using the SPEA algorithm presented in Section 3.6.

Based on final electricity production shares and allowances used as results from the RL algorithm, each generator will be asked to surrender their allowances. At this moment, generators could consider banking, borrowing, trading, and offset allowances depending on the market flexibility. As a result of the allowances surrender process, the operator will apply penalties to those generators who have exceed the CO_2 emissions and the H_2O usage equivalent to the allowances surrendered.

Detailed and overall results of CO_2 emissions, H_2O usage, operational production cost, supply shares, profits, and locational marginal prices are then saved for further detailed analysis. Caps for CO_2 emissions and H_2O usage allowances are reduced for the next quarter (evaluation time) where generators will bid again to get new allowances.

5.1.1 Further steps

In this Chapter, we propose the adaptation of our multi-objective stochastic optimization framework to evaluate the effects of the implementation of a cap-and-trade system on wholesale electricity markets for addressing the electricity-water-climate change nexus. Our model, can be also used to evaluate the implications and trade-offs of the different allowance allocation methods: auctioning, grandfathering, hybrid models; as well as the allowances trading mechanisms such as credits, banking, borrowing, and offsets. Besides this, the model can be used to find appropriate CO_2 emission and H_2O caps. Finally, comparison of taxation vs cap-and-trade program can be carried out to identify benefits and weaknesses of both environmental policy programs that would support the decision-making of policy makers related to the electricity-water-climate change nexus.

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