A QUANTITATIVE ASSESSMENT OF WIND POWER INTEGRATION IN KENYA: A CASE STUDY OF THE LAKE TURKANA WIND POWER PROJECT

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Kenya has set a target of increasing the total installed wind power capacity from the current state of less than 1% to approximately 13% of the nations projected total installed power generation capacity. The Lake Turkana Wind Power (LTWP) wind farm will be the largest wind farm, contributing to half of the projected installed wind power capacity in the country. A large increase in wind energy penetration in a country with little to no wind energy production introduces new challenges for the planning and operation of the power system. For Kenya particularly, the market structure and specifics of the LTWP purchase contract pose challenges to the system and have led to withdrawal of the World Bank's funding for the project. One possible solution to the inherent issues is the pairing of a wind farm with a storage system, which allows improved controllability of the net output and allows for improved look-ahead commitment.

The goal of the studies presented here is to address the concerns of the World Bank and seek to offer solutions to improve the integration of LTWP into the Kenyan power system. This is achieved in a series of three different studies. Firstly, we investigate the benefit of optimally integrating wind power in Kenya with pumped hydro storage. This approach includes development of an optimal control strategy to deploy paired wind and pumped hydro storage resources for the LTWP. The stochastic model, which maximizes expected revenue over the planning horizon, is developed taking the structure of the Kenyan electricity market into consideration. In the second study, we develop a two-stage stochastic model to determine optimal day-ahead power commitment and intra-day operation of the combined LTWP project with available storage, again taking into account the unique structure of the Kenyan power market and planned dispatch planning. Finally, in the last study we determine the impact of the addition of wind power from the simulated LTWP wind farm on the reliability of the Kenyan power system. The results indicate that storage can improve revenue for the wind farm owner considering the current power market structure. With the expected demand growth wind power from LTWP is found to improve the reliability of the Kenyan power system and the pairing with a storage unit is further found to reduce expected energy not served. Overall the optimal pairing of LTWP with a storage system benefits both the wind farm owner and power system.

BIOGRAPHICAL SKETCH

Maureen Murage is a 6th year Ph.D. Candidate in the department of Biological and Environmental Engineering department. She was awarded her non-thesis Masters in July 2013 and completed her Bachelor of Science in Mechanical Engineering at the University of Cincinnati in 2010. Her research has focused on applying various mathematical techniques to assess the integration of wind power into the Kenyan power market.

To Amani.

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CHAPTER 1

INTRODUCTION

Wind energy is becoming an increasingly popular alternative energy source. Over the last decade, there has been tremendous growth in the utilization of wind energy to meet electricity demand. The addition of wind power benefits a power system by reducing fossil fuel requirements, which consequently reduces both emissions and operational costs of the power system. Additionally, in comparison to other variable renewable energy sources, wind power has the lowest levelized costs in the U.S, where levelized costs represent the per kilowatt-hour cost (in real dollars) of building and operating a generating plant over an assumed financial life and duty cycle [1]. These attributes have resulted in the rapid development of wind farms worldwide, with a total worldwide installed capacity of 370 GW in 2014, a 16% increase from the previous year [2] and a further increase of 22% in 2015. Wind power however has its own shortcomings. It is variable on all time scales and uncertain, that is difficult to accurately predict. These wind power properties make planning and operation of a power system more difficult and in some cases also lead to changes in the operation of the conventional units in the system by increasing start-ups and shut-downs and introducing steeper ramps [3, 4]. These issues become more of a concern as the percentage of wind power injected into the grid increases. As a result there has been a growing interest in the study of the effects of integration of variable renewable energy resources on power systems, with emphasis on assessing the impact of adding wind power to a power system and determining measures that can be taken to manage the intermittency of these power sources [5]. Some of the solutions suggested in the studies are:

- For a system with hydropower plants, co-ordinating the operation of these plants with that of a wind farm [6]
- Improved forecasting at shorter time-scale to deal with uncertainty of wind power
- Demand-side management
- Interconnection with other systems
- Addition of Energy storage systems

The goal of this work is to gain an understanding of the impact of integration of wind power into the Kenyan power system using the 300MW Lake Turkana Wind Power(LTWP) farm as a case study. Particularly, this work seeks to investigate the benefits to the system and wind farm owner of coupling LTWP with a storage system and to determine optimal operation of the coupled system. This is done using tools from statistics and optimization, and presented in three different publications. The focus is on highlighting the benefit of coupling LTWP with storage and proposing suitable strategies that could further advance the integration of wind power in the Kenyan power system. Additionally, there is a focus on addressing the World Bank's concerns, which led to withdrawal of its financial backing for the development of LTWP [7]. The World Bank's major concerns were that consumers would bear the burden of paying for curtailed wind power due to the take-or-pay terms of the contract and that the rapid installment of the 300 MW capacity would not keep in step with the growth in demand. This would run counter to the originally stated benefit of wind power development in the country, which was to reduce the high cost of power [8]. On take-or-pay terms, wind power is essentially considered as negative load, therefore the net load of the system is load less the wind generation. As the level of wind power in the system increases, the net load profile may sometimes change more dramatically than the load only profile [9].

The rest of this section presents some background on wind power integration and details on energy storage systems. Finally, the organization of the rest of the disseration is presented at the end of the section.

1.1 Wind Power Integration

To deal with the variability and unceraitinty of wind power, a power system needs to be flexible [9]. Flexibility is the ability of the power system to respond to changes in net load, where net load is load less variable generation [10]. The level of flexibility is dependent on the current state of the power system and wind power penetration levels. Wind integration at low shares of demand (5 to 10%) would not cause a big technical challenge to the operation of a power system nor require much change in system flexibility, provided that certain basic principles are followed. These principles include avoiding local concentration of wind power plants, ensuring that wind power plants contribute to stabilizing the grid when needed and using forecasts when planning the operation of the grid [11].

The main factors to consider when integrating a significant amount of wind power into an interconnected power system are [12]:

- The availability of a sufficient number of conventional power plants to cover periods of low wind power production
- The presence of fast control power plants

- The ability of the power system to withstand dimensioning faults i.e. the single largest fault
- The ability to regulate down available wind power during lower consumptions periods, taking into account local load plus possible export

To gain an understanding of ways in which other countries have successfully integrated large amounts of wind power into their power systems, we need to look at integration studies that have been carried out at country level. These studies investigate the potential challenges that come with high wind power penetration levels and in some cases the solutions implemented to overcome them. The lessons learnt from these studies need to be taken with caution as each power system is inherently different. Nonetheless there are a few key takeaways that can inform a country's energy policy when dealing with high wind power penetration levels. One key finding from experiences and studies conducted so far is that integrating wind power at penetration levels of more than 20% requires new tools for transmission planning and new operational practices [4].

There have been a great number of studies on wind power integration in European countries because they lead the world in both the share of total energy generation from wind and instantaneous wind production [9]. Some of the findings of the studies conducted in European countries (such as Denmark, Spain, Germany, Ireland and the United Kingdom) have discussed the challenges encountered and suggested solutions. These include:

- Increased indirect system costs due to, for example, extension or reinforcement of the existing power system or due to forecast errors. Indirect costs caused by volatility of wind energy are found to reduce with an increase in the integration of variable renewable energy sources into the power system [13].

- Reduced spot prices and reduction in working hours of conventional generators leading to reduced profitability [14] or shut-down altogether. This is of concern because certain conventional generators are needed to maintain the supply adequacy of the system in times of low wind power production. The proposed solution is to compensate these generators for capacity contribution especially during higher price depletion periods [15].
- Wind power and other renewable power sources in Spain, even after accounting for their resulting effect in reduction in market price, did not compensate for the public support they received in the form of subsidies [16]. The Spanish government implemented changes to the energy policy to deal with the problem.
- Wind power has the potential to create stiff competition for central power plants, which could pose a challenge for primary voltage control in the future Danish power system [17]. A potential solution that the authors note is using full-scale converter based wind farms connected at transmission voltage level.
- Intermittency of wind power may result in additional costs of operating the power system in the United kingdom due to the need for additional reserves that will be needed to maintain the balance between supply and demand at all times[18]. The authors in this study note that the use of storage in providing standing reserves could contribute to a cost effective integration of significant amounts of wind power.

In the United states the contribution of wind power at a national level is still relatively small, however in states such as North Dakota and Iowa, the wind power penetration level is at 20% [9]. From findings of integration studies in the US presented in [9], an NREL tech report, it has been suggested that for the system to accommodate significant renewables there is a need to :

- Encourage geographically diverse wind resources
- Improve forecasting of wind power
- Increase the frequency of commitment and dispatch intervals
- Enhance system flexibility through the use of storage technologies, demand-side options and energy curtailment
- Expand the transmission system
- Ensure that long-term generation planning and expansion are appropriately valued for flexible resources and their contribution to system capacity and balancing

The facts to consider when introducing high levels of wind power in an isolated system are considerably different than those in a well interconnected system, especially for an isolated system with long start up times and low ramp rates [10]. In Kenya, whilst the power system is connected with one neighboring country, imports/exports make up less than 1% of total power consumed [19] and are mostly used to stabilize neighboring systems. With low interconnection and a move away from flexible diesel and large hydropower plants, flexibility in the power system may be reduced and may increase the difficulty of increasing wind power penetration into the system. In response to these potential issues, expansion of interconnection systems and/or use of storage systems may assist the country in advancing the integration of wind power to projected levels. Due to the availability of large hydropower dams in the country, a pumped hydro storage (PHS) system is used as the storage system in this work, since hydropower dams could be converted to storage units with reversible pump-turbines. Furthermore, adding pump-back functionality to existing reservoir hydro plants is found to have the most favorable cost-benefit ratio when compared to regular storage systems [11].

With the increased integration of renewable energy sources, electrical energy storage (EES) systems are becoming increasingly important. Whilst storage systems are not the cheapest option for increasing flexibility they address many of the challenges that variable renewable energy power sources introduce to the grid. For example[11]:

- Although hydro plants can step-in during lower wind power generation periods, they cannot avoid wind power curtailment once net load becomes negative whilst EES systems can
- Wind power curtailment can help to reduce situations of wind power surplus, but it does not help resolving situations of very low wind power and solar PV output
- Storage reduces the need for fossil-fuel back-up generation capacity to deal with wind power variability and uncertainty

Generally speaking, EES systems allow for the maximized use of wind power resources, by storing energy during wind power generation surplus periods and releasing energy either during low wind power periods or high price periods. Energy storage is one of the most important components in enabling variable renewable sources to become reliable primary sources of energy [20].

Beyond enhancing the integration of variable renewal energy sources, other benefits of EES technologies include the following [21]:

1. Matching electricity supply to load demand
   Energy storage technologies can provide an economical and environmentally advantageous methods of responding to daily fluctuations in demand as long as the storage system is not charged by energy generated from fossil fuel
2. Reducing power quality problems
   Energy storage devices with quick response can be used to stabilize any sudden fluctuations of demand and reduce sags, spikes or harmonics. This is of most benefit to industries that require stable voltage and frequencies
3. Reducing risks of power outages
   Power outages, which can cause an overload on the power network, can result from the damage to transmission lines, failure of power stations or imbalance in the power system. Energy stored in an electrical storage device can be used to provide power during these situations.

There are certain criteria and requirements that dictate which particular energy storage technology is best suited for a particular function, such as being used to match electricity supply to load. A storage device that is used to ensure power quality (also referred to as power management) is usually applied for seconds and is required to have a quick response time. In contrast, a storage device used for matching supply to demand (also referred to as energy management) is required to have a large capacity, quick response time and the ability to be applied for a long duration of time. The technologies used for the latter application are usually categorized as real long-term response energy storage technologies [22]. PHS systems fall into this last category. They consist of a lower and upper reservoir and store/generate energy by pumping/releasing water between the two reservoirs. The pumping and releasing of water can be achieved by either a single reversible pump-turbine unit or by use of separate pump and turbine units. PHS systems have relatively quick response time (less than 1 min), which is important for network frequency regulation [23]. Additionally, in comparison to some other forms of EES systems, PHS are better suited for variable renewable energy integration[24].

1.2 Organization of the Disseration

The dissertation is structured as follows:

Chapter 2 : In this chapter, an optimization model is developed using dynamic programming to investigate the benefit to the wind farm owner of coupling LTWP with PHS. The model takes into account the renewable energy policy and structure of the Kenyan power market.

Chapter 3: A two-stage stochastic optimization model is formulated and solved in this chapter. The goal of the model is to determine the optimal day-ahead commitment and operation of the combined LTWP with PHS.

Chapter 4: The reliability of the Kenyan power system with wind power from LTWP is presented in this chapter. This is done by running sequential Monte-Carlo simulation to determine reliability indices at hierarchical level 1 (HL1), which is referred to as generating capacity reliability evaluation.

Chapter 5: In this chapter, the conclusion of all the 3 studies conducted is presented.

CHAPTER 2

CONTRIBUTION OF PUMPED HYDRO STORAGE TO INTEGRATION OF WIND POWER IN KENYA - AN OPTIMAL CONTROL APPROACH

This chapter investigates the benefit of optimally integrating wind power in Kenya with pumped hydro storage. The approach includes development of an optimal control strategy to deploy paired wind and pumped hydro storage resources, for the Lake Turkana Wind Power project. The model seeks to maximize the expected revenue over the planning horizon and is developed taking into the consideration the structure and running of the Kenya electricity market. The work in this chapter is based on work in [25] [1].

2.1 Introduction

Many African countries rely heavily on renewable energy resources to generate power [26], with hydropower dominating in Sub-Saharan African countries. A hydropower-dominated power system is vulnerable to large variations in rainfall and climate change resulting in power shortfalls [27] which leads to increased use of diesel generators to meet the shortfalls. In Kenya, hydropower constitutes approximately 50% of the total generation installed capacity and has experienced reduced power generation due to failure of long rains. The country also suffers from frequent intermittent outages, low electricity access rates for the country?s population and high power system losses [28]. The burden of power outages on the economy is estimated to be as high as two percent of GDP

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[1] ©2014 Elsevier. With permission from my co-author: C. Lindsay Anderson. ″Contribution of pumped hydro storage to integration of wind power in Kenya: An optimal control approach.″ Renewable Energy, 63(c), pp.698 – 707.

[29]. Over the last couple of years there has been a considerable increase in the demand for electricity and with reduced generation of hydropower, there has been an increase in the use of diesel thermal plants. This has come at a high cost to the environment and to the consumer as well, due to the increase in crude oil prices [30]. As a result the government is turning its interests to the production of wind power [31].

In Kenya, the total installed capacity in 2011 was approximately 1400 MW [32] with wind power accounting for less than 1% of this value at 5.45MW [33]. With incentives such as a Feed-in Tariff policy, introduction of a fixed tariff structure, and priority purchase of renewable energy sources [34] there is keen interest in the development of wind resources for power generation. There are specific locations within the country with relatively strong and persistent wind speeds throughout the year [35]. It is estimated that wind farms producing up to a total of 610MW of wind power are to be developed [33]. The first large wind farm to take advantage of the countries wind power potential is the Lake Turkana Wind Power Project (LTWP), which is currently under development, with a total installed capacity of 300MW consisting of 365 Vesta V52 850kW turbines [36]. Wind power in 2015 is expected to consist of approximately 17% of the total installed capacity [32]. The large increase in wind energy penetration in a country with previously little to no wind energy production introduces new challenges for the entire power system. In addition the market structure and specifics of the LTWP power purchase contract will also pose challenges to the system.

In the Kenyan electricity market, power is bought from the generators on the basis of negotiated Power Purchase Agreements (PPA), which are long-term contracts of approximately 15-20 years [33]. The terms in the agreements stipulate, among other things, the value of each unit of power generated, capacity charges, and the value of penalties charged. The terms agreed upon in the PPAs vary for different generation sources. The LTWP PPA, like most wind power PPAs, is on take-or-pay terms, meaning that payment for every kWh of energy delivered is made on the amount of energy available and not on how much is actually used. The take-or-pay clause coupled with the fact that renewable power generators are guaranteed priority purchase, transmission and distribution [34] could potentially pose a challenge in the power system operations and economics [37]. Based on these concerns, World Bank withdrew its backing for the LTWP project stating that the take-or-pay provisions in the PPA, would expose Kenya Power (system operator) to unacceptably large financial risk due to possible curtailment and defeat the project's primary purpose of reducing the cost of power in Kenya [7]. Due to these reasons, we consider the combined operation of the Lake Turkana Wind Power wind farm with pumped hydro storage.

Pumped hydro storage is a form of electricity storage and is the preferred storage system for Kenya because of the country's long standing use of hydro resources. Electricity storage offers a technological solution that can maximize the use of variable renewable energy production without the need of additional reserve or curtailment while also reducing chances of grid congestion and improving system reliability [38]. Energy storage could enhance wind energy by allowing limited control of dispatch from a wind farm and smoothing fluctuations in wind generation [39]. By optimally integrating a pumped hydro system with the LTWP wind farm the generator would be able to store energy during low consumption periods and generate power during the low wind and high consumption hours reducing the need for curtailment.

The integration of wind power with storage has been the basis of many studies [39, 40, 41, 42, 43, 44]. The focus of the studies has been on the optimal integration of wind with storage to enable wind power to competitively participate in the electricity market while maximizing revenue. We seek to find the optimal operation of a wind farm with storage in the Kenyan electricity market to show the benefit of storage in the operation of a wind farm. Many of the studies focus on countries in the west such as North America and Western Europe, where electricity markets? operation and structure differ significantly from markets in developing countries. In this model we specifically take into consideration that the Kenyan electricity supply industry structure is of the single buyer model with all generators selling power in bulk to Kenya Power for dispatch, onward transmission and distribution to consumers [33], with no bidding in a day-ahead market.

There have been different approaches to the optimization of wind farms with storage units, broadly categorized into deterministic and stochastic approaches. For example in [40] and [43] take a deterministic approach to solving the problem of the optimal dispatch schedule. In [40] the optimization is formulated as a linear programming problem and solved sequentially over various wind power scenarios and the average, maximum and minimum values are obtained and used to represent the proposed operation strategy. The authors in [43] assume that the forecasted wind velocity is equal to the mean historical wind speed for all the hours in the scheduling periods. Deterministic dynamic programming is employed to solve the problem. While deterministic models simplify the problem and achieve a solution faster than stochastic models, these models under-estimate risk from the uncertainty of wind speed. The ability to make optimal decisions requires consideration of all possible states of wind power over time with their respective probabilities, through the use of a stochastic model. The authors in [41, 42, 39, 45] take a stochastic approach to the optimization problem. In [41], a number of scenarios from a scenario tree are considered, each with an assigned probability in the optimization of the problem. The probabilities of each scenario are incorporated in the objective function. The authors in [42], use the forecasted generated wind power from a uniform distribution to find the optimal policy that maximizes the expected cumulative revenue. This is solved by use of stochastic dynamic programming. The authors in [39] randomly sample wind generation values from an empirical probability density function to calculate the optimal dispatch schedule that maximizes hourly profits over the set time horizon. They also solve the optimization problem by use of stochastic dynamic programming. In [45], the forecast errors of wind power are generated according to a probability distribution and used to calculate the maximum profits of the combined wind and storage system. Hybrid genetic algorithm and neural network methods are applied to optimize the problem.

Our model is solved via stochastic dynamic programming similar to [42] and [39] but differs in the following ways: 1. We do not seek to compute the optimal dispatch policy or quantities, but instead seek to find the optimal control strategy for the different wind power generation scenarios to meet the committed dispatch. 2. We calculate probabilities of different wind power generation scenarios by use of a Markov transition probability matrix. 3. We simulate the wind farm from the given wind speeds. 4. Unlike [42], wind in this paper is not a small player in the market. 5. Unlike [39], the wind farm operator signs a long-term contract to produce an agreed upon quantity of power. The model seeks to maximize the expected revenue over the operating horizon by reducing power deviation. Price inputs on the other hand are deterministic, which is characteristic of Kenyan electricity market. We investigate how best to operate the Lake Turkana Wind Power farm coupled with pumped hydro storage so as to maximize revenue and reduce variability, while considering the electricity sector and market conditions in Kenya. We show the benefit of coupling the Lake Turkana Wind Power farm with hydro storage and the need for storage due to high wind power penetration in the country.

The rest of the paper is organized as follows: In section 2.2, the electricity market structure used in the model, the inputs to the model and the mathematical formulation of the optimization model are discussed. In section 2.3, the results are presented, followed by conclusion in section 2.4.

2.2 Model

The mathematical model developed here uses an optimal control approach to maximize expected revenue by minimizing power deviation and thereby enhancing integration and operation of wind power into the Kenyan power system. Model inputs include hourly wind power scenarios, hourly scenario probabilities and storage parameters. The market price and penalty cost are set variables and are set to emulate the Kenyan electricity market prices as close as possible. The model is developed based on three primary assumptions:

1. The amount of committed power per hour is constant, as determined at the signing of a power purchasing agreement

2. Wind farm operators are charged a penalty for under production of power
3. Penalty charges are charged on a per kW basis, and are time varying on a deterministic basis

2.2.1 Prices

Independent Power Producers (IPP?s) operate under a PPA with the national utility for the sale of electricity generated. The price paid for each kWh generated is constant and does not vary through out the day. Similarly, in the case that the power generator does not conform to dispatch instructions the penalty per kWh, does not vary through out the day and is in accordance to a rate specified in the contract [46].

To incorporate the Kenyan electricity market structure, we keep the market price for each kWh of power generated constant. In the case the power generator produces more power than the system operator scheduled for, it will still be used under the rules of priority purchase and transmission of renewables. However, in our framework, power in excess of the contracted amount is remunerated at a fraction of the market price. Penalties incurred for power deviation vary through out the day and is directly proportional to hourly load.

Power deviation is the difference between the committed power and the available wind power and is positive when available wind power is greater than committed power and negative otherwise. During the hours when the demand for power is high, the high penalty costs will motivate the generator to ensure they meet the stated production. In Fig. 2.1, the penalty is shown to follow the load profile and varies from hour to hour.

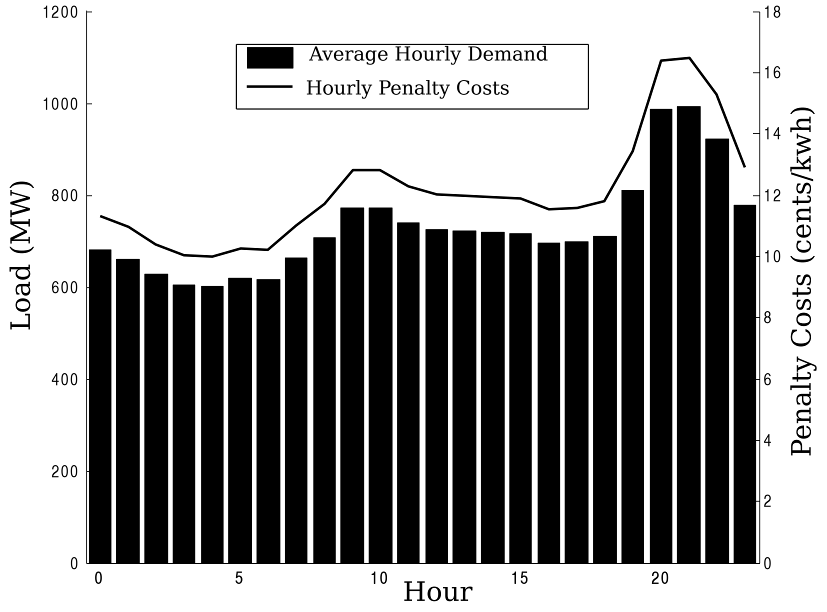

Figure 2.1: Hourly Load and Penalty Cost.©2014 Elsevier

Penalty is valued as the avoided cost of using medium/high speed diesel (MSD or HSD) plants, which between March and October 2009 varied between 8.72-13.40 US cents/kWh, but the cost of emergency power high speed diesel plants was much higher [34], therefore the penalty cost is between the two.

2.2.2 Pumped Hydropower Storage

Pumped hydropower storage is the most widely implemented and mature technology worldwide [47]. It is the only large energy storage system currently available in power systems [37]. Pumped hydro storage has a quick response time, in the range of seconds, and can vary the amount of electricity generated by changing rotation speeds. This form of storage technology also has longer equipment lifetime and less maintenance compared to other storage technologies. In addition pumped hydro storage is capable of operating at the level of the transmission system [38] and boasts a round trip efficiency of approximately 70% to 85%, with round-trip efficiency being a key parameter used in quantifying an energy storage system [39]. For these reasons pumped hydropower storage plants are used in this study.

In the model, during high wind and or low penalty periods, energy will be used to pump water up into the upper reservoir for storage, and then during low wind and or high penalty periods, stored water is released from the upper reservoir, turning the turbine to produce the required energy. We only keep track of the upper reservoir capacity over time to ensure that we never exceed the reservoir capacity. The reversible pump-turbine also has a limit on how much it can pump and release in a single time period, that is the ramp limit. At any one-time period t, the reversible pump/turbine can either pump or release but not both. Even though we do use a pumped hydropower storage unit in this study, this model can be modified to include any other form of storage technology. Due to the prevalence of hydro units in Kenya, we assume that the storage unit is already in place, and we do not include capital costs in the optimization.

2.2.3 Wind Power

The wind data uses is from Marsabit, since it experiences similar wind flow patterns to that at LTWP wind farm [35] and is also in close proximity. The wind data collected and used here are hourly average wind speeds for each day of the year for the period 1995-2000. There are two days of missing data over the 6-year period, one day in the year 1997 and the other in 1999. There was some error in the data, which may have been caused by instrumental failure or faults in the collection.

The wind speeds recorded in the Marsabit region are relatively high and the most frequent wind speeds experienced in the region are between 10.6 and 11.4 m/s [48]. These winds blow for more than 60% of the time [35], making it an ideal location for wind power generation and gives a good indication of the expected power output from the LTWP wind farm. The average hourly wind speeds for the 6-year period are developed into wind power scenarios, which are used in the model.

In order to create the wind scenarios, the wind speed data is clustered using a k-means clustering algorithm. Clustering is the process of grouping similar data together. K-means is chosen for its efficiency in clustering large data sets [49]. K, the number of clusters, is estimated such that any higher value of k will not have a significant reduction in the sum total distance of point to centroids for all clusters. It is firstly estimated via graphical methods and then narrowed down to an exact value by calculating the average silhouette value. Fig. 2.2 is a plot of the total sum distance within-cluster of point to centroids for all clusters and gives a rough estimate of what k, the number of clusters, for this particular data set should be. As shown, there is a large change in the sum total distance until around the fifth cluster, after which the marginal reduction in error declines significantly, therefore a good starting point is k equal to five.

The average silhouette value of the estimated k value is then calculated and compared to those of surrounding area. Silhouette value measures how well a data point suits its particular cluster, with values closest to 1 indicating that a

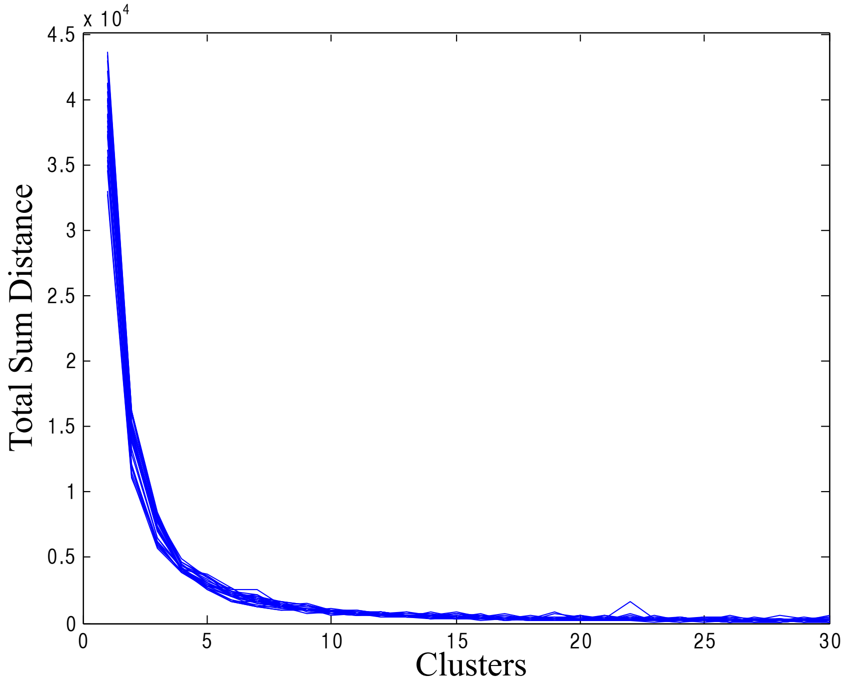

Figure 2.2: Sum total distance of point to centroid for different number of clusters. ©2014 Elsevier

data points have been well placed in its particular cluster. The best number of clusters is found to be 4 clusters.

The four different wind speed scenarios created from clustering are as shown in Fig. 2.3. Scenario one and four are the extreme case scenarios. The wind speeds in this region have a consistent diurnal pattern as depicted in Fig. 2.3, with a reduction in wind speed between hours eleven and to sixteen and an increase towards the end of the day

After clustering the wind speed data, the representative hourly wind speed scenarios are converted to respective wind power scenarios using the Multi-Turbine Power Curve [50] algorithm. The algorithm simulates a time series of the aggregated power generation from a cluster of wind turbines on the basis of the time series of wind speed in a single point [50]. To represent LTWP wind

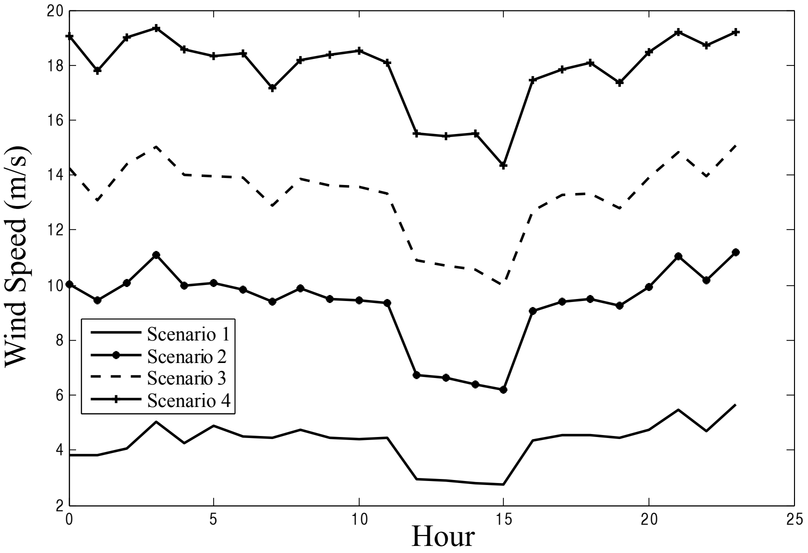

Figure 2.3: Four wind speed scenarios generated from the Marsabit wind speed data. ©2014 Elsevier

farm, we simulate a wind farm with 365 turbines each with a capacity of 850 kW each.

The hourly probabilities of each scenario are then estimated, by first calculating the four scenario Markov transition probabilities for each hour of the day. The one-step transition probability is defined as the calculated probability of moving from scenario i at time t to scenario j at time t+1 as expressed below:

$$\rho_{ij} = \mathbb{P}\{X_{t+1} = j | X_t = i\} \tag{2.1}$$

The one step transition matrix is calculated for each hour of the day for all days of the 6-year period. Using the transition matrix, the unconditional scenario probabilities for each hour are calculated as follows:

$$\mathbb{P}(X_{t+1} = j) = \sum_{i=i}^{C} \mathbb{P}(X_t = i)\rho_{ij} \qquad for\, 2 < t < T \tag{2.2}$$

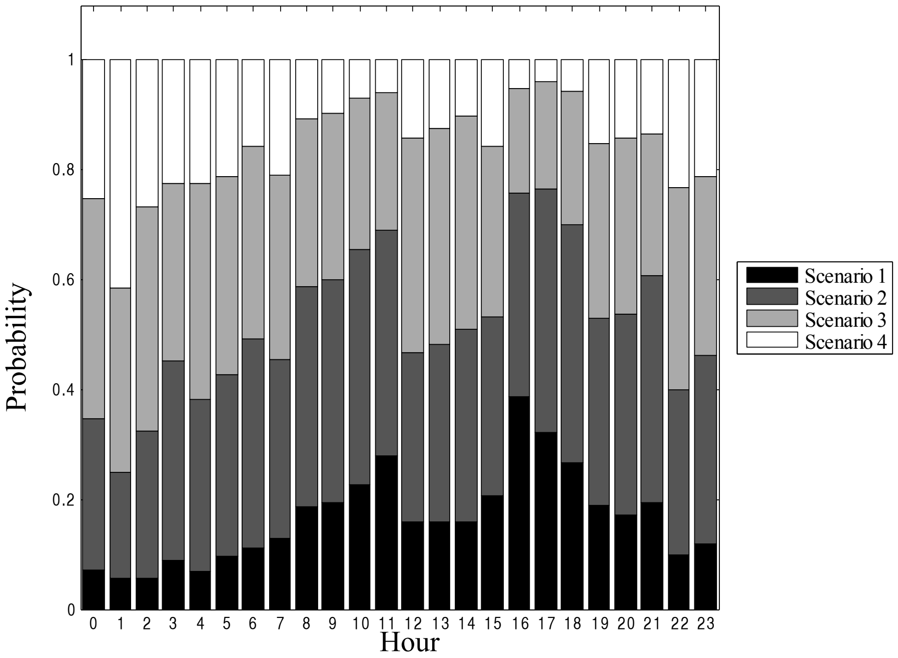

Figure 2.4: Hourly wind power probabilities of all the four scenarios calculated from Markov transition probabilities. ©2014 Elsevier

The calculated hourly scenario probabilities are shown in Fig. 2.4. We see that the probability of scenario four, which contains high wind speed scenarios, is more likely in the first five hours of the day. The lower wind speeds seem to have a higher probability of occurrence between the sixteenth and eighteenth hours of the day.

2.2.4 Mathematical Formulation

As is typical of the Kenya power market, the wind power operator is assumed to be an independent power producer who has agreed to produce a fixed quantity of power through out the day which is referred to here as the committed power. If at any time the operator has more power available than is committed, the operator could either choose to sell it to the system operator at a reduced price or store it for a later time when wind power produced may be less then the committed amount. The purpose of the model is to enable the wind power operator maximize the expected revenue over the operation horizon of the coupled wind farm with storage system. The state variable is the different storage levels and is discretized from minimum value to maximum full capacity.

The formulation is as follows:
The return function at each time period, for each wind power scenario is:

$$g_t\left(s_t, u_t, w_t^c\right) = \begin{cases} r_t\left(P_t^d\right) - c_t(P_t^d - P^c\Big)^- & P_t^d - p^c \leq 0 \\ r_t\left(P^c\right) + \gamma_t(P_t^d - P^c\Big)^+ & \text{otherwise} \end{cases} \tag{2.3}$$

$p_t^d = w_t^c - P_s(u_t)$, is the delivered power
The optimal value function:

$$v_t(s_t) = max_{u \epsilon U}\{g_t(s_t, u_t) + \sum_{i=1}^{C} v_{t+1}(s_{t+1}) p_{w_t^c}\} \tag{2.4}$$

- p^c is the committed power
- c_t is the per unit shortfall penalty
- γ_t revenue for each additional unit delivered
- r_t is the market price for each MW generated (constant)
- u_t is decision variable

The model seeks to maximize the expected revenue over the 24-hour operation period and is solved in a backward recursive manner. It total revenue at the end of the operation period will be the expected revenue over all the scenarios. In the return function at each time period/each state variable is total revenue received for power delivered less any shortfalls if any or plus each additional KW produced above power committed where $\gamma \epsilon$ [0 1]. The total power available/delivered at any time t for any one of the scenarios is equal to wind power is available less/plus power from storage.

The constraints are:

- State variable s_t: Discrete finite storage level $S = \{0, \ldots, S_{max}\}$
- Decision variable u_t: energy stored(released) $U = \{-\Delta s_{max}, \ldots, \Delta s_{max}\}$
- If u_t is negative, then energy is discharged from storage and $P_s(u_t) = \frac{u_t \eta_t}{\Delta t}$
- If u_t is positive, then energy is stored into storage and $P_s(u_t) = \frac{u_t}{\eta_p \Delta t}$
- $P_s(u_t) <= w_t^c$ can never store more than you have available
- V_T =0

Like any storage technology, there is a maximum amount of energy or power that can be stored due to pump-turbine limits and therefore u_t is constrained. There is a loss incurred when power is converted to stored energy and vice versa, and this is accounted for when converting u_t to $P_s(u_t)$. The efficiency (η_p, η_t) accounts for the aforementioned losses due to the pump-turbine. Storage in this study is assumed to have no value at the end of the day.

Table 2.1: Model parameters used in the optimization. ©2014 Elsevier

Power committed (MW)	Pump efficiency	Turbine efficiency	Market price (¢/KWh)	γ
170	84.7%	84.5%	9.4	0.5

2.3 Results

2.3.1 Implementation Parameters

The model was implemented over a 24-hour time horizon. The optimization was coded and solved in MATLAB. Two different storage parameters were compared to illustrate the impact of reservoir size on system benefits. Both the upper and lower reservoirs have the same maximum capacity. The maximum capacity of the storage units used in the model are set to be within the capacity range of large hydropower dams in Kenya. The system is constrained in this case to start and end with an empty upper reservoir, and stored energy at the end of the planning horizon is assumed to have no value, though this constraint could be relaxed for longer planning horizons. Storage, which is the state variable, is discretized in increments of 100kWh. The implementation parameters used in the model recorded in Table 2.1.

We consider the efficacy of the wind power system with and without the coupled pumped hydro storage. Scenarios are compared based on various metrics including revenue, deviation from schedule and number of hours of generation shortfall.

2.3.2 LTWP without Storage

In this section the results shown are for LTWP farm alone. Fig. 2.5 is a plot of the wind power output in each scenario and the expected wind power, calculated as a function of the wind power scenarios. The expected wind power is calculated using the probability weighted wind scenario output. The expected wind power is an indicator of what the power system would experience on average, in terms of power generated from wind. If the expected wind power pattern was similar to that of scenario four, which is equal to the installed capacity of the wind farm, then variability of wind would not be a problem and storage would be unnecessary. However the expected power varies throughout the day. To be able to achieve the 300 MW power generation would only be possible with constant high winds. Consequently it would be economically sub-optimal to commit to produce power at a constant rate without the ability to increase or decrease output from the wind farm.

In particular we note that wind power outputs of scenario one and two are relatively low and therefore they lower the value of the expected wind power especially in the afternoon hours. Scenario two has the highest hourly probability of occurrence and therefore has the greatest influence on the expected wind power pattern. Note as in wind power scenarios one, two and three, wind power generated does fluctuate throughout the day, requiring either some form of storage or higher reserve margin to maintain the security and/or stability of the grid.

The typical wind pattern has significantly reduced wind speeds in the early to mid-afternoon, with lowest generation typically experienced in hours eleven through fifteen. This is an indication of the diurnal wind speed pattern expe-

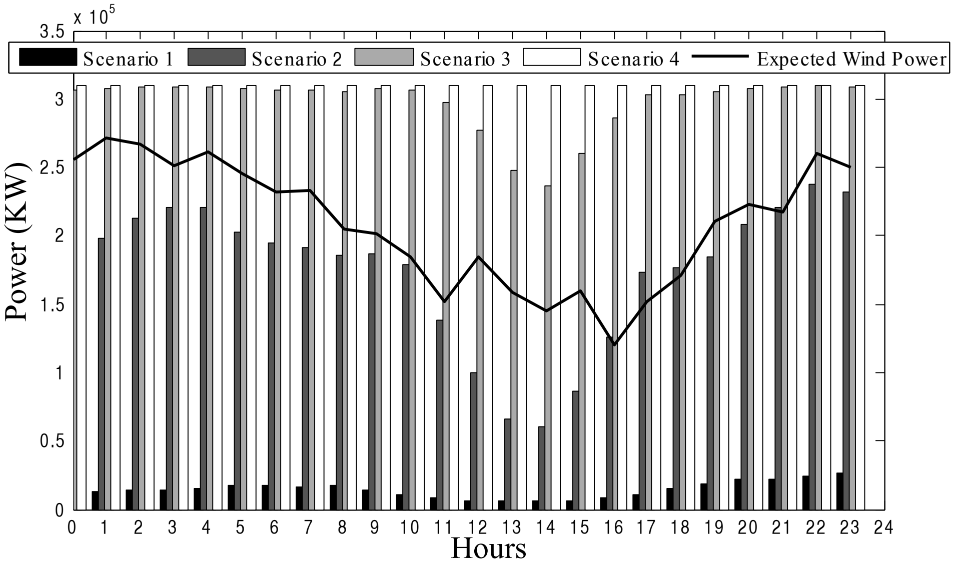

Figure 2.5: Four Wind power scenarios and probability weighted expected wind power. ©2014 Elsevier

rienced in the area. Similarly demand for power is not constant and fluctuates through out the day, with its own diurnal pattern. Fig. 2.6 is a plot of the average hourly demand and expected wind power. If the expected wind power pattern were similar to that of the demand, then its fluctuations would not be a significant challenge to the power system, because demand and supply of power would coincide. But we note in Fig. 2.6 that there is a disparity in the pattern. The expected wind power is high during the early morning, when demand is low. Conversely during the afternoon hours, demand is steadily increasing, while wind seems to decreasing until around 5pm where it starts to increase. It is only during hours 19-21, where both wind and load seem to both peak. Thus in the absence of storage, the system operator will have to schedule ramp up of other generators during the afternoon and late evening hours to make up for the shortfall. During the morning hours, the excess power from wind may not be needed, leading to curtailment to reduce wind power injected to the grid.

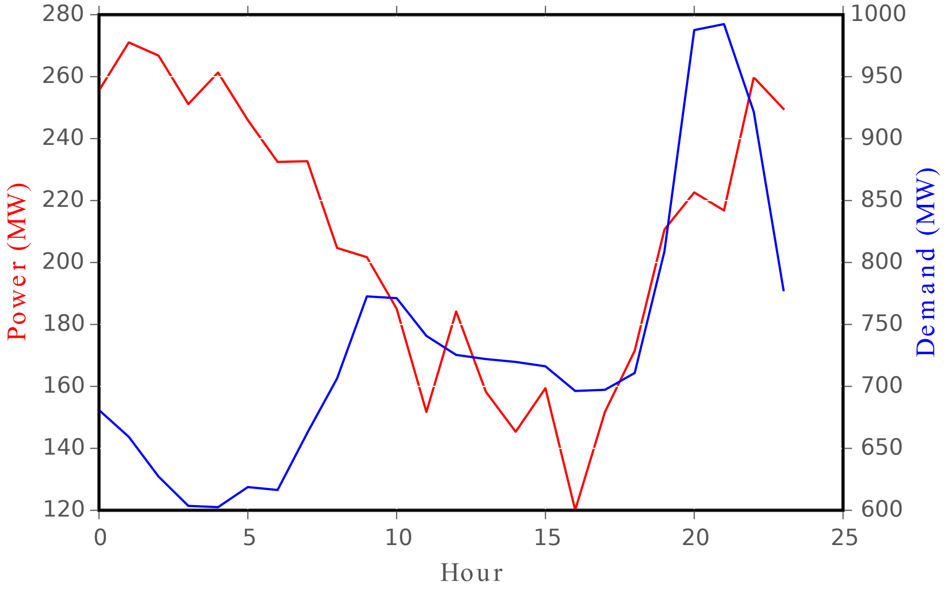

Figure 2.6: Comparison of average hourly daily demand pattern and expected wind power respectively.

2.3.3 Wind Power With Storage

A combined system of LTWP farm with pumped-hydro storage with a maximum reservoir storage capacity of 90MWh and pump-turbine limit, the ramp rate limit, of 40MW is considered in this section. The results of the optimization of wind power combined with storage are as in Fig. 2.7.

The purple line in Fig. 2.7 represents the committed power, the blue line the expected power production and the red line the total power dispatched, which is wind power plus stored power. In this figure, it can be seen that during the hours when power generated is higher than the committed power level, some of the excess power is stored and then released during the higher penalty/low production periods. During the hours when generated power is less than is committed, the system attempts to meet the committed level to reduce penalties

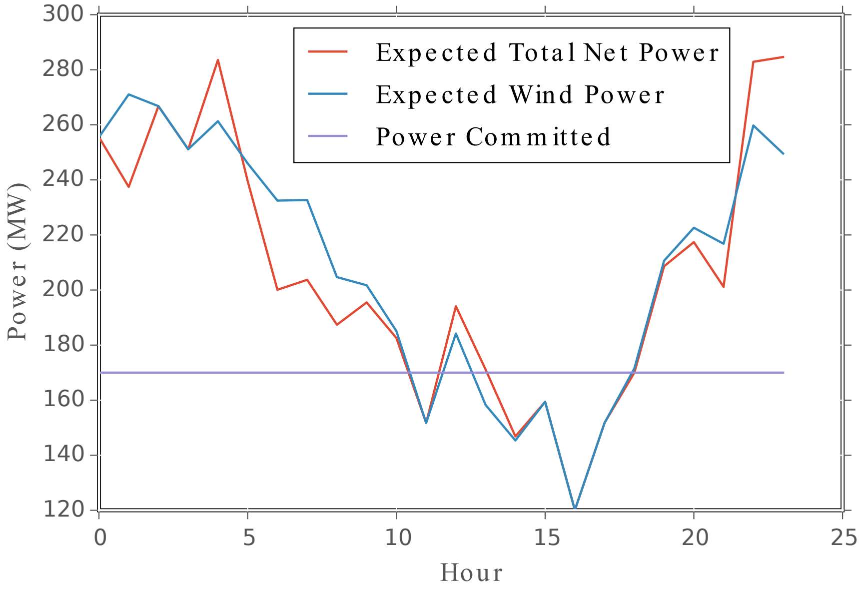

Figure 2.7: Comparison of committed power, expected wind power and total power dispatched.

for negative power deviation. Results shown here are presented with expected wind power, that is the weighted average of the scenario power outputs, but all the calculations in the optimization are based on the four wind power scenarios. Additionally, the total negative power deviation, that is the total kW shortage, is reduced by approximately 1.5%.

The quantity of expected energy pumped into and released from storage at each hour is shown in Fig. 2.8. It can be seen that the system ensures that the ramp limits of 40 MW are not exceeded at any time period. This limits how much power can be stored or released from storage at any one-time period and in effect limits the total amount of power that can be stored or released over the planning horizon. This is a limit set by the reversible pump-turbine used in the system. The positive value indicates that power is pumped up into the upper reservoir for storage and the negative values show the time periods when

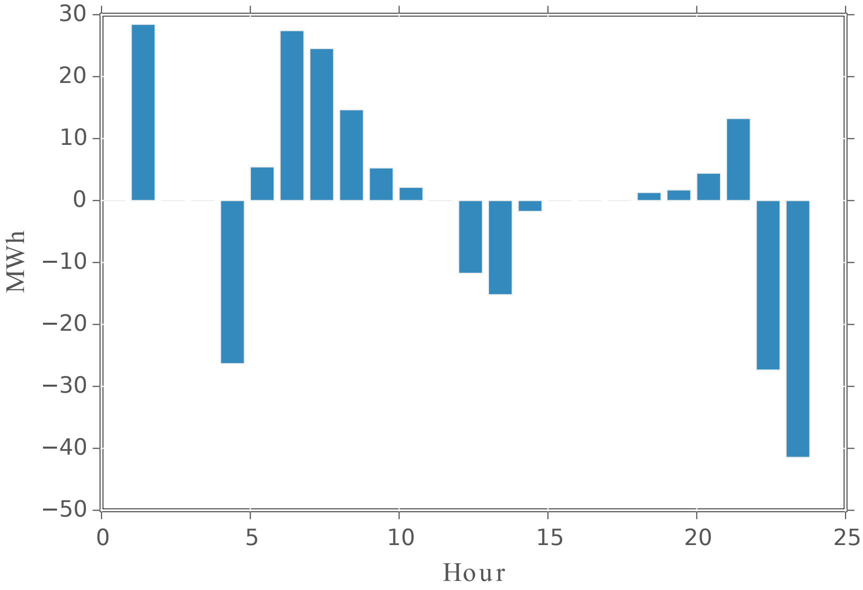

Figure 2.8: Energy stored into or released from storage at each time period.

energy is released generating power. The reversible pump-turbine unit cannot simultaneously store and release energy at any one-time period, but instead does either one of the operations.

The storage capacity at each hour of the operation horizon is show in Fig. 2.9. The storage system has a maximum capacity of 90MWh but this limit is never reached, indicating that a smaller storage unit could suffice. The decision on when and how much to store or generate from storage depends on the available wind power, available stored energy and the penalty cost. The decision framework described here ensures that revenue is maximized for the wind farm by reducing negative power deviations.

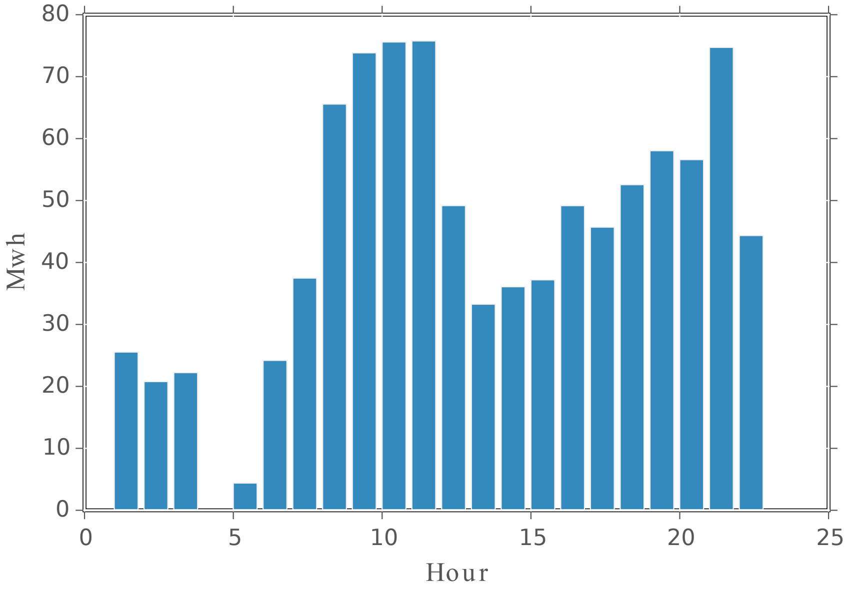

Figure 2.9: Hourly storage capacity of the upper reservoir of a 90 MWh storage unit.

2.3.4 Financial Benefit

The expected daily revenue of this stochastic sample system with and without storage over the operation horizon for committed power of 170 MW is shown in Table 2.2. The last column is the expected gross profit the wind farm operator would realize with the use of a pump-hydro storage. One case shows the expected revenue using a pumped-hydro storage unit with 90 MWh maximum storage capacity and the other with 150 MWh maximum storage capacity. We see that the addition of the pumped hydro storage unit increases the expected daily revenue by approximately 14%. With increased reservoir capacity, there is an increase in profit by approximately 8300 dollars per day. Thus the pumped hydro storage unit is seen to increase the value of the LTWP wind farm, however a larger storage unit does not mean a proportional increase in revenue. Appropriate sizing of the storage unit is therefore necessary in order to maximize the

Table 2.2: Expected revenue in dollars and profit for different storage capacity with committed power of 170MW

Configuration	Expected daily revenue	Gross Profit
LTWP	295,806	0
LTWP + 90MWh Storage	337,842	42,036
LTWP + 150 MWh Storage	346,157	50,348

Table 2.3: Storage Payback considering 90MW storage unit

Capital Costs	Payback (years)
576	3.4
1730	10.1

increase in expected revenue.

2.3.5 Storage Payback

If the storage system is not readily available to the wind farm owner and has to be installed, then in this section the payback duration is calculated. The capital cost of storage ranges between 500-1500 euros/KW [23], which is equivalent to 576-1730 dollars/KW. As seen in Table 2.3, in the worst case scenario, not accounting for any subsidies or feed-in tariffs it would take 10 years to pay off. The general duration of a power purchasing contract is 15-20 years, therefore the wind farm owner would recoup the cost of installing a storage unit within that duration and enjoy a profit.

2.4 Conclusion

We found that even though wind energy is variable, if optimally combined with storage,it can be more predictable and controllable, resulting in further benefit to the power system. The pumped hydro storage resource enhanced the ability to control the dispatch of power output and could potentially ease scheduling of generators by the power system operator. In addition, storage was seen to add value to the wind farm by reducing the occurrence and magnitude of negative power deviations and easing any challenges the system operator may experience due to the terms of the Power Purchasing Agreement thus addressing the World's Bank concern.

Sizing of the storage unit was found to have an effect on the wind farm operator's revenue. An increase in the size of the storage unit resulted in higher expected revenue for the wind farm operator. We found that if the wind farm were to be operated without storage, the wind farm operator would have to commit to generate a relatively low power level to reduce negative power levels as well as potential penalties. Storage could in the future also be used to ease the integration of other variable or intermittent renewable energy sources into the Kenyan power system.

CHAPTER 3

A STOCHASTIC APPROACH TO THE OPTIMAL MANAGEMENT OF A KENYAN WIND FARM COUPLED WITH STORAGE

In this chapter a two-stage stochastic model is developed to determine optimal day-ahead power commitment and intra-day operation of the combined Lake Turkana Wind Power project with available storage, taking into account the unique structure of the Kenyan power market. The work in this chapter has been accepted for publication and is copyright of IEEE [1].

3.1 Introduction

The relatively low levelized costs and negligible emission rates of power generated from wind has led to an ongoing investment in this technology worldwide. The global capacity of installed wind generation has reached 370GW, with an increase of nearly 15% in 2014 alone[2]. The greatest investments in wind generation have been in China, the US and Germany. While the development of this resource is lagging in Africa as a whole, some specific countries, such as Kenya, are investing heavily. Specifically, Kenya is seeking to increase the per-

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centage installed wind generation capacity from 1% to a total of 10% of the total installed capacity in 2017. The Lake Turkana Wind Power project (LTWP) is a key to this expansion, and when complete will be equivalent to 14% of the current 2015 installed capacity. The addition of wind power and geothermal in the country is projected to lower the cost of electricity to the consumer [8]. However, some country specific studies [51, 52] showed that high wind power penetration resulted in increased consumer electricity rates, for example due to increased demand for backup power and feed-in tariff regulations. Consequently, the concern over accessibility of retail electricity at reasonable rates led to the withdrawal of World Bank funding for the LTWP Project in 2012[7].

One of the primary challenges of wind is its variability, which leads to difficulty in accurate prediction. This non-dispatachable nature can pose a major problem to the planning and operation of the power system, which becomes a significant concern as the percentage of wind power injected into the grid increases. In Kenya, where the grid is characterized by high tariffs, voltage fluctuations, power shortages and frequent power outages [53], the addition of wind power could exacerbate current problems and potentially introduce additional challenges to the system [54, 31]. As such, the authors in [55] recommend that for proper utilization and integration of wind resources in Kenya, the grid needs to be stabilized to enable this level of wind penetration. One possible alternative to mitigate potential problems is to coordinate and or combine LTWP with a storage unit. Energy Storage Systems (ESS) allow for energy arbitrage, output smoothing, frequency regulation, voltage control, power output control, reserve application and improved power system reliability among other uses [56, 57].

To ensure effective utilization of storage systems, it is essential to ensure the optimal coordination of a coupled wind-storage system. Joint coordination of wind and storage has the ability to increase controllability and revenue for the combined system. The problem of determining the optimal coordination and commitment of wind and storage has been the basis of many studies. For example in [41] a two stage stochastic model is introduced to determine the optimal day ahead spot market bid and operation of combined wind-hydro system. The random parameters in this study are hourly wind power generation and hourly market prices. A robust optimization model that seeks to determine the optimal day ahead bid for a coupled wind and generic storage system by maximize profit is presented in [58], where the uncertain parameters are market price and wind power generation. The authors in [42] formulate a model to derive the optimal commitment policy of wind and generic storage system using dynamic programming. Three different bidding strategies of wind with a reversible system for the day ahead market are compared and solved in [59]. This model is solved as a stochastic mixed integer linear programming problem with the addition of a risk factor and dynamic market prices. To achieve the optimal operation of ESS for wind energy time shifting, the authors in [45] propose the use of stochastic dynamic programming to maximize expected daily profit with wind and price as random variable. In [60] the optimal day-ahead strategy of a wind farm co-ordinated with ESS is determined using mixed integer nonlinear programming. The model seeks to maximize expected profit of the wind farm operator with varying market prices.

Determination of the optimal coordination of a coupled system is dependent on the particular market conditions. In the aforementioned studies, the market price for each unit of power delivered varies over the planning or operation period. However, in the Kenyan power market prices and penalty costs for all power producers are constant, regulated and stipulated in the power purchasing agreement (PPA). This market structure was first addressed in [61], with a dynamic programming approach using constant market prices for LTWP coupled with a storage system and further explored in [62] to determine the effect of the network on the coupled system. These previous studies considered optimal policies for the operation of the system, without determining the day-ahead commitment and consideration of real-time recourse. In this work a two-stage stochastic model is proposed that takes into account the Kenyan power structure to determine the optimal day ahead commitment and subsequent operation of the combined LTWP and storage system with ramp limits. This study considers the government's wind power policy, which requires the system operator to pay for all wind power produced regardless of dispatch decisions. The model seeks to derive the optimal power commitment that would lead to increased profits for the wind park owner and enhanced planning and operation of the power system. The optimal operation enables improved integration of wind power into the Kenyan power system. Inclusion of the storage unit can maximize profit for the wind farm owner, as well as decrease wind power curtailment, addressing the World Bank's concern about consumers paying for energy not used.

Specifically, a two stage stochastic optimization model is developed which seeks to minimize the expected difference between planned and actual wind system power output. In the first stage the power commitment for the day ahead planning is determined, and in the second stage recourse decisions determine the optimal operation given first stage commitment and the wind power realizations. The net power output ramp rate limits (RRLs) are included in the constraints of the day-ahead commitment, to ensure that inter-temporal variability is manageable without over-burdening ancillary services.

The rest of the paper is organized as follows: Section 3.2 gives the model overview, detailing model assumptions, the modeling of the wind power scenarios and formulation of the model. The results are presented and discussed in Section 3.3, and conclusions are presented in Section 3.4.

3.2 Model Overview

The goal of the model is to determine the optimal day-ahead commitment and operation of LTWP coupled with a storage system, taking into account the structure of the Kenyan power market. In the model, when the combined system produces more power than committed on the day of operation, the wind farm operator is remunerated for each additional MW at a fraction of the market power price. This is inline with the country's renewable energy policies. The wind farm operator incurs a penalty for producing less power than committed on the day of operation and this penalty varies through out the day. The penalty is introduced in the model to ensure that the wind farm operator does not consistently overcommit. The market power price, which is constant, is set at a reference price and labeled as unit price/MW, to avoid specific assumptions about electricity prices and foreign exchange rates. The penalties used in this study are linear and equivalent to the avoided costs of using a medium speed diesel generator. Net power RRLs are assumed to be dictated by the system operator. The scenario based approach is used to represent uncertainty in this model. The storage unit used in the model is a pumped-storage unit given the high availability of hydro power plants in the country that could be converted to storage units with reversible pump-turbines. Nonetheless, any type of storage unit could be substituted through minor modifications to model parameters.

3.2.1 Wind Power Scenarios

For a realistic day-ahead power commitment from the wind farm in a two stage model, a number of possible wind power scenarios are required. The wind speed realizations used here are simulated via time series analysis. Each possible realization that is simulated is taken to have an equal probability of occurrence.

Actual wind speeds from the Marsabit region are used to simulate possible realizations of wind power output from LTWP. This particular region experiences similar wind flow patterns to that at LTWP due to the Turkana jet [35] and the wind speeds are therefore adequate to simulate the particular wind farm. A detailed description of the wind data is found in [61]. The steps taken to simulate wind power realizations are described in Algorithm 1.

3.2.2 Stochastic Two-Stage Model

The main objective of the model is to determine the optimal commitment and operation of combined LTWP wind park with a pumped hydro storage unit (PHS). This is solved using the L-shaped method.

The formulation of the two-stage model is as follows:

Algorithm 1: Wind Power Scenario Generation

1: Transform wind speed x_t using Yeo-Johnson transformation [63]:

$$y_t = \begin{cases} \frac{(x_t+1)^{\lambda}-1}{\lambda}, & (x \geq 0, \lambda \neq 0) \\ \log(x_t+1), & (x \geq 0, \lambda = 0) \\ -\frac{(-x_t+1)^{2-\lambda}-1)}{2-\lambda}, & (x < 0, \lambda \neq 2) \\ -\log(-x_t+1), & (x < 0, \lambda = 2) \end{cases}$$

2: Standardize transformed time series y_t:

$$y_t^* = \frac{y_t - \mu_t}{\sigma_t}$$

3: Determine time series model using Box-Jerkins Methodology:

$$\text{ARIMA}(2,1,3): \ \phi_2(B) \nabla y_t^* = \theta_3(B)\epsilon_t$$

4: Simulate wind speeds $y_t^*(\omega)$ from ARIMA time series model by Monte Carlo simulation.

5: Undo standardization and perform inverse transformation:

$$y_t^*(\omega) \rightarrow y_t(\omega) \rightarrow x_t(\omega)$$

6: Convert simulated wind speed scenarios to respective wind power scenarios at wind farm level using the multi turbine power curve approach [50] algorithm.

First stage:

$$\min \sum_{t\in T}(-M_p P_c^t + \sigma^t(\alpha S_{\max} - S^t)) + \mathbb{E}[R(P_c, P_s, \omega)] \tag{3.1}$$

$$\text{s.t:} \qquad E_w^t - P_c^t - P_s^t = 0,\ t \in T \tag{3.2}$$

$$S^{t+1} = S^t + \eta \Delta t P_s^t,\ t \in\ T \tag{3.3}$$

$$\alpha S^{\min} \le S^t \le \alpha S^{\max},\ t \in T \tag{3.4}$$

$$P_s^{\min} \le P_S^t \le P_s^{\max},\ t \in T \tag{3.5}$$

$$RRL^{min} \le P_c^{t+1} - P_c^t \le RRL^{max},\ t \in T \tag{3.6}$$

Second stage:

$$\min \sum_{t\in\ T}(C_p^t(\omega)Q_-^t(\omega) - \gamma M_p Q_+^t(\omega) + \sigma^t((S_{\max} - S^t) - q_s^t(\omega))) \tag{3.7}$$

$$\text{s.t:} \quad P_w^t(\omega) - P_c^t - (P_s^t + Q_s^t(\omega)) = Q_+^t(\omega) - Q_-^t(\omega),\ t \in T \tag{3.8}$$

$$q_s^{t+1}(\omega) = q_s^t(\omega) + \eta \Delta t Q_s^t(\omega),\ t \in T \tag{3.9}$$

$$S^{\min} \le (q_s^t(\omega) + S^t) \le S^{\max},\ t \in T \tag{3.10}$$

$$P_s^{\min} \le (P_s^t + Q_s^t(\omega)) \le P_s^{\max},\ t \in T \tag{3.11}$$

Where $\gamma \in (0, 1)$ represents the fraction of the market price that is paid to the wind farm owner for producing more power than is committed. The fraction of storage that is used in making next day commitment is given by $\alpha \in (0, 1)$. The cost of storage is represented by σ^t. The model charges for keeping the storage unit empty basically ensuring that the storage unit is used when most needed, that is during the low cost periods. This also ensures that the storage system does not release all stored energy at the earliest time period. η accounts for conversion efficiencies, when pumping or releasing energy from the storage unit.

The objective function in the first stage (3.1) aims to minimize costs. It is constructed by subtracting revenue for each MW of power committed, P_c^t from storage costs and the expected second stage recourse cost. In the second stage, the objective function (3.7) includes the cost for any shortfalls, $Q_-^t(\omega)$, revenue from any surplus power generated,$Q_+^t(\omega)$, and cost for storage utilization for each wind power realization. Equation (3.2) and (3.8) are power balance constraints that ensure the system cannot generate more than is available. The storage constraints (3.3) and (3.9) ensure that the storage level at any time period is determined by the storage level at the previous time period, adjusted by any power added or discharged. Equations (3.4) and (3.10) are storage capacity constraints for making day ahead commitment S^t, and daily operation $q_s^t(\omega)$, respectively. The storage charge/discharge ramp constraint for commitment is described in (3.5) and for operation is described in (3.11) where the total storage charge/discharge quantity in the second stage is a function of expected first stage quantities. The power RRLs are described in (3.6), where the net hour to hour change in committed power is limited to a certain range.

3.3 Results and Discussion

The model is implemented over a 24 hour time horizon with hourly operation intervals. It is built and solved in CVX a package for specifying and solving convex programs [64] in MATLAB. The simulated LTWP wind farm has a capacity of 300 MW and the PHS unit has a maximum reservoir capacity of 60MWh. The up and down power RRLs are ±30MW/hr, however it is assumed that these limits are dictated by the system operator and could change from one operating day to another. Penalty cost ranges from 10 to 17 units of cost per MW and the market price per MW is 12 units of price. The PHS is designed with a reversible pump-turbine with an efficiency of 85%. Demand is low in the morning hours and slowly increases throughout the afternoon, with the daily peak is during the late evening hours. The total gross profit margin of the model is calculated both with and without storage. The expected total gross profit margin for the generator with a storage system is approximately 59,828 units of price and 58,943 units of price without a storage unit. Therefore the availability of the storage system could lead to an increase in total profit to the order of 890 units of price per day. Regarding the optimal commitment and operation decisions of the model, the first and expected second stage results of the model are shown in Fig. 3.1. The two-stage model, on average, reduces penalties by minimizing the difference between power committed and actual net power produced on the day of operation. The first stage power commitment solution is shown by solid starred line and the expected second stage solution is depicted by the solid line. The dashed line shows the expected wind power. The biggest difference between committed power and expected net power is seen during hours 0-5 and hour 15 when the load is low. However the difference is reduced and in some cases overlaps during peak hours of 7-9 and 19-21 as penalty costs are highest during these periods. The model is found to improve the average operation of the combined system. It is interesting to note that the model tends to under-commit during hours when the range in wind power is high, specifically between hours 9-19. Fig. 3.2 is a box plot of wind power scenarios, which shows the dispersion of wind power at each hour of the day, it can be seen that the highest variability coincides with the hours when the model under commits. This shows that the uncertainty in wind power affects the model's decision for power commitment.

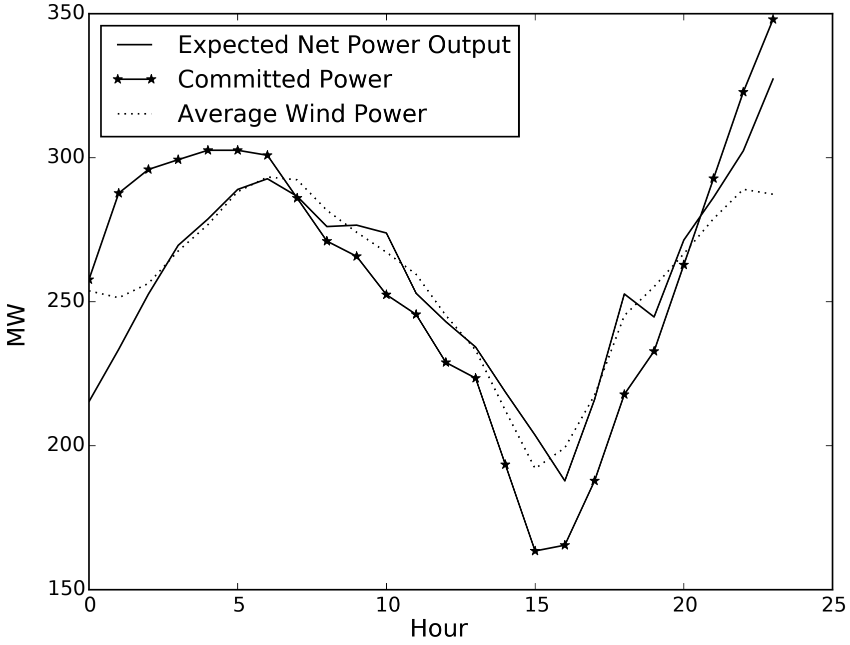

Figure 3.1: Commitment and Expected Net Output.©2016 IEEE

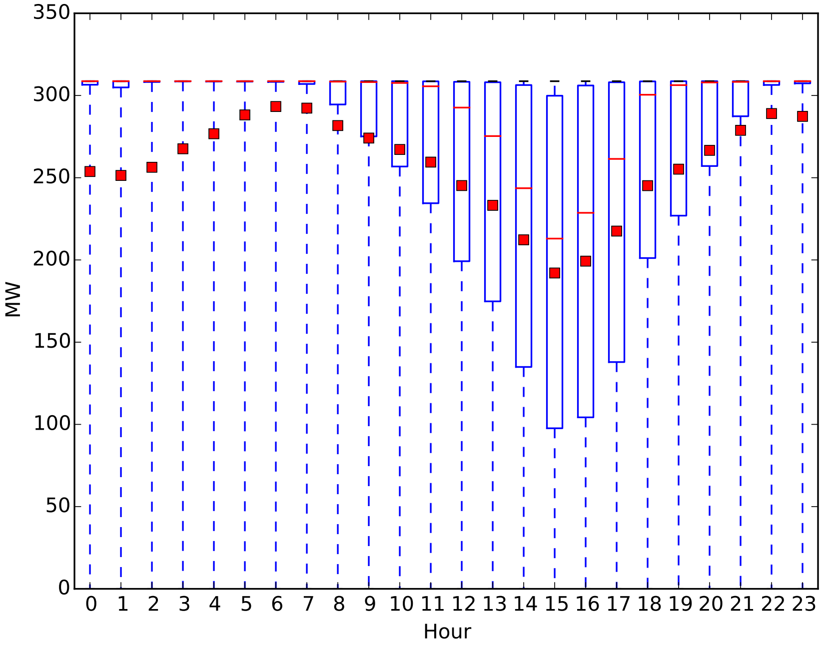

Figure 3.2: Box plot of Wind Power Scenarios. ©2016 IEEE

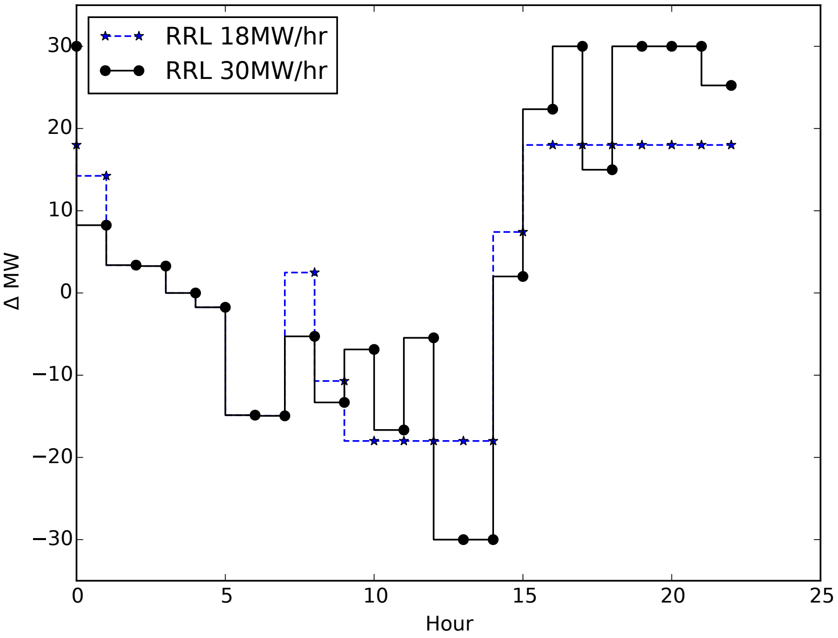

Figure 3.3: Hour-to-Hour Variations. ©2016 IEEE

3.3.1 Efficacy of Ramp Rate Limits

The purpose of the RRLs is to limit the hour to hour variability of the net power produced, reducing the need for the system operator to use ancillary services to balance the power system. Fig. 3.3 is a plot of the change in power commitment from one hour to the next at two different RRLs. In both cases, the power committed is kept within allowable limits, therefore the inclusion of limits in the model works at limiting the hourly variations of committed power to system dictated limits. Consequently, also restricting the second stage recourse actions as they are dependent on the power committed.

Table 3.1: Total Expected Penalty Costs. ©2016 IEEE

Load Following Penalty	Constant Penalty
7700	7876

3.3.2 Cost Comparison

Penalty Costs

In this model, the penalty costs vary throughout the day and are dependent on the load pattern. However when the results of this model are compared to the case of constant penalty, it is found that expected total penalty costs are higher. In Table 3.1 it is seen that the total penalty cost per day for constant case are higher than in the load dependent case even with the same average MWs short. This is due to the fact that with constant penalties, the model does not have the option to shift the difference between commitment and net power to periods of low penalties. Therefore, constant penalties imply higher costs for the wind farm operator and also cause a potential increase in operational difficulties for the grid operator during high load periods.

Storage Costs

The storage pump/release cycle is presented in Fig. 3.4. Positive values indicate energy is being pumped into the storage unit and negative values indicate that energy is being released from the storage unit. The dynamic storage costs are inversely related to the load profile, meaning that storage costs are higher when load is low and vice versa. For comparison, the case of running the model with

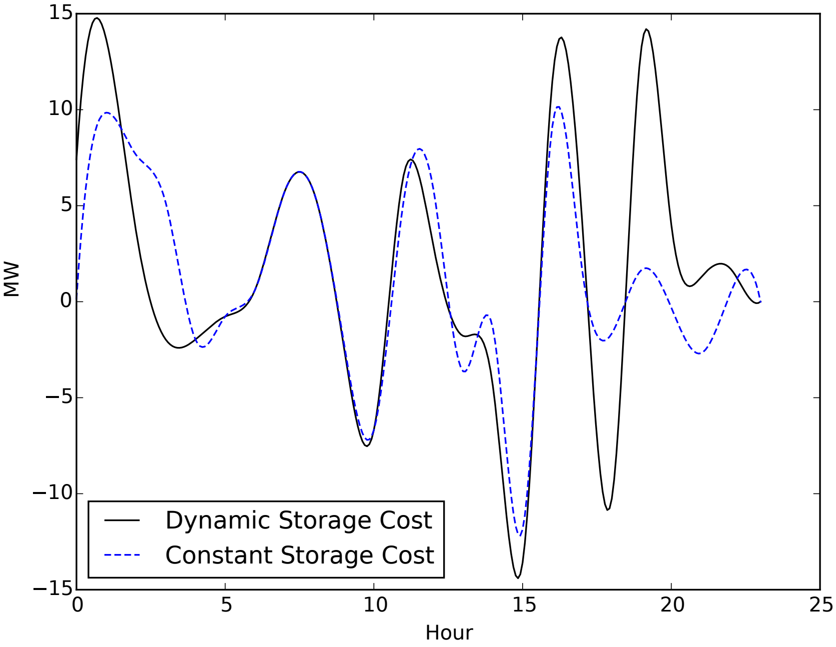

Figure 3.4: Pump/Release cycle for different storage cost. ©2016 IEEE

constant storage cost is included Fig. 3.4. This constant cost is set at the average of the dynamic cost structure. Between hour 6-12, when the difference in cost for the two cases is very small, it is seen that the charge/discharge cycle for both cases is approximately the same. The impact of storage cost policy is seen in the morning hours and late evening hours when prices are very high and low respectively. In the case of dynamic costs, the storage unit is found on average to charge/discharge higher quantities of energy than in the constant case especially during the peak demand period. Therefore to increase the use of the storage system during high demand hours, dynamic costs need to be implemented.

3.4 Conclusion

This paper has presented a two-stage stochastic optimization model to determine the optimal commitment of a combined wind-storage system based on the LTWP. A unique feature of this model is the implementation of the specific features of the Kenyan power market, storage costs, and inclusion of realistic RRLs. The model is run over a 24 hour operational horizon and storage costs are included in the model. The net results show that the addition of the RRLs restricts hourly variations of the net system power output. The limitation of variability in generator dispatch provides non-trivial benefits to the system operator. Additionally, the storage system is found to reduce running costs for the wind farm operator, resulting in increased gross profit margin. Results also show that the availability of the storage unit, in conjunction with dynamic penalty costs, allows the wind farm operator to shift generation shortage to hours with lower penalties. This ability leads to a reduction in the penalty costs faced by the wind farm operator.

Based on the results, we make the following recommendations : 1)Use of power RRLs in optimal operation to control variability of net power output from the wind farm 2) Adding storage costs to encourage efficient use of the storage unit. 3)If the system operator introduces penalties for wind farm operators, the penalties should be load following to maximize benefit for the power system and limit penalization to the operators of the wind-storage system. The introduction of penalty costs would incentivize improved forecasting.

In order to further advance the realism of the model presented here, different efficiencies for the pump and turbine could be included. This would account for the difference in losses between pumping and release of energy from the storage and may lead to alternatives in the wind-storage system operation that could impact the overall power system.The RRLs were only included in making the day ahead commitment, therefore further work will include adding a penalty term in the second stage objective function to account for violation of RRLs in the operation of the system so as to further limit the system's net power variability.

CHAPTER 4

IMPACT OF WIND POWER INTEGRATION ON THE RELIABILITY OF THE KENYAN POWER SYSTEM

In this chapter a study on the effect of the addition of wind power from the simulated LTWP wind farm on the Kenyan power system by conducting Sequential Monte Carlo reliability analysis with a focus on system generation adequacy is presented. This study determines the outcome of pairing LTWP with a storage system on the reliability of the Kenyan power system. Wind power is sampled using stratified sampling to reduce overall variance of the simulation. The strata are created using bisecting k-means clustering and proportional allocation applied to determine samples to use in the simulation.

4.1 Introduction

Reliability of a system is its ability to perform required functions under stated conditions for stated period of time [65]. Power system reliability looks at system adequacy and security. System adequacy refers to the ability of the power system to meet requirements of the customer and is associated with the planning of the system, while system security is the ability of a power system to withstand sudden transient disturbances [66, 65]. An increase in generation capacity, generally leads to an increase in the system's ability to meet load, and therefore an increase in reliability. However, the contribution of wind power to the reliability of a power system is site specific. In sites with high mean wind speeds, the contribution of wind power to the reliability of the power system is found to be significantly positive [67]. Whereas in other cases, the marginal contribution of wind capacity to the system reliability reduces as wind penetration increases [68]. The capacity of a wind farm that would be required to sustain a given reliability criterion can be considerably higher than that associated with conventional generating units [67]. Consequently it is important to critically assess the reliability of a power system when wind power is introduced in order to understand its resulting influence in relation to system adequacy. In Kenya where the wind capacity contribution to total installed generation capacity is projected to increase from the current 25MW to more than 300 MW, the reliability of the power system is a major concern. The major contributor to the increased wind capacity is the Lake Turkana Wind Power (LTWP) wind farm, which is currently under development.

The two main approaches that are used in evaluating power system reliability in terms of system adequacy are analytical methods [68, 69, 70] and simulation methods [71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81]. Analytical techniques represent the system by mathematical models and evaluate system risk indices using mathematical solutions [74]. For a power system with wind, analytical methods fall short in that they do not consider the chronological characteristics of wind and its effect on system output [82], but they can still provide system planners with reasonably accurate results to make objective decisions in fairly short computational times [66]. Simulation methods estimate the reliability indices by simulating the actual process and random behavior of the system [66]. Monte Carlo simulation(MCS) based methods are the most robust [83] and are frequently used for their flexibility and capability of handling high-order contingencies [80], however they can be computationally expensive. Simulation techniques include non-sequential MCS, sequential MCS and hybrid MCS methods. Non sequential MCS simulates the basic intervals of the system lifetime by choosing intervals randomly whereas the sequential approach moves chronologically through system states and have the benefit of being able to factor in the intertemporal aspects of hydropower, wind power and load [66]. Hybrid methods, as the name suggests, are a combination or either sequential or non sequential MCS with another technique to improve efficiency of the simulation by either improving computational time or improving sampling. Examples of hybrid methods include combining sequential MCS with techniques such as cross entropy [83, 84], taylor series approximation [85], smooth boot strapping technique [86], supervised learning [87] and unsupervised learning [88**?**]. However, none of these hydrid methods consider a power system with wind power. An example of sequential MCS with an improved sampling method, Latin Hypercube Sampling (LHS), for a power system with wind power, is detailed in [89], however the sampling is only applied generator states and not wind power sample space.

This paper attempts to assess the reliability of the Kenyan power system with wind power from LTWP wind farm and considers the impact of coupling the wind farm with an energy storage unit, taking into account the projected 2017 generation installments. This study seeks to determine a conservative estimate of the effect of wind power from LTWP on the power system adequacy since the wind farm is not yet operational. Stratified sampling, a variance reduction technique, is applied to improve the efficiency of the MCS. In stratified sampling, the data is split into homogenous non-overlapping groups referred to as strata and a sample from within each stratum is selected. A stratified sample with the desired number of units from each stratum in the population will tend to be representative of the population as a whole [90]. Bisecting k-means, a clustering technique, is applied to create the strata. This study differentiates itself in that:

- it considers system generation adequacy unlike [91], which considers operating reliability of the power system
- it applies sequential simulation approach unlike the analytical approach applied in [92] when determining the impact of coupling a wind farm with storage on the reliability of the power system
- it places no restriction on the maximum power output contribution of the combined wind and storage system to the power system unlike in [93]
- wind power conversion is simulated at wind farm level, unlike prior studies [94, 57, 95, 96] where it has traditionally been represented by the mathematical expression for the power curve [97]

The paper is organized as follows: a brief description of the Kenyan power system is introduced in section 2, and the generator modeling is described in section 3. Section 4 then details the steps for wind speed simulation and conversion to respective wind power scenarios and the bisecting k-means methodology. The sequential MCS reliability analysis methodology is presented in section 5, the results are presented in section 6 and finally the paper is concluded in section 7.

4.2 Kenya Power System

As of June 2015 the peak demand in Kenya was recorded to be 1512 MW with an estimated annual growth of 13.5 % [98]. The total installed generator capacity for the same period was recorded as 2204 MW [99]. About 62% of generated

Year	Hydro	Diesel	Imports	Co-gen	Gas Turbine	Geothermal	Wind
2013	46.7%	33.8%	0.0%	1.5%	3.4%	14.3%	0.3%
2015	36.2%	32.4%	0.68%	1%	2.4%	26.1%	1.1%
2017	28.6%	25.2%	0%	1.6%	1.9%	29.1%	13.6%

Table 4.1: Contribution of different generator types - Current and Projected

electricity is from renewable energy sources, with hydropower making up a majority of this percentage. The effective capacity of hydropower generation has however been approximately 10% less than its installed capacity due to failure of long rains in the recent past [99]. The climatic conditions of 1998 - 2000 and 2008 - 2009 for example, necessitated the curtailment of hydropower generation, which led to severe energy shortages, and culminated in power rationing [100]. The reduced hydro production coupled with the increasing demand for electricity has resulted in the increased dependence on diesel generators, which are run at full capacity [33] resulting in high electricity tariffs for end consumer. Consequently the government is pursuing measures to increase power production and diversify power generation sources. There are plans to develop 5000+ MW of additional capacity [99]. Currently, the total wind power installed capacity in the country is 25 MW, and it is estimated that by 2030 this will increase to 2036 MW [98]. In the near future, the 300 Lake Turkana Wind Power (LTWP) wind farm is expected to be the biggest contributor of installed wind power in the country. Table 4.1 shows the current and planned percentage contribution of each type of generator, showing a general increase in geothermal and wind power generators.

In previous reliability studies the Loss of Load Expectation (LOLE) used in Kenya was 10 days a year, which equates to a Loss of Load Probability (LOLP) of 0.027. However, recently a LOLE of 1 day in 10 years has been recommended for least cost planning studies, so in the country can achieve reliability criteria in line with the country's Vision 2030 goal. The respective LOLP would therefore be 0.00027 [33]. Although this is the planned recommendation, the addition of wind power and reduction of flexible generators such as hydro power and diesel generators, could have an impact on the system's reliability.

4.3 General Generator modeling

All generation units in this study, other than wind turbines, are modeled using markov two-state reliability model as in Fig. 4.1. This means that they are either available and operating at full capacity or unavailable due to forced outages. Transition to a down state is determined using failure rate ($1/MTTF$) and to an up state by using repair rate ($1/MTTR$). The thermal diesel and geothermal plants are assumed to be classed as base load generators for which the two state model is appropriate in modeling states of the generator. The hydropower generators are normally classified as peak generators, however, in Kenya are used as base generators and are therefore also modeled with the two state model. The high increase in demand and limited development of generators has necessitated the use of all generators at full capacity to meet the load. Forced outages of the wind turbines are not considered since they have minimal effect on reliability indexes [70].

To generate random time to failure and time to repair for each component, an exponential distributed generator is used. This generator produces random variables that follow an exponential distribution and are based on uniformly

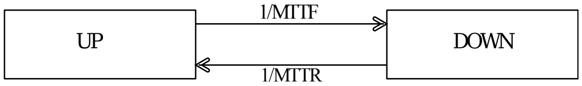

Figure 4.1: Markov Two State Generator Model. MTTF- mean time to failure and MTTR- mean time to repair

distributed random numbers between zero and one [101]. An exponential distribution is used since it is the most suitable distribution to describe failure of components in the normal life period (flat portion) of the bathtub component life curve.

The time to failure and repair is calculated as follows:

$$T = -ln(1 - U)/\lambda \tag{4.1}$$

Where:
U=uniform random number [0,1]
λ=mean value

4.4 Wind Power Modeling

The first step in the modeling of wind power scenarios is to generate wind speed scenarios using a time series model. The wind speed scenarios are converted to wind power using the Multi-Turbine Power Curve approach [50]. Bisecting k-means clustering is then applied to the simulated wind power scenarios to create strata from which a number of samples are selected for use in the MCS. The wind data used in detailing the model is generated from actual wind speeds collected in Marsabit, which is in close proximity to the Lake Turkana Wind Power (LTWP) wind farm and experiences similar wind speeds. The data contains hourly wind speeds collected over a period of two years. Further details of the wind speeds used can be found in [25].

4.4.1 Wind Speed Scenario Generation

Steps to simulating wind speeds:

1. Standardize wind speeds over the day

   The diurnal pattern of wind data from this region dominates any seasonal pattern and it is therefore necessary to standardize the wind speeds to this strong pattern. Standardization in this study also deals with seasonality, since it is computed over the month.

2. Determine the distribution of the data and transform if necessary

   The standardized wind speeds are found to have an approximately standard normal distribution after conducting the one-sample Kolmogorov-Smirnov test and also comparing the empirical cdf of the wind speeds to that of a standard normal distribution.

3. Check for stationarity and determine order of differencing

   The standardized data is found to be unit-root stationary after conducting the Augmented Dickey-Fuller test for a unit root.

4. Use ACF and PACF to estimate order of model

   The autocorrelation (ACF) and partial autocorrelation (PACF) function is used to give an initial estimate of a model that would be most suitable to model the wind data. The results indicate that an initial guess of a model would be an autoregressive process of order three.

5. Compare BIC values for different possible model order

   The Bayesian information criteria (BIC) for various model orders are compared, starting with the initial guess. The model order that is found to have the lowest BIC value is picked as the most adequate model order to proceed with.

6. Determine model parameters

   The model parameters are estimated using the maximum likelihood approach. The maximum likelihood method leads to a process described by:

   $$AR(3): \ \phi_3(B)y_t = \epsilon_t \tag{4.2}$$

7. Check model goodness of fit

   For an adequate model, the estimated residual should be gaussian white noise. Gaussian white noise is uncorrelated, has an approximate normal distribution and a variation uniformly distributed on all frequencies. The graphs in Fig.4.2 show that the residuals from the model meet these requirements, indicating that the model created is adequate to describe the data.

8. Simulate wind speeds

   Wind speed are simulated from AR model by Monte Carlo simulation

9. Unstandardize the wind speeds

   The simulated wind speeds are then unstandardized after which any negative wind speeds are set to zero. This is found to be an acceptable method to deal with negative values obtained from time series model in reliability analysis [94].

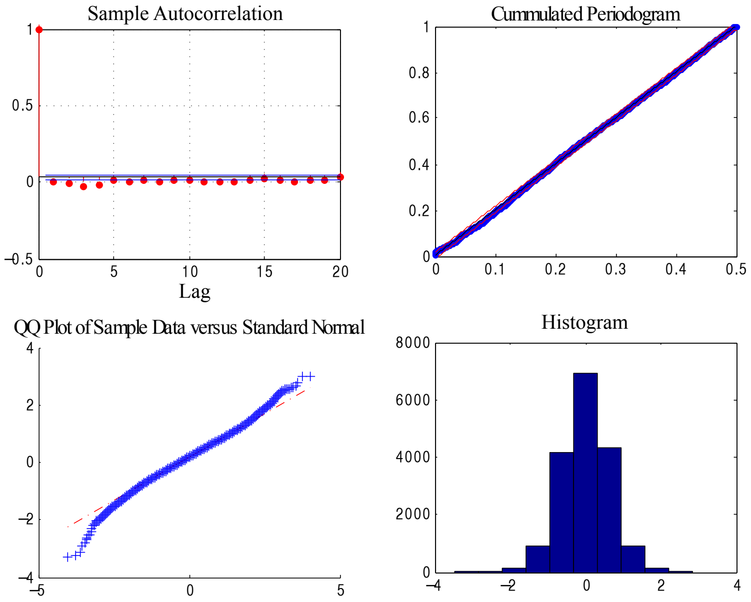

Figure 4.2: Autocorrelation function and Cumulated Periodogram of the residuals

4.4.2 Wind Power Simulation

The simulated wind speed are then converted to wind power at a wind farm level using the multi-turbine power curve approach [50]. This approach generates aggregated wind power output for a wind farm with multiple wind turbines from a single time series by taking into account the smoothing effects of both time and space. The algorithm applied is described in [50].

4.4.3 Wind Power Clustering

Bisecting k-means method is implemented to cluster the simulated wind power samples for stratified sampling. The bisecting k-means technique generates better quality clusters than regular k-means algorithm. The clusters generated are to be used as strata, which are made up of homogenous data, from which a number of samples are independently selected for use in the simulation. Since the wind power data to be clustered is aligned in the time axis, the use of euclidian distance as a measure of similarity is acceptable. The procedure implemented is described in algorithm 2.

Algorithm 2: Bisecting k-means

```
Start with one cluster for all data
Determine cluster centroid by finding average of cluster
    $c_k = \frac{1}{C}\sum_{i=1}^{C} x_i$    (4.3)
Calculate total sum distance (distance between each point and cluster centroid)
    $SumD = \sum_{k=1}^{K}\sum_{i=1}^{C}(x_{ki} - c_k)$    (4.4)
while number of clusters is less than k do
    for each cluster do
        Split into two clusters
        Determine cluster centroids for the new clusters
        Calculate new total SumD
    end for
    Bisect cluster that gives lowest total SumD when split
    Update original cluster list with new cluster assignments
end while
```

4.5 Sequential Monte Carlo Reliability Analysis

The MCS method estimates reliability indices by repeatedly simulating a number of trials to replicate hour-to-hour operation of a power system and random behaviors in the system [77]. The sequential MCS approach moves chronologically through system states enabling it to correctly represent renewable energy sources and their natural uncertainties. It is conducted by sampling the duration that each generator is in a certain state to generate chronological up-down cycles and combining the operating cycles of all units plus available wind power to determine the system available capacity. A large number of simulations are required in order to estimate the various reliability indices at a specified degree of confidence [101]. The use of a storage system is implemented in a myopic/-greedy strategy since the goal of the study is to determine if there is a benefit of coupling LTWP with a storage system to the reliability of the system.

The steps taken to perform the sequential Monte Carlo reliability analysis in this study are described in algorithm 3.

The stopping criteria used is the coefficient of variation of an index [101], most commonly of the EENS/LOEE index due to their low rate of convergence. The coefficient of variation is defined as:

$$\alpha = \frac{\sqrt{V(\bar{X})}}{\bar{X}}$$

Where:

α is the coefficient of variation

$\bar{X}$ is the estimate of a reliability index

Algorithm 3: Sequential Monte Carlo Simulation Steps

```
Use proportional allocation to select n number of samples from each stratum
repeat
    if number of simulation runs > than number of wind power samples then
        generate 50 new samples using proportional allocation from unsampled data
    end if
    Select wind power scenario from sample scenarios
    Simulate the duration of each component residing in a each state for the whole year. Each component is assumed to start each simulation in the available state.
    Calculate total system generation capacity
    Compare total generation to total load for the hour
    if using storage then
        Storage at beginning of each simulation run is empty
        if total generator capacity > than load - wind power > 1/2 installed capacity then
            store excess energy
        else
            release energy from storage system then compare total generation capacity+storage energy to load
        end if
    end if
    Record reliability indices
until $\alpha < 0.025$
```

$V(\bar{X})$ is the variance of the estimate

The basic indices usually calculated in generating system adequacy assessment and that are estimated here are:

- Loss of Load Probability (LOLP) - The probability of the system load exceeding available generating capacity

  $$LOLP = \sum_{i \in T} p_i \tag{4.5}$$

  Where: p_i: probability of of system state i

- Loss of Load Expectation (LOLE) -The average number of days/hours in an year in which the load exceeds generating capacity

  $$LOLE = \sum_{i \in T} p_i T \tag{4.6}$$

  Where: T: total period in hours

- Loss of Energy Expectation (LOEE) - The expected value of the actual energy not supplied by the generating system to meet actual demand

  $$LOEE = \sum_{i \in T} E_i p_i * 8760 \tag{4.7}$$

  Where: E: Load less available capacity when load > available capacity

4.6 Simulation Results

The simulation results are based on the projected 2017 load and generator capacity of the system. An 8% annual load increase from the current load level is assumed, based on past trends of annual load growth. This percentage is a conservative estimate of the expected 2017 load growth. The system used here includes wind power from LTWP and 37 generators, contributing to a total installed capacity of approximately 2740 MW and a peak load of approximately 1828 MW. The storage unit used has a capacity of 90MWh. As a current baseline, reliability indices for the 2015 system are estimated. The 2015 system consists of the existing 34 generators with an installed capacity of approximately 2200Mw and a peak load of 1512 MW. The simulation is run for 8760 hours per sample year.

For the base case results, LOLE is found to be 4.6 hours/year, which is far better than the 10 days a year that was previously used, but exceeds the recommended target LOLE of 1 day in 10 years. The expected energy not served is evaluated to be approximately 265 MWh and LOLP equal to 0.00052, which is higher than the recommended 0.00027. Fig. 4.3 is a plot of LOEE, which is the index used to calculate coefficient of variation and to determine simulation convergence. As seen in the plot, the simulation meets stopping criteria after approximately 4600 runs. A plot of total generation for all generators in the system accounting for random outages over one simulation run is shown in Fig. 4.4. For this particular simulation the maximum generation is 1937 MW and minimum generation is 1253 MW.

4.6.1 Results with Wind Power from LTWP

With the addition of wind power, planned generator expansion and forecasted load, the reliability overall is found to improve. Since the LTWP is planned to be gradually integrated into the power system, the reliability indices are estimated

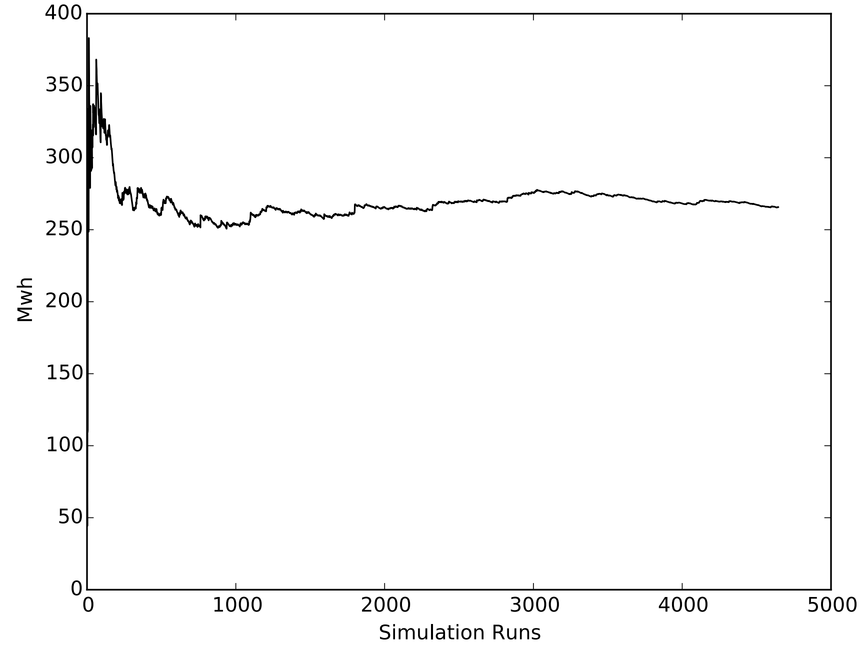

Figure 4.3: LOEE

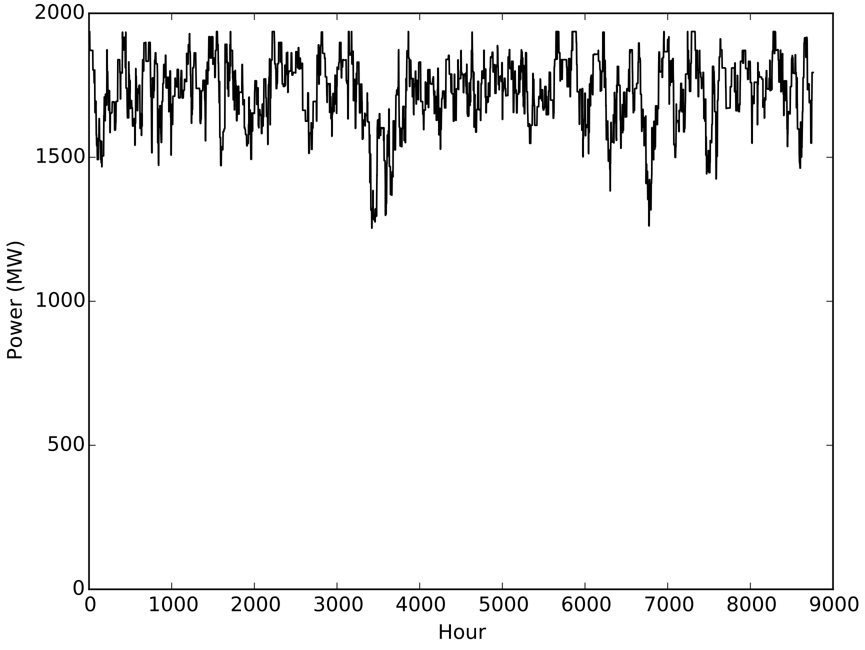

Figure 4.4: Total Generation for a Single Run

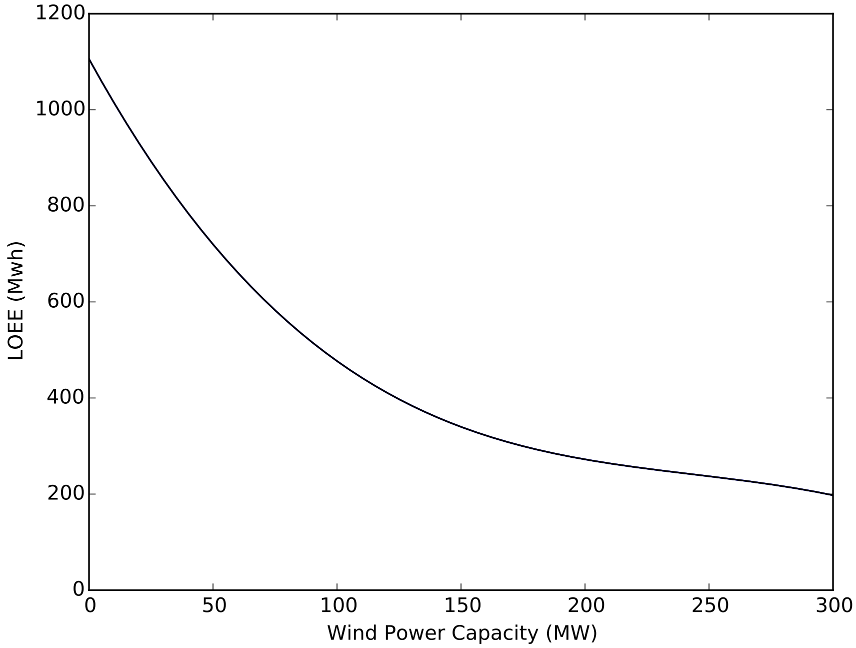

Figure 4.5: LOEE at different Wind Power Capacities

at different capacity levels to understand the impact on the power system. In this study, wind power is integrated at 50MW, 100MW and 300MW capacities, with 300MW being the full installed capacity of LTWP. In Fig. 4.5 a plot of LOEE of the system with different capacities of LTWP wind farm is shown. It can be seen that on average, the LOEE improves with increased wind power capacity, but after 200 MW the improvement in expected energy shortfall is only seen to minimally improve. At full capacity, the total LOEE of the power system is 197.6 MWh, while at 0 capacity it is 1105.7 MWh. The estimated LOLP and LOLE at different LTWP capacities are listed in Table 4.2. While a significant improvement in system reliability is seen in the table, it still doesn't meet the future recommended reliability criteria. When compared to the basecase, an improvement in reliability is only noted at full LTWP capacity.

Table 4.2: Reliability Indices at different LTWP Wind Farm Capacity

LTWP Capacity (MW)	LOLP	LOLE(hr/year)
0	0.0019	16.2
50	0.0012	10.9
100	0.00085	7.4
300	0.00035	3.7

4.6.2 Impact of adding Storage

The storage unit is coupled to LTWP wind farm and the reliability results are compared to the case of LTWP without storage capabilities. As seen in Table 4.3, with the addition of storage, there is a marginal improvement of LOLE and LOLP but a significant improvement of the total expected energy shortage, LOEE. In Fig. 4.6 a comparison of LOEE at the 50 MW and 100 MW capacity levels of LTWP with and without storage is shown. There is a significant decrease in LOEE, especially at that the 50 MW capacity level of LTWP. It is important to note however, that since the algorithm used was not optimal, the improvement to reliability might be much higher than indicated.

4.7 Conclusion

A study of generation adequacy of the Kenyan power system with wind power from LTWP is presented in this paper. The impact of coupling LTWP with a storage system on the generation adequacy of the power system is then compared.

Table 4.3: Reliability of System with LTWP Coupled with Storage

Reliability Index	LTWP	Storage+LTWP
LOLE	3.7	3
LOLP	0.00035	0.00034
LOEE	197.6	130.3

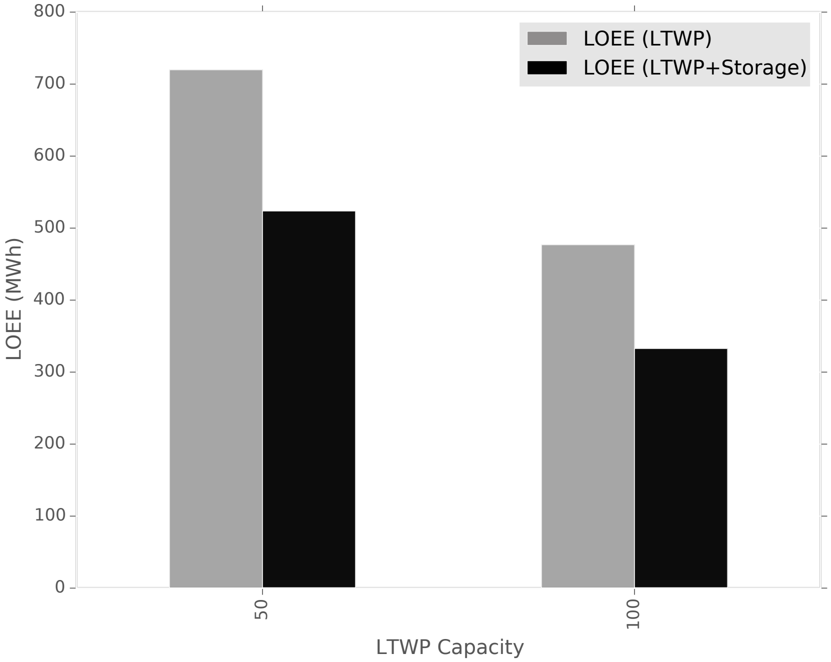

Figure 4.6: Comparison of LOEE

The reliability analysis is conducted on the projected 2017 system, therefore the results presented are a conservative estimate of the actual case. The wind power is sampled using stratified sampling, whereby strata are created using bisecting k-means clustering. Proportional allocation is implemented in selecting wind power samples from each stratum. The system adequacy metrics (LOEE, LOLP and LOLE) are determined for the current system without wind and the projected 2017 system with wind, both with and without storage. Results indicate that current reliability indices surpass the previously used reliability metrics but do not yet meet recommended metrics. With the addition of wind power from LTWP and planned generator expansion the system reliability is seen to improve. The biggest improvement is noted with the addition of wind from LTWP running at full capacity as would be expected. The coupling of LTWP with a storage unit is found to have the largest impact on the system's expected total energy shortfall. Overall, stratified sampling is effective in reducing the number of simulations to reach convergence, making it particularly promising for expensive simulations with high variance indices.

It is important to note that in this study the forecasted load is much lower than projected values, therefore the net effect of wind power in this paper may be more conservative than in reality. Further work will include adding the network constraints in adequacy analysis to gain a better estimate of the actual generation adequacy and applying an improved sampling method for generator states, to further improve efficiency of the simulation. It would also be interesting to look at the impact of a more sophisticated optimal operation of the storage system on the overall reliability of the system.

CHAPTER 5

CONCLUSION

Three projects are presented in this work, each of which consider different aspects of integration of wind power into the Kenyan power system. The first study seeks to determine if there is any benefit to the wind farm owner of coupling LTWP with a storage unit, particularly a pumped hydro storage system. This is achieved by creating a model that seeks to maximize revenue for the wind farm owner and is solved using stochastic dynamic programming. The market price of each KW generated is constant but penalty costs vary out through out the day and as a function of load. In the second study, the goal is to determine the optimal commitment and operation of the coupled system considering the Kenyan power market structure. A two-stage stochastic model is developed and solved to determine the optimal day-ahead commitment of the LTWP with a storage system and the optimal operation of the coupled system once the wind power is realized. Finally in the last study, the reliability of the Kenyan power system with wind power is evaluated. In this study the effect of the addition of wind power from the simulated LTWP wind farm on the Kenyan power system is determined by conducting Sequential Monte Carlo reliability analysis with a focus on system generation adequacy. Further, this study also determines the outcome of pairing LTWP with a storage system on the reliability of the Kenyan power system. Wind power is sampled using stratified sampling to reduce overall variance of the simulation. The strata are created using bisecting k-means clustering and proportional allocation applied to determine samples to use in the simulation.

The key findings of these studies are:

1. The storage system is found to increase revenue for the LTWP wind farm owner, with the increase being dependent on the size of the storage unit
2. The use of a storage system may address the World Bank's concerns about LTWP
3. In the worst case scenario, addition of a storage unit would take approximately 10 years to payback
4. Implementing penalty cost for large wind farm owners could incentivize improved forecasting
5. The addition of Ramp Rate Limits set by the system operator would be a good way to limit the variability wind power would introduce into the system
6. The addition of LTWP to the Kenya power system is found to improve reliability of the system but not to a level that meets recommended reliability metrics
7. Coupling of LTWP with a storage system is found to improve the reliability of the power system in terms of generation adequacy

Overall, storage could prove essential in advancing large scale integration of variable renewables in the country, however other solutions such as improved interconnection and changes to energy policy have not been addressed in these studies and may also play a role in advancing integration of renewables into the power system. Notwithstanding, the conclusions identified in the studies conducted here would serve to ease the integration of currently projected increases in wind power and aid Kenya in developing its power generation capacity to meet rapidly growing demand and in delivering on its target of becoming an industrialized nation by 2030.

APPENDIX A

KENYA POWER SYSTEM DISPATCH PLANNING

Dispatch planning in Kenya is based on economic merit order, generator availability, forecasted load and system stability. The power producers only have to inform the system operator of generator availability the day before operation and do not participate in bidding. Twenty-four hours before the day of operation, wind farm operator informs the system operator of the expected wind power forecast for the day of planning and is allowed to update the forecast up to 2 hours before day of operation upon which the dispatch orders are updated if necessary. On the other hand, traditional /conventional generators (such as thermal, large hydro and geothermal generators), inform the system operator of generator availability 24 hours before day of operation and receive their dispatch orders 7 hours before day of operation. The generators are penalized if they do not meet dispatch orders, however the wind farm operator and other independent power producers of non-firm energy are not penalized.

APPENDIX B

BISECTING K-MEANS CODE

```
function [clustInd,clustCent]=Bisecting_kmedoid(data,k)
%Similar to bisecting k-means but instead of using average point as
%centroid use member of the cluster as centroid.

%Written by: Maureen Murage



%Algorithm:
% 1. Start with all data in one cluster
% 2. Bisect the cluster into two clusters
% 3. Bisect each cluster then find the bisection
% that results in minimized
% SSD and replace this cluster with the
% two new clusters formed from bisecting
% 4. Repeat step 3 till you have k clusters

[ind,cent,sumd]=kmedoids(data,1);

NoClust=1;

while NoClust<k
    lowest_sumd=inf;
    totalLength=1:NoClust;
```

```
for i=1:NoClust
    datapoints4clust=data(ind==i,:);
    sz=size(datapoints4clust);
    if sz(1)>2
        [indsplt,centsplt,sumdsplt]=kmedoids(datapoints4clust,2);

        if NoClust>1
            sumd_withoutClusti=sumd(totalLength~=i);
            sumTotalSSE=sum(sumdsplt)+sum(sumd_withoutClusti);
        else
            sumTotalSSE=sum(sumdsplt);
        end

        if sumTotalSSE<lowest_sumd
            lowest_sumd=sumTotalSSE;
            bestClust2split=i;
            bestClustAss=indsplt;
            bestClustCent=centsplt;
            bestsumD=sumdsplt;
        end
    end
end
bestClustAss(bestClustAss==2)=NoClust+1;
bestClustAss(bestClustAss==1)=bestClust2split;
ind(ind==bestClust2split)=bestClustAss;
cent(bestClust2split,:)=bestClustCent(1,:);
```

```
    cent(NoClust+1,:)=bestClustCent(2,:);
    sumd(bestClust2split)=bestsumD(1);
    sumd(NoClust+1)=bestsumD(2);
    fprintf('best clust to split is %1.0f\n',bestClust2split)
    fprintf('total SSE is %.1f\n',sum(sumd))



    NoClust=NoClust+1;
end

clustInd=ind;
clustCent=cent;
end
```

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