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# Optimizing Generation Capacities Incorporating Renewable Energy with Storage Systems Using Genetic Algorithms

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**Abstract:** In grid advancement, energy storage systems are playing an important role in lowering the cost, reducing infrastructural investment, ensuring reliability and increasing operational capability. The storage system can provide stabilization services and is pivotal for backup power for emergencies. With a continuous rise in fuel prices and increasing environmental issues, the energy from renewable resources is gaining more popularity. The main drawbacks of some renewable sources are their intermittent energy generation and uncertain source availability, which has increased interest in energy storage systems (ESSs). This paper investigates the economic feasibility when ESSs are introduced in the electric grid with an expansion of a storage system as well as more percentage of the renewable energy integration and less percentage of fuel consumption by conventional power sources. The Artificial Neural Network is implemented to validate the forecasted load model. The uncertainties associated with the renewable energy system are handled by a chance-constrained model and solved by a genetic algorithm (GA) in MATLAB; selection criteria of GA for optimization process is also discussed in detail. The effectivity of the proposed methodology is verified by applying it to a case that lies in the western region of China.

**Keywords:** economic feasibility; Energy storage; minimize fuel cost; renewable energy systems

## 1. Introduction

The idea of generation expansion planning problem (GEP) is implemented to realize the minimum cost plan for installing new power generation facilities so that the future electricity demands can be met. The plan incorporates decisions such as plant type, allocation, capacity, time of addition, and the consumption of each plant in the subsequent years. Each plan is proposed while keeping in consideration several constraints like demand, energy, and reliability. In the past few years, the requirement of energy storage systems (ESSs) has become critical and is expected to grow over the next decade [1]. Traditionally, only conventional generation utilities like hydro, nuclear and thermal power plants are considered in the capacity expansion planning process. With limited resources and increasing burden on the environment, there is a rise in the growth of renewable energy sources (RES). Although the addition of RES in the generation system offers many monetary and reliability benefits, the widespread use of RES by utility companies is still restricted. The main barrier which averts the large-scale use of RES is not the deficiency of adequate technology, but the higher cost of generated electricity [2]. Therefore, RES cannot compete with conventional energy resources only if the economics of both sources are taken into consideration. So apart from economics, other factors like the impact of both sources on the environment, or social benefits of both sources must be considered in the capacity expansion planning process which can promote large-scale renewable energy integration. The large-scale integration of RES with ESS will have a dynamic role in controlling the environmental problems related to conventional power plants; the research problem is dealing with the reduction in fuel consumption with more increase in RES in an economical way.

Recently, China has had a more aggressive approach in the renewable area in comparison with the rest of the world as the health of millions is affected by an increase of a large-scale pollution problem. With the continuous industrial development, GDP growth and rising export demands, the electricity sector must play an important role in China's development. The installed capacity conventional power plants has been discussed in [3–5]. The electricity industry independently produced 4011 million tons of $CO_2$ in China in 2011 [6] due to the significant contribution of conventional coal-fired power plants, making China the world's biggest emitter of $CO_2$ [7,8]. China planned to begin large-scale renewable energy integration with storage systems in capacity expansion planning, and there is enormous wind power potential in many provinces of China [9]. The negative impacts due to RES and ESSs may require a cost increase for maintaining the same level of reliability. It is significant to analyze these potential drawbacks to make sure that the effects on the benefits are minimal. There are many studies completed regarding ESSs with RES. Some planners devised deterministic models while other proposed stochastic models to simulate expansion planning [10,11]. Several mathematical and heuristic methodologies including linear programming, dynamic programming, decomposition methods, fuzzy logic, and particle swarm optimization simulated annealing, immune algorithms, and have been successfully applied to solve the problem [12–20]. Kannan and Slochanal compared different meta-heuristic techniques applied to this expansion problem [21]. The chance-constrained optimization method which is a branch of stochastic optimization method was used by M. Mazadi to solve the expansion problem without including renewable energy sources (RES) [22]. Multiple research studies have included RES in the planning process stage. Impact of renewable resources on the planning process was first considered by S.A. Farghal, but he also considered power storage devices to tackle the intermittent nature of renewable energy sources and this method has limited application for large-scale renewable energy integration [23]. Some planners have been considering distributed generation influence in their objective function [24–28]. In study [29], authors considered large-scale renewable energy integration in the capacity expansion planning problem, but the results showed that RES cannot compete with conventional energy sources on the economic basis. In 2013, the developments in several grid storage technologies has been presented in a report published by the U.S. Department of energy on Grid aspects of energy storage systems [30–32]. There has been a report discussing the operation and development of renewable energy system, with energy storage, particularly highlighting the challenges to synthesize resources with the operation and planning of the remaining power grid, including customer requirements, current generation resources and the transmission technology [33]. Another report published by the U.S. Department of Energy office discussed research focused on technologies that store electricity in chemicals or batteries [34]. Another study presents software implementation of an optimal power flow planning model; in this research a multi-period based optimization problem is formulated [35]. Several research studies on storage system with renewable energy systems are demonstrated in [36–38]. The feasibility of 40 MW Castle River wind farm with pumped hydro storage at Oldman dam is analyzed. The result presented an increase in profitability by factors of four when wind generation is integrated with storage systems [39]. In a research study for New Brunswick province [40], the authors considered the pumped hydroelectric energy storage system with wind energy. The results obtained from the study showed the reduction in generation cost of the system with an increase in wind integration level [39]. Owing to a broad difference in technology with reference to performance characteristics, some storage system technologies are more optimal for certain grid applications [41]. Some storage methods are also discussed in [42]. In studies [43,44], the energy storage technologies with their prime applications and challenges which they currently faced are given in detail. There are multiple projects which have been done regarding energy storage around the globe [41].

This paper presents a mathematical formulation of the chance-constrained programming model for an expansion problem. The model's objective function, constraint functions and the effectiveness of the proposed model are discussed in detail. Furthermore, the genetic algorithm used to solve the model is explained along with its selection criteria for optimization process and significant benefits. The artificial neural network is implemented to validate the forecasted load model. The historical data needed for different predictors including holidays, weather etc. in the model are examined. Case studies are presented to show the efficacy of the proposed mathematical model. Economic evaluation, financial analysis and the comparative assessment of the different scenarios are achieved and presented in the research study.

## 2. Problem Formulation

The research study deals with generation expansion planning with renewable energy integration and energy storage system with the objective of the reduction of fuel-consuming power plants, a detailed financial analysis is performed with the following objectives. Minimizing the total cost of generation by introducing renewable energy systems and energy storage systems, formulating a chance-constrained programming model for capacity expansion planning that can deal with the intermittent nature of renewable energy sources. A case study is presented on a grid in West China (data from national key laboratory NCEPU) and the system's financial reliability is studied.

The presented model is based on a generation capacity expansion algorithm and optimal storage system planning with the purpose of analyzing the interaction of renewable energy systems and energy storage in the grid. The optimization problem formulated is solved by using a heuristic optimization technique (genetic algorithm).

### *2.1. Objective Function*

The proposed objective function aims to minimize the total cost. The cost represents the discounted present value of the amount which satisfies the demand for electricity during the planning period, considering the cost concerning storage systems. The cost components included in the objective function are: fuel cost, investment cost and operating and maintenance cost. The total cost to be minimized during the proposed planning period is given by the following equation:

$$C_{total} = I + O + F \tag{1}$$

where, $I$ = Investment Cost, $F$ = fuel Cost, $O$ = Operating cost. A brief description of all these cost components is as follows:

#### 2.1.1. Investment Cost

The investment cost of new units in \$/MWH is given by:

$$I = \sum_{t=1}^{T} \sum_{i \epsilon N} \left( I_{it} \cdot P_i^N \cdot \omega_{it} \cdot CF_i^N \cdot \Delta t_i^N \right) \tag{2}$$

where, $I_{it}$ is investment cost in \$/MW, $P_i^N$ is new power plant capacity of ith type in megawatts, $\omega_{it}$ is the quantity of each unit type $I$ needed in year $t$. Here, if the value of this discrete decision variable is 1, it means a unit capacity is added, $CF_i^N$ gives unit type $I$ capacity factor for new units, $\Delta t_i^N$, represents the average utilization hours considered annually for each new unit type $I$, $T$ time horizon (years), $t$ time period (years), $N$ set consisting of all the available generating technologies.

In this problem, energy storage and renewable energy are considered for initial investment plus conventional generating systems are installed to meet the load demand. Equation (3) presents the overall investment cost.

$$\begin{gathered} I = \sum_{t=1}^{T} \sum_{s \epsilon S} \left( I_t^s \cdot S^s \cdot \omega_{st} \cdot CF^s \cdot \Delta t^s \right) + \sum_{t=1}^{T} \sum_{r \epsilon R} \left( I_t^r \cdot R^r \cdot \omega_{rt} \cdot CF^r \cdot \Delta t^r \right) + \\ \sum_{t=1}^{T} \sum_{tr \epsilon TR} \left( I_t^{tr} \cdot TR^{tr} \cdot \omega_{trt} \cdot CF^{tr} \cdot \Delta t^{tr} \right) \end{gathered} \tag{3}$$

where, $s$ is the energy storage type in set $S$ consisting of available energy storage units, $r$ is renewable generation type in set $R$ consisting of available renewable generation type, $I^s$ investment cost for energy storage systems, $I^r$ investment cost for renewable energy generators, $I_t^{tr}$ is the investment cost of a thermal generating unit of type $tr$, $w_{st}$, $w_{rt}$ are number of each unit type s or r needed in year $t$ respectively, $S^s$ capacity of storage system of types, $R^r$ capacity of renewable generators of type $r$, $CF^s$ and $CF^r$ are capacity factor of type s and $r$ generating technology, $\Delta t^s$ and $\Delta t^r$ are average utilization hours taken annually of unit type $s$ and $r$ respectively, $T$ time horizon (years), $t$ time period (years).

### 2.1.2. Fuel Cost

The fuel cost of existing and new power plants is given as:

$$F = \sum_{t=1}^{T} \sum_{i \epsilon E} \left( F_{it}^{E} \cdot P_i^E \cdot CF_i^E \cdot \Delta t_i^E \right) \tag{4}$$

For new power plants:

$$F = \sum_{t=1}^{T} \sum_{i \epsilon N} \left( F_{it}^{N} \cdot P_i^N \cdot \omega_{it} \cdot CF_i^N \cdot \Delta t_i^N \right) \tag{5}$$

where, $E$ is a set consisting of all existing generating technologies and $N$ is a set representing new generating units, $P_i^E$ is the capacity of existing generating units of $i$th type, $F_{it}^E$ is representing the cost of fuel in \$/MWH for existing generating unit type $i$ in year $t$, $CF_i^E$ is representing the capacity factor of existing unit type $i$, $\Delta t_i^E$ is average utilization hours taken annually of existing power units. Here fuel cost of already existing thermal plants and new thermal plants are taken.

$$F = \sum_{t=1}^{T} \sum_{tr \epsilon TR} \left( F_t^{tr} \cdot TR^{tr} \cdot \omega_{trt} \cdot CF^{tr} \cdot \Delta t^{tr} \right) \tag{6}$$

$tr$ denotes the type of thermal unit in available unit $TR$, $TR^{tr}$ is the capacity of thermal unit of type $tr$, $w_{trt}$ are representing the quantity of each generating unit $tr$ required in the year $t$, $CF^{tr}$ is the capacity factor of type $tr$ generating technology, $\Delta t^{tr}$ is the average utilization in hours taken annually of the unit type $tr$, $F_t^{tr}$ is the fuel cost of thermal generating unit of type $tr$.

### 2.1.3. Operation and Maintenance Cost

The model representing the operation and maintenance cost of existing and new power plants are given as:

$$O = \sum_{t=1}^{T} \sum_{i \epsilon N} \left( O_{it}^{N} \cdot P_i^N \cdot \omega_{it} \cdot CF_i^N \cdot \Delta t_i^N \right) \tag{7}$$

where $O_{it}^N$ represents the operating and maintaining cost of new unit type $i$ in \$/MWH in $t$ years.

$$O = \sum_{t=1}^{T} \sum_{i \epsilon E} \left( O_{it}^{E} \cdot P_i^E \cdot CF_i^E \cdot \Delta t_i^E \right) \tag{8}$$

where $O_{it}^E$ represents the cost of operating and maintaining existing unit type $i$ in \$/MWH in years $t$.

Overall operation and maintenance cost is given by:

$$\begin{aligned} O = {} & \sum_{t=1}^{T} \sum_{s \epsilon S} \left( O_t^s \cdot S^s \cdot \omega_{st} \cdot CF^s \cdot \Delta t^s \right) + \sum_{t=1}^{T} \sum_{r \epsilon R} \left( O_t^r \cdot R^r \cdot \omega_{rt} \cdot CF^r \cdot \Delta t^r \right) + \\ & \sum_{t=1}^{T} \sum_{tr \epsilon TR} \left( O_t^{tr} \cdot TR^{tr} \cdot \omega_{trt} \cdot CF^{tr} \cdot \Delta t^{tr} \right) \end{aligned} \tag{9}$$

The considered problem is formulated mathematically after combining these Equations (3), (6), and (9).

$$Min_{cost} = f(I, O, F) \tag{10}$$

$$\begin{aligned} Cost = {} & \sum_{t=1}^{T} \sum_{s \epsilon S} \left( I_t^s \cdot S^s \cdot \omega_{st} \cdot CF^s \cdot \Delta t^s \right) + \sum_{t=1}^{T} \sum_{r \epsilon R} \left( I_t^r \cdot R^r \cdot \omega_{rt} \cdot CF^r \cdot \Delta t^r \right) + \\ & \sum_{t=1}^{T} \sum_{tr \epsilon TR} \left( I_t^{tr} \cdot TR^{tr} \cdot \omega_{trt} \cdot CF^{tr} \cdot \Delta t^{tr} \right) + \sum_{t=1}^{T} \sum_{tr \epsilon TR} \left( F_t^{tr} \cdot TR^{tr} \cdot \omega_{trt} \cdot CF^{tr} \cdot \right. \\ & \left. \Delta t^{tr} \right) + \sum_{t=1}^{T} \sum_{s \epsilon S} \left( O_t^s \cdot S^s \cdot \omega_{st} \cdot CF^s \cdot \Delta t^s \right) + \sum_{t=1}^{T} \sum_{r \epsilon R} \left( O_t^r \cdot R^r \cdot \omega_{rt} \cdot CF^r \cdot \Delta t^r \right) + \\ & \sum_{t=1}^{T} \sum_{tr \epsilon TR} \left( O_t^{tr} \cdot TR^{tr} \cdot \omega_{trt} \cdot CF^{tr} \cdot \Delta t^{tr} \right) \end{aligned} \tag{11}$$

### 2.2. System Modeling and Constraints

#### 2.2.1. Energy Storage Cost Analysis

The factors included in the life cycle cost of the energy storage system are a capital cost, recharging energy cost and equipment replacement cost which is affected by storage system efficiency, system service life or life cycle cost. The present worth cost of the storage system is calculated considering its service life and inflation and discount rate factors. The present worth factor provides a methodology to represent payment for a given number of years; the cost is then leveled for the proposed period. Multiple references are used to study the current storage system trend and are utilized in the system cost analysis [45–59].

Methodology

Major components of the energy storage system contribute to overall cost are the storage unit ($/kWh), the power conversion unit ($/kW) and the charging source. The general form for capital cost calculation is given in Equation (12), Equation (13) is representing the proportionality of system rated power with power conversion equipment and Equation (14) shows proportionality of amount of energy stored with storage unit cost.

$$Cost_{total}(\$) = Cost_{Pc}(\$)\ + Cost_{storage}(\$) \tag{12}$$

$$Cost_{Pc}(\$) = \ UnitCost_{Pc}(\$/\text{kWh})\ \times\ P(\text{kW}) \tag{13}$$

$$Cost_{storage}(\$) = Unit\ Cost_{storage}(\$/\text{kWh}) \times E(\text{kWh}) \tag{14}$$

Here, $E = P \times t$, where $E$ is the energy stored capacity, t is the storage time and $P$ is the Power. Considering system inefficiency Equation (14) can be modified as follows with η representing efficiency. Equation (16) represents the capital cost considering power ratings.

$$Cost_{storage}(\$) = Unit\ Cost_{storage}(\$/\text{kWh}) \times E(\text{kWh})/\eta \tag{15}$$

$$Cost_{system}\left(\frac{\$}{\text{kW}}\right) = Cost_{total}/P \tag{16}$$

The present worth value of a given system cost is calculated using Equation (17) for the $PW$ factor for a 5-year service life, economic assumptions used is presented in Table 1, where $i$ represent the year, $e$ is annual price escalating rate (%/year) and $d$ = discount rate (%/year).

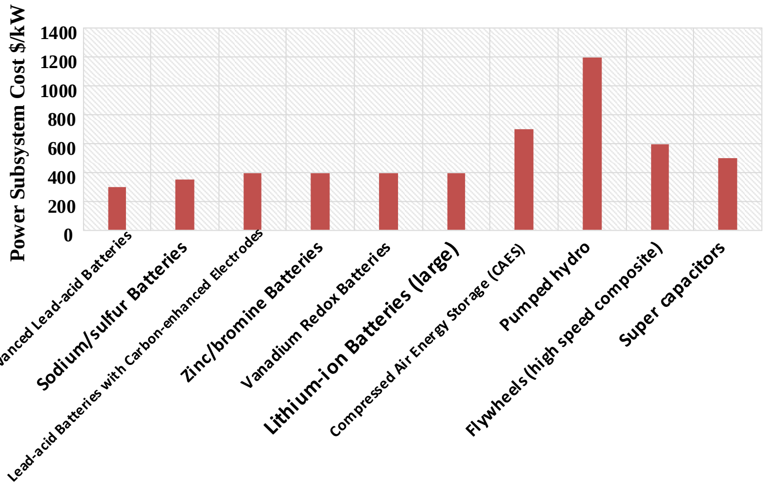
$$\sum_{i=1}^{5} \frac{(1\ +\ e)^{i}}{(1\ +\ d)^{i}} \tag{17}$$

The costs in Figure 1a,b are based on certain standard assumptions considering different storage system category and their applications, and meant for comparative analysis. The number of cycles and round-trip efficiencies for a different system are presented in Figure 1c,d. Actual cost might vary and depend on many factors and the calculation method and assumption used here are under continuous debate among experts.

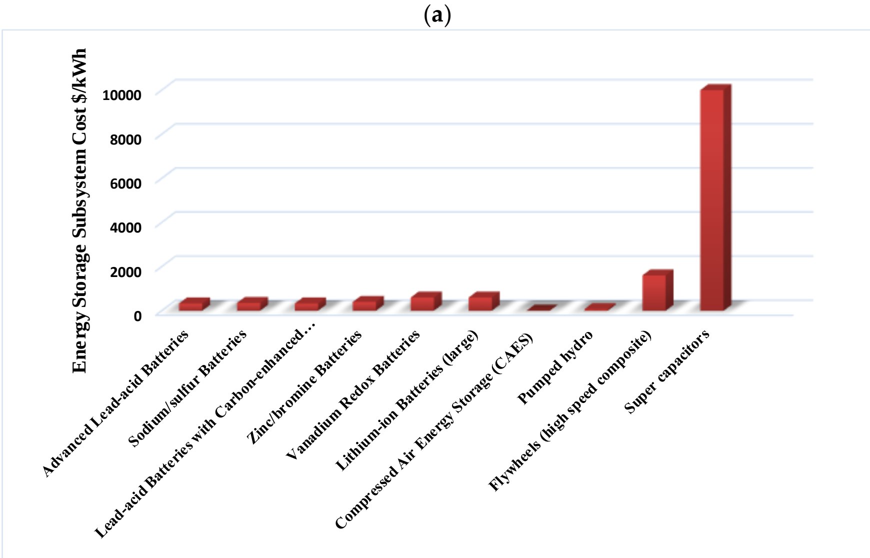
**Table 1.** Assumptions for cost analysis [60].

| Parameters | Value |
|---|---|
| Fuel Cost | $5/MBTU |
| Electricity Cost for Charging | 10¢/kWh |
| Customer Fixed Charge Rate | 15% |
| Utility Fixed Charge Rate | 11% |
| Inflation Rate | 2% |
| Discount Rate | 10% |
| Service life | 5 years |

The result in Figure 2 shows that the present worth cost is depending in variable manner on different technologies and their storage durations (Storage duration 4 h, unless otherwise specified) Table 2 represents the storage duration, capacity of the system and their application detail. Long storage tends to require more storage capacity; similarly, frequent use is expensive and, hence, it reflects in the cost analysis in Figure 2. With present worth cost analysis it is possible to evaluate the benefits from different technology types in our study; we have used the average levelized cost 250 $/MWH for frequent discharge long storage system considering no replacement cost with the average life cycle of 14,000 and efficiency of 70–85% in a 5-year lifespan.

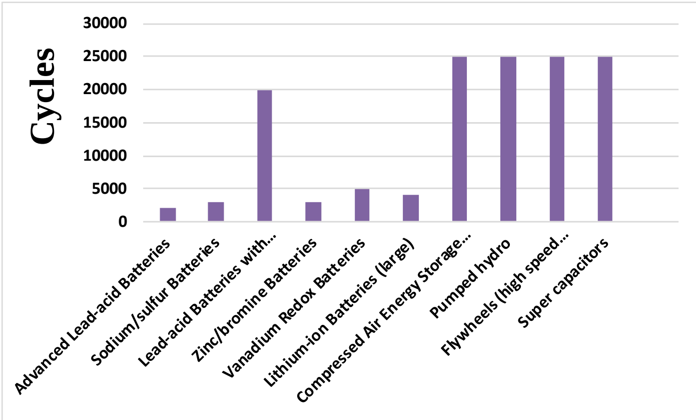



(**a**)

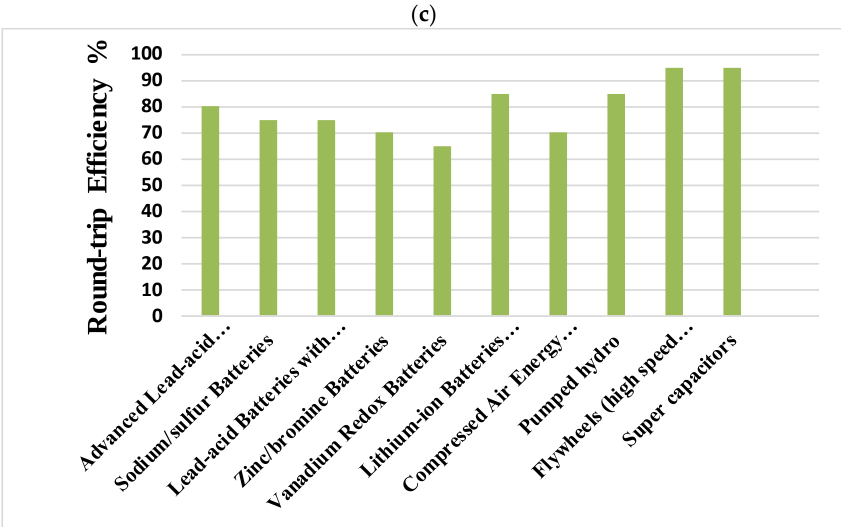



(**b**)

**Figure 1.** *Cont.*




(**c**)




(**d**)

**Figure 1.** Cost and performance assumptions: (**a**) Power subsystem cost for different storage technologies; (**b**) Energy Storage subsystem cost for different storage technologies; (**c**) Number of cycles for different storage technology types; (**d**) Round trip efficiency for different storage technology types [60].

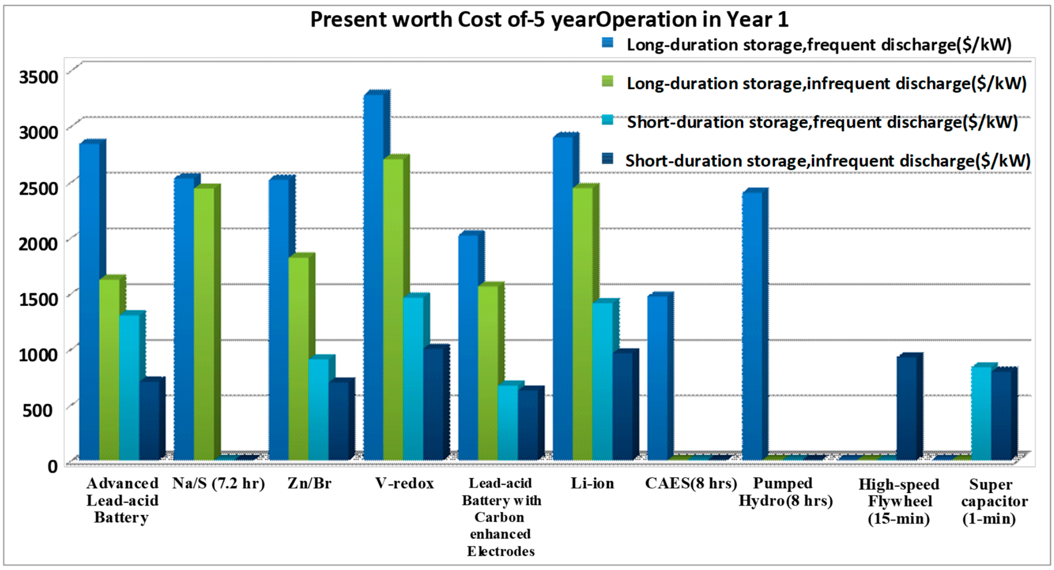



**Figure 2.** Present worth Cost of 5-year Operation in Year 1 ($/kW).

**Table 2.** Technology and Application type.

| Type | Storage Duration | Capacity | Function |
|---|---|---|---|
| Long storage duration, frequent discharge | 4–8 | 1 cycle/day × 250 days/year | Load-leveling, source-following, arbitrage |
| Long storage duration, infrequent discharge | 4–8 | 20 times/year | Capacity credit |
| Short storage duration, frequent discharge | 0.25–1 | 4 × 15 min of cycling × 250 days/year= 1000 cycles/year | Frequency or area regulation |
| Short storage duration, infrequent discharge | 0.25–1 | 20 times/year | Power quality, momentary carry-over |

Energy Storage Constraint

The constraint representing charge and discharge power and amount of stored is given as follows:

$$0 \le S_t^s \le S_{max}^s \tag{18}$$

$$0 \le P_t^{s,+} \le P_{max}^{s,+} \tag{19}$$

$$0 \le P_t^{s,-} \le P_{max}^{s,-} \tag{20}$$

The amount of energy stored should be in the range from nil to maximum stored capacity. The charging and discharging capacity of the storage system of types should be within a range from nil to their maximum charging and discharging capacity.

### 2.2.2. Renewable Energy Generators

$R_t^r$ denotes the renewable energy generation from unit type $r \in R$ during the time period $t$, $R_{max}^r$ denotes the installed capacity of renewable generating system of type $r$.

$$R_t^r = r_t^r R_{max}^r \tag{21}$$

Here, $r^r$ is a random variable representing renewable energy generation per unit generating capacity.

### 2.2.3. Annual Energy Demand Constraint

The annual energy generated from the combination of existing and new generating units must exceed the annual total demand for energy.

$$\sum\nolimits_{i\in N} P_i^N \cdot CF_i^N \cdot \Delta t_i^N \cdot \omega_{it} + \sum\nolimits_{i\in E} P_i^E \cdot CF_i^E \cdot \Delta t_i^E \ge PL_t \cdot H_t \tag{22}$$

where, $PL_t$ represents Peak Load for the year $t$, $H_t$ represents utilization hours by load in the year $t$.

### 2.2.4. Power Generation Constraint

In order to satisfy the load and spinning reserve requirement by the generation capacity, the power generation constraint is formulated. Since the large-scale renewable energy integration with the storage system is considered (which brings intermittent power in the system), their availability rates are integrated into the constraint which makes certain that the generation is always surplus to the load requirements.

$$Pr\left(\sum\nolimits_{i\in N}(P_i^N \cdot \omega_{it} \cdot \rho_N) + \sum\nolimits_{i\in E}(P_i^E \cdot \rho_E) \ge PL_t(1 + SR_t)\right) \ge \gamma \tag{23}$$

where, $\rho_N$ represents the availability rate of the new generation unit during peak load, $\rho_E$ represents the availability rate of the existing generation unit during peak load, $SR_t$ represents the system spinning reserves requirement in year $t$ and $\gamma$ represents pre-defined power confidential level.

#### 2.2.5. Upper and Lower Bond Constraint

This constraint is formulated to set a bound on the decision variable. This constraint describes that the number of units of a particular type should increase progressively throughout the planning horizon and each year the number of units of a particular type should be greater than the number of units of the same type in the preceding year. Similarly, the number of units of a particular type added in a particular year should not exceed the upper bound defined for that technology in that year.

$$\omega^{min} i(t-1) \leq \omega_{it} \leq \omega^{max} i(t+1) \tag{24}$$

where, $\omega^{min} i(t-1)$ Number of units that had been underutilization at the beginning of $t-1$ year, $\omega^{max} i(t+1)$ Maximum units quantity that can be installed in the given area.

### *2.3. Genetic Algorithm*

Capacity Expansion Planning models can be either deterministic or stochastic. The deterministic models are used when we have some pre-defined scenarios, while stochastic models find their application when uncertainties come into consideration. Mostly, deterministic techniques are used to solve the conventional expansion problem. When we deal with the systems, which considered large-scale integration of a renewable energy system, uncertainty comes into the system, and deterministic techniques are unable to solve the problem. Therefore, for the case of expansion planning considering higher percentage of RES, stochastic techniques are applied to solve large scale, non-linear optimization problems [61].

Genetic algorithm (GA) is a method to solve optimization problems based on a selection process. It starts by initializing a population of possible solution. Each candidate solution is then coded as a vector, termed a chromosome or genome. A fitness score of each chromosome is then calculated according to the defined objective. A probability of reproduction is assigned to each chromosome so that its chances of being selected in the next generation are proportional to its score relative to other chromosomes in the current population. The offspring of the next generation are generated by applying reproduction, crossover or mutation operator on the selected chromosome [62]. The process stops if a suitable solution is found, or if the available computing time is exceeded. Otherwise the new chromosomes are evaluated and the cycle repeats. The chances of obtaining a global optimal solution are quite high using GA and it requires great computational time.

The advantages of GA over conventional optimization techniques are as follows [62]:

1. GA does not use derivatives or other auxiliary data, the algorithm required only payoff information.
2. In comparison with conventional point-to-point methods, GA looks for solutions among populations of points, simultaneously works from a set of points and in parallel climbs many peaks, which leads to reduction in false peak finding probability.
3. GA utilizes probabilistic transition rules to guide a search toward the search space region with enhancement in payoff, while conventional optimization techniques use deterministic rules.
4. Instead of working with parameters, it works with a coding of parameter sets.

#### 2.3.1. Solution Procedure Using GA

The fitness function is defined by Equations (1)–(9). The decision vector $\boldsymbol{W_t}$ which is to be determined in the fitness function depends on following two factors:

1. Number of years in the planning horizon.
2. The type of technologies considered.

The length of the decision vector is determine by the product of number of years and number of technologies used in the planning horizon. For base case, having a 5-year planning horizon with five candidate plant, the state vector length would be 25. The fitness function can be represented by Equation (25).

$$min f(\omega_1, \omega_2, \omega_3, \omega_4, \omega_5) = k_1\omega_1 + k_2\omega_2 + k_3\omega_3 + \ldots k_{25}\omega_{25} \quad (25)$$

Here $k$ represents the cumulative cost of a particular technology type.

2.3.2. Genome Structure

For the above example considered, a random genome can be modeled by Equation (26).

$$\boldsymbol{W_t} = (\boldsymbol{\omega_{11}}, \boldsymbol{\omega_{21}}, \boldsymbol{\omega_{31}}, \boldsymbol{\omega_{41}}, \boldsymbol{\omega_{12}}, \boldsymbol{\omega_{22}}, \boldsymbol{\omega_{32}}, \boldsymbol{\omega_{42}}, \ldots, \boldsymbol{\omega_{15}}, \boldsymbol{\omega_{25}}, \boldsymbol{\omega_{35}}, \boldsymbol{\omega_{45}}) \quad (26)$$

where the first subscript denotes the type of technology and the second subscript de-notes the year in planning horizon. Alternatively, in matrix form where rows represent the number of years and columns represent the type of technologies, a particular element $\boldsymbol{\omega_{it}}$ in the matrix represent the number of $i$ type units required in year $t$.

$$\boldsymbol{W_t} = \begin{bmatrix} \boldsymbol{\omega_{1,1}} & \cdots & \boldsymbol{\omega_{4,4}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{\omega_{5,1}} & \cdots & \boldsymbol{\omega_{5,4}} \end{bmatrix} \quad (27)$$

The vector, $\boldsymbol{W_t}$, whose length is the number of variables in the problem, is a genome. The sum of all the elements of $i$th column represents the number of units of $i$th type required in the planning horizon.

The size of the population is set to 100, the population can be represented by a 100-by-15 matrix.

$$\boldsymbol{Population} = \begin{bmatrix} \boldsymbol{\omega_1^1} & \cdots & \boldsymbol{\omega_{15}^1} \\ \vdots & \ddots & \vdots \\ \boldsymbol{\omega_1^{100}} & \cdots & \boldsymbol{\omega_{15}^{100}} \end{bmatrix} \quad (28)$$

GA performs a series of computations, on each iteration, on the current population to generate a new population. Each successive population is termed as a new generation.

## 2.4. Operator Probabilities

Genetic algorithm uses the following three operators to produce children of next generation: selection; crossover; mutation. Population converges because of selection and crossover operators while mutation aids in maintaining diversity if early convergence or undue diversity occurs and the search becomes ineffective. The following GA parameters are set to get the solution: Population size (100); maximum number of generations (100); selection probability (0.02); crossover probability (0.4); mutation probability (0.04). The most troublesome section of chance-constrained programming is to make sure that the inequality constraints carrying the random variables are satisfied, to handle that a random simulation technology is applied. The power generation constraint as defined by Equation (23) is a chance constraint which holds the generation unit availability rate as a random variable.

$$Pr\{k_i(\omega, \varepsilon) \leq 0, i = 123\ldots I\} \geq \gamma \quad (29)$$

Equation (29) shows a general inequality chance constraint in which $\omega, \varepsilon$ represents the decision variable and random variable respectively.

## 2.5. Applied Algorithm

In the applied algorithm, the new generating units are considered as genes and the following steps are applied to reach the maximum number of generation sets.

1. The required data by algorithm is gathered.
2. Random population and genome feasibility testing is initialized.
3. Score evaluation of each genome in the population. In the current population, the genomes with best fitness function are taken as parents, which after applying different operators generate children of next generation either by mutation (making random changes to single parent) or by crossover (combing vector entries of pair of parents).

Repeat step 3, for new generation. The process stops when the maximum number of generations set is reached. The algorithm flow chart is given in Figure 3.

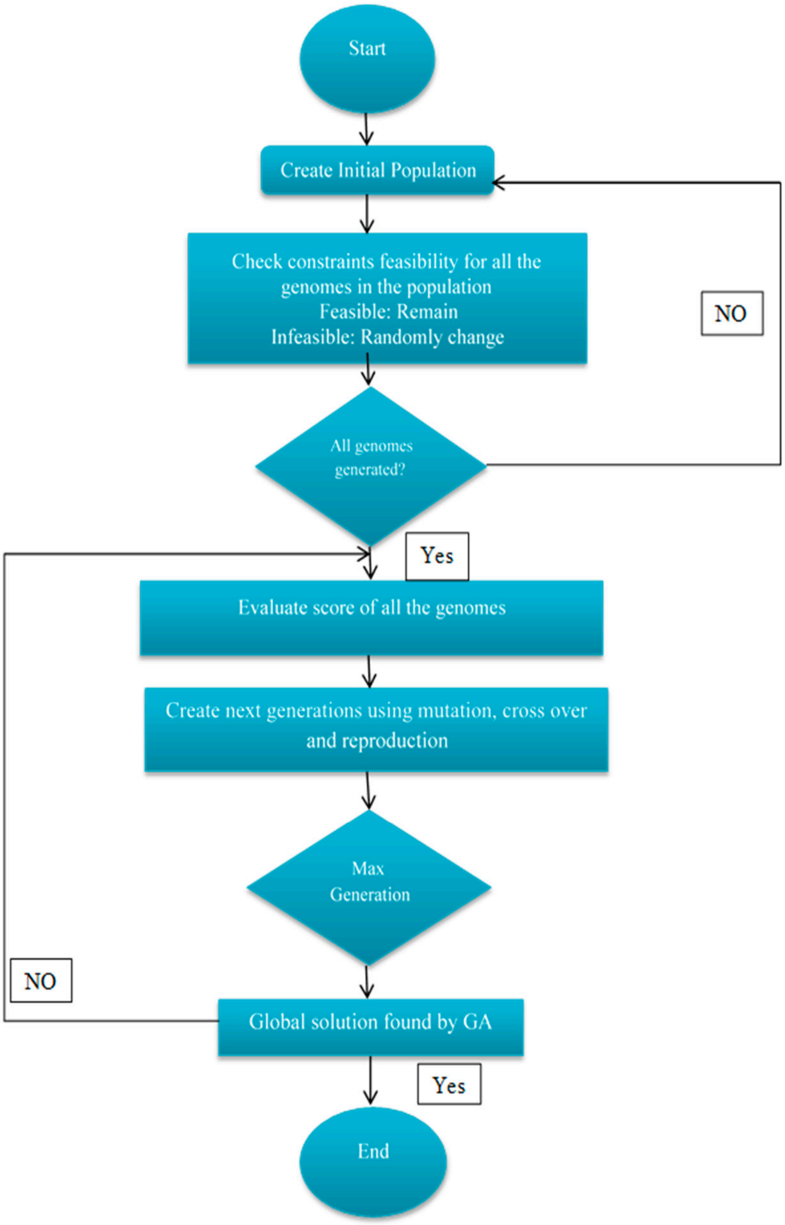



**Figure 3.** Applied algorithm flow chart.

## 3. Data Descriptive Analysis

The focus of the model and algorithm developed is applied to actual storage expansion problem. The case is taken from a power company in West China. The power company has a combined capacity of 2000 MW consisting of thermal power plants, 400 MW of each three coal-fired plants, one natural gas combined cycle with the capacity of 300 MW and two gas-fired power plants 250 MW each. They have high capacity factors serving as a base load. In the case presented, we are analyzing the economic impact on power generation companies while incorporating the costs of future energy production technologies into the planning process. The case study covers a 5-year time span from 2016 to 2020 by considering the regional capacity data with no new installed capacity since 2016.

Base Case: In the basic case, the system does not contain any storage system. The current trend in providing energy to consumers is taken into consideration and economic analysis is carried out.

Proposed Case: In the proposed case scenario, storage system with renewable energy is integrated into the planning process and the economic change is analyzed. More contribution from renewable energy sources with the storage system is made.

The scope is limited to several technologies which are considered in the planning process:

1. Integrated gasification combined cycle (IGCC) power plant.
2. Natural gas combined cycle (NGCC) power plant.
3. Pulverized coal combustion (PC) power plant.
4. Solar power plant.
5. Wind power plant.

The power plants currently existing meeting the energy requirements are all fuel (coal, gas, oil) based such as:

1. Natural gas-fired power plant;
2. Coal-fired power plant;
3. Combined cycle natural gas-fired power plants.

The optimization model considers several unique features of each supply technology such as economic and operational specifications of each available plant and evaluates the optimal mix of supply sources to fulfill the energy requirements. The technical and financial data of the existing and new power plants are taken from the generation company.

### *3.1. Case Study Data*

The required data is given in sections below.

#### 3.1.1. Existing Power Plants

Table 3 shows the financial and technical data associated with existing power plants.

**Table 3.** Specifications of Existing Power Plant.

| Type (Power Plant) | Capacity (MW) | O&M Cost ($/MWH) | Fuel Cost ($/MWH) | Capacity Factor | Efficiency |
|---|---|---|---|---|---|
| NGCC | 300 | 2.3 | 49.4 | 0.35 | 0.30 |
| Natural gas fired | 500 | 3.5 | 83 | 0.75 | 0.45 |
| Coal fired | 1200 | 4.8 | 32.2 | 0.85 | 0.36 |

#### 3.1.2. New Power Plants

The model determines the number of each type of new plants needed to fulfill the energy requirements along with the time horizons. The generating technologies considered in the storage planning process are as follows:

1. Natural gas combined cycle (NGCC) power plant.
2. Integrated gasification combined cycle (IGCC) power plant.
3. Pulverized coal combustion (PC) power plant.

4. Solar power plant (with storage system).
5. Wind power plant (with storage system).

In addition to the above-mentioned technologies, other technologies can also be considered but the scope of this paper is limited to the above-mentioned technologies. All considered power plants have distinctive characteristics and vary greatly from each other in terms of economic and operational parameters. Some technologies require high capital costs while other technologies require lower capital costs but have high fuel rates and, thus, high generating costs are associated with them. In terms of capital cost, construction of large capacity power plants over smaller ones is considered favorable economically. The operation of two smaller capacity units is expensive as compared to a single large unit having the same generating capacity. The financial and technical data of the considered power plants is given in Table 4 [63–66].

**Table 4.** New power plant cost detail.

| Type (Power Plant) | Per Unit Capacity (MW) | Levelized Capital Cost ($/MWH) | Fuel Cost ($/MWH) | O&M Cost ($/MWH) | Capacity Factor | Efficiency |
|---|---|---|---|---|---|---|
| Storage system | 100 | 250 | 0.0 | 1.3 | 0.70–0.90 | 0.70–0.85 |
| Wind power plant | 100 | 70.3 | 0.0 | 13.1 | 0.34 | 0.30 |
| Solar power plant | 100 | 130.4 | 0.0 | 9.9 | 0.25 | 0.40 |
| PC combustion power plant | 100 | 65.7 | 29.2 | 4.1 | 0.85 | 0.36 |
| IGCC power plant | 100 | 88.4 | 37.2 | 8.8 | 0.85 | 0.42 |
| NGCC power plant | 100 | 17.4 | 48.4 | 1.7 | 0.87 | 0.51 |

## 3.2. Data for Load Forecast

The forecasting of future energy requirements is achieved using statistical techniques to ensure better expansion planning [67]. Long-term load forecasting of one generation company which resides in the western region of China has been considered, based on the increasing industrialization and rapid growth in gross domestic product (GDP). In particular, the forecast results of annual energy demand, annual peak load demand, and annual load utilization hours are considered. The forecasting is performed in MATLAB using ANN toolbox considering GDP, regional temperature and holidays as predictors. The model is validated with best validation performance error of 2.08% at epoch 107, where similar paths are followed by the test set and validation set's error shown in Figure 4. Table 5 demonstrates the load forecast results for the planning area.

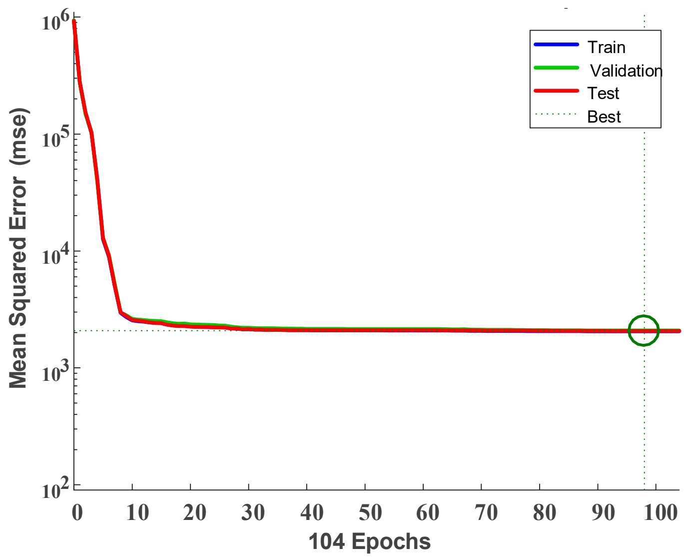



**Figure 4.** Model Validation Plot.

**Table 5.** Load Forecast of Planning Area.

| Year | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|
| Energy Demand (Annual-GWH) | 32,204 | 40,243 | 46,621 | 53,459 | 61,459 |
| Annual load utilization hours | 5705 | 5940 | 6175 | 6410 | 6645 |
| Annual peak load demand (MW) | 5645 | 6775 | 7550 | 8340 | 9249 |

### *3.3. Assumptions*

The following assumptions have been made for the research study:

1. There is no connection between the average power price and total power demand. Furthermore, selection of individual supply technologies is influenced by their relative prices and emissions.
2. Since the study considers the large-scale integration of the RES with a storage system, as RES generates random and intermittent power, the system's spinning reserve requirement is assumed to be 20%.
3. Fuel and fixed O&M costs of all power generation facilities are supposed to stay constant throughout the planning duration, and the number of units per technology should increase in the coming year.
4. A discount rate of 10% is considered for the present study.
5. The case study done is according to installed capacity, not according to allocated power.

## 4. Results and Discussions

### *4.1. Base Case*

This scenario considers that the on-going strategy of power production is continued i.e., no energy storage units are installed in the power system. This case study further assumes that existing generation capacity continues to meet the load demand along with the new installed capacities in the current system. Figure 5 describes the installation scenario of different kind of power plants in the base case.

The contribution of renewable energy is only 13% in this case. NGCC plants contributed to 30%, owing to their low emissions, high efficiency and cheap operation shown in Figure 6. Fossil fuel-fired power plants have a high capacity factor and average annual utilization hours, and their capital cost is relatively below wind and solar units; therefore, they contribute significantly in this case. Since solar panels have very high capital costs, their total installed capacity is limited to just 1800 MW.

The results indicate that fossil fuel-fired power plants continue to dominate the power generation industry. Due to the poor capacity factor of renewable energy sources and intermittent power generation, their contribution was reduced to a small proportion. Power plants utilizing fossil fuels produce expensive electricity and generate hazardous pollutants, however, they still take lead on renewable energy generation sources. Although the electricity generated in this case is cheap, the environmental damage to the ecosystem is costly [68].

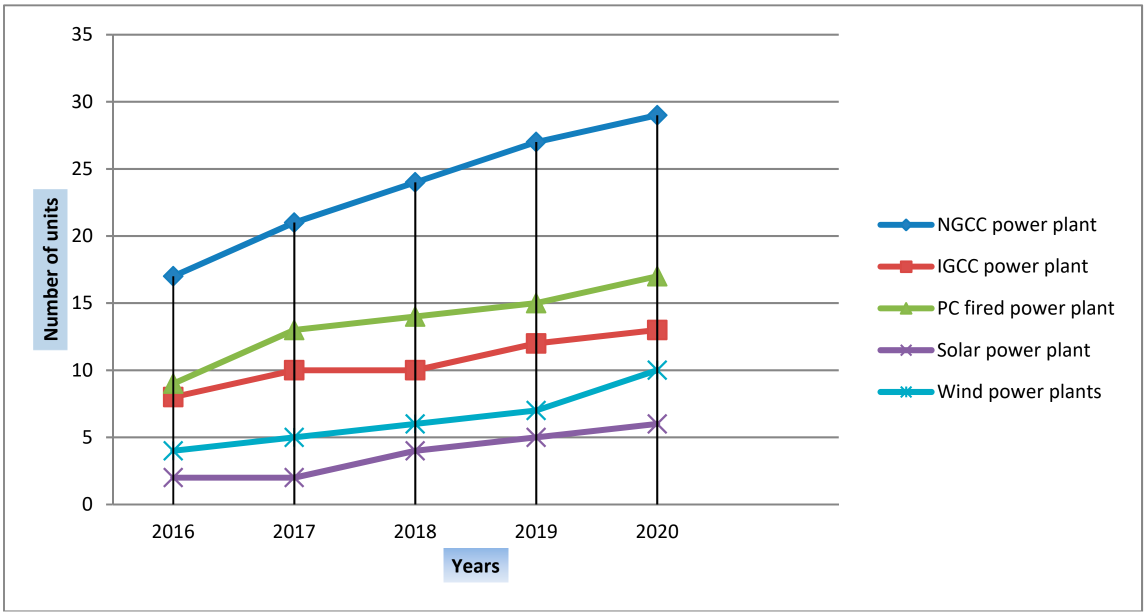



**Figure 5.** Base case unit installed scenario.

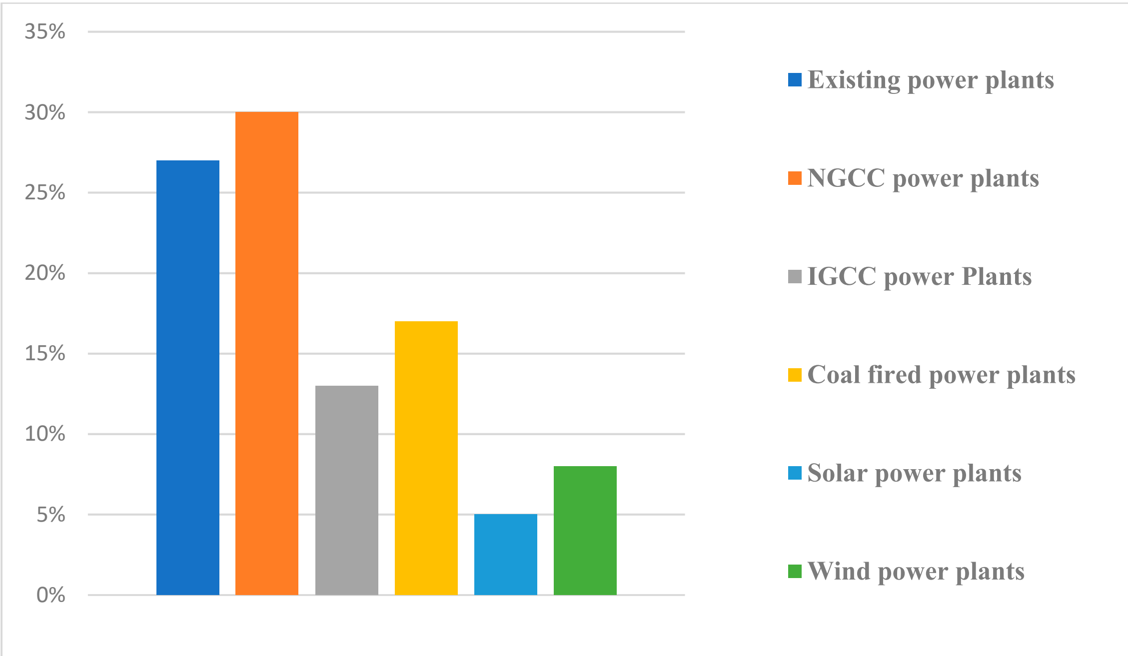



**Figure 6.** Percentage of the unit type utilized.

Financial Analysis Base Case

Investment, operation, maintenance and fuel costs are considered in this section. We have the highest fuel cost in our case which is 11,063.9 million dollars, with 9164.1 million dollars of investment, having 1523.01 million dollars of operation and maintenance cost as baseload plants were mostly installed. Total expansion without energy storage cost up to 21,751.01 million dollars, with an average of 0.65 $/kWh, the analysis is given in Table 6. The cost for environmental damage must be considered, though the electricity produced in this case is inexpensive.

Cost analysis of different technologies is given in Figure 7. NGCC units make the most of the cost in each year in the base case, the capital cost related to renewable energy units is more, and a lower number of renewable energy generators is installed. A summary of base case financial and load analysis is given in Table 7.

**Table 6.** Total Cost Analysis of Unit Type in Base Case.

| Years | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|
| Existing Plant cost (M$) | 840.04 | 840.04 | 840.04 | 840.04 | 840.04 |
| New plant cost (M$) | 2510.1 | 3235.7 | 3561.7 | 4043.3 | 4497.7 |
| Total cost (M$) | 3350.14 | 4075.74 | 4401.74 | 4883.34 | 5337.74 |

**Table 7.** Annual Summary Base Case.

| Case Study | Base Case | | | | |
|---|---|---|---|---|---|
| Years | 2016 | 2017 | 2018 | 2019 | 2020 |
| Annual Peak Load Demand (MW) | 5645 | 6775 | 7550 | 8340 | 9249 |
| Annual Energy Produced (GWH) | 49,450.2 | 59,349 | 66,138 | 73,058.4 | 81,021.24 |
| Total Installed Capacity (MW) | 6000 | 7100 | 7800 | 8600 | 9500 |
| Annual Expenditure (M$) | 3350 | 4075.6 | 4401.7 | 4883.4 | 5337.7 |
| Average Electricity Cost (cents/kWh) | 6.77 | 6.87 | 6.66 | 6.68 | 6.59 |

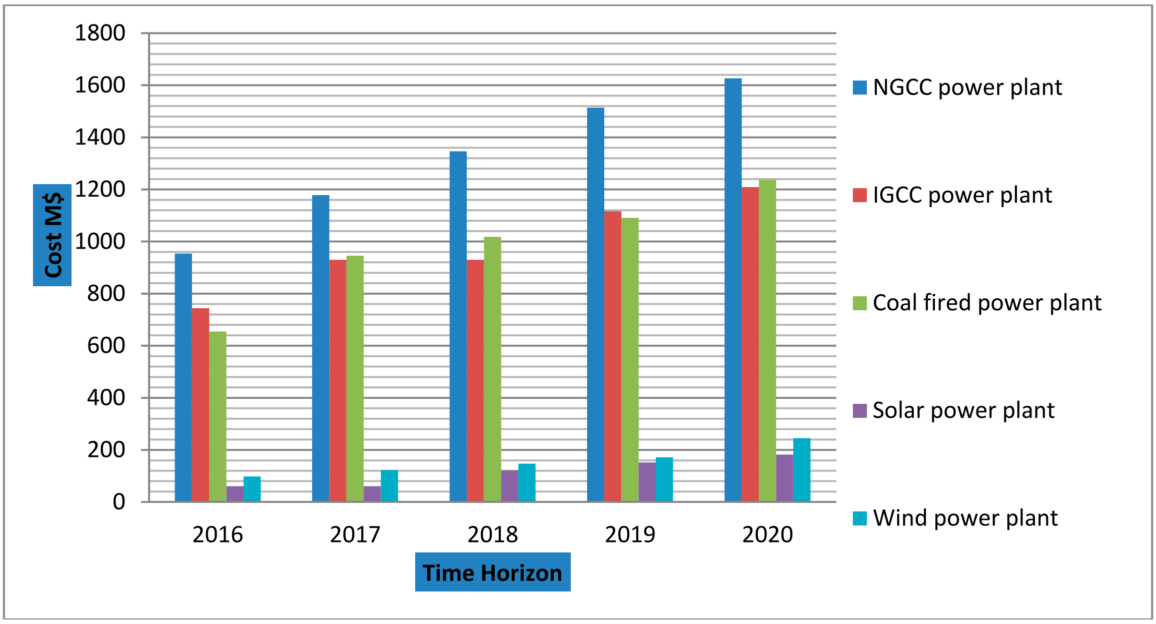



**Figure 7.** Cost analyses of different technologies.

### *4.2. Proposed Case*

In this scenario, a storage system with renewable energy is integrated into the planning process and the economic changes are analyzed with external cost taken into account. More contribution from renewable energy sources with storage system is made in order to control the fuel and external gas emission. A brief explanation of external cost is given, and overall cost is compared with the base case.

In each year, an increasing number of wind power plants are selected as compared to IGCC and NGCC power plants but still the major contribution of the total cost during each year is caused by NGCC power plants as shown in Figure 8. This shows that the operation of RES is quite cheap compared with costs of fossil fuel power plants. The clean energy contribution in the proposed case is increased from 13 to 39 percent and gas a 35.6 percent decrease in fossil fuel-fired power plants as shown in Figures 9 and 10.

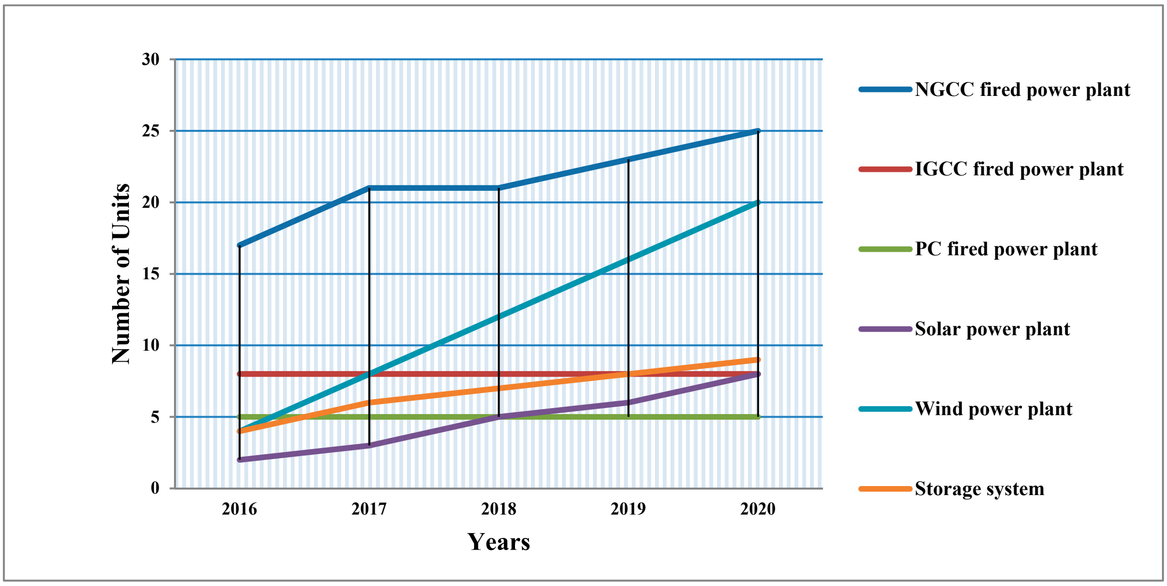



**Figure 8.** Proposed case unit installed scenario with a planning horizon.

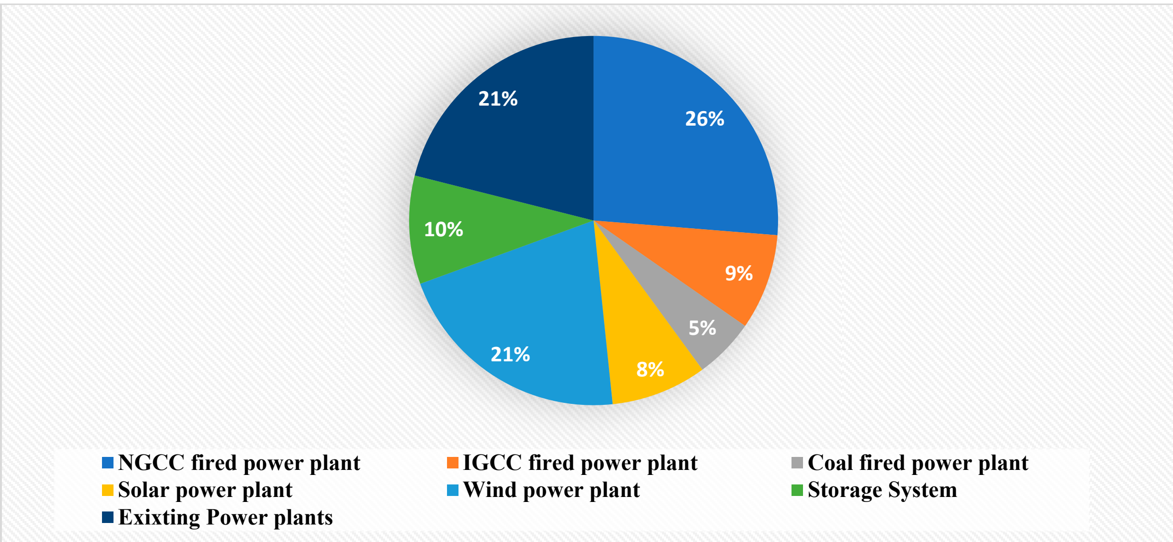



**Figure 9.** Percentage of installed capacity of each unit type in proposed case.

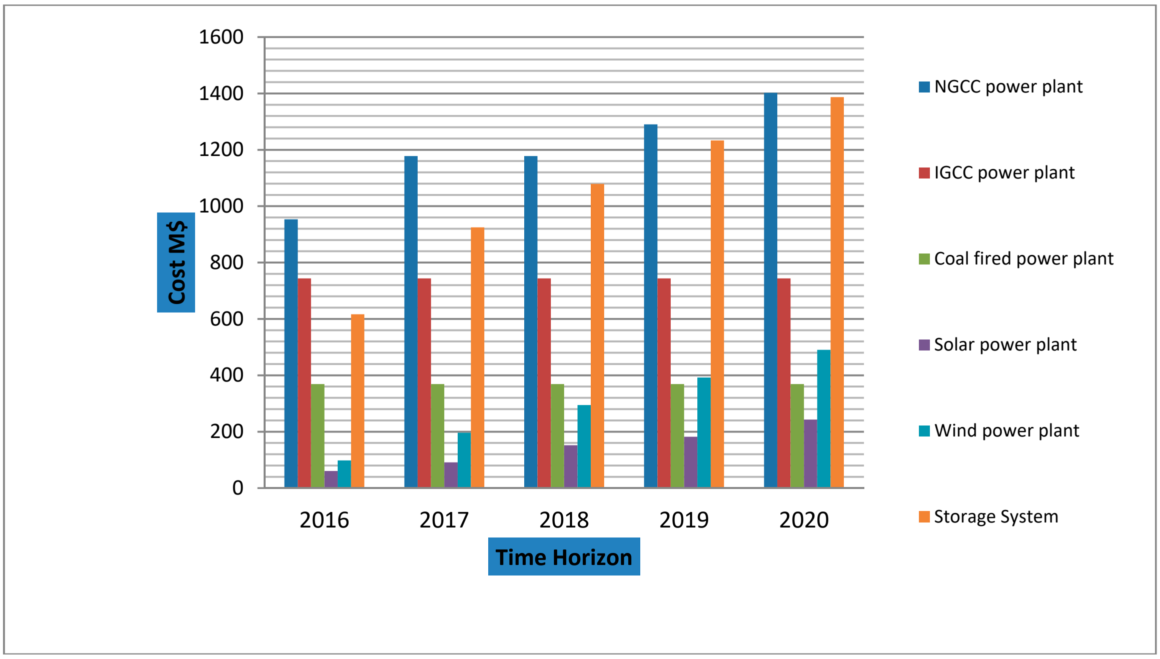



**Figure 10.** Cost analysis of each unit type proposed case.

Financial Analysis Proposed Case

Total expenditure is 23,198.9 million dollars, with a fuel cost of 9519.94 million dollars, investment cost of 12,622.51 million dollars and O&M cost of 1003.84 million dollars. Electricity generated in this scenario was 0.67 cent $/kWh expensive than that of the base scenario because the storage system associated with the electricity generation was considered in this scenario. Table 8 gives the detailed total analysis of existing and new power plants installed. A summary of the proposed case is given in Table 9. The storage system is making 36.4% of the total cost in a five-year planning horizon with an increase in total cost of 6.67% from base case cost which if further analyze for the long term may be further reduced. The result shows that the total cost while utilizing a storage system is respectively high.

**Table 8.** Total Cost Analysis of Unit Type in Proposed Case.

| Year | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|
| Existing Plant cost (M$) | 840.04 | 840.04 | 840.04 | 840.04 | 840.04 |
| New plant cost (M$) | 2840.665 | 3501.46 | 3814.16 | 4208.757 | 4633.657 |
| Total cost (M$) | 3680.705 | 4341.5 | 4654.2 | 5048.8 | 5473.7 |

**Table 9.** Annual Summary—Proposed Case.

| Case Study | Proposed Case | | | | |
|---|---|---|---|---|---|
| Years | 2016 | 2017 | 2018 | 2019 | 2020 |
| Annual Peak Load Demand (MW) | 5645 | 6775 | 7550 | 8340 | 9249 |
| Annual Energy Produced (GWH) | 49,450.2 | 59,349 | 66,138 | 73,058.4 | 8,1021.24 |
| Total Installed Capacity (MW) | 6000 | 7100 | 7800 | 8600 | 9500 |
| Annual Expenditure (M$) | 3680.7 | 4341.5 | 4654.2 | 5048.8 | 5473.7 |
| Average Electricity Cost (cents/kWh) | 7.44 | 7.32 | 7.04 | 6.91 | 6.76 |

### 4.3. Comparison of Case Study

In Table 10, a comparison of two cases is given in different terms. The comparison of these two case studies suggests that the costs of energy in the capacity expansion program serves as an important policy factor for large-scale integration of clean energy systems as the share of clean sources increases from 13% in the base case to 39% in the proposed case. The average cost of electricity generated is almost comparable with a 35.6 percent decrease in fuel cost and $CO_2$ emission. The overall fuel cost is decreased with an increase in renewable energy integration.

The total cost analysis with the storage system and without storage system is shown in Figure 11.

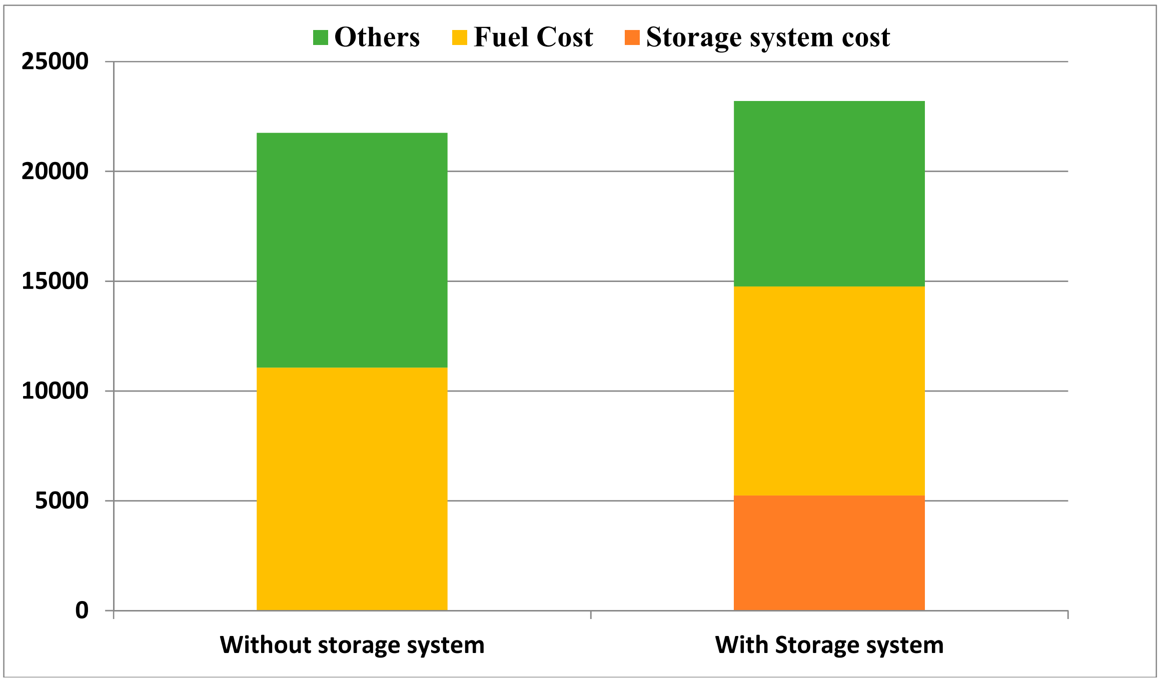



**Figure 11.** Case analysis with and without storage system.

The storage system is making 36.4% of the total cost in a five-year planning horizon with an increase in total cost of 6.67% from base case cost.

**Table 10.** Cases Comparison.

| Terms | Base Case | Proposed Case |
|---|---|---|
| Total Expenditure (million $) | 21,751.01 | 23,198.9 |
| Fuel Cost (million $) | 11,063.9 | 9519.94 |
| Clean Energy Contribution (%) | 13 | 39 |
| Average Cost of Electricity (cents $/kWh) | 6.59 | 6.74 |
| $CO_2$ Emission (Thousand Tons) | 109,066 | 38,827 |

## 5. Conclusions

Renewable energy systems have poor capacity factors and availability rates, are intermittent in nature and are costly. Hence, they cannot compete with conventional fossil fuel-fired power plants. The focus of research here is to increase the use of clean energy with large-scale RES integration, which leads to lowering of fuel usage by conventional power plants. This has a counter effect on less fuel consumption and less emission of hazardous gases. The economic feasibility is evaluated when ESSs are introduced in the electric grid with an expansion of a storage system as well as more percentage of the renewable energy integration and less percentage of fuel consumption by conventional power sources. The artificial neural network is used to validate the forecasted load model with historical weather and holidays as input predictors. The uncertainties associated with the renewable energy system are handled by a chance-constrained model, and solved by a genetic algorithm (GA) in MATLAB. The results suggested an increase in proportion of clean energy from 13 to 39%, leading to a sharp drop in $CO_2$ emissions to 35.6%, thereby reducing the devastating effect on the environment. The result revealed that for the betterment of the environment, the role of the storage system is critically significant to renewable energy integration. If the financial assessment of the used grid data is analyzed by considering gas-related external costs, it would produce more promising results toward adoption of storage and renewable energy systems.

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