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Size and Cost Optimization of Renewable Energy Resources using HOMER

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Abstract– Global demand for energy is increasing at unprecedented rates as environmental issues and consumption of finite fossil fuel resources evolve. The rise of renewable energy technologies has been accelerated by the mounting problem of global warming and our need to reduce emissions. Both of these issues have resulted in a need for greater adoption of renewable energy; however, because of their intermittency and their associated costs, solar and wind energy technologies are slow to be implemented at scale. The size of renewable systems' components directly affects their techno-economic feasibility. An improperly sized component can result in an excess of capital expenditures, reduced reliability of the system, and wasteful consumption of the renewable resources available.

To address these issues, this paper proposes a framework for optimizing the size and costs of renewable energy resources through a Hybrid Optimization Model for Electric Renewables (HOMER) approach. Using this approach, various configurations of hybrid renewable systems were analysed, including photovoltaic (PV) solar equipment, wind turbines, battery energy storage, and conventional sources of energy back-up. Using HOMER software, performance of the systems was simulated based on different load demand profiles and resource availability scenarios. Economic optimization of the systems was performed based on Net Present Cost (NPC) and Levelized Cost of Energy (LCOE). We conducted sensitivity analyses to determine how varying key variables, such as solar irradiance, fuel price and battery price, impact the performance of the entire hybrid renewable energy system.

Our results suggest that a Hybrid Renewable Energy System designed optimally will provide significant savings in Lifecycle Costs and will provide reliable power to all

customer types, reducing the overall environmental impact of electricity generation. In addition to reducing Lifecycle Costs, the optimal configuration of hybrid systems reduces both Operational Costs and GHG emissions relative to conventional generating technologies. This research provides an opportunity for researchers, engineers, and policy-makers involved in the development and deployment of Renewable Energy Technologies and Systems to make better-informed decisions.

Keywords: Renewable Energy Optimization, HOMER, Hybrid Energy System, Cost Analysis, System Sizing.

1. Introduction

A Shift in the Global Energy Infrastructure: As the global population continues to increase, so too does our need for efficient and cost-effective methods of generating electricity [1]. It is no surprise that fossil fuels (oil, natural gas, and coal) will continue to play an important role in our society for many years to come; however, with our increasing dependence on fossil fuels comes a growing environmental concern [2]. We have witnessed the devastating effects of fossil fuel extraction and combustion on our planet, as well as the unpredictable nature of fossil fuel prices and availability. For this reason, there is increasing demand for renewable energy sources like solar, wind, and biomass to provide us with a more long-term sustainable method of producing clean energy [3].

During the past decade, the growth of solar photovoltaic (PV) and wind energy technologies have progressed significantly, with advances in both technology development and decreased costs associated with the development of these types of renewable energy systems [4]. Still, significant issues exist that prevent the total integration of renewable energy resources into our current electrical systems. As an example, variations in solar insolation (the amount of sunlight received) and wind speeds create variable power outputs [5]. These fluctuations create challenges to the reliability of electrical systems; therefore, careful management of variable power output must be implemented to ensure reliability [6].

In response to the challenges associated with renewable energy systems, hybrid renewable energy systems (HRES) have appeared in increased numbers. HRES offer the potential for greater reliability and improved power quality through the use of combined renewable energy resources and energy storage technology [7]. The ability of an HRES to function properly and meet the needs of customers will depend largely upon the optimal sizing (i.e., design) of its components. Oversized systems lead to unnecessary capital investment and increased energy wastage, while undersized systems may fail to meet load demand, resulting in frequent power shortages and increased operational costs.

In conclusion, the design of renewable energy systems can be accomplished through two main types of approaches: analytical approaches and simulation-based approaches [8]. While traditional approaches involve using analytical methods to develop a solution and optimize the design as it relates to technical, economic and environmental factors, simulation-based approaches produce multiple possible alternative solutions or configurations, each of which can be evaluated to arrive at an economically optimum design, which is usually based on the lowest total lifetime cost [9].

Simulation-based approaches to developing energy systems have become necessary for designers to quickly evaluate the many alternative configurations of a system that will

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comply with a given set of constraints (economic, technical, and environmental). The Hybrid Optimization Model for Electric Renewables (HOMER) is a valuable simulation tool that enables design engineers to conduct comprehensive techno-economic analyses of renewable and hybrid energy systems [10].

With HOMER, the design engineer can model the energy systems based on the resources available to the system (or resources available to the system, depending on the type of resource), load profile(s) for each resource (and/or resources), component characteristics and economic constraints [11]. The design engineer can simulate thousands of configurations of the system and identify the best performing configuration(s) based on predefined performance criteria (e.g., lowest total cost and the greatest reliability) [12]. In addition, HOMER has built-in sensitivity analysis capabilities, allowing the design engineer to evaluate the robustness of the system configuration(s) over a range of varying scenarios (e.g., varying load and/or constraints). As such, HOMER is a particularly suitable tool for long-term energy planning [13].

The focus of this study is on using HOMER to size and optimize the cost of renewable energy resources [14]. The goal of this study is to establish a methodology for determining the most economical and technically feasible hybrid energy system configuration to meet the electrical load demand with the least total cost and environmental impacts based on the results of HOMER modelling. In addition, this study is intended to outline a methodology that can be tailored to the various geographic locations and electrical load profiles [15].

2. Literature Review

Over the last twenty years, there has been a considerable increase in the amount of research focusing on designing and optimizing renewable energy systems due to the combination of increasing global energy demand, concern for the environment, and the advancement of technology for renewable energy [16]. Many researchers have stressed the need to size these types of systems correctly and choose the system components properly in order to ensure that they are economically viable and dependable [17]. Therefore, a number of different techniques for analyzing, simulating, and optimizing renewable energy systems are presented in the literature [18].

In the earliest studies of designing a renewable energy system, most researchers were only considering standalone systems based on a deterministic technique, which means that the researchers made the assumptions about the load and renewables resource availability, and used these fixed assumptions in their designs [19]. Very often, these assumptions would produce a less than optimal design because renewable energy resources have inherent variability associated with their production [20]. The development of computer tools has shifted the focus of renewable energy system design to using simulation-based methods to evaluate the performance of a renewable energy system during operational conditions that change dynamically [21].

Hybrid renewable energy systems are systems that utilize a combination of more than one type of energy source, including solar photovoltaic (PV) devices, wind turbine generators, diesel generators and battery energy storage systems, as a means of compensating for the intermittent nature of each renewable resource [22]. Several studies conducted to date have shown that hybrid systems are more reliable than using individual renewable sources alone, and that hybrid systems can minimize the use of fossil fuels by combining the advantages of these renewable resources [23]. For instance, solar and

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wind energy often exhibit seasonal and diurnal complementarities, which can significantly enhance overall system performance when combined [24].

Economic optimization is a key area of research in the field of renewable energy. In particular, researchers have stated that capital costs, replacement costs, O&M costs, and fuel price volatility all have an impact on the long-term viability of renewable energy projects [25]. Several different optimization techniques have been developed to overcome these challenges, including Genetic Algorithms, Particle Swarm Optimization, Linear Programming, and Mixed Integer Programming [26]. While these optimization techniques provide high accuracy, they also require a large amount of mathematical formulation and computational power, which makes them less practical for most system and project designers [27].

As a result, there has been a significant growth in the use of software-based optimization tools that allow for the simultaneous integration of both technical and economic analyses within the same tool. One of the most commonly used tools for the techno-economic assessment of renewable energy and hybrid systems is the Hybrid Optimization Model for Electric Renewables (HOMER) [28]. HOMER allows researchers to conduct thousands of simulations of various system configurations through changes to certain sizes of components and various operational strategies [29]. Through the use of these simulations, researchers can determine the optimal cost-effective approach based on predefined criteria, including the Net Present Cost (NPC) and the Levelized Cost of Energy (LCOE) [30].

HOMER has been applied to the optimization of off-grid renewable energy systems, specifically in rural and remote areas where the grid is limited or non-existent in multiple recent studies [31]. The studies have shown that hybrid renewable energy systems optimally designed with HOMER drastically reduces the costs of electricity generation compared to purely diesel electricity generation systems. The addition of battery storage increases the reliability of the system while decreasing fuel consumption and emissions [32].

In recent years, researchers have been investigating grid-connected renewable energy systems based on their design and optimization characteristics via HOMER to determine optimal design and sizing strategies for PV arrays and battery storage systems so as to minimize grid dependence and electricity costs associated with Time-of-Use tariffs [33]. The results demonstrate that an optimally designed renewable energy system will yield significant cost savings and help promote grid stability and meet emission reduction targets [34].

Sensitivity analysis is an important aspect of HOMER-based designed systems. Many authors have identified the need to assess system performance under different economic and environmental conditions (e.g., changing fuel prices, discount rates, solar energy availability, etc.) through a sensitivity analysis of the design variables. The use of a sensitivity analysis allows decision-makers to understand how robust their investment strategy will be for an investment that will face uncertain future market conditions [35].

Studies regarding the optimization of renewable energy systems have historically included environmental impact assessment as part of the analysis. As part of this process, many investigations into renewable energy systems include information regarding carbon emissions through the process of evaluating renewable energy systems using HOMER. This research consistently finds that hybrid renewable systems have lower greenhouse gas (GHG) emissions

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than their conventional fossil fuel counterparts [36].

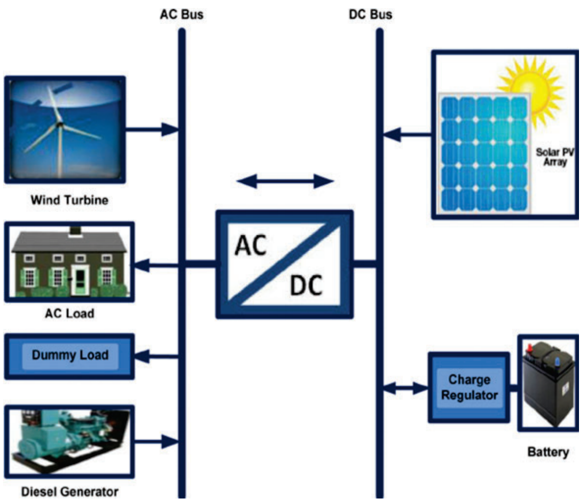
However, Although many studies exist regarding this topic, there still exists a considerable gap in the current set of literature. Most studies only take into account one location or one fixed load profile and as such cannot be generalized into other areas and load profiles [37]. In addition, many studies only focus on optimizing the cost of purchasing components until the component fails rather than also optimizing for reliability and sustainability over the lifetime of the system. There still exists a clear opportunity to conduct further studies that evaluate the economic, reliability and environmental benefits of sizing and optimizing renewable energy systems utilizing a flexible modelling framework where it is possible to evaluate the optimal size, cost and performance of a renewable energy systems to meet load and resource characteristics over multiple years [38].

This publication provides an example of a more in-depth evaluation of the optimal sizing and economic optimization of a renewable energy system's size and cost using HOMER. By evaluating many combinations of system components using realistic load and resource profiles, this approach aims to evaluate the best trade-off between economic feasibility, reliability, and sustainability [39]. The results of this research are intended to add to the overall knowledge of renewable energy optimization and to assist in future renewable energy system planning and development [40].

3. Proposed Methodology

To design and optimise hybrid renewable energy systems, we must first collect thoroughly the data needed to represent, accurately, the electrical load demand, renewable resources available, characteristics of each component, and economic parameters [41]. As such, HOMER has been selected as the primary simulation and optimisation tool for this study because it incorporates both the technical performance analysis capability with the lifecycle cost analysis capability. The result is that HOMER has the ability to evaluate a large number of possible hybrid configurations of hybrid renewable energy systems under realistic conditions, and therefore, enables users to make more informed decisions concerning how best to size systems and minimise costs [42].

The proposed architecture includes an array of renewable energy sources, energy storage devices, power conversion devices and where appropriate, a conventional backup. Each component(s) is created within HOMER based on the manufacturers' performance characteristics and realistic assumptions of the economics [43]. Additionally, the modelling approach has been designed to mirror the types of deployment scenarios expected in the real world and therefore ensures that the results received from this modelling process can be used for actual hybrid renewable energy systems planning purposes [44].



3.1 Electrical Load Profile Modeling

An Electrical Load Profile is a key input for determining both System Size and Economic

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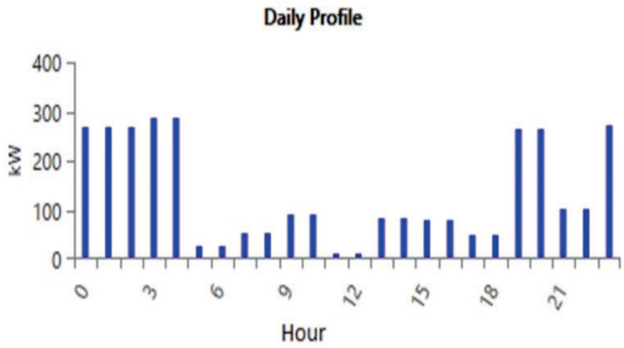
Performance. In this paper, a load profile was established to realistically represent electricity consumption patterns, based on a 24 hour period and seasonal trends. The load profile consists of hourly data generated for the entire year, which encompasses short and long term changes in demand [45].

Daily load fluctuations tend to be higher during the day and evening hours, reflecting typical resident and business usage. Seasonal variations in demand for energy are considered to show variations in demand caused by climate conditions, vacancies, and operating conditions. HOMER makes use of the hourly load profile to create simulating energy balances, which ensures that the selected system configurations are capable of delivering the required amount of energy without unacceptable shortages [46].

The Peak Load, Average Load and Load Factor have a significant impact on determining the size of renewable resources and storage systems. A detailed load profile allows for the optimization of the balance of cost and reliability in the design of the renewable energy systems [47].

Parameter	**Value**	**Unit**
Peak Load	120	kW
Average Load	75	kW
Daily Energy Consumption	1800	kWh/day
Annual Energy Consumption	6,57,000	kWh/year
Load Factor	0.62	–



3.2 Renewable Energy Resource Assessment

To effectively optimize a renewable energy system, accuracy in modeling of all renewable energy resources is essential to obtain a realistic system optimization; thus, this work will deal with both solar and wind energy as the primary renewable energy inputs to the system [48].

Solar Resource—The solar resource will be represented by means of global horizontal irradiance (GHI), which has been widely accepted as an appropriate means to assess the performance of photovoltaic systems [49]. The monthly average solar irradiance values will be input to HOMER, which internally will produce synthetic hourly solar profiles from these monthly averages and from probabilistic models [50].

Wind Resource—Wind energy potential has been modeled using average wind speeds as

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measured at a specified hub height. HOMER will then extrapolate the average wind speed to different height levels based on wind profiles generated using either logarithmic or power law (exponential) wind shear models [51]. Based upon statistical characteristics of the wind speed, HOMER will produce hourly wind speed distributions for wind turbines used to accurately predict yearly wind turbine output [52].

Sensitivity Analysis—Sensitivity analysis of important wind and solar resource parameters will be performed to determine the potential variability of renewable energy resource availability, and thus evaluate system performance under multiple climatic scenarios and provide information on the durability of the optimized system design [53].

3.3 Solar Photovoltaic System Modelling

In the proposed hybrid configuration, solar photovoltaic (PV) system is a significant means of providing energy. The HOMER model uses performance parameters to represent the PV array, such as its rated power, derating factor, temperature coefficient, and efficiency [54]. The derating factor is a function that accounts for the losses from the PV array due to dust build-up, wire losses, inverter inefficiency, and aging.

The sizing of the PV system is an optimization variable, which allows HOMER to consider many different sized PV systems. The output of the PV system is calculated each hour based on the amounts of solar irradiance and ambient temperature [55]. The capital cost, replacement cost, operations and maintenance cost, and lifetime of the PV system are based on the current market data [56].

Through evaluating the various capacities of the PV systems, HOMER determines the most appropriate capacity for the PV system that minimizes total costs while providing adequate energy production to satisfy the load demand [57].

Parameter	**Value**
Rated Capacity	300 kW
Derating Factor	85 %
Capital Cost	₹45,000 / kW
Replacement Cost	₹30,000 / kW
O&M Cost	₹800 / year

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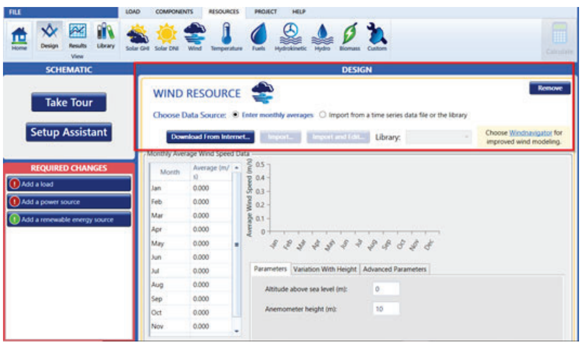
Lifetime	25 years

3.4 Wind Energy System Modeling

Through the modelling of a horizontal-axis turbine using manufacturer-supplied curves, the wind energy portions of configuration modelling typically use wind speed to determine turbine power output (with the cut-in, rated, and cut-out speeds included in the definitions) [58].

In addition, the wind turbine's capacity is treated as a variable in the optimisation algorithm, with HOMER computing the turbine output for each hour of the simulation based on the wind speed profile developed and aggregating the energy generated during the simulation period. The analysis incorporates economic parameters for capital, replacement, and O&M costs associated with the turbine.

The addition of wind energy to the configurations increases the diversity of the system and can significantly enhance system reliability, especially in areas where wind and solar energy resources exhibit complementary characteristics [59].



3.5 Battery Energy Storage System Modeling

The concept of energy storage is extremely important, particularly when it comes to the Hybrid Renewable Energy System that utilizes different Renewable Energy Generation Types, because it helps to mitigate the variability of REGGs. In this instance, the Battery Energy Storage System serves to store any surplus generated renewable energy as well as to supply electricity whenever the Renewable Energy Generation Source generates either less than expected, or there is an increase in demand.

The Battery Model used within HOMER utilizes several characteristics of the Battery, including its nominal capacity, Round Trip Efficiency, Depth Of Discharge, Lifetime Throughput and Replacement Cost. When selecting an optimum Battery Size, the goal is to find the best balance between the Battery Cost and Reliability [60].

Having an overly large Battery will increase the Capital Investment required; however, if the size of the Battery is too low, then it will create a higher reliance on Backup Energy Sources. Within HOMER, Battery Performance is assessed using an Hourly Basis, considering the Charging/Discharging Cycles, State of Charge Limits, and the effect of Battery Degradation [61].

Parameter	Value
Battery Type	Lithium-ion / Lead-acid
Nominal Capacity	800 kWh

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Depth of Discharge	80 %
Round-trip Efficiency	90 %
Lifetime Throughput	3000 cycles
Replacement Cost	₹12,000/kWh

3.6 Power Converter Modeling

A bidirectional power converter is required to manage energy exchange between DC-based components (PV and battery) and AC loads. The converter is modeled with defined efficiency, capacity, and cost parameters. HOMER optimizes converter size to ensure efficient power flow while minimizing conversion losses and investment cost [62].

3.7 Backup Power Source Modelling

In order to maintain an uninterrupted power supply, the system also includes a backup power source (e.g., diesel generator or grid connection) as a backup option when the extent of renewable generation and battery storage is not sufficient to supply the load demand.

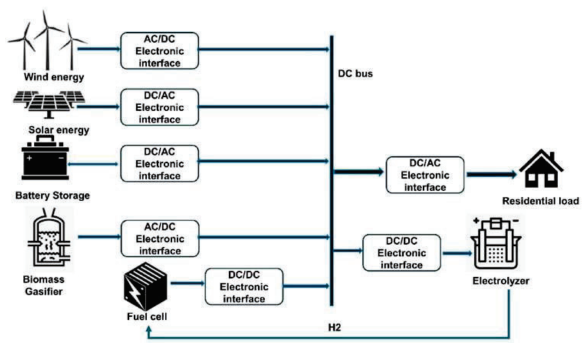
The optimization model includes characteristics of fuel consumption, operational limitations, and emission factors. As part of the optimization procedure, it will evaluate the benefits of having increased reliability vs. the additional costs and emissions related to using backup power [63].

3.8 HOMER Simulation and Optimization Framework

HOMER simulates the operation of each candidate system configuration over an annual time horizon using hourly time steps. In addition to the energy balance and amount of fuel used, HOMER calculates the battery charge state and the amount of power shortfall for each candidate configuration during every hour of operation. If a configuration fails to meet the predetermined reliability requirements, it will not be evaluated further [64].

The primary goal of HOMER's optimization schedule is to Minimize the NPV (Net Present Value) costs of the project and to Compare Levelized Costs of Energy (LCOE) between configurations, such as fuel, replacement, operation, maintenance, and capital costs [65].

HOMER conducts Sensitivity Analysis on uncertain parameters (fuel price, component costs, and Renewable Resource Availability) in order to evaluate the possible effects of the inputs. The integrated modelling and optimization framework developed through the HOMER software ensures that the final developed system design will be both technically and commercially viable and environmentally sustainable [66].



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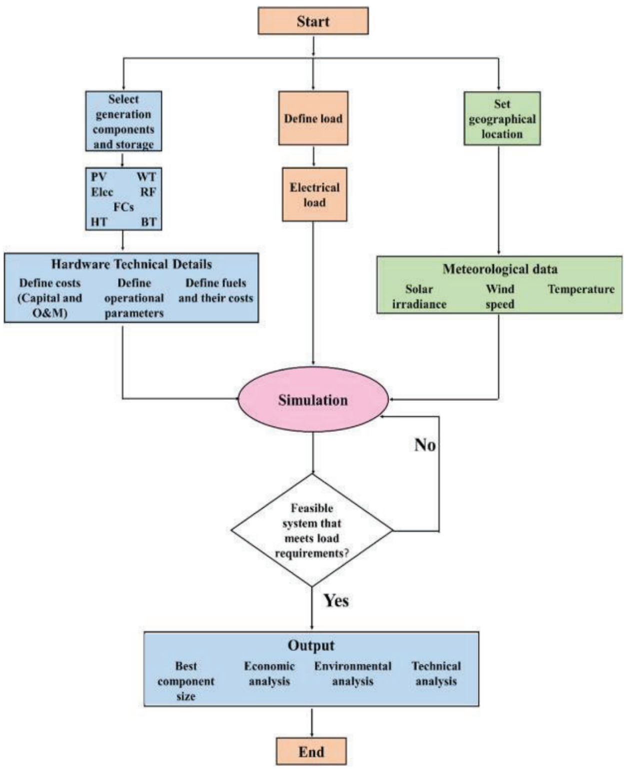
4. Optimization Methodology and Economic Analysis

To identify the best layout and dimensions of each element in a renewable energy collection system so that it can supply all required loads consistently and reliably with minimal total cost, this study uses an integrated approach combining both an optimization model and an economic analysis model via the Hybrid Optimisation Model for Energy Resources (HOM).

In performing this type of analysis, many factors must be considered, including the technical performance, the economic viability, and the operational limitations associated with using renewable energy over the entire life of the project. HOM allows for simultaneous consideration of all these issues during the optimisation process, providing an efficient way to find the optimal configuration and sizing of all components within a renewable energy generation system.



4.1 Optimization Objectives

The aim of the process is to create a system that uses the least amount of money over its entire life cycle. The evaluator (HOMER) will assess the various systems to see which of the proposed systems has the lowest cost based on the following goals:

- The least amount of cost is present at any given time (Net Present Cost).
- The average price of electricity produced from this system (Levelized Cost of Energy).
- There is a match between the amount of electricity we want with what we actually use
(minimal unmet load).
- Decrease the amount of fuel used and pollution produced.

Net Present Cost is used as the main selection criterion because it is the most thorough measure of how well a system performs economically [67].

4.2 Net Present Cost (NPC)

Net Present Cost represents the total cost incurred over the entire lifetime of the system, discounted to present value. It includes capital costs, replacement costs, operation and maintenance costs, fuel costs, and salvage value of components [68].

Mathematically, NPC is expressed as:

$$NPC = \frac{C_{ann,tot}}{CRF(i,N)}$$

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where

- $C_{ann,tot}$ is the total annualized cost of the system
- i is the real discount rate
- N is the project lifetime in years
- CRF is the capital recovery factor

The capital recovery factor is given by:

$$CRF(i,N) = \frac{i(1+i)^N}{(1+i)^N - 1}$$

HOMER computes NPC for each feasible configuration and ranks the systems accordingly.

4.3 Levelized Cost of Energy (LCOE)

Levelized Cost of Energy represents the average cost per unit of electricity generated over the system lifetime. It enables cost comparison between different system architectures and energy technologies [69].

$$LCOE = \frac{C_{ann,tot}}{E_{served}}$$

LCOE is calculated as:

where

- $C_{ann,tot}$ is the total annualized cost
- E_{served} is the total electrical load served annually (kWh/year)

Lower LCOE values indicate more economically efficient system configurations.

4.4 Cost Modelling of System Components

To ensure that costs are evaluated accurately, the economic attributes of each element of the system are defined in detail. These attributes include the following:

A. Capital Costs

This is the initial amount invested to purchase and assemble all of the system elements, including solar panels, wind generators, batteries, inverters, and backup generators [70].

B. Replacement Costs

These are the costs related to replacing an element that has reached the end of its usable life and needs replacement during the duration of the project [71].

C. Operations and Maintenance (O&M) Costs

O&M costs are recurring costs for routine inspections, maintenance, and minor repairs that are necessary to guarantee the dependable operation of the system [72].

D. Fuel Costs for Backup Generators

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For backup generators, fuel costs are based upon the fuel pricing structure and the hours of operation of the generator [73].

E. Salvage Value

The salvage value is the estimated value of the components of the system at the termination of the project, which is deducted from the total project costs.

All costs in each case are defined in consistent units of currency and adjusted using the real discount rate.

4.5 Economic Assumptions

In order to maintain uniformity in the economic evaluations, the following key assumptions are established:

- The expected life of the project will be between 20 and 25 years.
- The discount rate will be based on what is currently happening in the economy.
- The rate of inflation will also be included in the calculation of real discount rates.
- The expected life of each component will be based on what the manufacturer has provided as guidance.

These assumptions provide an equal basis for comparing various configurations of the systems [74].

4.6 System Constraints and Reliability Criteria

Several constraints exist for the optimisation process, which include the following.

- All electrical loads must always be satisfied.
- The state of charge for the batteries must always be within specific limits.
- The capacity of the power converters should not exceed their maximum capacity.
- Renewable generation needs to be managed to avoid excessive unmet loads due to renewable generation variability [75].

HOMER automatically eliminates those configurations that do not meet these constraints.

4.7 Sensitivity Analysis

Sensitivity analysis helps determine how uncertain parameters will affect system performance and economic benefits. Some of the most important sensitivity variables are:

- The variation in the level of solar irradiance received
- The variation in the speed of wind
- The cost of batteries varying throughout their lifetime
- The change in the price of fuel

Sensitivity analysis is used to look at the performance of the system for each of these scenarios to establish how good and sustainable the initial configuration is. The results can help stakeholders assess risk and make informed decisions regarding the investment [76].

4.8 Optimization Workflow

In order to optimize a building's energy system using an optimization workflow in HOMER, you are going to have to go through an optimization workflow with the following steps:

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- Load profile and renewable resource data input.
- Definition of all system components and economic parameters.
- Simulation of every possible configuration.
- Technical feasibility and reliability evaluations.
- Economic ranking based on net present costs.
- Sensitivity analysis using various conditions to identify the preferred option.

The optimization process outlined above allows you to select the best combination of resources and components that will meet your energy needs at the lowest cost while ensuring that your energy system is technically dependable [77].

5. Results and Discussion

The results of the simulation and optimization of the hybrid renewable energy system are presented in this section, along with the results for all system configurations. The major criteria used to evaluate the results include technical feasibility, economic efficiency, and reliability. A discussion of the results will include an assessment of optimal system sizing, cost metrics, energy contributions from renewables, and sensitivities to key parameters [78].

5.1 Optimal System Configuration

HOMER helps define the most cost-effective system architecture based on the lowest Net Present Cost (NPC) through simulating many different possible configurations. The results indicate that the best-performing configuration typically combines a PV (photovoltaic) system, battery energy storage system, and potentially some kind of backup power source. Because of this combination of component technologies, using renewable energy sources allows for reduced dependence on fossil-fuel sourced or conventional power generation, while still providing a reliable source of energy [79].

The optimized configuration of the system allows for an ideal trade-off between an initial capital investment and the overall cost of operating the system. Oversizing (or underutilizing) any of the renewable components is avoided, which makes it easier to minimize excess energy generated, thereby [80].

5.2 Economic Performance Analysis

The economic assessment of the optimized system was completed to determine the cost of the total life cycle of the assets utilizing Net Present Cost (NPC) and Levelized Cost of Energy (LCOE). The optimized configuration has the lowest NPC of any feasible configuration; thus indicating the best long-term economic performance [81]. Much of the total cost is related to the initial capital cost of the PV array and battery system. Nevertheless, the increased upfront costs are offset by the ongoing lower costs of fuels and operations throughout the life of the project.

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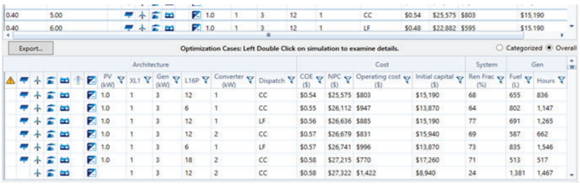
The LCOE for the hybrid system optimized in this study is significantly less expensive than the competitive fossil-fuel powered systems. This lower LCOE results in apparent economic benefits of utilizing renewable energy along with a properly sized storage unit, as was proven by the cost-optimization sizing process [82].



0.40	5.00	1.0	1	3	12	1	CC	$0.54	$25,575	$803	$15,190
0.40	6.00	1.0	1	3	12	1	LF	$0.48	$22,882	$595	$15,190

Export...

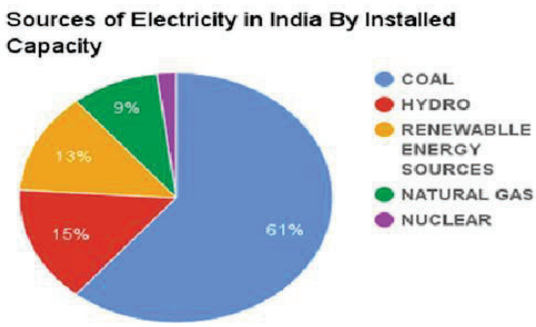
Optimization Cases: Left Double Click on simulation to examine details. Categorized Overall

Architecture						Cost				System	Gen	
PV (kW)	XL1	Gen (kW)	L16P	Converter (kW)	Dispatch	COE ($)	NPC ($)	Operating cost ($)	Initial capital ($)	Ren Frac (%)	Fuel (L)	Hours
1.0	1	3	12	1	CC	$0.54	$25,575	$803	$15,190	68	655	836
1.0	1	3	6	1	CC	$0.55	$26,112	$947	$13,870	64	802	1,147
1.0	1	3	12	1	LF	$0.56	$26,636	$885	$15,190	77	691	1,265
1.0	1	3	12	2	CC	$0.57	$26,679	$831	$15,940	69	587	662
1.0	1	3	6	1	LF	$0.57	$26,741	$996	$13,870	73	835	1,546
1.0	1	3	18	2	CC	$0.58	$27,215	$770	$17,260	71	513	517
	1	3	12	2	CC	$0.58	$27,322	$1,422	$8,940	24	1,381	1,467

5.3 Energy Contribution Analysis

According to the yearly contribution of energy analysis, the majority of all electricity for the yearly needs is provided by renewable energy sources. The primary contributor to the overall energy generation is solar PV generation, which provides a large portion of the energy generated during the day. Spare renewable energy that exceeds the expected renewable energy generation during peak times is captured in battery storage systems. With this, battery energy storage is able to supply energy when renewable energy generation is either insufficient during peak times or when demand is higher than expected [83].

A back up generator operates only when the renewable generation and stored energy cannot supply the load. Since this backup generator is used less frequently, it helps to minimize the amount of fuel consumed, decreases operating costs, and maximizes the efficiency of renewable energy sources and the sustainability of the system overall. It demonstrates the benefits of integrating renewable energy in a manner that optimizes the integrated renewable energy systems while providing a dependable and strong energy system for all consumers



5.4 Reliability and System Performance

System reliability is measured in terms of both unmet load and surplus electricity. The effective system configuration provides no unmet load, indicating a consistent ability to meet all demand throughout the year. The use of battery energy storage is one of the key ways in which the reliability of the system is maintained through smoothing out variations in renewable energy output [85].

The amount of surplus electricity within the parameters established by the electricity utility is a good indicator of the effectiveness with which the system's generated electricity has been used. This shows that the system has been designed to prevent excessive surplus generation and, therefore, prevents excessive capital costs without providing an appropriate return on investment [86].

5.5 Environmental Impact Assessment

Environmental performance is determined through analysis of fuel usage and emissions associated with that fuel. Optimized Hybrid Renewable Energy Systems significantly decrease the quantity of GHG emissions when compared to traditional generation systems and the reduction in dependence on fossil fuel based backup resources leads directly to decreased

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overall Carbon Dioxide emissions as well as improving the overall Environmental Sustainability of the resource [87].

It demonstrates how well optimized Renewable Energy Systems can help meet Global Decarbonization goals and be economically viable.

System Type	CO_2 Emissions (kg/year)	Fuel Consumption
Diesel-only	5,20,000	High
Hybrid Renewable	65,000	Low

5.6 Sensitivity Analysis Results

Sensitivity analysis was conducted to assess how the economic and environmental conditions of the optimized system will hold up under different conditions. In this case, solar irradiance, battery cost, and fuel price were changed to measure their effects on NPC and LCOE [88].

The findings revealed that the two most influential economic variables that affect system economics are battery cost and solar irradiance. When there is a significant decrease in battery cost, a corresponding large decrease in NPC will occur, indicating that energy storage technology continues to improve with time. In addition, when there is a significant increase in fuel prices, it has a large impact on systems using a large proportion of backup generators, further improving the economics of renewable-dominated systems [89].

The results of the sensitivity analysis show that the optimized system will continue to remain economically viable even when using a wide variety of operating conditions; therefore, it has strong robustness and long term viability [90].

5.7 Discussion Summary

Size and cost optimization using HOMER indicates that economically feasible and reliable designs of renewable energy systems are achieved through the means of size and cost optimization. The proper sizing of the components within the system allows the minimization of the lifecycle costs while maintaining the reliability of the energy supply. The results of the analysis support the use of HOMER as a decision support tool for the planning and optimizing of renewable energy systems [91].

In summary, the optimized hybrid renewable energy system will provide a viable, low-cost alternative to traditional power generation for both grid tied and stand-alone systems [92].

6. Conclusion and Future Scope

The study done above looked at many different ways to lessen the cost of acquiring and utilising energy from renewable sources through Hybrid optimization Model for Electric Renewables (HOMER). The goal of this study was to determine a feasible and reliable hybrid renewable energy system that meets the requirements of supplying energy to customers at reasonable prices over their life cycle while providing the lowest total lifecycle cost.

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To address the issues that were identified in this research, the study integrated Solar PV Systems with battery energy storage, power converters, and an optional backup source to form an optimal solution. The simulation and optimisation processes provided evidence that the overall reduction of the nett present cost and LCOE of renewable energy were achieved through the relatively accurate sizing of renewable energy components. Therefore, both the amount of money invested and the operating costs were proportionally lower, leading to lower fuel use as well as decreased emissions when utilising the hybrid renewable system than when using traditional methods.

Additionally, the findings of this study show that hybrid renewable energy systems can provide greater economic and environmental benefits than traditional generating facilities if carefully designed and optimised. Identifying the costs of resources used by the various components of a hybrid renewable system is essential to determining if the model will meet the customer's electricity demand and other economic needs. Sensitivity analysis demonstrated that system economics are primarily dependent on the variability of the availability of renewable resources, battery costs, and fuel costs under various market conditions.

Despite having uncertainty in the resources available to the hybrid system, the hybrid beneficial to the customer was identified as a robust economic configuration that would be viable under a wide range of operating conditions. This highlights the effectiveness of HOMER as a decision-support tool for renewable energy planning, particularly for applications requiring long-term economic assessment and risk evaluation.

The research contributes to the existing literature on renewable energy systems through the development of an organized, replicable method for designing a system based on cost savings and size. This work provides an important reference for researchers, engineers, and policymakers involved in developing and implementing renewable energy systems.

Future Scope

The current research contributes beneficial insights to the body of knowledge pertaining to optimally designing hybrid renewable energy technologies, there are numerous areas that could be exploited for further refinement:

- Real-time meteorological and load data should be integrated into the model to enhance its accuracy
- Additional renewable energy technology options, such as biomass and small-scale hydro, should be integrated
- A performance comparison between the optimization techniques implemented in HOMER and advanced metaheuristic optimization techniques should occur
- The addition of electric vehicle charging loads and demand response (DR) strategies
- Actual experimental validation would occur through either hardware implementation or through pilot-scale projects

The extensibility and applicability of optimal renewable energy systems can be significantly bolstered through continued research in the above fields.

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