

Integrated Modeling of Renewable Energy Systems for Power Supply Optimization and Economic Sustainability

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This study examines the integration of renewable energy into Iran's electricity grid to meet growing demand while reducing the environmental burden of fossil fuel generation. A Unit Commitment (UC) model is used to simulate power generation schedules and to calculate the Levelized Cost of Energy (LCOE) for each generation technology. In the baseline case, combined cycle, gas, and steam power plants supplied about 91% of Iran's electricity demand, while wind and solar power together contributed less than 0.2%, highlighting the limited role of renewables in the current generation mix. Three scenarios were evaluated: redistribution of 10% of non-renewable capacity to wind and solar, raising the renewable share to 16.11%; meeting a 10% increase in demand through renewable expansion, yielding a combined wind and solar share of 14.9%; and increasing solar and wind capacity to 10 GW each, achieving a total renewable share of 23.52%. The results indicate that an optimal energy mix drawing on Iran's abundant solar and wind resources could reduce dependence on fossil fuels, strengthen grid resilience, and support a more economical and sustainable power system.

Keywords: Energy Economics, Energy Modelling, Renewable Energy, Unit Commitment, Energy Mix Optimization, Energy resilience.

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Nomenclature

d	Representative days	$sdc_{d,t,i}$	Shutdown cost of generating unit i
t	Hourly periods	$fuel_cost_{fu}$	Fuel cost of fuel type fu
i	Generating units	$efficiency_i$	Efficiency of generating unit i
j	Startup cost segments	var_cost_chst	Variable cost of storage charging
b	Generation blocks	var_cost_dchst	Variable cost of storage discharging
s	Bus	var_cost_stst	Variable cost of stored energy
fu	Fuel types	$curtail_penalt$	Curtailment penalty cost
st	Storage technologies	$vre_capacity_{vre}$	Installed capacity of renewable technology vre
vre	Renewable technologies	$vre_cap_factord_{t,vre}$	Hourly capacity factor of renewable technology vre
$mode$	Operating modes	$efficiency_{st}$	Charging/discharging efficiency of storage technology st
tt	Time index used in the min. up-/down-time summation	$self_dischargest$	Self-discharge rate of storage technology st
var_cost_i	Variable operating cost of generating unit i	$ded_{t,s}$	Electricity demand at bus s
vre_cvre	Cost of renewable (VRE) generation	G_{imax}	Maximum generation capacity of generating unit i
$suc_swi_{i,j}$	Stepwise start-up cost of generating unit i		

<i>ChargeCapacity_{st}</i>	Maximum discharge capability of storage technology st
<i>ReserveMargin</i>	Required spinning reserve margin
<i>conv_factor_{fu}</i>	Conversion factor of fuel type fu
<i>fu_cons_{fu}</i>	Maximum available amount of fuel type fu
<i>conv_factor_{NG}</i>	Conversion factor of natural gas
<i>NG_limit_d</i>	Maximum allowable natural gas consumption on day d
<i>g_max_{i,b}</i>	Maximum generation limit of generation block b of unit i
<i>NumDay_d</i>	Number of calendar days represented by representative day d
<i>charge_capacity_{st}</i>	Maximum charging/discharging capability of storage technology st
<i>impd_t</i>	Imported electricity
<i>expd_t</i>	Exported electricity
<i>Gd_{t,i,mode}</i>	Power generated by conventional unit i
<i>VRE_GEN_{d,t,vre}</i>	Renewable electricity generation
<i>Xt_{t,i}</i>	Binary unit commitment (on/off) variable
<i>Yd_{t,i}</i>	Binary start-up variable
<i>Zd_{t,i}</i>	Binary shutdown variable
<i>CHARGEd_{t,st}</i>	Charging power of storage technology st
<i>DISCHARGEd_{t,st}</i>	Discharging power of storage technology st
<i>STORAGEd_{t,st}</i>	Stored energy of storage technology st
<i>CURTAILd_t</i>	Curtailed renewable energy
<i>G_RESERVED_t</i>	Available operating reserve
<i>CAP_FACTOR_i</i>	Annual capacity factor of generating unit i
<i>CAP_FACTOR_ST_{st}</i>	Annual utilization factor of storage technology st

1. Introduction

The rapid increase in population and an industrial boom in recent years have created a pressure on energy supplies to enable their demand. By now, fossil fuels are the principal means of meeting the challenge, having at one point been considered as almost one most limitless energy source. But this reliance upon fossil fuels has taken a huge toll on our environment. The burning of fossil fuels increases greenhouse gas emissions; deteriorates air quality, pollutes the atmosphere with harmful emissions notwithstanding the modeling of climate change effects [1, 2]. As the urgency of these matters is becoming worldwide knowledge, so too is the drive for development into alternative forms of energy that adhere to sustainable practices. Renewable energy, hence, derived from naturally replenished sources like sunlight or wind, immediately becomes an interesting possibility. These resources are safer for the environment. Such stands are therefore highly significant in the withdrawal from fossil fuels [3-5]. The adoption

of renewable energy formulating the stepping stone to mitigating the environmental catastrophes resulting from the age old energy sources and starting the way to a clean sustainable future [6, 7].

The Paris Agreement, established in 2016, marks this transition of commitment from 195 countries under the auspices of the United Nations Framework Convention on Climate Change. With an implementation contribution starting in 2020, it upholds two key objectives: to limit the rise of global temperatures to a maximum of 2°C above pre-industrial levels, and to attempt to set it at a maximum of 1.5°C if possible [2]. The search for two-thirds of the renewable sources should be pursued by the year 2050 if this goal is to be achieved [7, 8].

Although renewable energy has great potential, its incorporation into existing energy grids faces several challenges. One of the major setbacks is the inherent variations between renewable sources of wind and solar energy that tend to cause energy not to be available or fluctuating in [9-11]. Such fluctuations magnify uncertainties in electricity supply and demand chain requiring a highly flexible grid to remain stable [6]. Therefore, energy systems' flexibility must be improved to support renewable energy management and operation. That is, it is essential for a system to react quickly to supply-demand schedule variations to allow a seamless energy transition from one source to the other [4, 5]. However, it is vital to maintain reliable renewable energy supplies. For a fully-fledged sustainable energy system, the generation of energy must be both reliable and the distribution and transmission systems adequately robust in coping with the anticipated variability in renewable output [7, 8, 11].

The preliminary studies on renewable energy sources and energy security began with the research of Wei et al.[12], who, through comprehensive statistical analysis and examining global trends, found that in 2009, renewable resources supplied 19.1% of the world's energy. By studying energy consumption patterns and technological development trends, they predicted that by 2035, this share would reach one-third of the world's electricity. The researchers also provided a practical framework for the development of developing countries, including strategies to reduce dependence on fossil fuels and enhance energy security. Complementing this research, Zohuri [13], using advanced mathematical modeling and scenario analysis, calculated the optimal energy mix. His study results indicated that solar energy could supply 30%, wind energy 25%, and nuclear energy 40% of low-carbon energy. He also showed, using risk assessment models, that this optimal mix could reduce risks from crises and cyberattacks by up to 15%, significantly increasing the energy system's resilience.

Within the area of regional studies, the comprehensive study by Nair et al. [14] was conducted in Malaysia. Employing system dynamics modeling, detailed causal loop diagrams, and stock-flow diagrams, they tested many energy-security-related scenarios for both the short and long run. The finding was that increasing the share of renewable energy up to 31% can result in a substantial reduction in import dependency and an increase in energy efficiency. In a complementary study, Wang et al. [15] in China innovatively combined the Divisia index method and gray relational model to analyze the factors affecting renewable energy development. By examining 20 years of data, they showed that energy security (174.12 Mtoe), carbon reduction (48.87 Mtoe), and low-carbon economy (27.77 Mtoe) directly affected renewable energy consumption. Their modeling also showed that in a renewable energy development scenario, dependence on oil imports would decrease by 55%, which would have a direct impact on national energy security.

Cergibozan [16], through an original analysis, explored the nexus between renewable energy and energy security risks in 23 OECD countries using advanced second-generation panel data techniques. He carried out a detailed country-by-country analysis by adopting cross-sectional dependence tests and the CIPS unit root test. Results with a

cross-sectional dependence value of 6938.233 showed that, out of countries considered, wind energy in 13 countries, hydro energy in 5 countries, and total renewable energies in 9 countries significantly decrease the risk of energy security. Supporting the findings, a large-scale study was conducted by Tugcu and Menegaki [17] for G7 countries from 1980 to 2018. Using the ARDL model and the Granger panel causality test, they discovered a one-way causal relationship from renewable energy to energy security with W-Stat of 2.797 and Zbar-Stat of 2.926 in the short term. Their long-term analysis showed that the renewable energy production coefficient was -0.711, indicating a 71.1% reduction in energy security risks.

Li et al. [18] developed a new analysis in the Yangtze River Delta. In their paper, new indices of electricity security and carbon emission reduction were developed by integrating entropy methods and CRITIC. The results showed that energy synergy in Zhejiang and Jiangsu provinces had a vital driving effect on the energy security level, and there existed a U-shaped relationship between renewable energy production and energy security in Jiangsu and Anhui provinces. Gökgöz and Güvercin's study [19] is in complete agreement with this one, representing a comprehensive analysis of the relationship between renewable energy deployment and energy security in the European Union. Employing DEA and the SML index, they documented upward efficiency and productivity trends, underlining how technological innovations and EU policies have contributed to such advances.

According to Khan et al. [20], the advanced "moving window" method will be very useful in critical studies of the causal relationship that exists between renewable energy and energy security. The statistical results obtained showed a p-value of 0.000 for the United States and 0.044 for the United Kingdom, thus proving the vital importance of renewable energies in promoting energy security. They also accurately simulated the temporal variations of this relationship. In a complementary study, Heuberger et al. [21] developed the innovative "system value" (SV) framework to assess power generation and storage technologies. Their modeling showed that by 2035, the system value for energy storage would decrease from £4500/kW to £500/kW, while the value for wind energy would drop from £200/kW to £120/kW, and for CCS, it would fall from £150/kW to £100/kW.

Coudray [22], by developing a complex hybrid deep learning model that included time series decomposition and convolutional LSTM networks, predicted the flexibility needs of the electricity system in Oxy Tanya. His modeling results indicated that by 2050, the total system cost would reach €97,236 million and €64,167 million, showing a 30% improvement compared to the current situation. Complementing these findings, Elliott [23] demonstrated that the intelligent use of smart grids and supergrids could reduce storage needs by up to 50% and significantly lower system costs.

Aized et al. [24] assessed four different scenarios, including the current situation, Green Pakistan, nuclear, and optimization for Pakistan's renewable energy policy using the LEAP model. It was noted from their evaluation that under the "Green Pakistan" scenario, the scenario with the least cost and environmental damages in the future, electricity generation costs will rise from \$121.7 million in 2012 to \$171.7 million in 2030. Together with this research, Nie and Yang [25] developed a complex theoretical model to analyze the impact of energy supply shocks on social came up with a complicated model for studying the effect of energy supply shocks on societal welfare and energy security-theorizing that cheaper renewable energy would not only reduce the conventional energy consumption but would also enhance energy security by making the economy less vulnerable to price shocks.

The study by Corrêa da Silva [26] in Brazil's dependency on hCorrêa da Silva [26] study's evaluates Brazil's reliance on hydropower and vulnerability in electricity supply, focusing on

renewable sources such as wind, solar, and small hydropower to improve energy security. The results revealed that such renewable sources have the potential to enhance energy security to a greater extent. As a key measure towards meeting resilience goals, the study also recommended improvement of water flow management and power generation from sugarcane waste through thermal plants. In the same way, Kulkarni et al. [27] identified barriers to wind energy development in India using the Analytical Hierarchy Process (AHP). They found policy, organization, and awareness hurdles, where policy and organizational hurdles were found to be high impact. The finding shows that the two areas would make a remarkable difference in renewable energy adoption rates in India, as they hinged on supportive policies and increased awareness. These studies, thus, point to the fact that both countries need to work on renewable energy sources as one of the major strategies for the improvement of energy security.

Sadeghi et al. [28] have carried out research regarding modeling and optimization of energy systems using a dynamic model, which has induced a decrease in the operational costs along with increased flexibility of the system. According to the simulation results available for the model, an operational cost reduction of 15% has been modeled with respect to 6-bus and 118-bus IEEE systems along with a 20% improvement in the system response to wind production instability. These achievements again fit well in the context of Heptonstall and Gross [29], who used system modeling for assessing costs and impacts regarding the integration of variable renewable energy (VRE) sources, such as wind and solar. Their results indicated that flexible integration costs are only between 2% and 6% of the overall costs of electricity production, while in non-flexible systems costs are multiplied.

Nakayama et al. [30] assessed the economic value of flexible resources in relieving variable renewable energy specific production constraints and reduced costs associated with electricity production through an innovative production cost model that evaluated the economic value of flexible resources. Study results indicated that the use of flexible resources, such as coal-following load capacity, pumped storage hydropower (PSH), and energy exchange among grids, can release VRE constraints from 55% to 9% and, consequently, avoid economic losses caused by these constraints. This concurs well with the findings of Heptonstall and Gross [29] for both studies indicate flexibility as an important concern in electricity systems to minimize costs and improve efficiencies in energy systems; they also show how correct market design and regulations can do a better job of integrating renewable energy sources.

Iran's strategic geographic location, bordered by the Caspian Sea in the north and the Persian Gulf and the Sea of Oman in the south, provides ideal conditions for implementing desalination systems powered by renewable energy (RE). According to, the country's abundant renewable energy potential, particularly solar and wind energy, presents significant opportunities for sustainable development and energy independence [31].

With an average of 300 sunny days per year and solar irradiation ranging from 5.5 to 8.5 kilowatt-hours per square meter per day, Iran is well-positioned to become a global leader in solar energy. This abundant sunshine, combined with the country's vast deserts and arid landscapes, creates perfect conditions for large-scale solar power plants to thrive. The country's technical potential for solar thermal energy is estimated at around 91,000 terawatt-hours. Regions in central, southern, and southeastern Iran, such as Yazd, Kerman, South Khorasan, and Zahedan, enjoy consistent high levels of solar radiation throughout the year. These regions, known for their dry climate and clear skies, are prime locations for harnessing solar energy. Additionally, northern provinces exhibit significant potential for photovoltaic energy. [32].

Iran also possesses substantial wind energy resources. The utilization of wind energy in the country dates back to the era of windmills around 200 BC. Back then, people used these ancient

structures to harness the power of the wind to grind grain and pump water. Today, approximately 1.3% of the country's land area (2.1 million hectares) experiences average annual wind speeds of 8 meters per second or higher, making these regions perfect for wind power generation. These regions, often characterized by vast plains and mountainous terrain, provide ideal conditions for wind turbines to capture the wind's energy. Iran's total wind energy potential is estimated at around 18,000 megawatts, significantly surpassing the country's nominal installed power capacity in 2017 (7,801.7 MW). Provinces such as Gilan, South Khorasan, Sistan and Baluchestan, Semnan, and Qazvin have the highest wind energy potential and host most of the country's wind farms. These provinces, strategically located in areas with consistent wind patterns, are well-positioned to play a major role in Iran's renewable energy future. [32].

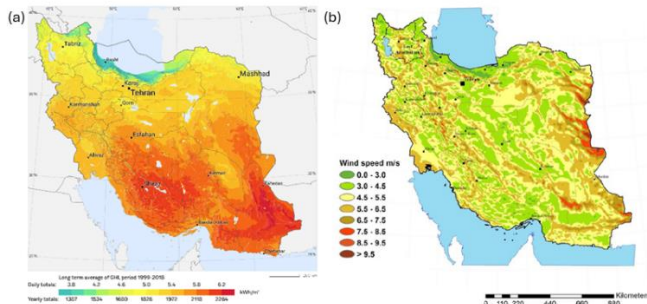


Fig. 1. (a) Solar and Wind Energy Potential in Iran based on Horizontal Solar Radiation Map [33] (b) Average Wind Speed at 40 Meters [34]

The findings from the above-mentioned research thus point out that renewable energy constitutes a crucial issue in enhancing energy security and cutting back on the dependency on fossil fuels. The increased sharing of these resources in the energy mix could pull the import of energy down and make the system more flexible. Besides, the establishment of storage technologies, as well as the optimization of the distributed systems for the efficient utilization of these resources, also plays a key role. The mix of the various sources of energy and margined government policies are the necessary keys in the movement of sustainable and secure energy sources.

The major contribution of this research is the development of a detailed Unit Commitment model, which simultaneously takes into account several of the most necessary elements. It assumes grid flexibility to be a static variable and applies a set of technical constraints for the power generation infrastructure, among them start-up time, availability of capacity, minimum load, as well as renewable generation potential. A further development of the model is that it can simulate the dynamic behavior of the power grid reacting to variable production and demand situations, while at the same time carrying out an economic analysis by calculating the Levelized Cost of Electricity (LCOE) for various classes of power generation plants. This integrated and unified approach allows simultaneous optimization of costs and assets in grid systems with both renewable and variable power sources. This model represents a significant development because it not only contains the technical but also the economic dimensions of power generation but is also able to integrate renewable energies at the same time. Thus, it appears to be an important tool for grid planning and optimization.

2. Mathematical Calculation

To understand the impact of increasing VRE on Iran's power grid, this study employs a unit commitment model. This model assesses how VRE penetration affects power plant scheduling and dispatch. By calculating the LCOE for different power plants, the study provides valuable insights into the economic implications of

VRE integration.

2.1. Input Data

The model draws on technical, economic, and demand data for Iran's power generation fleet for the 2019 reference year (1398 in the Iranian calendar), compiled from Iran's national Energy Balance Sheet and the Niroo Research Institute.

The generation fleet comprises 136 individual units spanning six technologies: combined cycle (30 units, 22.07 GW), gas (47 units, 16.83 GW), steam (20 units, 14.40 GW), hydropower (37 units, 11.15 GW), nuclear (1 unit, 1.02 GW), and diesel (1 unit). Each unit is characterized by its minimum and maximum output, ramp-up and ramp-down limits, minimum up-time and down-time, conversion efficiency, fuel type, variable operating cost, and stepwise start-up cost, allowing the model to capture the operational flexibility and constraints specific to each plant.

Hourly electricity demand for 2019 forms the basis of the load profile. To keep the unit commitment problem computationally tractable while preserving its seasonal and daily variability, the full 8,760-hour year is reduced via K-means clustering to 13 representative days, consisting of 12 typical days and one peak-demand day, each weighted by the number of calendar days it represents.

Fuel supply is represented through four fuel types (natural gas, mazut, gasoil, and uranium), each assigned a cost, a conversion factor, and an annual consumption ceiling; natural gas is additionally constrained during the peak-demand period, when its availability to the power sector is limited. Three energy storage technologies (pumped-hydro storage, hydrogen, and battery storage) are modeled with their respective storage and charge/discharge capacities, round-trip efficiency, self-discharge rate, and operating costs. Hourly capacity factors for solar and wind generation, reflecting site-specific weather variability across the modeled year, are obtained from the Renewable Ninja platform.

2.2. Unit Commitment

The UC problem addresses the challenge of determining the optimal schedule for generating units to meet the electricity demand at the minimum cost. This process involves minimizing costs while ensuring that each generating unit operates within its technical constraints, which typically include ramp rate limits and minimum up/down time constraints. In essence, units that are selected to generate power during a specific time period are committed to production during that interval [31, 35].

The UC problem is formulated as a Mixed-Integer Nonlinear Programming (MINLP) problem, requiring efficient optimization techniques for its solution. Given the increasing penetration of variable renewable energy sources like wind and solar power in power systems, the importance of uncertainty management techniques in UC modeling has grown. Stochastic programming and robust optimization are among the techniques employed to handle uncertainties. These techniques assist system operators in making optimal decisions under conditions of uncertain energy generation forecasts, mitigating the risks associated with inaccurate forecasts [35]. While such techniques are widely applied in the literature, the present study adopts a deterministic formulation, for the reasons set out in Section 2.2.11.

In this study, demand data for the year 2019 and technical specifications of power plants are fed into the UC model in order to simulate Iran's power supply. This model allows one to determine the best power generating plan by taking into consideration variables such as minimum and maximum output, ramp rates, and startup/shutdown limits. New formulas have also been introduced into the model and some modified, not only for increasing the simulation accuracy but also for better capturing novelty in elements such as generation limitations and temporal fluctuations in ramp rates.

In this research, a UC model was employed to simulate Iran's power supply, utilizing 2019 demand data and the technical specifications of power plants. This mathematical model, considering technical constraints such as minimum and maximum output, ramp rates, and startup/shutdown limitations, optimizes the power generation schedule for each hour of the day. To improve the computational efficiency of the optimization model, the original hourly demand and renewable energy generation time-series were reduced using the K-means clustering algorithm. Based on the clustering results, 13 representative days, consisting of 12 typical days and one peak-demand day, were selected to preserve the seasonal and daily variability of electricity demand and renewable energy generation. Each representative day was assigned a weighting factor equal to the number of actual days it represents in the original dataset. The weighting factors sum to 365 days (8760 hours) and were incorporated into the optimization model through the parameter $NumDay_d$. This representative-day approach significantly reduces the computational burden of the MILP unit commitment model while maintaining a high level of accuracy in representing the annual operating conditions.

The main contributions of this study lie in the development of an integrated Mixed-Integer Linear Programming (MILP) Unit Commitment model that jointly optimizes conventional generation, renewable energy (wind and solar), and energy storage for Iran's power system, combined with a K-means clustering approach that reduces 8,760 hourly time steps into 13 representative days, substantially lowering computational burden while preserving seasonal and daily variability in demand and renewable generation. Within this same framework, the Levelized Cost of Electricity (LCOE) is calculated for each generation of technology, enabling direct cost comparison across fossil, nuclear, hydro, and renewable sources. Three renewable-expansion scenarios are further evaluated to quantify the trade-offs between renewable penetration, system cost, and curtailment, providing policy-relevant, Iran-specific insights on the technical and economic feasibility of large-scale wind and solar integration to support future national energy planning. By employing this model, we aimed to minimize production costs while ensuring reliable power supply to meet demand. The model also allowed us to assess the impact of various factors, including load variations, unexpected plant outages, and fuel price fluctuations, on the optimal generation schedule. The primary goal of the model is to minimize costs within the energy system. This encompasses all costs associated with energy generation, storage, power plant startup, and renewable energy. These costs include fuel costs, storage costs, costs incurred from starting and stopping power plants, operational costs, and costs related to curtailment. Essentially, this objective function is specifically designed to reduce these costs, ensuring optimal utilization of energy resources while minimizing expenses.

2.2.1. Mathematical Formulation

The proposed optimization framework is formulated as a Mixed-Integer Linear Programming (MILP) model to determine the optimal scheduling of conventional generating units, renewable energy sources, and energy storage systems while minimizing the total annual operating cost of the power system. The mathematical formulation incorporates the technical and operational characteristics of thermal power plants, renewable generation technologies, and storage systems together with system-wide operational requirements such as power balance, reserve margin, fuel availability, and transmission constraints.

The optimization model is composed of sets, parameters, decision variables, an objective function, and a series of operational constraints. The representative days obtained from the K-means clustering process are denoted by the set d , while the parameter $NumDay_d$ specifies the number of actual calendar days

represented by each representative day in the optimization model.

The objective function minimizes the total annual operating cost of the power system, whereas the operational constraints guarantee the secure, reliable, and economically efficient operation of the generation fleet. These constraints include unit commitment constraints, renewable energy generation constraints, energy storage constraints, power balance constraints, reserve requirements, hydropower operating limits, fuel availability constraints, and capacity factor constraints. The complete mathematical formulation is presented in the following subsections.

2.2.2. Objective Function

The objective of the proposed optimization model is to minimize the total annual operating cost of the Iranian power system while satisfying all technical and operational constraints. The optimization problem is formulated as a Mixed-Integer Linear Programming (MILP) model that simultaneously determines the optimal commitment and dispatch of conventional generating units, renewable energy sources, and energy storage systems. The objective function considers all major operating cost components, including variable operating costs, fuel costs, start-up and shutdown costs, energy storage operating costs, renewable energy generation costs, and renewable energy curtailment penalties.

The hourly operating cost is calculated according to Equation 1:

$$\begin{aligned}
 obj &= \sum_{i, mode} (var_cost_i \times G_{d,t,i, mode}) \\
 &+ \sum_{vre} (VRE_GEN_{d,t,vre} \times vre_c_{vre}) \\
 &+ \sum_{i,j} (suc_sw_{i,j} \times Y_{d,t,i}) + \sum_i (sdc_{d,t,i} \times Z_{d,t,i}) \\
 &+ \sum_{i, mode} \left(\frac{fuel_cost_{fu} \times G_{d,t,i, mode}}{efficiency_i} \right) \\
 &+ \sum_{st} (var_cost_ch_{st} \times CHARGE_{d,t,st} \\
 &- var_cost_dch_{st} \times DISCHARGE_{d,t,st} \\
 &+ var_cost_st_{st} \times storage_{d,t,st}) + CURTAIL_{d,t} \\
 &\times curtail_penalt
 \end{aligned} \tag{1}$$

Equation (1) presents the objective function of the proposed MILP model, which minimizes the total operating cost of the power system. The objective function includes the variable operating cost of conventional generating units, renewable generation cost, start-up and shutdown costs, fuel cost, charging, discharging and storage operating costs, and the penalty associated with renewable energy curtailment.

where $G_{d,t,i, mode}$ is the power generated by conventional unit i , $VRE_GEN_{d,t,vre}$ is the renewable electricity generation, $SUC_{d,t,i,j}$ and $Z_{d,t,i}$ denote the start-up and shutdown decision variables, $CHARGE_{d,t,st}$, $DISCHARGE_{d,t,st}$, and $STORAGE_{d,t,st}$ represent the charging power, discharging power, and stored energy of storage technology st , respectively, and $CURTAIL_{d,t}$ denotes the curtailed renewable energy. This objective function minimizes the overall operating cost while satisfying all technical and operational constraints of the power system.

2.2.3. Unit Commitment Constraints

The unit commitment (UC) constraints determine the operating status of conventional generating units while satisfying their minimum up-time and minimum down-time requirements. These constraints prevent excessive start-up and shutdown operations and ensure the secure and reliable operation of thermal generating units. Equation represents the minimum up-time constraint, which requires a generating unit to remain online for at least its minimum up-time after

being committed.

$$\sum_{tt} Y_{tt,i} \leq X_{t,i} \quad (2)$$

Where $Y_{tt,i}$ is the binary start-up variable, which equals 1 if generating unit i starts up during period tt , and $X_{t,i}$ is the binary commitment variable, which equals 1 when the generating unit is online during period t . Similarly, Equation represents the minimum down-time constraint, ensuring that once a generating unit is shut down, it remains offline for the required minimum down-time before it can be recommitted.

$$\sum_{tt} Z_{tt,i} \leq 1 - X_{t,i} \quad (3)$$

where $Z_{tt,i}$ is the binary shutdown variable, which equals 1 if generating unit i is shut down during period tt , and $X_{t,i}$ denotes the operating status of the generating unit. Together, Equation and prevent frequent switching of generating units and maintain operational feasibility by enforcing the minimum up-time and minimum down-time requirements throughout the scheduling horizon.

2.2.4. Renewable Energy (VRE) Generation Constraint

The electricity generated by variable renewable energy (VRE) technologies is constrained by the installed generation capacity and the corresponding hourly capacity factor. The hourly capacity factor reflects the availability of renewable resources and varies according to meteorological conditions such as solar irradiance and wind speed. Therefore, the maximum available renewable generation changes throughout the scheduling horizon. Equation limits the renewable electricity generation according to the installed capacity and the hourly capacity factor.

$$VRE_GEN_{d,t,vre} \leq vre_{capacity_vre} \times VRE_{CAP_Factor\ d,t,vre} \quad (4)$$

Where $VRE_GEN_{d,t,vre}$ is the electricity generated by renewable technology vre during hour t of representative day d , $vre_{capacity_vre}$ is the installed capacity of renewable technology vre , and $vre_{cap_factor\ d,t,vre}$ is the hourly capacity factor representing the availability of the renewable energy resources. As shown in Equation, renewable electricity generation cannot exceed the available generation potential determined by the installed capacity and the hourly capacity factor. This constraint captures the intermittent nature of renewable energy resources and enables the optimization model to realistically represent the variability of wind and solar power generation.

2.2.5. Energy Storage Constraints

Energy storage systems play a crucial role in improving the flexibility and reliability of the power system by storing excess electricity during low-demand periods and supplying it during peak-demand periods. In addition, they facilitate the integration of renewable energy sources by compensating for the variability of wind and solar power generation. Equation describes the energy balance of the storage system by considering the charging process, discharging process, storage efficiency, and self-discharge losses.

$$\begin{aligned} & STORAGE_{d,t,st} \\ &= STORAGE_{d,t-1,st} \\ &+ (CHARGE_{d,t,st} \\ &\times efficiency_{st,st}) \\ &- (DISCHARGE_{d,t,st} \\ &/ efficiency_{st,st}) \\ &- (STORAGE_{d,t-1,st} \\ &\times self_discharge_{st}) \end{aligned} \quad (5)$$

Where $STORAGE_{d,t,st}$ denotes the amount of energy stored in storage technology st during hour t of representative day d ; $CHARGE_{d,t,st}$ and $DISCHARGE_{d,t,st}$ represent the charging and discharging power, respectively; $efficiency_{st}$ is the charging/discharging efficiency of the storage technology; and $self_discharge_{st}$ is the self-discharge rate of the storage system.

As shown in Equation (5), the stored energy at each time step is determined by the energy stored in the previous period, the charged energy adjusted by the storage efficiency, the discharged energy considering efficiency losses, and the energy lost due to self-discharge. This constraint ensures energy conservation within the storage system and enables the optimal scheduling of storage technologies for balancing electricity supply and demand while enhancing the integration of renewable energy resources.

2.2.6. Curtailment Constraint

Renewable energy curtailment represents the amount of available electricity that cannot be delivered to the power system due to operational limitations, transmission constraints, or insufficient demand. Incorporating curtailment into the optimization model allows the economic and technical impacts of surplus renewable generation to be quantified. Equation calculates the curtailed energy as the difference between the total available electricity and the electricity utilized by the system.

$$\begin{aligned} CURTAIL_{d,t} = & \sum_{i,mode} G_{d,t,i,mode} \\ & + \sum_{vre} VRE_GEN_{d,t,vre} \\ & + imp_{d,t} - exp_{d,t} - de_{d,t,s} \\ & - \sum_{st} (CHARGE_{d,t,st} \\ & + DISCHARGE_{d,t,st}) \end{aligned} \quad (6)$$

Where $CURTAIL_{d,t}$ denotes the curtailed energy during hour t of representative day d ; $G_{d,t,i,mode}$ is the electricity generated by conventional generating unit i ; $VRE_GEN_{d,t,vre}$ is the renewable electricity generation from technology vre ; $imp_{d,t}$ and $exp_{d,t}$ represent imported and exported electricity, respectively; $de_{d,t,s}$ is the electricity demand at bus s ; and $CHARGE_{d,t,st}$ and $DISCHARGE_{d,t,st}$ denote the charging and discharging power of storage technology st , respectively.

As shown in Equation, renewable energy is curtailed whenever the total available electricity exceeds the amount that can be absorbed by the system after considering electricity demand, power exchange with neighboring systems, and storage operation. This constraint enables the model to quantify renewable energy losses and assess the effectiveness of storage technologies in reducing renewable energy curtailment.

2.2.7. Power Balance Constraint

Maintaining the balance between electricity supply and demand is one of the fundamental requirements for secure power system operation. The total electricity generated by conventional power plants and renewable energy sources must be sufficient to satisfy the system demand as well as the charging requirements of energy storage systems. Equation represents the power balance constraint imposed on the optimization model.

$$\begin{aligned} & \sum_{i,mode} (G_{d,t,i,mode}) + \sum_{vre} (VRE_GEN_{d,t,vre}) \\ & \geq de_{d,t,s} \\ & + \sum_{st} (CHARGE_{d,t,st} - DISCHARGE_{d,t,st}) \end{aligned} \quad (7)$$

Where $G_{d,t,i,mode}$ is the electricity generated by conventional generating unit i , $VRE_GEN_{d,t,vre}$ denotes the renewable electricity generation, $de_{d,t,s}$ represents the electricity demand at bus s , and $CHARGE_{d,t,st}$ and $DISCHARGE_{d,t,st}$ are the charging and discharging power of storage technology st , respectively.

As indicated in Equation, the total available electricity must satisfy the system demand while accounting for the charging and discharging operations of energy storage systems. This constraint guarantees the continuous balance between electricity generation and consumption throughout the scheduling horizon.

2.2.8. Reserve Constraint

Operating reserve is required to maintain system reliability under unexpected generation outages or sudden demand fluctuations. The reserve requirement ensures that sufficient spare generation capacity is available at every scheduling interval. Equation 8 defines the available operating reserve.

$$G_RESEVE_{d,t} = \sum_i (G_i^{max} - G_{d,t,i}) + \sum_{st} (ChargeCapacity_{st} - DISCHARGE_{d,t,st}) \quad (8)$$

The operating reserve must also satisfy the minimum reserve requirement given by:

$$G_RESEVE_{d,t} \geq ReserveMargin \times de_{d,t,s} \quad (9)$$

where $G_RESERVE_{d,t}$ denotes the available operating reserve, G_i^{max} is the maximum generation capacity of generating unit i , $ChargeCapacity_{st}$ is the maximum discharge capability of storage technology st , $ReserveMargin$ is the required spinning reserve margin, and $de_{d,t,s}$ is the system demand.

Equations 8 and 9 ensure that adequate reserve capacity is maintained to enhance system security and operational reliability under uncertain operating conditions.

2.2.9. Fuel Constraints

Fuel availability is one of the important operational limitations in power system optimization, especially for thermal power plants that depend on limited fuel resources. In the proposed model, fuel consumption limits are considered to represent the availability constraints of different fuel types, including natural gas, mazut, and gasoil. The fuel consumption of each generating unit is calculated based on its electricity generation, efficiency, and fuel conversion factor.

The total annual consumption of each fuel type is limited by the available fuel resource. This constraint is formulated as follows:

$$\sum_{d,t,i,mode} \left(\frac{G_{d,t,i,mode}}{efficiency_i} \right) \times conv_factor_{fu} \leq fu_cons_{fu} \quad (10)$$

where $G_{d,t,i,mode}$ represents the electricity generation of generating unit i under operating mode $mode$ during hour t of representative day d , $efficiency_i$ denotes the efficiency of generating unit i , $conv_factor_{fu}$ is the conversion factor of fuel type fu and fu_cons_{fu} represents the maximum available amount of fuel type fu .

In addition to the annual fuel limitation, specific constraints are applied to natural gas consumption during critical periods when gas availability is restricted. The natural gas limitation is expressed as:

$$\sum_{d,t,i,mode} \left(\frac{G_{d,t,i,mode}}{efficiency_i} \right) \times conv_factor_{NG} \leq NG_limit_d \quad (11)$$

where NG_limit_d represents the maximum allowable natural gas consumption during representative days with gas supply restrictions.

Equations 10 and 11 ensure that the optimization model considers fuel availability limitations and prevents unrealistic utilization of thermal generating units under limited fuel supply conditions.

2.2.10. Capacity Factor Constraints

The capacity factor represents the utilization level of generation technologies over the planning horizon and indicates the ratio between the actual electricity generated and the maximum possible generation. In the proposed model, capacity factor constraints are applied to conventional generating units to maintain realistic operational behavior and prevent unrealistic dispatch patterns.

The capacity factor of each generating unit is calculated using Equation 12:

$$CAP_FACTOR_i = \frac{\sum_{d,t} G_{d,t,i,mode} \times NumDay_d}{\sum_b g_max_{i,b} \times 8760} \quad (12)$$

Where CAP_FACTOR_i is the annual capacity factor of generating unit i , $g_max_{i,b}$ represents the maximum generation limit of generation block b , and 8448 represents the total number of hours considered in the planning horizon.

The capacity factor is limited to an acceptable operational range as follows:

$$CAP_FACTOR_i \geq 0 \quad (13)$$

Where the lower bound ensures that the capacity factor remains physically meaningful. Similarly, the utilization factor of energy storage systems is calculated based on their annual discharge operation:

$$CAP_FACTOR_ST_{st} = \frac{\sum_{d,t} DISCHARGE_{d,t,st} \times NumDay_d \times efficiency_{st}}{charge_capacity_{st} \times 8760} \quad (14)$$

where $CAP_FACTOR_ST_{st}$ represents the annual utilization factor of storage technology st , and $charge_capacity_{st}$ denotes the maximum charging/discharging capability of the storage system.

The capacity factor constraints represented by Equations 12-14 ensure that the operation of generation units and storage technologies remains within realistic utilization limits and provides a more accurate representation of the long-term performance of system components.

2.2.11. Treatment of Uncertainty

The optimization model developed in this study is deterministic. Rather than representing renewable availability through a set of probabilistic scenarios, the model uses a single hourly capacity-factor time series for wind and solar generation, derived from the Renewable Ninja platform and applied across the 13 representative days obtained by K-means clustering. This approach captures the temporal and seasonal variability of renewable resources, including diurnal cycles and seasonal differences in wind speed and solar irradiance, but it does not represent forecast error or inter-annual weather variability as stochastic events with assigned probabilities.

This modeling choice reflects the objective of the study, which is

to evaluate the long-run economic and operational implications of alternative generation-capacity mixes rather than to optimize short-term operational decisions under forecast uncertainty. For capacity-oriented analysis at annual resolution, a deterministic representation based on a representative meteorological year is a widely adopted and computationally tractable approach, particularly for a system of the size modeled here (136 generating units over 13 representative days).

This does, however, constitute a limitation of the present work. Renewable generation in practice deviates from any single representative profile, and such deviations affect reserve requirements, curtailment volumes, and total system costs. Extending the present framework to a two-stage stochastic or robust unit commitment formulation, in which wind and solar availability are represented by a set of weighted scenarios with associated probabilities, is identified as a priority for future research.

2.3. Levelized Cost of Energy

In this paper, using the results obtained from modeling, which includes the amount of production from each type of power plant throughout the year, we can calculate the LCOE for each type of power plant. This model allows us to have a precise understanding of the production costs of energy from different power plants and resources, enabling us to make more optimal decisions regarding the selection of power plants and the energy mix.

LCOE is a metric that represents the total cost of energy production in a power project per unit of energy produced (usually expressed in MWh or kWh). This metric is widely used to compare the costs of producing energy from different sources (such as fossil, nuclear, renewable, etc.) [36, 37].

$$LCOE = \frac{\sum_n \frac{Capex_n + Opex}{(1+r)^n}}{\sum_n \frac{g}{(1+r)^n}} \quad (15)$$

Equation 15 helps us calculate the total costs of the project over time and divide it by the energy produced to obtain the cost per unit of energy produced. LCOE is an important metric in economic decision-making within the energy industry, especially when comparing different projects [36, 37].

3. Results

In 2019, Iran's electricity demand surged to a substantial 310,173.71 GWh, underscoring the nation's growing energy appetite. Peak demand days pushed consumption even higher, reaching 1254.065 GWh, highlighting the critical need for robust and efficient power supply planning.

The installed generation capacity of the modeled fleet totals 65.86 GW, distributed across seven technologies as summarized in Table 1.

Table 1. Installed Generation Capacity of the Iranian Power System by Technology, 2019

Technology	Units	Capacity (GW)	Share of capacity (%)
Combined cycle	30	22.07	33.5
Gas	47	16.83	25.6
Steam	20	14.40	21.9
Hydropower	37	11.15	16.9
Nuclear	1	1.02	1.5
Wind	–	0.286	0.4
Solar	–	0.106	0.2
Total	136	65.86	100.0

To accurately model renewable energy, particularly wind and solar power, hourly capacity-factor data from the Renewable Ninja

platform was utilized. Because these profiles are derived from historical meteorological reanalysis, they reflect the observed temporal variability of renewable resources, including diurnal cycles and seasonal differences in wind speed and solar irradiance. Incorporating this variability allows the model to provide a more realistic representation of renewable generation patterns than would be obtained from average capacity factors alone.

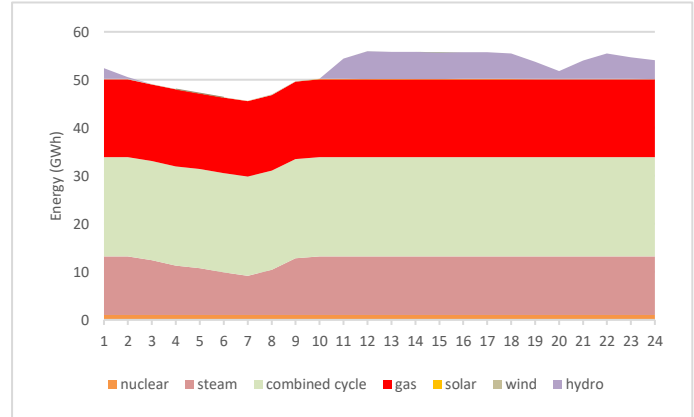


Fig. 2. Power Plant Composition during Peak Load Periods

As shown in Fig. 2, nuclear and steam plants operate as baseload units with near-constant output, whereas combined cycle and gas plants follow the diurnal demand profile. Hydropower is dispatched primarily for peak balancing, particularly during summer months. The contribution of wind and solar is not discernible in the dispatch profile owing to their negligible installed capacity in the reference year.

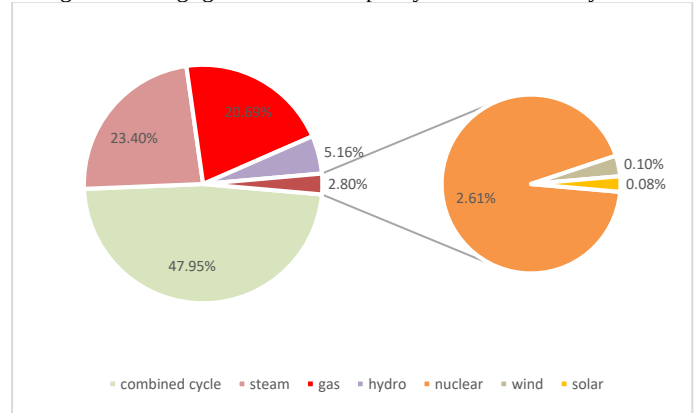


Fig. 3. Share of Electricity Generation from Different Power Sources

The optimized dispatch for the baseline case (Fig. 3) shows that combined cycle plants supply 47.95% of total electricity generation. Steam and gas plants provide 23.40% and 20.00% respectively, while hydropower and nuclear contribute 5.16% and 2.80%. Wind and solar together account for 0.18% of generation, reflecting their marginal installed capacity. The full generation mix for the baseline case and all scenarios is presented in Table 3.

3.1. Scenario Design

Three scenarios were constructed to evaluate the technical and economic consequences of increasing renewable penetration. The design parameters are summarized in Table 2.

Scenario 1 reallocates 10% of non-VRE capacity to wind and solar under unchanged demand, isolating the effect of substituting renewable for thermal capacity. Scenario 2 retains the same renewable buildout but imposes a 10% demand increase, testing whether renewable expansion alone can accommodate demand growth without additional thermal capacity. Scenario 3 applies a fixed 10 GW of solar

and 10 GW of wind while reducing gas capacity to maintain system balance.

Table 2. Design Parameters of the Baseline Case and Renewable Expansion Scenarios

Parameter	Baseline	Scenario 1	Scenario 2	Scenario 3
Electricity demand	310,173.71 GWh	Unchanged	+10%	Unchanged
Non-VRE capacity	As installed (2019)	Reduced by 10%	Unchanged	Gas capacity reduced
Solar capacity (GW)	0.106	9.537	9.537	10.00
Wind capacity (GW)	0.286	25.783	25.782	10.00

3.1.1. Scenario 1: Variable Renewable Energy Expansion

In this scenario, we simulated a 10% reduction in the capacity of non-VRE power plants and allocated the freed capacity to solar and wind power. This resulted in a significant increase in solar and wind power capacities to 9.537 GW and 25.783 GW, respectively. The primary objective of this scenario was to assess the impact of a substantial shift towards renewable energy sources on the overall cost of electricity generation. It should be noted that the wind capacity of 25.783 GW simulated in this scenario exceeds the 18,000 MW wind energy potential reported for Iran in the Wind Energy Potential section. This discrepancy arises because the 18,000 MW figure represents the technical potential estimated under current land-use, grid-access, and site-suitability criteria, whereas Scenario 1 is a theoretical, capacity-driven sensitivity analysis designed to explore the economic and operational implications of a much larger renewable buildout than is presently considered feasible. The scenario should therefore be interpreted as an upper-bound exploration of system behavior under aggressive renewable expansion, rather than a realistic near-term deployment pathway. Realizing such a capacity in practice would require substantial revision of current site-suitability assessments, land allocation, and grid infrastructure planning, which is beyond the scope of this study.

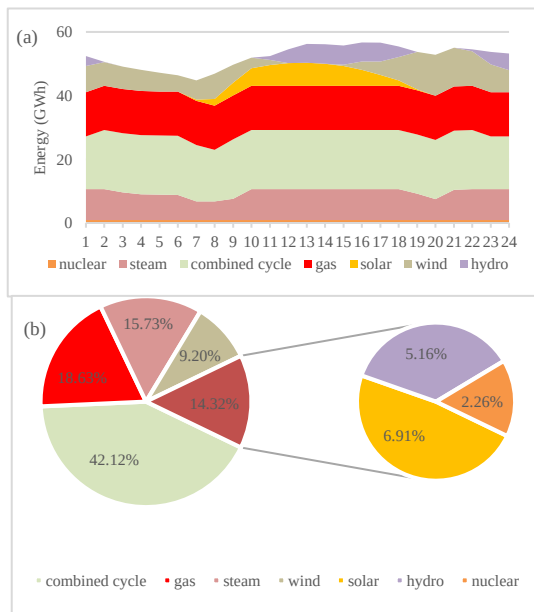


Fig. 4. Electricity Generation Profile for First Scenario: a) Power Plant Distribution during Peak Load Periods, b) Electricity Generation Share by Energy Source

As illustrated in, this scenario resulted in a significant

transformation of the country's power generation mix, characterized by a substantial reduction in fossil fuel power plants and a corresponding increase in VRE sources. Specifically, combined cycle power plants saw a decrease to 42.12%, while gas and steam power plants declined to 18.63% and 15.73%, respectively. In contrast, wind and solar power plants experienced significant growth, reaching 9.20% and 6.91%, respectively. Hydropower maintained its steady contribution at 5.16%, and nuclear power slightly increased to 2.26%. Shifting to a renewable-heavy energy mix is a meaningful step toward relying less on fossil fuels and moving toward a more sustainable future.

3.1.2. Scenario 2: Meeting Increased Demand with Renewable Energy

In this scenario, we simulate a 10% increase in electricity demand while maintaining the capacity of traditional non-VRE power plants. To accommodate this growing demand, we significantly expand the capacity of solar and wind power plants to 9.537 GW and 25.782 GW, respectively. This scenario explores the potential of renewable energy sources to meet future energy needs without relying solely on fossil fuel-based generation.

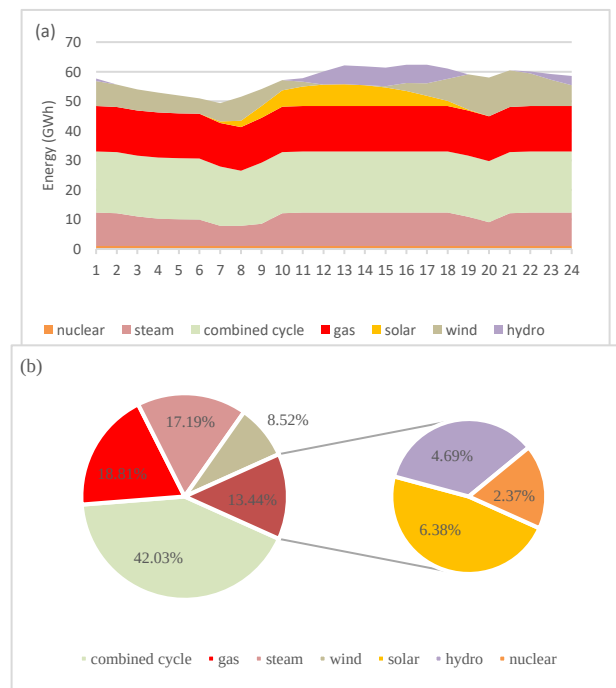


Fig. 5. Electricity Generation Overview for Second Scenario: a) Power Plant Distribution during Peak Load Periods, b) Electricity Generation Share by Energy Source

Scenario 2, as illustrated in, explores the impact of a 10% increase in electricity demand while maintaining the capacity of traditional non-VRE power plants. To meet this increased demand, the model significantly expanded the capacity of solar and wind power plants. As a result, combined cycle power plants, though still dominant, saw a slight decrease to 42.03%. Gas and steam power plants experienced a modest increase, reaching 18.81% and 17.19%, respectively. Notably, wind and solar power plants witnessed substantial growth, contributing to 8.52% and 6.38%, respectively. Hydropower and nuclear power, while still significant, saw a slight decline to 4.69% and 2.37%. This shift to a more renewable-focused energy mix shows how the power system can adapt to growing demand while placing a strong emphasis on sustainable energy sources.

3.1.3. Scenario 3: Renewable Energy Growth under Stable Demand

In this scenario, the effect of increasing the capacity of renewable energy sources, particularly solar and wind power, on Iran's power grid was studied. The capacity of solar and wind power plants increased to 10 GW, while the capacity of gas power plants was reduced to maintain grid balance.

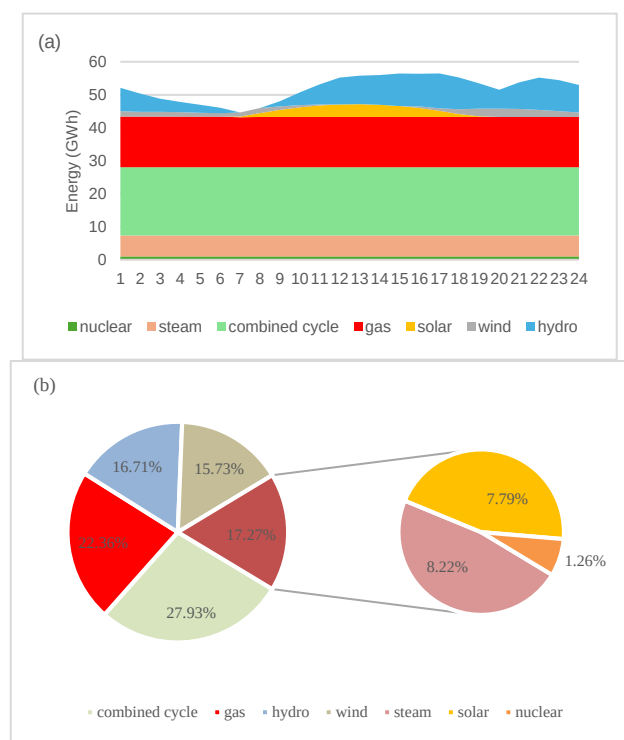


Fig. 6. Electricity Generation Profile of third Scenario: (a) Power Plant Distribution during Peak Load Periods, (b) Electricity Generation Share by Energy Source

As shown in, the modeling results indicate that combined cycle power plants continue to dominate electricity generation, accounting for 27.93% of the total. Gas power plants and hydropower plants follow, contributing 22.36% and 16.71%, respectively. Notably, the shares of wind and solar energy have significantly increased, reaching 15.73% and 7.79%, respectively. Steam power plants contribute 8.22%, and nuclear power plants account for 1.26%.

This scenario demonstrates that, with proper planning, the share of renewable energy in Iran's national energy mix can be significantly increased. The combined 23.52% share of wind and solar energy highlights the high potential of these resources to contribute to the country's electricity supply while keeping production costs within an acceptable range.

3.2. Generation Mix across Scenarios

Across all three scenarios, renewable expansion displaces thermal generation, though the pattern of displacement differs. In Scenarios 1 and 2, the reduction is borne mainly by steam plants, whose share falls from 23.40% to 15.73% and 17.19% respectively, while combined cycle output declines more modestly. In Scenario 3, the displacement is more pronounced across all thermal technologies, with combined cycle falling to 27.93% and steaming to 8.22%, while hydropower rises to 16.71%.

3.3. Levelized Cost of Electricity

According to Table 4 hydropower and solar photovoltaic generation exhibit the lowest levelized costs across all cases, at

approximately 0.033 and 0.037 USD/kWh respectively, followed by combined cycle plants at 0.077 USD/kWh. Wind power records the highest LCOE at approximately 0.171 USD/kWh, reflecting its low-capacity factor relative to installed capacity in the Iranian context.

The LCOE of solar, combined cycle, and wind remains essentially stable across all scenarios, indicating that their unit costs are insensitive to the changes in system composition examined here. In contrast, gas and steam plants show scenario-dependent variation: their costs rise in Scenario 2, where higher demand requires increased thermal output, and fall in Scenario 3, where reduced gas capacity alters their utilization.

Table 3. Optimized Electricity Generation Mix by Technology (%)

Technology	Baseline	Scenario 1	Scenario 2	Scenario 3
Combined cycle	47.95	42.12	42.03	27.93
Steam	23.40	15.73	17.19	8.22
Gas	20.00	18.63	18.81	22.36
Hydropower	5.16	5.16	4.69	16.71
Nuclear	2.80	2.26	2.37	1.26
Wind	0.10	9.20	8.52	15.73
Solar	0.08	6.91	6.38	7.79
Total VRE	0.18	16.11	14.90	23.52

Table 4. Levelized Cost of Electricity by Technology (USD/kWh)

Technology	Baseline	Scenario 1	Scenario 2	Scenario 3
Hydropower	0.033	0.033	0.037	0.033
Solar	0.037	0.037	0.037	0.037
Combined cycle	0.077	0.077	0.077	0.077
Nuclear	0.104	0.104	0.104	0.100
Gas	0.104	0.104	0.117	0.101
Steam	0.107	0.107	0.123	0.096
Wind	0.170	0.171	0.171	0.171

4. Discussion

The main objective of this study is to investigate and evaluate the technical and financial aspects of energy systems that will integrate energy storage and renewable energy sources into the modern electrical grid. New insights into the functionality of renewable energy resources and the associated financial challenges are provided by the results from simulation models based on cost optimization and analysis of trends in energy generation and consumption over time. These results offer some creative ways of reducing operating cost, developing energy sustainably, and making energy grids more efficient.

Among major benefits and contributions of this study is the accuracy of modeling and simulation of different systems for generation and storage of renewable energy. The models have allowed analysis in depth about how variables impact energy generation, taking into account specific features of the operation under various conditions, including time and environmental aspects. For example, it was observed that weather largely influences energy produced from variable renewable sources like solar and wind, which may further lead to unpredictable fluctuations in generation. This underlined the importance of energy storage devices in mitigating negative impacts caused by the fluctuation of generation.

Table 5. Comparison of Key Studies on Renewable Energy and Energy Security

Researchers	Methodology	Findings	Conclusion	Comparison with This Study
Wei et al. [12]	Statistical analysis and global trend review	Renewable sources supplied 19.1% of global energy. Predicted share to reach one-third by 2035.	Framework for reducing fossil fuel dependency and enhancing energy security in developing countries.	This study goes beyond global trends and focuses on dynamic modeling of grid flexibility, offering a more technical perspective on integrating renewables into power systems.
Zohuri [13]	Mathematical modeling and scenario analysis	Optimal share: solar 30%, wind 25%, nuclear 40%. Risk reduction for crises and cyberattacks by 15%.	Increased resilience of the energy system.	The current study incorporates economic analyses like LCOE, which Zohuri does not address.
Nair et al. [14]	System dynamics modeling and causal-loop and stock-flow analysis	Increased renewable share to 31%, reduced import dependency, and improved energy efficiency.	Significant impact on reducing energy import dependency.	Focused on Malaysia; this study provides a broader application and includes cost assessments, unlike Nair et al.
Wang et al. [15]	Divisia index method and grey relational analysis model	55% reduction in oil import dependency. Energy security at 174.12 Mtoe, carbon reduction at 48.87 Mtoe.	Improved energy security	Unlike Wang et al., this study models grid behavior dynamically and includes technical constraints such as startup times and minimum loads.
Tugcu and Menegaki [17]	ARDL model and Granger causality test	Unidirectional relationship between renewable energy and energy security. 71.1% risk reduction in the long term.	Renewable energy is a key driver for reducing energy security risks.	The current study evaluates not only security but also LCOE, providing a more comprehensive approach.
Khan et al. [20]	"Moving window" methodology	Confirmed causal relationship between renewable energy and energy security. Simulated temporal changes in the relationship.	Renewable energy is vital for energy security.	This study uses advanced dynamic simulation models, which provide more detailed insights compared to Khan et al.'s static analysis.
Coudray [22]	Hybrid deep learning model	30% reduction in system costs. Predicted need for power system flexibility.	Improved cost-efficiency and performance with smart grids.	While both studies emphasize system flexibility, this study includes constraints and economic analysis, which Coudray does not.
Li et al. [18]	Entropy methods and CRITIC for electricity security indices	U-shaped relationship between renewable energy production and energy security. Vital energy synergy between provinces.	Synergy in energy production enhances security.	Unlike Li et al., this study directly simulates grid behavior and integrates dynamic constraints, offering a broader scope in its approach.
Gökgöz & Güvercin [19]	DEA and SML index analysis	Trends show efficiency and productivity increases in renewable energy deployment within the EU.	Technological innovations and EU policies enhance renewable energy adoption.	This study provides a more holistic view of energy system modeling, including grid flexibility and cost optimization.
Aized et al. [24]	LEAP model and scenario assessment	Electricity generation costs rise under the "Green Pakistan" scenario, with environmental damage minimized.	Green Pakistan" scenario with the least cost and environmental damage.	This study provides detailed optimization of grid systems, including economic and technical constraints, unlike Aized et al.'s focus on scenario-based cost assessment.

The important thing this study has pointed out is the role of energy storage devices in peaking demand reduction. Energy storage devices store additional power produced at off-peak times and help regulate the demand for energy at busy periods. The results showed that for maximum utilization of renewable energy and stabilization of energy supply during high demand, massive investments in advanced storage technology would be needed. However, the study postulated that caution should be taken in the economic implications when considering the use of energy storage devices to widespread usage that is entailed with a very large capital outlay initially.

This study also looked into several of the financial issues surrounding the installation of storage and renewable energy systems. One main barrier is the huge initial outlay required in the

setting up of the storage systems and renewable energy facilities. Even though usually the operating cost for this kind of set-up is less than that of a power plant running on fossil fuel, these preliminary expenses stand in the way of wider utilization. This is compounded by limited funding options; hence, offering financial incentives and government assistance in speeding up the switch to renewable energy technology is critical.

Another problem that this study tries to fix is the big changes in how much energy renewable sources make. Because of the changes in weather and time of day, the energy these sources produce isn't easy to predict. Therefore, sometimes the amount of energy produced is huge, and at the same time, there is a sudden decline. Ups and downs like these make it hard to keep a steady flow of energy. This is because when the demand is great, and the non-renewable sources cannot work hard enough, we might find ourselves not having enough. Handling

these changes in the way a good power grid functions requires adaptive and affordable ways of storing energy, just like changes to renewable sources.

Results also depicted that integrated energy systems comprising storage and renewable sources can perform better in terms of variability management and customer demand satisfaction. These results can guide politicians and energy industries management to understand the importance of the fact that with proper policy formulation; it would not only result in a reduction of energy production cost but could also improve efficient capability in the use of renewable energy.

The research primarily will add to the knowledge of the existing financial opportunities and challenges related to the integration of renewable energy sources and storage into energy infrastructures. There are technological, societal, and economic issues to be resolved even if the results prove to be very beneficial for the complete realization of such objectives. It might contribute to green energy policy and reduce dependence on fossil fuels by providing a theoretical and practical basis for developing sustainable energy projects around the world.

5. Conclusions

This research discusses Iran's electrical generation methods and points out possible ways to increase the use of renewable energies. Different models and economic assessments have been carried out with a view to an improved energy mix, while demand for electricity grows and the need for reduction in fossil fuel use is increasing. It assesses the potentials for solar and wind under varying scenarios, supported by data derived from the Renewable Ninja platform. This enables an outlook on renewable resource potential that is wider for Iran. The above-named economic study on the generation cost of energy opens a whole new dimension in assessing these derived renewable energy sources. Though this deals with renewable energies, further detailed study keeping climate change in focus and improvement on those forecasts in variable renewable resources would go further to raise the model's accuracy. More attention should also be directed toward long-term implications of switching to a renewable energy mix in particular, the costs involved in society. It results in the fact that Iran can reduce the dependence on thermal power plants and approach a more sustainable energy system through enhancing the role of renewable sources of energy, primarily solar and wind power. This will open up more avenues for increased energy security, reduced environmental impact, and decrease the overall generating cost of electricity. The reason is that even with higher capital costs than fossil fuel-based plants, solar and wind power facilities are normally more economical in the long run, since their LCOE is lower. Moreover, they will play a role in decreasing the overall generating cost of electricity.

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