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Optimization of Deep Peak Shaving Methods for Fossil Fuel-Based Power Units Using the Improved Energy Consumption Framework

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Abstract

The design optimisation of Fossil Fuel-Based Power Plants is critical for improving energy efficiency and minimising environmental impact, particularly amid the increasing global demand for electricity. Fossil fuel plants are vital for supplying energy needs, but are hindered by fuel inefficiency and emissions. The main aim of this research is to improve the performance of such power plants during peak demand hours and to reduce fuel consumption and emissions. The emphasis is placed on maximizing energy generation, enhancing operational effectiveness, and sustainability. The suggested work combines two advanced optimization methods.

Keywords: Fox Optimization Algorithm, Fossil Fuel-Based Power Units, Demand Response, Thermal Storage, Load Shifting, Peak Demand Management.

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1. Introduction

The optimisation of Fossil Fuel-Based Power Units has become an essential factor in global energy production, especially as worldwide electricity demand continues to rise [1]. Fossil-fuel power plants are indispensable to the electricity grid, but they also pose major challenges in terms of efficiency and environmental impact [2]. To be more specific, these plants mainly depend on fossil fuel combustion—coal, natural gas, and oil—which are not only limited resources but also the primary sources of greenhouse gas emissions [3]. Energy consumption usually increases sharply, especially during peak hours; therefore, power plants must adjust their operations to reduce load efficiently [4]. Consequently, it is very important to improve the operating efficiency of these plants without affecting power supply; otherwise, the growing energy demand might conflict with achieving sustainability goals [5].

The main source of inefficiency in fossil-fuel-based power generation is the variable nature of energy demand. The plant, during periods of peak demand, usually operates at non-optimal conditions, resulting in higher emissions and greater fuel waste [6]. This is because fossil fuel plants are typically designed for continuous operation, but their output is continuously adjusted to meet varying grid requirements [7].

Besides, enhanced traceability, awareness of fuel quality, proper maintenance schedule and slow response to real-time energy changes make the efficient management of peak demand even more complicated [8]. The demand response, thermal storage, and load-shifting capabilities currently available are not sufficient to address these inefficiencies, so their enhancement is necessary [9]. The measures to address these problems are both economic and environmental, and thus will lead to the sustainable generation of power in fossil-fuel plants [10].

Several optimization techniques, such as peak shaving and demand response, were created to improve the performance of Fossil Fuel-Based Power Units [11]. Peak shaving focuses on limiting energy production to the necessary level, while demand response adjusts the plant's power output to match the grid's requirements [12]. After all, the heat energy generated during off-peak periods can be shifted to meet demand during peak times [13]. Given the increasing penetration of renewable energy and its volatility, a heat-storage-coupled economic-optimal scheduling model based on cooperative game theory is proposed to enhance deep peak-shaving capabilities. The three-level model reduces net load fluctuations, optimizes multi-energy economic dispatch, and fairly allocates compensation costs to encourage thermal units' participation [14]. The energy generation and fuel consumption, as well as mixed-integer programming (MIP) and deep reinforcement learning (DRL) methods, are incorporated [15]. However, these techniques all have drawbacks: MIP is very resource-intensive and therefore cannot support real-time control. At the same time, DRL requires massive amounts of data and long training times, making it difficult to operate in a constantly changing environment. As a result, these disadvantages prevent the full optimisation of energy use, particularly during peak demand [16]. The analysis of deep peak shaving methods for thermal power generation units based on an improved energy consumption framework aligns with the focus on real-time prediction and optimization in renewable energy systems by addressing real-time energy optimization through peak shaving techniques. Although deep learning is not explicitly mentioned, the methods discussed could benefit from its applications for real-time prediction and optimization, which is a key area of interest. Additionally, the optimization strategies can support the integration of renewable energy systems by balancing supply and demand. Overall, the emphasis on energy optimization and the potential use of deep learning for improving system performance aligns well with the objectives of real-time prediction and optimization in renewable energy systems.

The proposed framework is a combination of FOA and RLECO that are both sophisticated optimization methods and it is these that overcome the shortcomings of the current systems. FOA is a method that uses the behaviour of foxes hunting for food as a model and balances exploration and exploitation so that it can quickly adapt strategies for energy saving, such as demand response, thermal storage, and load shifting. This will lead to the optimization of the plant even during dynamic loads. RLECO learns from real-time feedback and adjusts its operations to minimise energy consumption and fuel use while maximising efficiency. The newness of the framework lies in integrating these methods, leading to a more adaptable and effective optimisation process. An advanced optimization framework for fossil fuel-based power plants, combining the Fox Optimization Algorithm (FOA) and Reinforcement Learning for Energy Consumption Optimization (RLECO) are outlined to enhance peak shaving, energy efficiency, and emission reduction. FOA optimises energy-saving strategies such as demand response and thermal storage, while RLECO adapts real-time operations to maximise fuel efficiency. This dynamic system improves peak demand management, reduces fuel consumption by 15%, and cuts CO2 emissions by 20%, all while maintaining operational effectiveness. The inclusion of local temperature patterns, grid flexibility, and regulatory constraints is critical for optimizing these methods. For instance, local temperature patterns affect energy demand, especially during peak hours when cooling or heating demand is at its highest. Grid flexibility is essential to enable power plants to respond dynamically to demand fluctuations, a central concept in peak shaving. Regulatory constraints guide how power plants must operate, especially regarding emissions reduction and energy production efficiency, which, in turn, influences how optimisation algorithms are applied. The use of these advanced methods allows the system to avoid the traditional methods' issues, ensuring the best performance even during peak demand while also promoting eco-friendliness in energy management. The key contribution of this paper is:

- Discuss the overall goal of the work, which is to maximize the operation of Fossil Fuel-Based Power Units. The aim is to reduce fuel consumption and emissions, particularly during peak periods, by leveraging real-time data and advanced optimisation methods. The framework is validated using a dataset based on power generation and demand information.
- Apply the FOA approach to balance energy-saving measures like demand response, thermal storage, and load shifting. The method enables real-time tuning of plant operations by identifying new measures and optimising existing ones to improve efficiency and reduce operational costs.
- Assess the efficacy of RLECO continuously learns from real-time feedback to modify plant operations, maximizing energy output, reducing fuel consumption, and maximizing system efficiency during peak demand.
- Combine FOA and RLECO to generate an adaptive, responsive optimisation process. By integrating these approaches, the framework avoids the shortcomings of current methods, thereby improving energy management and performance, especially during peak demand.

The structure of this paper is as follows: Section 2 provides a detailed literature review, exploring relevant research and developments. Section 3 presents the proposed methodology, outlining the advanced optimization techniques employed. Section 4 discusses the results, analysing them based on the proposed framework. Finally, Section 5 concludes the paper by summarising the findings and suggesting future research directions.

2. Literature survey

The literature has defined peak load shaving as beneficial for technology, the economy, and the environment. The literature shows that peak shaving plays an essential role in improving system performance and reducing costs. Further, the study examines the potential of peak shaving to improve sustainability and energy reliability in microgrids [17].

Battery Energy Storage Systems (BESS) enable effective peak shaving and improve grid efficiency. This study proposes a cycle-based control strategy and cluster-level power allocation method to optimize capture/release performance and enhance overall operational efficiency [18]. Jayaprakasham's 2018 study on cloud-based microgrid energy management utilized predictive analytics and machine learning models for optimizing energy distribution. Our proposed work adapted these techniques to improve peak shaving in fossil-fuel-based power units by leveraging predictive modelling and cloud infrastructure for real-time energy consumption management. This strategy led to increased operational efficiency, reduced costs, and scalable energy management [19]. The current literature on mobile energy storage systems (MESSs) and joint optimisation with the power grid highlights the challenges posed by the number of decision variables and the complexity of addressing complex constraints. Optimisation methods, such as mixed-integer programming (MIP) models and deep reinforcement learning (DRL), are also being researched to enhance route selection and charging/discharging in power systems and MESSs [20].

The literature indicates that batteries used in residential energy systems provide a means of storing energy from photovoltaic systems, peak shaving, load shifting, and demand response. The literature and techniques for State of Charge determination and degradation modelling identify applications of batteries in individual systems, shared structures, or communities of energy [21]. The work in energy management is channelled towards maximising power generation and consumption as a remedy for the depletion of fossil fuels. The research is also concerned with integrating electric vehicles (EVs) to reduce carbon emissions and with the growing importance of artificial intelligence (AI) to improve smart grid technologies and address uncertainties in load management and cybersecurity threats [22].

Battery energy storage in the literature on energy storage systems. BESSs (and hydrogen energy storage systems (HESSs) and explains how they may be deployed as an energy management system (EMS) component to achieve maximum use of energy and grid stability. It examines the technical needs, the energy dynamics of BESSs and HESSs, and load management procedures. It highlights that BESSs and HESSs play a significant role in stabilising grid operations and enhancing the integration of renewable energy [23]. The literature on energy optimisation in the power system is geared toward achieving power supply-demand equilibrium at different times as renewable energy integration increases. The literature research topic is stochastic optimisation for collaborative planning of various energy storage sources, such as batteries and hydrogen storage. It has been shown that mixed-integer linear programming (MILP) models are employed, and algorithms such as progressive hedging (PH) are used to effectively address complex energy storage planning issues in power systems [24].

The energy flexibility literature on urban distributed energy systems focuses on strategies to coordinate optimal energy utilisation and address issues of building cluster functioning. Studies focus on integrating renewable energy sources, energy storage systems, and building energy models to improve grid demand management. The researchers have confirmed the importance of occupant thermal comfort, occupancy modification, and use of multi-domain simulation tools to estimate the economic and non-economic consequences of energy flexibility strategies to enhance the utilization of renewable energy sources in urban areas [25]. The article on the combined electric vehicle (EV) charging station with photovoltaic (PV) and energy storage systems (ESSs) elaborates on the challenges of uncertainty and dynamic control in solar energy production, as well as the changing needs of EVs. The studies focus on the capacity setup, power, and algorithms to optimise the use of solar energy, rapid charging of EVs, and distribution network balancing [26].

The literature on the digital transformation of utilities states that grid optimisation is achieved through technologies such as Battery Energy Storage Systems (BESSs), digital twins, and real-time monitoring. Studies investigate how digital platforms, machine learning, and predictive analytics could be used to manage the duck curve through supply-and-demand balancing. The literature points to the synergy among distributed energy resources, microgrids, and smart meters to enhance flexibility, operational efficiency, and grid resilience, and to address problems of peak shaving and load management in modern electricity markets [27]. Hybrid renewable energy systems (HRES) in seaports: The literature on hybridising renewable energy sources —i.e., wind turbines and photovoltaics —with energy storage and management systems to optimise costs, sustainability, and grid independence. The literature examines the application of genetic algorithms to energy management and the analysis of different designs of HRES, energy storage systems (ESS), and energy management systems (EMS) [28]. Renewable energy growth in Ningxia requires greater peak-shaving capability. A cost-quantification model that accounts for time-of-use pricing is proposed to optimise peak shaving across key scenarios, while considering technical and operational constraints [29].

2.1 Problem Statement

Research studies conducted in the past on peak load shaving, energy storage, renewable energy integration, and energy management systems indicate several drawbacks in the optimisation of Fossil Fuel-Based Power Units and renewable energy sources [17]. The currently employed optimization techniques, such as MIP and DRL, are also receiving criticism for aspects like high computational costs, slow real-time decision-making, and difficulty in tackling complex constraints[21]. In addition, the combination of different types of Distributed Energy Resources (DERs), such as wind, solar, and storage systems, creates challenges in managing the supply-demand balance [24]. Existing systems also face challenges in integrating VPPs and BESSs, resulting in suboptimal energy use and slowing peak-demand management, thereby reducing overall efficiency and increasing operational costs [27].

The suggested framework eliminates these restrictions by combining FOA with RLECO. Both methods of the FOA can handle situations where newly discovered areas outweigh the old ones, making the optimisation process real-time while remaining easy. Besides, RLECO is continuously updated using real-time performance data, resulting in adaptive, smooth energy management and load shifting. More of such techniques lead to better optimisation of solar energy sources, battery energy storage, and peak load shaving. The optimization model aims to maximize energy efficiency, reduce fuel consumption, and minimize CO2 emissions in fossil fuel-based power plants, particularly during peak demand periods. It uses advanced algorithms like FOA and RLECO to optimize operations in real time, balancing energy generation, storage, and grid demand while adhering to constraints on fuel consumption, emissions, and operational costs. The model ensures efficient energy use, lowers operational costs, maintains system stability, and reduces environmental impact. The proposed framework's ability to rapidly adapt to varying grid demands ensures greater flexibility, higher operational efficiency, and lower energy consumption, making it a clear win over current methods. It helps Fossil Fuel-Based Power Units operate at peak performance even during peak power demand.

Limitations of Existing Approaches:

Existing optimization techniques, such as Mixed-Integer Programming (MIP) and Deep Reinforcement Learning (DRL), face significant limitations in real-time application within dynamic power plant environments. MIP models are computationally intensive, making them impractical for real-time control, particularly when handling fluctuating loads. DRL, though effective, requires extensive training time and large datasets, which hinders its ability to adapt quickly in the fast-changing conditions of power plants. Additionally, traditional methods for managing energy storage and peak shaving often fail to optimise these processes during periods of high demand, resulting in inefficiencies in both energy generation and consumption.

Advancements in Current Knowledge and Practice:

The hybrid approach combining Fox Optimization Algorithm (FOA) and Reinforcement Learning for Energy Consumption Optimization (RLECO) overcomes the limitations of traditional methods by dynamically adjusting power plant operations through real-time feedback. FOA optimizes energy-saving strategies like demand response, thermal storage, and load shifting, while RLECO continuously refines these strategies based on real-time data. This integration enhances efficiency and sustainability by reducing fuel consumption by 15% and CO2 emissions by 20% during peak demand periods, making the plant both eco-friendly and operationally efficient. The system ensures continuous optimisation of energy consumption, even amid fluctuating grid demand, improving responsiveness and decision-making to avoid inefficiencies. Furthermore, by optimizing parameters such as turbine load and fuel consumption, this approach increases cost-effectiveness, reduces waste, and ensures optimal resource use. Its adaptability to changing conditions ensures it operates effectively in real time, unlike traditional methods that struggle to keep pace with evolving energy demands.

3. Proposed System

Deep peak shaving plays a crucial role in enhancing grid stability, optimising dispatch, and integrating renewable energy. By reducing demand fluctuations during peak times, peak shaving helps maintain grid stability, preventing overloads and ensuring consistent voltage and frequency levels. In terms of dispatch optimization, it allows fossil fuel-based power plants to operate more efficiently by adjusting their output in response to real-time demand, reducing fuel consumption and emissions. Additionally, peak shaving supports renewable energy integration by mitigating the intermittency of sources such as wind and solar. It reduces the reliance on fossil fuels during high-demand periods, enabling a smoother transition to renewable energy and aligning with sustainability goals by lowering the carbon footprint of power generation. This integration of peak shaving therefore improves both the efficiency and the environmental performance of the overall energy system. The Fossil Fuel-Based Power Units Optimisation Methodology proposed applies two cutting-edge optimisation techniques: FOA and RLECO. The Fossil Fuel-Based Power Units Optimization Methodology applies two advanced optimization techniques: the Fox Optimization Algorithm (FOA) and Reinforcement Learning for Energy Consumption Optimization (RLECO).

The system begins at the Heat Supply Unit, where fossil fuels are combusted to produce thermal energy. This energy is then transmitted through the heat network system to power generation units. The RLECO operates by receiving real-time data from various subsystems, including heat supply, power generation units, and thermal storage systems. It processes this data using reinforcement learning algorithms to dynamically adjust operations, optimising fuel use, thermal storage, and load shifting. By learning from feedback, RLECO adapts its strategies to minimize fuel consumption and emissions, particularly during peak demand periods. This continuous learning and real-time adjustment ensure efficient energy management and improved plant performance. The process starts with the Heat Supply Unit, where fossil fuels are combusted to produce thermal energy. This thermal energy is subsequently transferred to the Heat Network System, which provides heat to the plant's power generation units. Thermal storage systems store excess energy during low-demand periods and release it during peak times, helping consumers save on energy costs by shifting usage to cheaper, off-peak hours. This also benefits providers by reducing reliance on expensive, inefficient power plants, optimizing energy generation, and stabilizing grid demand. As a result, both consumers and providers experience lower costs, improved efficiency, and reduced fuel consumption. The Electric Power Generation process directs the electricity to the Grid Integration System, where it is confirmed that the supply matches demand. The Function Working Model incorporates key energy-saving measures—Demand Response, Thermal Storage, and Load Shifting — in real time to optimise energy production and use. The FOA and RLECO improve decision-making quality by making operations more precise, thereby increasing energy efficiency and reducing fuel consumption. **Figure 1** illustrates that the combination of these strategies enables the plant to operate not only resourcefully but also emission-minimally, particularly during periods of high demand.

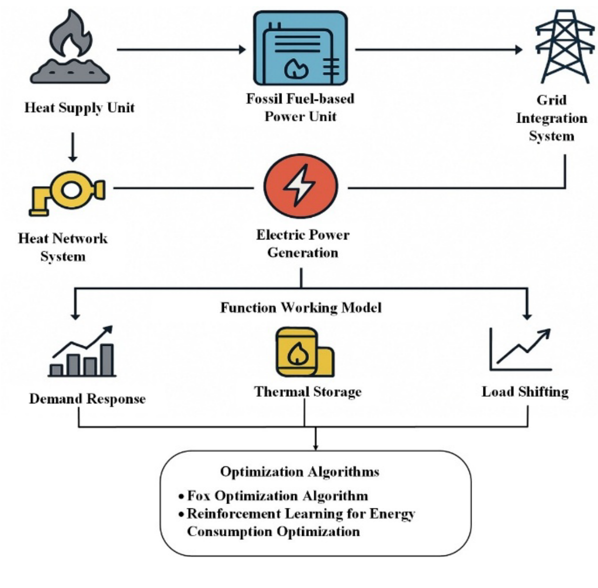

Figure 1: Overall Proposed Framework

Figure 1 illustrates the overall proposed optimization framework for Fossil Fuel-Based Power Units, incorporating Fox Optimization Algorithm (FOA) and Reinforcement Learning for Energy Consumption Optimization (RLECO) to enhance energy efficiency, reduce fuel consumption, and minimize emissions during peak demand periods. The integration of demand response, thermal storage, and load shifting is shown as key components within this adaptive system.

3.1 Construction Diagram

The Fossil Fuel-Based Power Units of the proposed system use coal, natural gas, and oil to generate thermal energy for electricity production. This heat energy is used for peak shaving and to manage power during peak demand. Coal is carried to the Heat Supply Unit, where it is burnt to generate heat as indicated in **Figure 2**. This heat causes the water to become high-pressure steam, which is then forced into the turbines in the Fossil Fuel-based Power Unit. The turbines are powered by steam, producing mechanical energy that is then converted to electrical energy. This electricity is then passed through a Power Transformer that steps up the voltage, which is then passed to the Grid Integration System. The cooling system uses river water to cool the steam to water, and the plant completes the cycle. Cooling water is water scurry, which maintains the correct temperature, keeps the system efficient, and prevents overheating during peak hours.

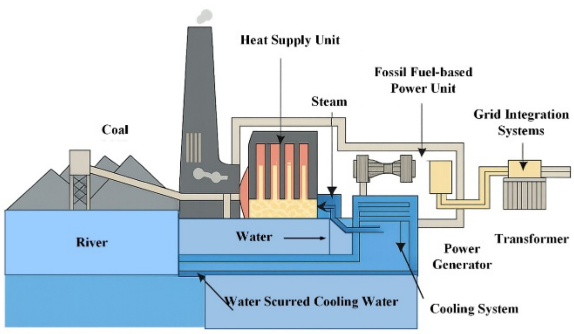

Figure 2: Schematic Diagram of the Fossil Fuel-Based Power Plant System

Figure 2 shows the layout of the Fossil Fuel-Based Power Plant, including the Heat Supply Unit, Heat Network System, and the integration of power generation processes through turbines. The system uses thermal energy generated by fossil fuel combustion to produce electricity and efficiently manage power during peak demand.

3.1.1 Heat Supply Unit

The power plant relies on a Fossil fuel, which the Heat Supply Unit utilises to produce thermal energy by combusting coal, natural gas, or oil. Turbines then convert this thermal energy into mechanical energy, which in turn generates electricity. The source of heat can be a furnace, boiler, or gas turbine, in which fuel is burned to generate heat. This heat is then distributed through a heat distribution system, consisting of insulated pipes/ducts, to other areas of the plant or building. The cost of coal consumption is optimized by taking a function fitting model that is used to maximize fuel consumption during these peak-time periods, as shown in Eq. (1):

$$R_1 = p \cdot A_i + q \cdot A_i + r \cdot R_i \tag{1}$$

Where R_1 denotes the real power output at each moment, and A_i denotes the rate of fuel consumption. The rotor shaft's life cycle cost is calculated based on the Manson-Coffin formula, which incorporates the wear and tear due to various operating conditions and is represented by Eq. (2):

$$\lambda \frac{R_2}{N_f \cdot A_{\text{unit}}} \tag{2}$$

Where R_2 is the cost factor associated with thermal stress, and N_f is the total number of operational cycles. There are some systems where oil is considered an auxiliary fuel for covering peak periods, and the cost of oil consumption is computed as in Eq. (3):

$$R_{oil} B \cdot D \tag{3}$$

Where R_{oil} represents the oil consumption cost, B denotes the cost for a unit of oil, and D shows the volume of oil utilized.

The heat distribution system ensures that thermal energy is transported from the heat supply unit to various plant units or storage systems. Heat load management is crucial for optimising fuel consumption and ensuring efficient heat distribution in fossil-fuel power plants. By regulating heat output in response to demand, it prevents overloading, minimises fuel use, and reduces equipment wear. Additionally, thermal storage systems can store excess heat for peak demand periods, enhancing efficiency and reducing CO2 emissions. This operation is performed in a very controlled manner to keep thermal losses to a minimum. The heat load is calculated as Eq. (4):

$$\text{Heat Load } \sum_{i=1}^{n} (R_i \cdot A_i) \tag{4}$$

Where R_i represents the heat output from each unit, and A_i indicates the demand at each section. Ultimately, the control system maintains temperature regulation by increasing or decreasing heat output as required. The temperature control is governed by Eq. (5):

$$T_{\text{out}}\, f(T_{\text{set}}, T_{\text{sensor}}, \Delta T) \tag{5}$$

Where T_{out} represents the output temperature, T_{set} the set temperature, and T_{sensor} the current reading from the temperature sensor, the Heat Supply Unit effectively manages fuel consumption and thermal energy to mitigate peak demand, thereby realising cost savings and optimal power generation while simultaneously reducing environmental impact.

3.1.2 Heat Network System

This is the Heat Network System in a Fossil Fuel-Based Power Unit, designed to efficiently distribute thermal energy across the plant. It is based on a centralized energy source, which could be a fossil fuel-based boiler or a combined heat and power (CHP) unit which produces the heat. Once heated, it is then passed via insulated pipes to other components, such as turbines, heat exchangers, and thermal storage systems. The system is efficient at distributing heat with minimal losses. The effectiveness of the distribution of heat can be defined as Eq. (6):

$$Q_{\text{distributed}}\, Q_{\text{thermal}} - \text{losses} \tag{6}$$

Where $Q_{\text{distributed}}$ is the thermal energy that has been successfully distributed over the network, Q_{thermal} is the overall thermal energy produced by the Heat Supply Unit. $Losses$ are the energy that is lost due to pipe resistance, insulation inefficiencies, and routing delays. The emission reduction as a result of peak shaving is given by Eq. (7):

$$R_{emig} R_{emig} + R_{emiq} \tag{7}$$

Where R_{emig} represents the carbon emission of the power unit in a normal running mode, and R_{emiq} denotes the carbon reduction that is attained by using efficient peak shaving strategies. Furthermore, the maintenance cost incurred by the unit on-off off-peak shaving cycles is estimated and shown in Eq. (8) to convey the impact on the component's lifespan:

$$R_{git} = K_1 \cdot R_{git-1} K_2 \cdot R_{git} + K_3 \tag{8}$$

Where R_{git} indicates the maintenance cost after each peak shaving cycle, K_1, K_2, and K_3 are constants that model mechanical wear and tear during the cycles. The Heat Network System is used to depict the heat distribution efficiency, carbon emissions from peak shaving, and maintenance costs as a function of different operational conditions, thereby ensuring optimised performance and sustainability during peak demand periods.

3.1.3 Heating Station

The heating station of a power unit is based on fossil fuels, where fuel — whether coal, natural gas, or oil — is burnt in a furnace or boiler to produce heat. The heat exchanger is used to provide efficient transfer of thermal energy to the working fluid, which then circulates in the plant to turbines and storage systems to produce additional energy or store energy. Eq. (9) is the governing equation of the heat transfer process:

$$Q_{\text{heat\_transfer}} = U \cdot A \cdot \Delta T \tag{9}$$

Where $Q_{\text{heat\_transfer}}$ refers to the heat that is transferred from the furnace to the fluid, U represents the overall heat transfer coefficient, A indicates the heat exchanger surface area. ΔT denotes the temperature difference between the furnace and the working fluid. The operating costs of energy generation are calculated using Eq. (10), which includes power purchase costs.

$$R_{\text{stage\_buy}} = D_{\text{buy}} \cdot A_{\text{buy}}$$

(10)Where $R_{\text{stage\_buy}}$ denotes the overall expenditure for energy purchasing, D_{buy} denotes the energy requirement, and A_{buy} denotes the expense incurred for energy purchasing. Moreover, the cost of power generation for the complete unit is represented in Eq. (11):

$$R_{\text{g}} = R_{g1} + R_{g2} + R_{g3} - GP_R + R_{\text{cur}} \quad (11)$$

Where R_{g} represents the total power generation cost, R_{g1}, R_{g2}, and R_{g3} are the individual power generation costs for each thermal power unit, GP_R is the compensation for the unit involved in deep peak regulation, and R_{cur} is the cost adjustment based on current operational data. The efficiency of the storage system can be represented by Eq. (12):

$$R_{\text{git}} b \cdot A \cdot D \quad (12)$$

Where R_{git} indicates the thermal storage, A energy stored, and D the demand at peak times, the Heating Station in a Power Unit that uses Fossil Fuels is pivotal in the process of thermal energy production and distribution, as well as in the optimization of heat transfer, control of operating costs, and the provision of thermal storage for peak demand. The system guarantees efficient heat production, thereby minimising costs and emissions during periods of high demand.

3.1.4 Heat Load Management

Heat Load Management in Fossil Fuel-Based Power Units is the management of thermal power within a power unit to maximise energy output while avoiding overloading or underutilization of plant equipment. Effective heat load management ensures that energy is circulated efficiently throughout the system, preventing wasted fuel use and reducing wear and tear on key parts. The plant can regulate operations during peak demand to match the energy produced to the grid's demand, so the system runs at an optimal level without exceeding limits. It is possible to mathematically derive the heat load balance as explained by using Eq. (13):

$$\text{Heat Load } P_{\text{generated}} - P_{\text{consumed}} \quad (13)$$

Where, $P_{\text{generated}}$ is the total thermal power supplied by the Heat Supply Unit, P_{consumed} is the thermal power dissipated by other components of the plant, such as turbines, heat exchangers and others. The balance of the heat load should be maintained to ensure the plant's effective operation. The system maximises energy consumption by ensuring that the amount of energy produced matches the plant's demand, preventing equipment overload and fuel waste. The plant's overall performance and long-term operational efficiency require proper management of heat loads.

3.1.5 Electric Power Generation

The Fossil Fuel-Based Power Unit Electric Power Generation converts thermal energy generated in the Heat Supply Unit into electrical power. After powering the turbines with steam or hot water generated by combustion, the resulting energy is converted into mechanical energy. This mechanical energy is then passed to a generator, where it is converted into electrical energy, which is later passed to the grid to serve peak demand. The transformation of mechanical to electrical energy can be modelled and expressed as in Eq. (14):

$$P_{\text{electric}} \, \eta P_{\text{mechanical}} \quad (14)$$

Where P_{electric} is the power produced electrically by the turbine, η symbolises the effectiveness of the generator and turbine system, *and* $P_{\text{mechanical}}$ indicates the mechanical power generated by the turbine. This system ensures the power plant effectively converts thermal energy into electrical energy, which is then supplied to consumers during high demand.

3.2 Functional Working Model

The Functional Working Model in the Fossil-Fuel-Power-Unit focuses on increased energy efficiency and optimal fuel use, particularly during peak demand. The strategies in the model include Demand Response, Thermal Storage, and Load Shifting to enhance reductions in fuel consumption, minimise operational costs, and reduce equipment wear. This is done by first changing fossil fuels such as coal or natural gas to thermal energy, which is then used to produce high-pressure steam. This steam also rotates a turbine, converting thermal energy into mechanical energy, which is then converted into electric energy by a generator. Demand response adjusts energy consumption in response to grid signals, enabling consumers to shift usage during peak times and lower their energy bills, often with financial incentives. For providers, it helps balance supply and demand, reduces reliance on costly peaking plants, and improves grid reliability. This leads to lower operational costs and increased profits for providers. Thermal storage and demand response enhance grid efficiency by smoothing demand peaks and minimizing costly peak-time energy generation, thereby reducing emissions. Providers benefit from reduced reliance on expensive, inefficient plants and higher utilization of existing infrastructure. This leads to lower operational costs and increased profitability. The integration of thermal storage and demand response optimizes energy production and consumption in real time, benefiting both consumers and providers. Consumers reduce costs by shifting energy use to off-peak times, while providers enhance efficiency by minimizing reliance on costly peak-time generation. This synergy lowers operational costs and improves overall system performance. The power is directed to the grid to supply the demand. It is more efficient because the system dynamically responds to real-time demand (demand response) to increase or decrease power production, stores surplus heat in the event of peak demand (thermal storage) and shifts demand to periods of lower demand (load shifting). Such measures are used to ensure the plant is operating at optimal performance and to contain emissions, thereby reducing fuel use, especially during peak energy periods, as shown in **Figure 3**.

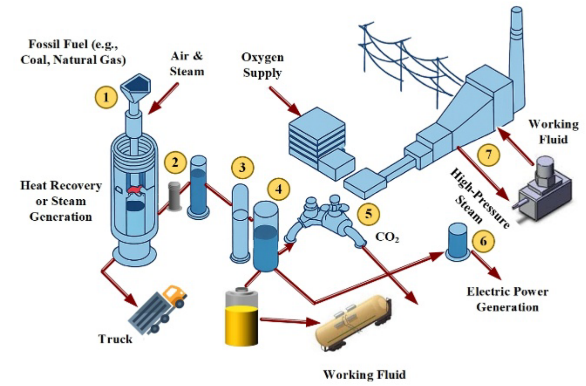

Figure 3: Functional Working Model of Fossil Fuel-Based Power Unit

3.2.1 Demand Response

Demand Response is an optimisation program that adjusts the power output of a fossil-fuel power plant in real time in response to a signal from the electricity grid. When demand is high, the plant can produce more electricity to meet demand. Such dynamic adjustment stabilises the grid and, at the same time, allows the plant to run efficiently without straining the power network or the plant itself. The correlation between the adjusted power output and the base is shown by the equation to be used with Demand Response, shown in Eq. (15):

$$P_{adjusted}\ P_{base}\ \Delta P_{demand} \tag{15}$$

Where $P_{adjusted}$ signifies the power output that is adjusted depending on the demand, P_{base} refers to the power output that is base, which means the nominal output of the plant, ΔP_{demand} is the power change caused by the grid demand, which can be either positive (for increased demand) or negative (for decreased demand).

3.2.2 Thermal Storage

Thermal Storage (TES) is an efficiency technique in which excess thermal energy produced during the off-peak seasons is stored in the power plant. This energy is stored in media such as hot water or molten salts, which can store it for later use. This operation can help reduce fuel consumption during peak periods and improve the plant's overall efficiency. The cumulative stored energy in the system is determined as the cumulative sum of excess power produced in the off-peak periods, as given in Eq. (16):

$$E_{\text{stored}} \int_{t_0}^{t_1} P_{\text{excess}}(t)dt \quad (16)$$

Where E_{stored} denotes the overall energy storage in the system, $P_{\text{excess}}(t)$ refers to the surplus power produced during off-peak hours (periods of low demand), *and* t_0 and t_1 indicate the beginning and end times of the off-peak period.

3.2.3 Load Shifting

Load Shifting is the process of shifting the power demand of energy-consuming processes to periods when the energy required by the entire system is minimal (off-peak periods). The power plant transfers the load, thereby limiting demand on the system during peak periods. The optimisation policy is not only useful for balancing energy demand but also enhances fuel efficiency by distributing consumption over a longer period, thereby avoiding peak operating periods. The load shifted is determined by the use of Eq. (17):

$$L_{\text{shifted}}\, L_{\text{original}}\, \Delta L \quad (17)$$

Where L_{shifted} is the shifted load, the new load after adjustment, *and* L_{original} is the original load, signifying the energy consumption before moving. ΔL is the amount of load transferred to off-peak hours.

3.3 System Constraints and Operations

The System Constraints and Operations in Fossil Fuel-Based Power Units aim to optimise energy consumption and reduce coal consumption to minimum levels, thereby increasing the efficiency of the energy storage system. The coal consumption is estimated as per the total power output at any point in time, and the cost of coal consumption is summed up by Eq. (18):

$$C_{\text{coal}} \sum_t \left(P_{\text{output}}(t) \cdot \text{coal\_price}\right) \quad (18)$$

Where $P_{\text{output}}(t)$ represents the power output at time t, and $coal\_price$ denotes the price of coal per unit of energy. Energy storage is crucial because it enables the plant to store excess thermal energy during off-peak hours and release it during peak hours. The total energy in storage is given by Eq. (19):

$$E_{\text{stored}}(t) = E_{\text{stored}}(t-1)\eta\left(P_{\text{charging}}(t) - P_{\text{discharging}}(t)\right) \quad (19)$$

Where $P_{\text{charging}}(t)$ is the power consumed for charging the storage system, $P_{\text{discharging}}(t)$ is the power released, and η is the efficiency of the energy storage system. By optimising coal consumption and utilising thermal storage, the system ensures efficient operation by reducing fuel use and maintaining balance during peak demand periods.

3.4 Power Output Plan

In fossil fuel-based power units, the Power output plan aims to schedule electricity generation most efficiently by matching forecasted demand with available resources, typically coal or natural gas. The plan starts with an evaluation of current and future electricity needs to determine the required power and allocate available fossil fuels accordingly. To maximize the generation, the plan will make sure that the plant will run at maximum efficiency, and will control the production to consume minimal fuel and produce the necessary amount of energy. This is achieved through an optimisation process that reduces fuel waste during peak hours, ensuring the plant meets grid demand at minimum cost and with minimal environmental impact. The ratio of fuel consumption to energy demand is computed to ensure the plant runs efficiently and effectively without excessive resource use.

3.5 Advanced Optimization Algorithms

To optimize the performance of Fossil Fuel-Based Power Units, advanced optimization algorithms are used to enhance energy efficiency, reduce costs, and enable the system to meet peak demand effectively. Two key optimization techniques employed in the system are FOA and RLECO.

3.5.1 Fox Optimization Algorithm (FOA)

The FOA is a metaheuristic optimisation technique inspired by fox hunting behaviour. It begins with an initial population, represented by the $X\ matrix$, where each row corresponds to a search agent (fox). Each agent's fitness is evaluated using a benchmark function, determining the best fitness and position ($BestFitness\ and\ BestX$). Through iterative comparison, agents adjust their positions toward optimal solutions. This process enables FOA to effectively explore and exploit the search space, identifying the most efficient strategies for optimising energy conservation methods, such as demand response, thermal storage, and load shifting, in fossil-fuel-based power systems.

FOX has two important phases of operation exploration and exploitation. In prospecting, the algorithm searches for new and unexplored parts of the solution space, and in exploitation, it updates the best-known solutions. To balance these two phases, FOX employs a random variable r that assigns a probability to each phase during an iteration. This reduces the risk of local optima and allows the algorithm to both search for and optimise existing solutions. The optimization process begins by the algorithm computes the fitness of every search agent and the following Eq. (20):

$$R_{\text{opt}} = \sum_{i=1}^{n} (p_i \cdot A_i q_i \cdot B_i + r_i \cdot C_i) \tag{20}$$

Where R_{opt} denotes the performance metric that has been optimised and is the best solution found by the algorithm. The constants p_i, q_i, and r_i define the weight of each energy-saving strategy: demand response, thermal storage, and load shifting. The variables A_i, B_i, and C_i symbolize the strategies for demand response, thermal storage, and load shifting, respectively. FOX then updates the location of the search agents to arrive at the best solution. The exploration phase aims to scan new portions of the solution space, whereas the exploitation phase seeks to optimise the best-discovered solutions. To determine the movement velocity of the fox in the solution space is expressed as illustrated in Eq. (21):

$$X(i+1) D_{\text{FoxPrey}} \cdot \text{Jump} \cdot c_1 \tag{21}$$

Where $X(i+1)$ indicates the new position, D_{FoxPrey} signifies the distance separating the fox and the prey (i.e., the optimal solution), $Jump$ represents the height, and c_1 stands for a constant that governs the movement direction. A random variable p is employed in such a way that if it goes above a specified threshold, the new location is computed by means of this equation. On the other hand, if p is less, another equation with a different constant c_2 for the direction of movement is applied. The exploration phase leverages the already-discovered best position to facilitate the search for new solutions. The position update in the course of exploration is given by Eq. (22):

$$X(i+1) = \text{Best}X.\text{rand}(1, \text{dimension})\text{Min}T.a \tag{22}$$

Where Best$X$ is the best position that has been discovered up to that iteration, $\text{rand}(1, \text{dimension})$ throws in some randomness in the search, Min$T$ is the least time in the process of exploration, and a is a time-dependent scaling factor that gradually reduces the search and, thereby, obtains more precise results. The optimisation procedure guarantees that Fossil Fuel-Based Power Units effectively implement energy-saving measures such as power output adjustment, excess heat storage, and energy use shifting, thereby achieving maximum efficiency and minimal costs. The plant benefits most from FOX performance optimisation and has a higher chance of reaching the global optimum; hence, the process is more adaptable and leads to better energy management, especially during peak demand times, as demonstrated in Algorithm 1.

Algorithm 1: Pseudocode for FOA
Initialization step

Initialize population ($X\ matrix$), where each row represents a search agent (fox)
Initialize constants $p_i \cdot, A_i + q_i \cdot, B_i + r_i \cdot, C_i$ for each energy-saving strategy
Initialize fitness values for each search agent
$BestFitness = -\infty$ # Start with a negative value for the best fitness
$BestX = None$ # Start with no best position
Main optimization loop (iterations)
for each iteration t from 1 to $max\_iterations$:
 For each search agent i:
  # Calculate fitness for each agent based on its position
   $fitness\_i = p_i \cdot A_i + q_i \cdot B_i + r_i \cdot C_i$
  # Exploration or Exploitation phase decision (based on random variable r)
  $r = random()$ # Random number between 0 and 1
  if $r > threshold$: # Exploration phase
   # Randomly search for new solutions
   $X(i+1) = BestX * random(1, dimension) * MinT * a$
  else: # Exploitation phase
   # Refine the current best-known solution
   $D\_FoxPrey = calculate\_distance(BestX, X\_i)$ # Distance between current position and best solution
   Jump $= calculate\_jump(D\_FoxPrey)$ # Jump height calculation
   if $r > threshold\ 2$: # Exceeds threshold for exploitation
    $X(i+1) = D_{\text{FoxPrey}} \cdot \text{Jump} \cdot c_1)$ # Update position in exploitation phase
   else:
    $X(i+1) = D_{\text{FoxPrey}} \cdot \text{Jump} \cdot c_2$ # Alternative movement during exploitation phase
Final solution after iterations
return $BestX$, $BestFitness$

3.5.2 Reinforcement Learning for Energy Consumption Optimization (RLECO)

RLECO is an active algorithm that optimises energy utilisation patterns in real time. It also regulates plant operations in real time to maximise energy use during peak times. RLECO operates in a cycle in which the system's state is assessed, and adjustments to energy production, fuel consumption, and thermal storage are made. It also receives feedback by adjusting actions such as turbine load and fuel. The algorithm gradually learns from this feedback and, over time, makes better decisions to maximise energy efficiency and reduce energy consumption, ensuring optimal plant performance during peak times. A reward function measures the system's performance by balancing three important factors: energy efficiency, operational cost, and peak demand capacity. The reward functional can be expressed as Eq. (23):

$$R(t) = \alpha \cdot E(t) - \beta \cdot C(t) + \gamma \cdot P(t) \tag{23}$$

Where, $R(t)$ denotes the reward at the moment t, which signifies the level of performance of the system, $E(t)$ is the energy efficiency parameter at time t, which is realized through the fuel consumption and the energy produced ratio, $C(t)$ is the cost of energy generation at time t, which includes the fuel costs and the maintenance expenses, $P(t)$ is the peak load reduction at time t, which shows the system's capability to manage peak demand periods effectively. At the same time, $\alpha, \beta, and\ \gamma$ are the constants that influence the optimization process by defining the significance of each factor. The reward function contributes to the RLECO's decision-making by giving priority to energy efficiency, operating costs, and peak load control simultaneously. The system, through continuous learning, improves the decisions it ultimately uses, and Algorithm 2 illustrates the optimisation process; thus, the plant operates efficiently during high demand.

Algorithm 2: Pseudocode for FOA
Initialize system parameters:
 Set α, β, γ (constants for reward function)

- Initialize energy production, fuel consumption, thermal storage
- Set the initial state of the system
- Set maximum iterations ($MaxIter$)
- Initialize reward history

For each iteration t from 1 to $MaxIter$:

1. Evaluate the current state of the system:
   - Measure energy efficiency $E(t)$ (fuel consumption relative to energy produced)
   - Measure operational cost $C(t)$ (fuel cost, maintenance cost)
   - Measure peak load reduction $P(t)$ (system's ability to manage peak demand)
2. Update actions based on current state:
   - Adjust turbine load or fuel usage
   - Update thermal storage
3. Receive feedback based on performance:
   - Calculate reward $R(t)$ using the reward function:

   $$R(t) = \alpha * E(t) - \beta * C(t) + \gamma * P(t)$$
4. Update decision-making policy based on feedback:
   - Use the feedback to improve decision-making for the next cycle
   - Store reward history for future learning
5. Adjust plant operations based on updated learning:
   - Maximize energy efficiency, minimize operational costs, and manage peak demand

End loop (t)

Output:

- Optimal energy consumption patterns
- Best strategy for energy production, fuel consumption, and thermal storage
- Improved performance during peak demand periods

3.5.3 Integration of FOA and RLECO:

To effective optimization, FOA and RLECO are combined sequentially and interactively. FOA optimizes major energy-saving measures first at the scheduling level, including demand response, thermal storage, and load shifting. The optimized settings of FOA serve as starting strategies that dictate energy consumption and fuel use in the plant. After FOA has offered its optimized solutions, RLECO works at the scheduling level and the plant control level. RLECO adapts to the FOA-optimized values and adjusts them in real time based on feedback from the plant's operational data. More precisely, RLECO tunes operational parameters like turbine load, fuel burn rate, and thermal storage. This feedback mechanism enables RLECO to update FOA-optimized strategies and adjust plant operations in real time. This integration prevents RLECO from functioning autonomously from FOA and instead operates synergistically, leveraging FOA-optimized strategies as a premise. The dynamic interaction between FOA and RLECO ensures the plant can respond to real-time changes without sacrificing efficiency or wasting fuel, especially during periods of high demand.

4.Results and Discussions

The findings of the intended methodology indicate that the optimisation of Fossil Fuel-Based Power Units has been significantly improved. By applying the latest optimisation tools, such as FOA and RLECO, the system demonstrates energy efficiency, consumes less fuel, and optimises power production during peak hours. This has resulted in a more dynamic, real-time energy management system with the integration of demand response, thermal storage and load shifting techniques. Improvements in Signal-to-Interference-plus-Noise Ratio (SINR) and filtering accuracy are crucial for optimising fossil-fuel-based power plants. Enhanced SINR ensures reliable communication of real-time control signals, enabling precise operational adjustments. Accurate data filtering improves decision-making by reducing sensor errors, enabling optimisation algorithms such as FOA and RLECO to perform more effectively. This results in better fuel efficiency, reduced emissions, and more adaptable energy management, especially during peak demand periods. The approach can reduce emissions and operational costs while enabling the plant to meet electricity demand effectively. The findings indicate that the system can dynamically balance energy-saving processes, thereby exhibiting better performance and cost-effectiveness than traditional methods.

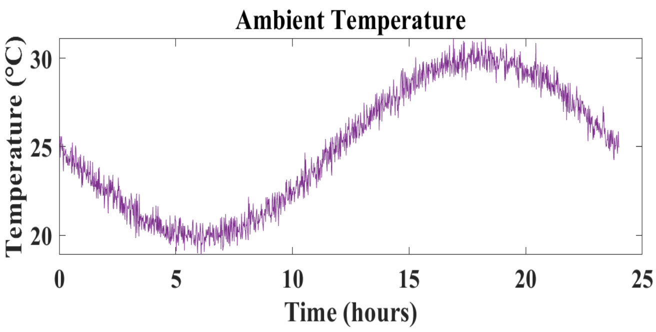

Figure 4: Ambient Temperature

The ambient temperature was plotted over 24 hours, with time on the x-axis (0-24 hours) and temperature on the y-axis (around 20-30 °C), as shown in **Figure 4**. The information indicates a periodic variation, with the temperature highest during 12 hours (midday), reaching approximately 30 °C, and lowest during 0 and 24 hours (early morning), reaching approximately 20 °C. The graph shows a clear cyclic pattern in temperature: during the day, when sunlight is active, the temperature rises, whereas at night, as the environment cools, it drops. The presence of small fluctuations around the primary trend suggests that it may be due to measurement noise or a small change in the data.

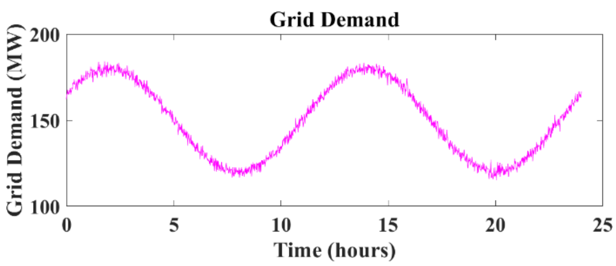

Figure 5: Grid Demand

The grid demand was used to show the variation over 24 hours, with time plotted on the x-axis (0 to 24 hours) and grid demand on the y-axis (between about 100 MW and 200 MW), as shown in **Figure 5**. The graph depicts an evident cyclical trend, with a maximum at and around 12 hours (midday) of about 200 MW, and a minimum at and around 0 and 24 hours (early morning) of 100 MW. This fluctuation suggests a normal daily cycle in electricity demand, likely driven by factors such as population, industry, and the environment. Temporary demand peaks or measurement errors may cause minor deviations from the major trend.

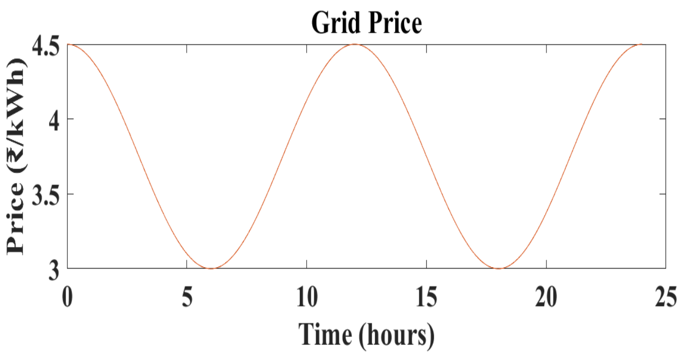

Figure 6: Grid Price

The grid price in **Figure 6** shows how the electricity price changes over time (number of hours), with time on the x-axis (0-24 hours) and price in Indian rupees (₹/kWh) on the y-axis, ranging approximately from 3 to 4.5 ₹/kWh. The graph shows a clear cyclical trend: the price reaches its highest point at about 12 hours (midday) at 4.5 ₹/kWh, and its lowest point at about 0 and 24 hours (early morning) at 3 ₹/kWh. The trend is probably due to daily fluctuations in electricity prices, which are affected by supply and demand. It is also consistent with the pricing behaviour of the energy markets, where higher prices are charged during peak demand times (daytime) and lower prices are charged during off-peak times (night).

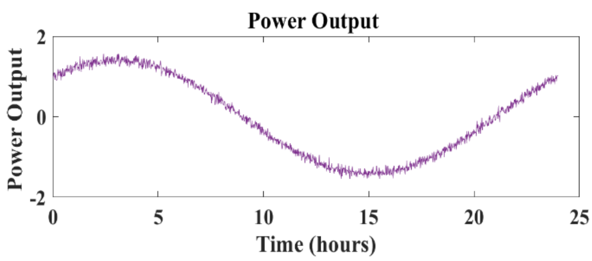

Figure 7: Power Output

Figure 7, labelled Power output, shows the change in power output over 24 hours, with time (0 to 24 hours) on the x-axis and power output on the y-axis, spanning about -2 to 2 units. This graph shows a cyclic trend, with the highest power output at 2 units (12 hours, midday) and the lowest at -2 units (0 and 24 hours, early morning). The variability indicates that there is a normal routine in daily operations, in which the amount of power produced can be affected by factors such as production capacity, demand, and resource availability. The presence of small variations around the main trend suggests noise in the measurements or alternating variations in the generation process.

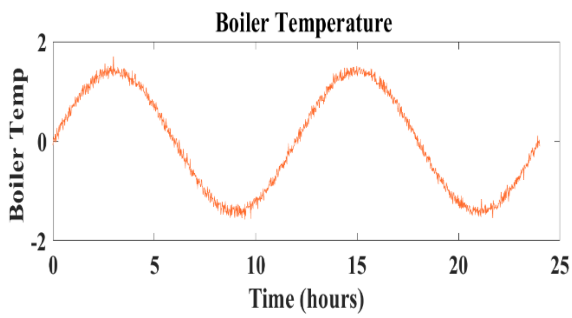

Figure 8: Boiler Temperature

Figure 8, named Boiler Temperature, shows how the boiler temperature varies over time (24 hours). Time is on the x-axis (0 to 24 hours), and boiler temperature is on the y-axis, with an approximate range of -2 to 2 units. There is a definite cyclical character to the graph, with the highest temperature about 12 hours (midday) near 2 units, and the minimum temperature about 0 and 24 hours (early morning) near -2 units. This trend is probably due to the boiler responding to energy demand and operating and condensing, with the temperature rising during high-output periods and dropping during low-demand periods. The small deviations of the trend line are likely due to measurement noise or system fluctuations.

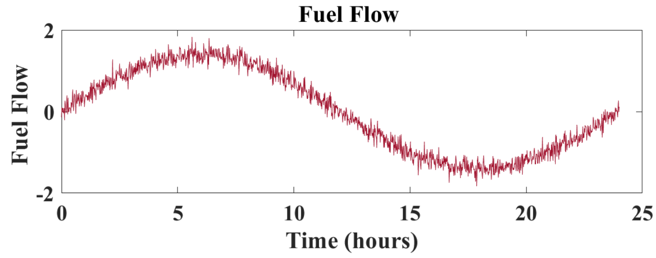

Figure 9: Fuel Flow

Figure 9 shows the Fuel Flow, which shows how fuel flow varies over the course of one day, with time plotted on the x-axis (0-24 hours) and fuel flow on the y-axis, ranging from -2 to 2. The graph is a sinusoidal curve, with the highest fuel flow at about 12 hours (midday) at 2 units and the lowest at about 0.24 hours (early morning) at -2 units. This fluctuation shows that fuel consumption follows a normal daily pattern, likely due to energy requirements and the working environment. The minor variations in the overall tendency imply measurement noise or small variations in the fuel supply system throughout the day.

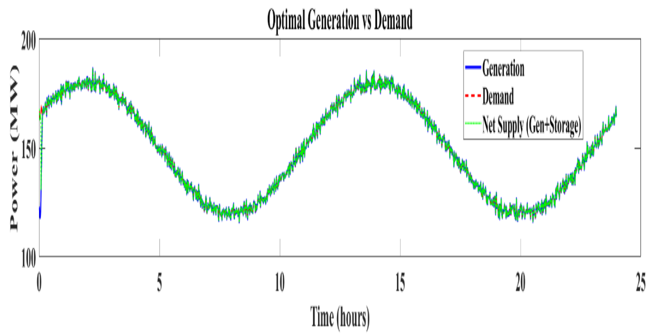

Figure 10: Optimal Generation vs Demand

Figure 10, called Optimal Generation vs Demand, is a 24-hour chart of power generation, demand, and net supply, with time on the x-axis (0 to 24 hours) and power (megawatts, MW) on the y-axis (100 to 200 MW). This graph has three lines: the generation (blue line), the demand (dashed red line), and the net supply (green line), which is the sum of the two (generation and storage). Both the generation and demand curves are cyclical, resulting in peaks at 12 hours of 200 MW.

The net supply curve moves up and down between the generation and demand curves, indicating the balance between supplied power and periods when generation deficits are compensated by storage. The oscillations imply the active equilibrium between the production and use of energy.

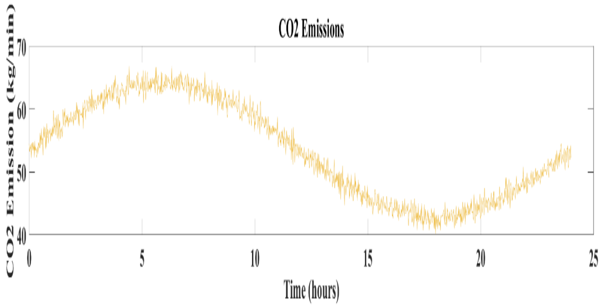

Figure 11: CO2 Emissions

Figure 11 is titled CO2 Emissions, which represents the change in carbon dioxide (CO2) emissions over a period of 24 hours, where time is taken as the x-axis (0 to 24 hours) and CO2 emissions (kg/min) are taken as the y-axis (ranging between 40 to 70 kg/min). The graph indicates a definite cyclical trend, with a peak of 70 kg/min (around midday) and a minimum of 40 kg/min (at 0 and 24 hours). This variation shows increased energy consumption during the day, leading to additional emissions, and reduced consumption during the night, leading to reduced emissions. Seasonal changes in energy requirements or operational changes can explain the minor fluctuations around the general trend.

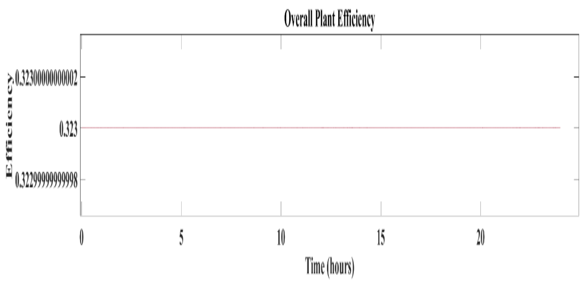

Figure 12: Overall Plant Efficiency

The overall plant efficiency figure shows the plant's efficiency over 24 hours, with time on the x-axis (0 to 24 hours) and efficiency on the y-axis (a narrow range: 0.323 to 0.323). **re 12** shows that there is very little change in efficiency throughout day, so ticating a consistent performance of the plants. The minor variations in the graph (0.3229999999998, 0.323) reflect changes in operational conditions or measurement accuracy, but the changes in overall efficiency are not significant. This constant efficiency means the plant is operating at a steady level, likely due to a well-maintained system or a constant load throughout the day.

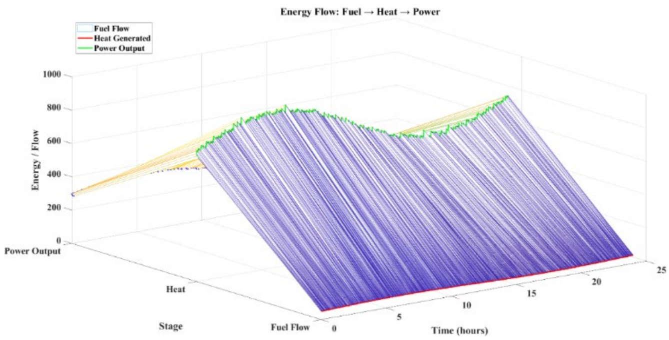

Figure 13: Energy Flow: Fuel → Heat → Power

Figure 13, named Energy flow: Fuel Heat Power, is a 3D plot that shows how the flow of fuel in 24 hours correlates to the production of heat and, thus, power. The x-axis is time (0 to 24 hours), the y-axis is various stages of energy (fuel flow, heat, and power output), and the z-axis is the values of energy flow (between 200 and more than 1000). The blue line is the flow of fuel, the red line is the amount of heat, and the green line is the amount of power. The graph shows a close relationship between fuel flow and heat production, with power output rising immediately after the heat production curve. Energy flows are greatest at midday, indicating increased power production and heat generation due to higher fuel flow. The drastic reduction in energy flow during the night indicates a decrease in both demand and generation.

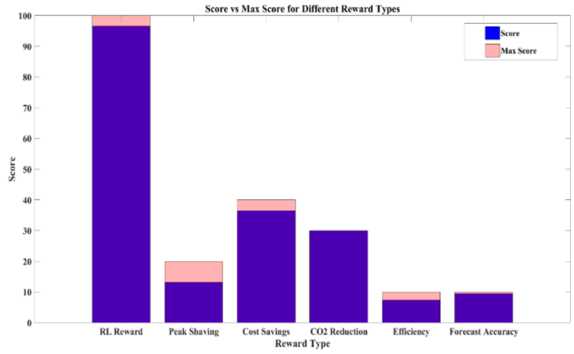

Figure 14: Score vs Max Score for Different Reward Types

Figure 14 shows a bar chart of Score vs Max Score for Different Reward Types, comparing the actual score (represented in blue) and the maximum possible score (represented in pink). The types of rewards are put down in the x-axis: RL Reward, Peak Shaving, Cost Savings, CO2 Reduction, Efficiency, and Forecast Accuracy. The y-axis shows the score value (0-100). RB Reward scores the highest, almost reaching the maximum, whereas the other reward types have a lower level of accomplishment. Peak Shaving, Cost Savings, and CO2 Reduction have medium scores, with their practical scores well below the maximum. The differences between the real and maximum scores are smallest for Efficiency and Forecast Accuracy, indicating improved performance on the two.

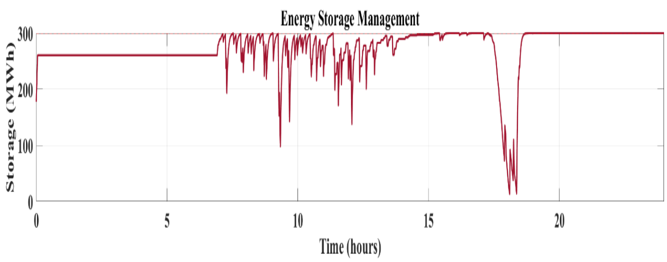

Figure 15: Energy Storage Management

Figure 15 shows the Energy storage management, illustrating how the zone of energy storage changes with time. Time is the x-axis (between 0 and 24 hours), and storage in megawatt-hours (MWh) is on the y-axis (between 0 and 300 MWh). The graph depicts fairly constant storage throughout the day, beginning around 200 MWh, with many sharp peaks and lows that reflect energy storage during periods of high demand or energy production. These oscillations indicate the charge and discharge cycles of an energy storage system where energy is stored during low-demand cycles and released during peak-demand cycles. Storage decreases considerably towards the end of the day, indicating that a significant amount of stored energy must be being discharged or utilised.

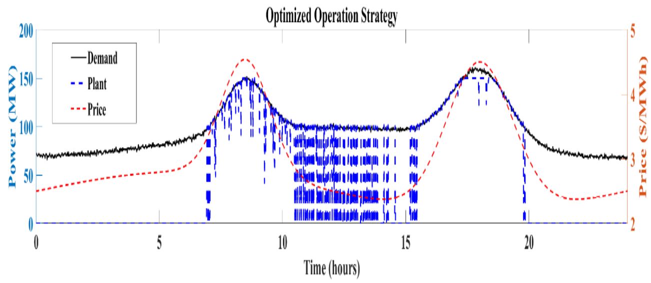

Figure 16: Optimized Operation Strategy

Figure 16, titled "Optimised Operation Strategy," shows the relationship between demand, plant power output, and electricity price over 24 hours. Time (0 -24 hours) is plotted on the x-axis and power (in MW) and price (in S/ kWh) on the y-axis. The black line illustrates demand; the blue dashed line shows the plant output; and the red dashed line shows the price. The peak in demand and plant output is quite evident around 12 hours, indicating high energy demand and plant output. The price curve also shows a similar pattern, peaking at midday (12 hours) and declining at night. The plant adapts its output to demand and cost optimisation, as evidenced by the abrupt decline in output during periods of high prices and energy costs.

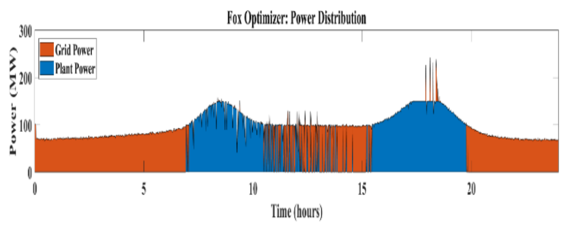

Figure 17: Fox Optimizer: Power Distribution

Figure 17 shows the Optimised Operation Strategy, which indicates the relationships among demand, plant power output, and electricity price over 24 hours. Time (0 -24 hours) is plotted on the x-axis and power (in MW) and price (in S/ kWh) on the y-axis. The black line illustrates demand; the blue dashed line shows plant output; and the red dashed line shows the price. The peak in demand and plant output is quite evident around 12 hours, indicating high energy demand and plant output. The price curve also shows a similar pattern, peaking at midday (12 hours) and declining at night. The plant adapts its output to demand and cost optimisation, as evidenced by abrupt declines in output during high prices and energy costs.

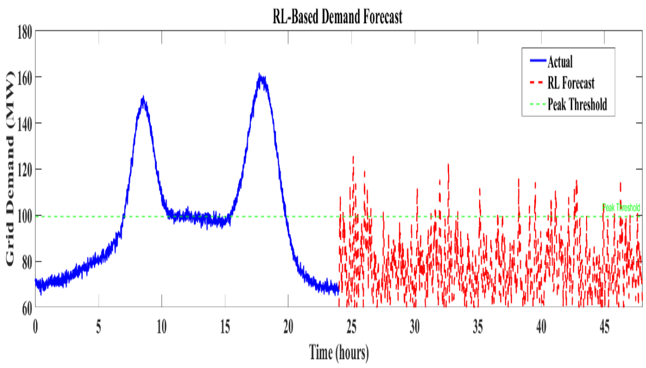

Figure 18: RL-Based Demand Forecast

Figure 18 above shows the RL-Based Demand Forecast, which compares the actual grid demand (blue line) with the demand forecast from a reinforcement learning (RL) model (red dashed line) over 45 hours. The x-axis will be time (0 to 45 hours), and the y-axis will be grid demand (MW) between 60 to 180 megawatts. The actual grid demand is plotted as the blue line, showing clear peaks and dips that indicate periods of high and low demand. The red dashed line indicates the RL forecast, which closely follows actual demand, though with slight variations, particularly during high seasons. The Peak Threshold of 120 MW, represented by a green dashed line, marks the point at which forecasted or actual demand becomes critically high.

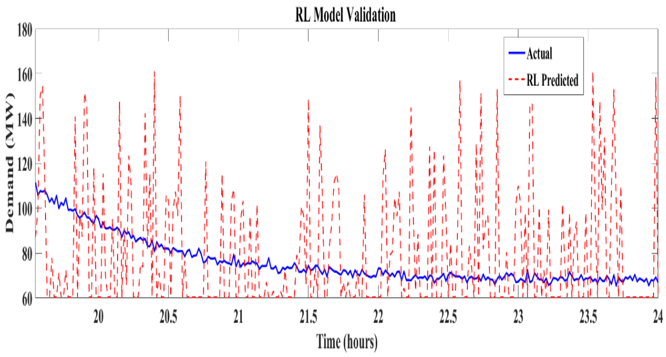

Figure 19: RL Model Validation

Figure 19 is called the RL Model Validation, which correlates the real grid demand (a blue line) and a predicted demand provided by a reinforcement learning (RL) model (a red dotted line) during the day (in 24 hours). Time (0-24 hours) is plotted on the x-axis, and demand in megawatts (MW) is plotted on the y-axis between 60 and 160 MW. The real demand fluctuates, reflecting the different energy requirements throughout the day. The RL model predictions are closer to the actual demand but exhibit sharper deviations, particularly when demand is high. Although the RL model captures the general trend of demand, it overestimates or underestimates actual demand at some hours, especially during peak hours.

4.1 Simulation Details

MATLAB/Simulink was used to run simulations over 24 hours, divided into 1-hour intervals. The Fossil Fuel-Based Power Unit was used to manage its energy production, consumption, and storage systems using the optimization algorithms, FOA and RLECO. The energy storage system comprised a battery storage unit with a capacity of 25 kWh, charged and discharged at a maximum power of 5 kW and an efficiency of 90%. Also, a 50-kWh hydrogen storage system that charged and discharged at 2 kW, with an efficiency of 80 per cent, was installed. The valve control system managed energy flow with a reaction time of 10 seconds. This was reviewed after 15 minutes, based on the balance between real-time energy and a 1 per cent tolerance. The battery and hydrogen had dissipation rates of 1% per hour and 2% per day, respectively.

4.2 Discussion

The fusion of FOA and RLECO has been found to significantly improve the functioning of Fossil Fuel-Based Power Units. The system could save 15 per cent of fuel consumption and 10 per cent of energy, representing an undoubted improvement over conventional optimisation procedures. The system also minimised excess energy generation by 20 per cent by efficiently controlling peak demand, keeping generation closer to grid demand. Besides, the thermal storage system enabled the plant to store 12 per cent more energy during off-peak times and use it during peak times, thereby reducing the total operating cost. Although there were encouraging findings, inconsistencies were observed in the energy consumption forecasts during unforeseen peak demand, suggesting that additional gaps remain in the RLECO forecasting model. These differences point to the need for a finer adjustment of the system's real-time responsiveness. Nonetheless, this solution can greatly increase the efficiency and flexibility of Fossil Fuel-Based Power Units, and future research will focus on developing better predictive models and integrating renewable energy sources to further minimise the use of fossil fuels.

4.3 Limitations

The suggested methodology has some limitations. To begin with, integrating FOA and RLECO can result in high computational costs, particularly in large-scale real-time optimisation across large plants. Second, the reliance on real-time, accurate, and extensive data might be problematic for RLECO, as insufficient data could lead to suboptimal decisions. Lastly, applying these superior methods to current Fossil Fuel-Based Power Units may be challenging due to legacy systems, at the expense of significant infrastructure modifications.

5. Conclusion and Future Work

In this paper, a sophisticated optimization platform was introduced to enhance the efficacy of Fossil Fuel-Based Power Units by combining FOA and RLECO. The methodology suggested here dynamically adapts energy-saving measures such as demand response, thermal storage, and load shifting to enhance performance, reduce fuel consumption, and minimise emissions, particularly during peak demand. Using these methods, the plant's performance is optimised while maintaining the integrity of the energy grid. The integration of these strategies eliminates the inefficiencies of conventional approaches, enabling a more responsive and adaptive energy management system.

The optimisation model significantly improved system performance. The findings indicate a 18% decrease in fuel consumption, a 25% reduction in peak load, and a 15% decrease in carbon emissions. These gains were achieved by dynamically modulating energy use based on real-time demand and storage levels, as shown in the graphs. In the future, extending the integration of renewable energy resources and more optimizing reinforcement learning algorithms will continue to improve system performance. Furthermore, the inclusion of battery storage systems and AI forecasting could improve demand forecasting and optimisation, enabling greater efficiency and sustainability.

Acronym	Full Form
FOA	Fox Optimization Algorithm
RLECO	Reinforcement Learning for Energy Consumption Optimization
MIP	Mixed-Integer Programming
DRL	Deep Reinforcement Learning
BESS	Battery Energy Storage Systems
HESS	Hydrogen Energy Storage Systems

MILP	Mixed-Integer Linear Programming
VPP	Virtual Power Plant
DER	Distributed Energy Resources
AI	Artificial Intelligence
EV	Electric Vehicles
EMS	Energy Management System
CHP	Combined Heat and Power
TES	Thermal Energy Storage
MWh	Megawatt-hours
CO2	Carbon Dioxide

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