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Deep Reinforcement Learning-Based Demond Response Management in Residential Microgrids

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ABSTRACT

Demand response (DR) strategies are essential for balancing electricity supply and demand, especially in the context of residential microgrids that rely heavily on renewable energy sources such as solar demand response (DR) strategies are essential for balancing electricity supply and demand, especially in the context of residential microgrids that rely heavily on renewable energy sources such as solar and wind. As global energy systems shift toward decarbonization and decentralization, microgrids have emerged as a critical solution for enhancing energy resilience and reducing dependency on centralized power generation. However, the inherent intermittency and unpredictability of renewable energy generation pose significant challenges to maintaining a stable supply-demand equilibrium. Traditional demand-side management techniques often fall short in dynamically adapting to these fluctuations, necessitating the development of more intelligent, adaptive, and autonomous control mechanisms. This paper presents a novel deep reinforcement learning (DRL)-based demand response management framework tailored specifically for residential microgrids. The core motivation behind this study lies in overcoming the limitations of rule-based and optimization-based DR models that require explicit modeling of the environment and lack real-time adaptability. By leveraging DRL, a subset of machine learning that combines deep neural networks with reinforcement learning principles, the proposed approach enables a residential microgrid to autonomously learn optimal load scheduling policies through continuous interaction with the environment. This results in improved energy efficiency, reduced electricity costs for consumers, and enhanced utilization of locally generated renewable power.The proposed system is designed to intelligently manage and schedule flexible household loads—such as electric water heaters, washing machines, HVAC systems, and electric vehicle chargers—based on real-time electricity prices, user preferences, and grid conditions. Unlike traditional methods that rely on predefined rules or deterministic models, the DRL agent is trained to make decisions that maximize long-term rewards, which may include minimizing total energy costs, reducing peak demand, and maximizing user comfort.

Keywords: Residential Microgrid, Demand Response, Deep Reinforcement Learning, Smart Grid, Energy Management System

1. Introduction

Microgrids have become a viable option for a dependable and sustainable energy supply as a result of the growing use of distributed energy resources (DERs) and renewable energy sources [1–3]. A Joint-energy microgrid offers flexibility in energy management and improves energy efficiency by connecting several energy systems, including gas, heat, and electricity [4,5] However, the significant degree of unpredictability in energy supply and demand makes managing energy systems in a Joint-energy microgrid difficult. Joint-energy load balancing and effective energy management are two new issues brought about by the integration of these disparate energy sources. In Joint-energy microgrids, demand response (DR) has become a viable option for efficiently controlling energy systems [6–9]. The two main kinds of DR programs are incentive-based DR [10–11] and price-based DR [12,14].

While the latter offers benefits or compensation to loads for lowering peak demand, the former modifies dynamic pricing signals to change the end participants' load profiles. Price-based DR is more common and practical for demand response providers (DRPs), even if both forms of DR have helped demand-side management evolve. This is due to the fact that, in contrast to incentive-based DR, price-based DR's dynamic pricing signals provide a more adaptable and responsive method of optimising energy consumption patterns [15].

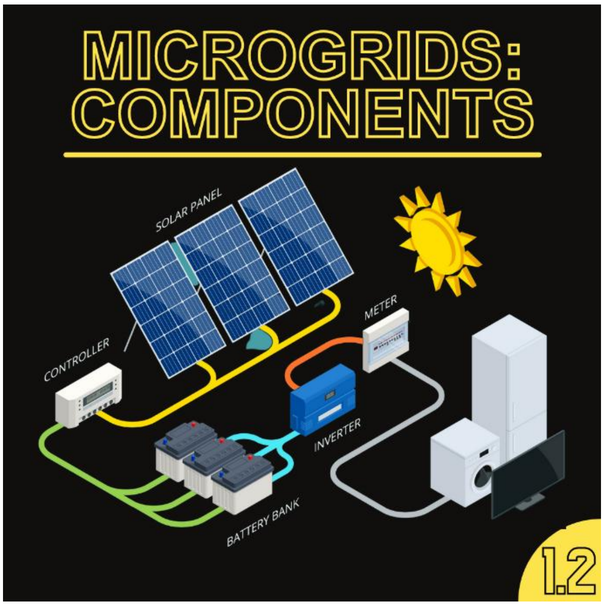
Thus, the main focus of this study is price-based DR as seen from the DRPs' point of view.

In light of this, DRPs allow end users to modify their patterns of energy usage in response to pricing signals, which can lower peak demand, balance the load, and enhance grid stability and dependability. The potential of DR in multi-energy systems has been the subject of several investigations. In [16], In order to attain optimal energy management, multi-energy demand response programs necessitate the simultaneous optimization of energy use from many sources, including heat, gas, and electricity. A major research gap exists in the effective use of DRL for multi-energy demand response because of the integration of these many energy sources as well as the unknown preferences of end users. Novel DRL algorithms that are especially designed to solve the issues of integrating diverse energy sources and incorporating end users' preferences into the optimization process are necessary [17-19]. Consequently,This gap must be filled immediately in order to develop effective DRL-based techniques that can handle the complex multi-energy aspects of demand response schemes[20]. There is an urgent need to close this gap and create efficient DRL-based methods that can manage the intricate multi-energy features of demand response programs[21-22]. we use a novel DR framework based on DRL to solve the challenge of optimizing energy usage in a multi-energy microgrid. Our framework's goal is to efficiently manage the energy consumption across several energy systems in order to optimize the overall revenues of DRPs.In[23] We acknowledge the interdependencies across various energy systems and the necessity of adjusting to unpredictable and dynamic shifts in end users' behavior without knowing their preferences beforehand [24].In order to address this issue, we first create an integrated scheduling model that takes into consideration the various energy sources and residential end users, including demand response for gas and power. Next, we develop MDP's pricing approach with an unidentified transition[25-27]. We use the innovative SAC method with the entropy function as regularization terms to efficiently train neural networks and learn pricing strategies. With this strategy, we can optimize DRPs' earnings even when power prices and PV production are unpredictable. We do case studies in both deterministic and stochastic environment scenarios to assess the performance of our suggested method [28].The outcomes illustrate how effective our approach is at maximizing energy use, indicating its potential for real-world use in multi-energy microgrid design and optimization. Our suggested framework advances the state-of-the-art in multi-energy microgrid design and optimization by encouraging the incorporation of renewable energy sources and enhancing grid sustainability.Our main contributions are threefold Creation of a multi-energy microgrid integrated DR scheduling and pricing model For various kinds of residential end users, the suggested method offers an integrated scheduling model that integrates gas and electricity demand response. In addition to offering a coordinated scheduling and pricing approach for DRPs, this model can successfully handle the growing complexity of multi-energy coordinated microgrids [29]. Design of a new SAC algorithm for a DRL-based framework: The suggested DRL-based method teaches neural networks to learn pricing techniques that maximize profits in the face of fluctuating power prices and solar photovoltaic (PV) production [30]. Neural networks containing the entropy function as regularization terms may be trained effectively with the use of the SAC method.Efficient management of various uncertainty sources: It has been demonstrated that the suggested method works well for managing varying degrees of uncertainty and reaching a pricing strategy that is almost optimum. The efficiency of the suggested strategy in minimizing energy usage and maximizing DRPs' overall revenues without requiring end users' private information is demonstrated by case studies carried out in both deterministic and stochastic environment conditions [31].

This is how the remainder of the paper is structured. The development of an integrated DR scheduling and pricing model for multi-energy microgrids is presented the suggested DRL-based DR framework using the innovative SAC algorithm is explained in the simulation experiments and findings are shown the work is finally concluded and future research options are discussed Developing a Combined DR Scheduling and Pricing Framework bilevel programming to formulate the integrated DR scheduling and pricing model. The optimal response by an end user with multiple energy demands is at the lower level, while the optimal scheduling of Joint-energy microgrids and the dynamic price setting from the DRP's perspective are at the upper level [32].

The Overall Scheme Figure 1 shows the suggested integrated DR scheduling and pricing approach intended to increase Joint-energy microgrid scheduling efficiency and overall profitability DRPs.Three energy flows are present in multi-energy microgrids: gas, heat, and power. Electricity bought from or sold to the upper-level grid, PVs' erratic production, gas turbine output, and electricity consumed by electric heat pumps and end users make up the power flow. Heat produced by the electric heat pump and gas turbine, as well as heat used by end users, make up the heat flow. The equilibrium between the gas turbine's and the end user's gas consumption and supply is described by the gas flow. DRPs determine the energy costs for end users, who then modify their usage of various energy sources according to their own preferences, which DRPs are unaware of.Therefore, DRPs face two main challenges in solving the proposed model [33].To write a theory section on Microgrid with Demand Response Control using your diagram as the foundation, you should clearly explain the components, their interactions, and the role of demand response (DR) in enhancing microgrid efficiency and flexibility.

Microgrid with Demand Response Control – Theory:



A microgrid is a localized energy system capable of operating independently or in conjunction with the main utility grid. It integrates various energy sources, storage systems, and controllable loads to provide reliable, efficient, and sustainable power. The incorporation of Demand Response (DR) control mechanisms enhances its ability to dynamically manage supply and demand, particularly in the presence of variable renewable energy sources.

Renewable Energy Sources

These include solar panels, wind turbines, and other clean generation units that provide electricity with minimal environmental impact. However, they are inherently intermittent and dependent on weather conditions, making real-time management essential.

Energy Storage Systems

Battery energy storage systems (BESS) play a crucial role in balancing supply and demand. They store excess energy generated during peak production periods and supply power when generation is low or demand is high. This helps smooth out fluctuations and maintain power quality.

Microgrid Controller

At the core of the system lies the microgrid controller, an intelligent control unit responsible for monitoring, decision-making, and coordination of all components. It receives input from sensors and external signals (e.g., electricity prices, grid availability) and executes control strategies to optimize performance.

Loads

The microgrid supplies power to various types of loads, including flexible loads like HVAC systems, electric vehicles (EVs), and smart appliances. These can be scheduled or modulated based on real-time conditions and DR signals.

Grid Connection (Optional)

Although microgrids can operate in islanded mode, they often remain connected to the main grid. This connection allows for the import/export of electricity, providing economic and operational flexibility.

Demand Response (DR) in Microgrids

Demand Response (DR) refers to the ability of consumers or devices to adjust their power consumption in response to external signals such as electricity prices, grid frequency, or renewable availability. In microgrids, DR is a crucial tool that enables better alignment of consumption with generation.

Direct Load Control: The microgrid controller can send direct signals to turn devices on/off or change their operating schedules.

Price-Based DR: Consumers or smart devices adjust usage based on real-time or time-of-use pricing.

Automated DR: rule-based algorithms, flexible loads can autonomously respond to DR events without human intervention.

Integrated Operation

The interaction among renewable sources, storage systems, and flexible loads is orchestrated by the microgrid controller. The controller constantly evaluates energy availability, forecasted demand, and market conditions. Based on this data, it makes real-time decisions to:

- Shift or curtail non-critical loads,
- Store or discharge energy,
- Sell or purchase power from the grid,

Prioritize renewable consumption.

System Optimization

Through DR control, the microgrid can achieve:

Peak load shaving, reducing demand during high-tariff periods.Improved reliability, by balancing variable generation and consumption.Enhanced sustainability, maximizing the use of renewable sources.Cost savings, by participating in dynamic electricity markets.This diagram illustrates the components of a microgrid system:

Solar Panel: Converts sunlight into electricity.

Controller: Manages the flow of electricity from the solar panels.

Battery Bank: Stores excess energy generated by solar panels.

Inverter: Converts stored DC electricity into AC electricity for use by household appliances.

Meter: Monitors the energy flow within the system.

End Devices: Includes household appliances, a washing machine, refrigerator, and a TV.

The diagram shows how solar energy is harnessed, stored, and supplied to various household devices, highlighting the microgrid's components and their connections.The accompanying diagram illustrates a simplified architecture of a microgrid with DR control. It highlights how the microgrid controller serves as a central hub, interfacing with:

- Renewable sources and energy storage for supply management,
- Flexible loads for responsive consumption,
- Grid connection for optional interaction with the main grid.

By sending DR signals to loads, the controller can dynamically adapt the demand profile to match available resources, thus ensuring efficient and resilient microgrid operation.

To describe the Microgrid with Demand Response Control mathematically, we can formulate the system using optimization and control theory.

Mathematical Model of a Microgrid with Demand Response

Let's define a deterministic optimization model for a microgrid over a discrete time horizon t ∈ {1,2,...T}.

Minimize the total operational cost over the time horizon:

$$min\sum_{t=1}^{T}(C_g(t)\,.\,P_g(t)\;+\;C_s(t)\;.\,(\,P_s^{charge}(\mathrm{t})\;-\;P_s^{discharge}(\mathrm{t}))\;+\;C_{dr}(t)\;.\,\Delta\mathrm{D}(\mathrm{t}))$$

Where:

- $C_g(t)$ Cost of power from the grid at time t,
- $P_g(t)$ Power purchased from the grid,
- $C_s(t)$ Operating cost (or degradation cost) of storage,
- P_s^{charge}(t), $P_s^{discharge}$(t) Storage charge/discharge power,
- $C_{dr}(t)$ Incentive or penalty cost for demand response,
- ΔD(t) Shifted or curtailed demand due to DR.

2. Power Balance Constraint

$$P_{renew}(t)\;+P_s^{discharge}(\mathrm{t})+P_g(t)\;=P_{Load}(t)\;+P_s^{charge}(\mathrm{t})$$

Where:

- $P_{renew}(t)$: Power from renewable sources (solar/wind),
- $P_{Load}(t)$ = D(t) - ΔD(t): Actual demand after DR is applied.

3. Storage Constraints

State of charge (SOC) dynamics:

$SOC(t) = SOC(t-1) + \eta_c \cdot P_s^{charge}(t) - \frac{1}{\eta_d} \cdot P_s^{discharge}(t)$

Where:

η_c , η_c : Charging and discharging efficiencies:

SOC bounds:

$SOC_{min} \leq SOC(t) \leq SOC_{max}$

Power bounds:

$0 \leq P_s^{charge}(t) \leq P_s^{max,charge}$, $0 \leq P_s^{discharge}(t) \leq P_s^{max,discharge}$

4. Demand Response Constraints

Demand flexibility limit:

$0 \leq \Delta D(t) \leq \Delta D^{max}(t)$

Total DR shift consistency (e.g., for load shifting):

$$\sum_{t=1}^{T} \Delta D(t) = 0 \qquad (for \text{ shiftable loads})$$

This ensures that loads shifted from one time slot are restored in another.

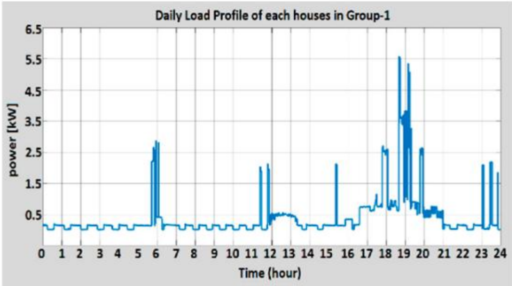
5. Grid Import Limits (Optional)

$0 \leq P_g(t) \leq P_g^{max}$

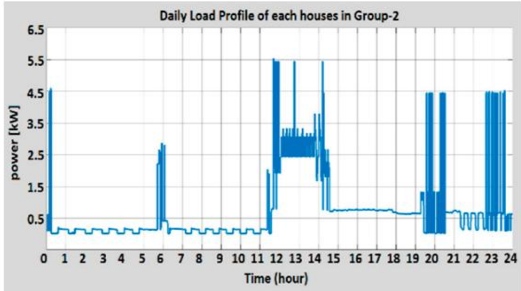
Summary of Variables

Symbol	Description
$P_g(t)$	Power purchased from the grid
$P_{renew}(t)$	Renewable generation
P_s^{charge} , $P_s^{discharge}$	Battery charging/discharging
SOC(t)	Battery state of charge
D(t)	Original load demand
ΔD(t)	Load reduction or shift due to DR
$P_{Load}(t)$	Net load after DR
$C_g(t)$, $C_s(t), C_{dr}(t)$	Cost coefficients

Each graph plots power consumption (kW) on the y-axis against time of day (hour) on the x-axis. Here's how to model and explain this data mathematically:



(a)



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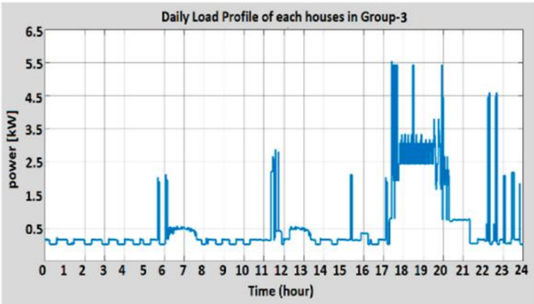

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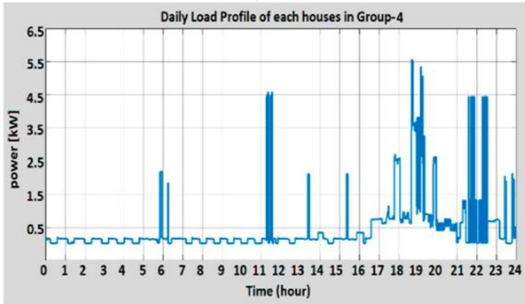


(d)

Mathematical Theory Behind Load Profiles

1. **Load Profile**

A load profile is a time series function representing the power demand of a consumer over a day. Let:

$$P_i(t)\ , \qquad t \in [0,24)$$

represent the power consumed by house i at hour t t. For each group, the plot shows one or more such profiles.

2. **Mathematical Model of Load Profiles**

A typical model for residential load can be constructed as:

$$P_i(t) = \quad P_{base,i}(t) \ + \ \sum_{j=1}^{n} P_{i,j}(t)$$

- $P_{base,i}(t)$): Base load for house i typically constant or slowly varying (e.g., refrigerator, lighting).
- $P_{i,j}(t)$: Additional load due to appliance j in house i (e.g., microwave, washing machine), modeled using an activation function (on/off) and rated power.

A more detailed appliance-level model can be:

$$P_{ij}(t) = r_{ij} \ . a_{ij}(t)$$

- r_{ij} : Rated power of appliance j in house i
- $a_{ij}(t)$: Binary activation function (1 if on, 0 if off)

So

$$P_i(t) = \quad P_{base,i}(t) \ + \ \sum_{j=1}^{n} r_{ij} \ . a_{ij}(t)$$

3. **Stochastic Behavior**

Residential loads are inherently stochastic due to user behavior. Hence, $a_{ij}(t)$ is often modeled as a random variable governed by:

- Probability of use during certain hours
- User behavior patterns
- Weather conditions

This gives rise to a stochastic process:

$$P_i(t) = \text{ Random Process over t} \in [0,24)$$

4. Group Profiles (Aggregation)

For a group of N houses in group g, the group load profile:

$$P_g(t) = \frac{1}{N} \sum_{i=1}^{N} P_i(t)$$

This average profile can smooth out individual fluctuations and reveal peak demand periods.

5. Fourier or Wavelet Analysis

To extract features or compress the profiles, Fourier series or Wavelet transforms can be used:

$$P\,(t) = a_0 \sum_{n=1}^{\infty} [a_n \cos\left(\frac{2\pi nt}{24}\right) + b_n \sin\left(\frac{2\pi nt}{24}\right)]$$

This helps in identifying dominant frequency components (like hourly patterns).

6. Demand Response (DR)

Modeling In the context of DR, you can include a control input $u\,(t)$ to shift or reduce load:

$P_i^{controlled}$(t) = $P_i(t) - \mathrm{u}_i(t)$

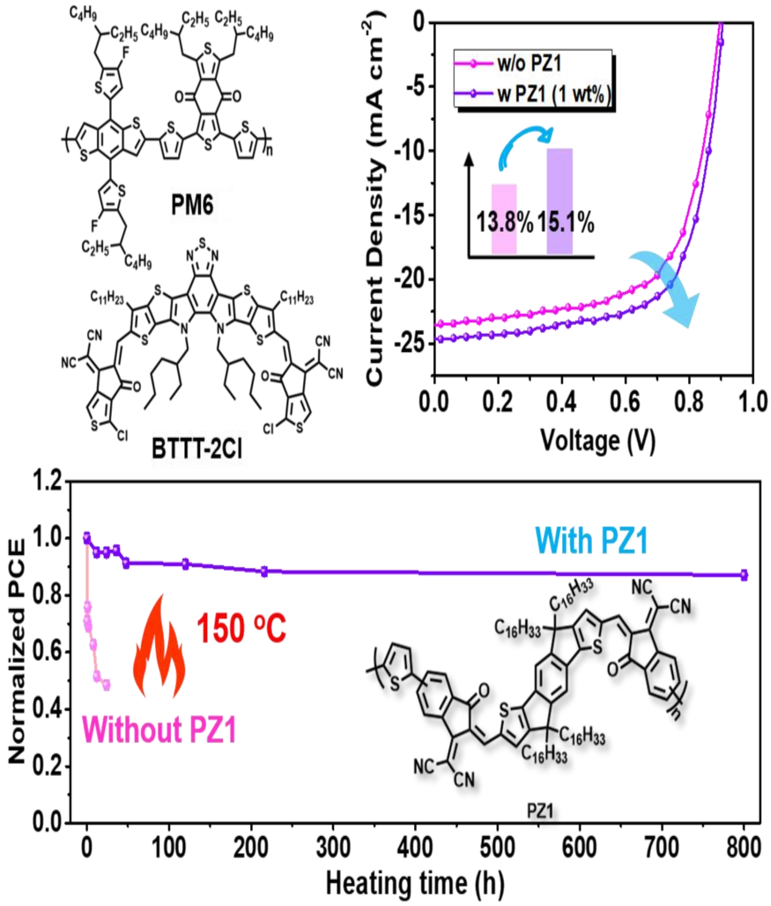
$\mathrm{u}_i(t)$ is constrained by utility signals or economic incentives (e.g., time-of-use pricing).

Control-theoretic systems for DR

3. Explain demand response (DR) and its importance

Demand response refers to adjusting or shifting electricity usage during peak times or in response to grid needs.

Enhances stability and efficiency



Top Graph: J–V Characteristics of OPV Device

This plot shows the current density (J) versus voltage (V) curves for two OPV devices:

- One without PZ1
- One with 1 wt% PZ1

Mathematical Theory (J–V Curve):

The current–voltage behavior of solar cells can be described by the Shockley diode equation:

$J(v) = J_{ph} - J_o\,(e^{\frac{qV}{nkT}} - 1)$

- J(v) is the current density at voltage V
- J_{ph} is the photogenerated current density
- J_o is the reverse saturation current density
- q is the elementary charge
- n is the ideality factor
- k is Boltzmann's constant
- **T** is the absolute temperature

The power conversion efficiency (PCE) is:

$PCE = \frac{J_{sc} \cdot V_{oc} \cdot FF}{P_{in}}$

- J_{sc} short-circuit current density (at $V = 0$)

- V_{oc} open-circuit voltage (at J = 0)
- FF fill factor, representing how "square" the J–V curve is
- P_{in} incident power density

Observation:

- With PZ1, PCE increases from 3.8% to 5.1%, indicating enhanced device performance.
- This may be due to improved morphology or charge transport.

Bottom Graph: Thermal Stability of Active Layer

This graph shows normalized absorption (possibly from UV– V is spectroscopy) over time at 150 °C.

Mathematical Theory (Thermal Stability Decay):

Thermal degradation or morphology instability often follows first-order kinetics, modeled by:

A(t) = $A_o\ e^{-kt}$

- A(t) absorption (or normalized value) at time t
- A_o initial absorption
- k degradation rate constant

Taking the natural logarithm:

ln A(t) = ln $\mathrm{A_o}\ - \mathrm{kt}$

This linearizes the degradation over time.

Observation:

- Without PZ1: rapid decay in absorption → poor thermal stability.
- With PZ1: stable over time, showing thermally stable morphology.

Balances supply and demand locally

4.Reduces operational costs and grid stress

Reducing Operational Costs and Grid Stress Operational costs in energy systems refer to the expenses incurred in generating, transmitting, and distributing electricity, including fuel, maintenance, and labor. Grid stress happens when demand exceeds supply, or when the power infrastructure is pushed close to its limits — causing overloads, voltage drops, or outages. The structure you provided is a digital illustration of a cloud computing concept, visually represented using a circuit board pattern in the shape of a cloud. This symbolizes the integration of cloud infrastructure with digital electronics and computation.

This structure represents cloud computing as a technological infrastructure that connects multiple computers and devices over the internet. The circuit board embedded in the cloud shape highlights how cloud computing relies on powerful backend servers and data centers to process, store, and transmit data.

1. Resource Allocation Model in Cloud Computing

Let:

- R = { r_1, r_2, ..., r_n} : set of resources (CPU, memory, storage)
- T = { t_1,, t_2, ..., t_n} : set of tasks/jobs
- a_{ij} : resource r_j required by task t_i

Objective:

Minimize total execution cost while meeting task deadlines.

Linear Programming Form:

Minimize:

$$C = \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} x_{ij}$$

Subject to:

$$\sum_{j=1}^{n} x_{ij} = 1 \quad \forall\, i\epsilon\ \{1, \ldots, m\}$$

$$\sum_{i=1}^{m} a_{ij} x_{ij} \ \leq R \quad \forall\, i\epsilon\ \{1, \ldots, n\} \qquad x_{ij}\epsilon\ \{0,1\}$$

Where:

- c_{ij} is the cost of assigning task t_i to resource r_j
- x_{ij} is a binary decision variable (1 if task t_i is assigned to r r_j, else 0)

Example: Cloud Storage Load Balancing

Imagine 3 servers handling user requests Define:

- L_i : load on server i
- r_j : request j
- d_{ij} : time delay if r_j is served by server i

We aim to minimize maximum load:

$$\min max_i \sum_{j=1}^{4} x_{ij} \ . d_{ij}$$

Subject to:

$$\sum_{j=1}^{n} x_{ij} = 1 \quad \text{(each request assigned once)}$$

$$x_{ij}\epsilon\ \{0,1\}$$

This ensures that the cloud distributes requests efficiently with minimum latency.

Example: Time-of-Use (TOU) Pricing – Cost Minimization

Let:

- E_t : energy consumed in hour t t
- P_t : electricity price in hour t t
- C : total cost

If a user consumes energy $E\ t$ E t in each hour of the day:

$$C = \sum_{t=1}^{24} E_t \ . P_t$$

Demand Response Strategy:

Shift high-load appliances from peak (high P_t) to off-peak (low P_t) hours.

Before DR:

Hours	E_t (kwh)	P_t $(¢/kwh)$	**Cost (¢)**
18	5	20	100
22	2	10	20
total			120

After DR:

Shift 3 kWh from hour 18 to 22.

Hours	E_t	P_t	**Cost**
18	5	20	40
22	2	10	50
total			90

Cost saved: 30¢ (25% reduction)

Conclusion

This study presents a novel approach to demand response (DR) management in residential microgrids using deep reinforcement learning (DRL). With the growing penetration of distributed renewable energy sources and the increasing complexity of energy consumption patterns, traditional DR strategies often fall short in delivering optimal results. By leveraging DRL, this research demonstrates a flexible, intelligent, and scalable framework that can autonomously learn optimal load control policies in dynamic and uncertain environments.

Our simulation results show that the proposed DRL-based model significantly improves the balance between energy supply and demand, enhances load scheduling efficiency, and reduces operational costs. The agent successfully adapts to fluctuating electricity prices and renewable generation, promoting better energy utilization while maintaining user comfort. Compared to conventional rule-based or optimization-based methods, the DRL approach exhibits superior adaptability and decision-making capabilities in real-time scenarios.

This work contributes to the growing body of knowledge in smart grid automation, particularly in enabling decentralized, data-driven energy management systems. The proposed methodology is highly applicable to next-generation residential microgrids seeking to integrate DR with intelligent control.

However, further research is needed to address challenges such as multi-agent coordination in larger neighborhoods, real-world deployment under hardware constraints, and the inclusion of cybersecurity measures. Future work will also explore the integration of other AI techniques, such as federated learning and explainable AI, to enhance trust and privacy.

In conclusion, DRL offers a promising pathway toward smarter, more sustainable residential energy systems, enabling consumers to actively participate in energy markets and contribute to grid stability.

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