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Article

Edge-Cloud Computing for Scheduling the Energy Consumption in Smart Grid

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Abstract: Nowadays, smart electricity grids are managed through advanced tools and techniques. The advent of Artificial Intelligence (AI) and network technology helps to control the energy demand. These advanced technologies can resolve common issues such as blackouts, optimal energy generation costs, and peak-hours congestion. In this paper, the residential energy demand has been investigated and optimized to enhance the Quality of Service (QoS) to consumers. The energy consumption is distributed throughout the day to fulfill the demand in peak hours. Therefore, an Edge-Cloud computing-based model is proposed to schedule the energy demand with reward-based energy consumption. This model gives priority to consumer preferences while planning the operation of appliances. A distributed system using non-cooperative game theory has been designed to minimize the communication overhead between the edge nodes. Furthermore, the allotment mechanism has been designed to manage the grid appliances through the edge node. The proposed model helps to improve the latency in the grid appliances scheduling process.

Keywords: Edge-cloud computing; smart grid; smart home; energy scheduling; non-cooperative game theory

1 Introduction

In a smart grid, there is a critical requirement of an intelligent framework that can perform effective leading peaks deduction in energy consumption. Energy consumption is rising day by day due to population growth, technological development, and high load. Sometimes careless behavior also causes a rise in energy consumption in different sectors. Smart grids with cloud technology play an essential role in saving a high amount of energy and cost. An intelligent management structure that performs effectively, leading to peak reduction in energy consumption, is desperately needed in a smart grid [1]. Using a smart grid is a potential option for coordinating today's world's impending requirements. Traditional power systems cannot fulfill today's electrical demand. The idea of a smart grid with Edge-Cloud computing for scheduling energy consumption is established to address this requirement. Smart grids are established to fulfill today's rising electricity demand due to population growth and increased electricity usage. A smart grid is a type of power grid that enables the bidirectional movement of data and energy with the use of electronic communication systems to monitor and adjust the changes in demand [2].

In the previous few years, where Cloud-IoT was used to accomplish adequate energy consumption is smart energy; this subject has been covered in detail in the paper [3]. Nations have created energy efficiency research, businesses, and institutions to produce tools for monitoring, regulating, and monitoring energy use within homes, buildings, and grids. Various research projects have made possible new device solutions like sensors, smart meters, or controllers [4]. The issue persists, and a solution must be found, despite the efforts made to educate consumers about the value of lowering energy use in public areas, workplaces, and at home. Public spaces are where unchecked energy usage and waste are most apparent. Still, several factors contribute to this, including many users and the variety of choices and comfort needs. The age of the buildings and the inadequate funding for the initial setup of technology would fit in their facility's infrastructure [5].

The edge layer includes the intermediary storage, communication, and computational capabilities between the smart grid control center and the rest of the system. The idea of the edge is a relative one. The smart meter is an illustration that relates to the tier if it is just used for data collection and transmission; the edge layer serves as the foundation for domestic energy analysis. The considerable resources in the edge layer may be separated into sub-layers according to their positions. The sub-layers nearer to the objects are comprised of a variety of high-performance and low-power resources. They are primarily made to carry out local and immediate analytics. Resources with powerful processing capabilities are accurately placed in the sub-layers nearer to the control center. They can interact via a dependable communication link to conduct detailed, extensive research and monitoring.

Since the advent of cloud computing, complicated issue solving has been assigned to the cloud platforms having powerful CPUs, ample storage space, and memory capacities. Thus, several smart grid services, including those that handle devices, schedule operations, and optimize energy use, employ cloud services to enhance productivity [6]. However, there may be significant latency concerns due to the great distance between users and cloud services and the massive volume of data created by linked user appliances. Therefore, edge computing is an intriguing solution to address this issue since they are moving data processing near the end-users. Instead of replacing cloud computing, the term Edge-Cloud computing is used to take the benefit of both [7]. Edge computing provides end users with many intriguing services within the smart grid and smart urban sectors. As a result, increasingly more studies are looking at leveraging future technologies like edge computing in a smart grid setting.

In this research work, we look at the issue of household demand scheduling for appliances. Our primary goal is to spread out power consumption more evenly throughout the day and to prevent or lower energy needs at peak times. Then, in order to motivate customers to reduce their power use, we employ an Edge-Cloud multi-agent environment. As per the previous work done by authors, ideal incentives mechanism at different networking layers have been suggested to lower the overall energy distribution cost to reduce the cost of the world's electricity consumption. The two goals of the optimization challenges are to minimize cost and each appliance's waiting period to the absolute minimum. However, both plans may be at odds with one another. In this case, cutting costs may result in longer wait times and vice versa. The writers have tried to establish a compromise between the two goals.

The main aim is to arrange each energy load individually; we want to prevent each customer from acting selfishly to maximize his profit. This behavior does not address the issue of peak demand; instead, this creates new peaks throughout low-price hours. As a result, we want to reduce the overall cost of energy among all users, where every appliance's schedule is dependent on the other appliance's schedule. In this paper, we suggest an edge computing-based paradigm in which job scheduling task is processed in edge nodes. The cloud environment handles the uncertainties and loads in peak hours. Additionally, we offer an optimization technique for assigning edge nodes that tries to optimize the usage of every node's resources while minimizing the delay of energy rescheduling.

2 Related Works

Researchers have used several methodologies and ways to handle demand planning problems over the years. That includes distributed artificial intelligence approaches, which have proved helpful for management control, and upcoming technologies like cloud, edge, and fog computing. Planning strategies frequently employ various tactics and processes concurrently to maximize their advantages and make their most effective use. Following is a summary of relevant studies and the techniques and methods used.

In [8], the authors demonstrated an energy control solution with real-time load data to control power and minimize cost, considering accessibility. According to its usage over time, devices inside a single residence were categorized as: thermostatically controlled, elastic, inelastic, regular, and user aware. Subscribers might manually regulate the delay time of devices to maximize user accessibility. The knapsack was used to manage cost reduction, which was accomplished using the genetic algorithm. The findings suggest that the proposed method efficiently managed energy usage by coordinating the schedules of the devices.

In order to reduce energy costs and user discomfort, the authors in [9] use a smart recharging and clustering idea to address the issue of peak formation in demand. In accomplishing the desired goals, the aggregation sites optimally schedule equipment and battery charging and discharging within a cluster. The results showed that applying this method under the RTP signal allows users to save the most money possible on their energy costs. Similarly, the authors [10] created an analytical approach with a recursive algorithm for reducing energy consumption peaks through scheduling power usage. Using different social welfare situations, the proposed analytical method with a recursive algorithm is analyzed for electricity costs and Peak-to-Average Ratio (PAR) reductions. Chouikhi et al. [11] focused on more equally spread daily energy usage to prevent or lessen consumption at peak times. Consequently, they offer a methodology for scheduling energy requirements based on fog computing using the cost of energy usage as a motivator. In the proposed model, the edge nodes coordinate the appliance actions to minimize the electricity bills on a personal scale and the cloud on a global scale to honor customer choices.

In [12], a Genetic algorithm (GA) is used to schedule equipment and use “supervisory control and data acquisition (SCADA)” to control the residential sectors for energy consumption. By limiting energy usage to peak power levels, the energy management system keeps supply and demand in balance. The scheduler considers price signals and user preferences to place appliances in a given time slot as efficiently as possible. Additionally, a case study using the “Intelligent Energy System Laboratory” has been conducted. It has three different energy-producing components: wind turbines, fuel cells, and solar energy. The outcomes of the suggested approach are also contrasted with MINLP at the conclusion.

Regarding the smart grids, the Multi-Agent System (MAS) techniques are implemented for various purposes. MAS has demonstrated expertise in demand management. MAS can perform and make smart decisions without human involvement, making the demand monitoring systems self-sufficient, scalable, fault-tolerant, and adaptable. An ontology-oriented multi-agent energy monitoring system was proposed to regulate and manage houses and buildings [13]. To attain the optimum operating strategy, various agents have been developed. The suggested technique used communication and cooperation among decision-making agents to fix the demand/supply management issues. The mass has been used by Klaimi et al. [14,15] to reduce end-user bills. In this proposed solution, the system’s entities, like consumers, storage techniques, and producers, are depicted as agents to exchange information with each other. For high entity gain, stability of demand, and supply of power generation, the researchers expanded their work [16] and described methodologies for negotiating processes and cooperation among agents. The authors of [17] proposed a demand-side management solution entirely related to the Internet of energy. They focused on decreasing latency by implementing an intelligent gateway between cloud and fog domains. A dynamic scheduling sequence was created to organize the appliances based on customer relevance, regulations, and the status of power sources. By utilizing an enhanced particle swarm optimization algorithm, the authors [18] have taken advantage of fog to schedule and balance a smart manufacturing load over to production cluster centers. In [19] studies, the smart energy savings in public work establish an edge-IoT framework.

The proposed technique suggested in [20] is based on an edge-fog-IoT architecture with responsive peak load control and optimization. The researchers [21] implemented an energy management-as-a-service feature using a fog-cloud environment. This feature allows the end-user to custom-make power management at a low expenditure. The authors have adopted a smart grid [22] comprising three layers of fog-cloud computing components. It can handle and manage a large number of smart energy grid systems, including IoT devices. Moreover, the authors suggested a cost-cutting prototype to identify information on customer association, workload distribution, and QoS constraints for fog-edge devices.

3 Problem Formulations

We focus on reducing the overall everyday expense of all customers. Thus the objective function '*h*' is defined as follows:

$$h = \sum_{t \in T} \Omega_t \left(\sum\nolimits_{a \in \alpha} \sum\nolimits_{b \in \beta_a} d_b^t \right) \tag{1}$$

The optimum consumption scheduling is the answer to the restricted minimization issue shown below:

$$min_y\ h(Y) = \sum_{t \in T} \Omega_t \left(\beta \sum_{a \in \alpha} \sum_{b \in \beta_a} \sum\nolimits_{k=1}^{K_b} y_{bk}^t s_{bk}^t \right) \tag{2}$$

This is subject to the restrictions outlined in the 3, 4, 5, 6, 7, and 8 equations. Its judgment vectors or schedule is $Y = [y_b]\ \forall\ b \in \beta_a$ and the entries of y_b are y_t^{bk}. Several convex problem-solving methods, like the 'Interior Point Method' (IPM) [23], can be used to tackle issues in the cloud computing platform. Moreover, the data of energy usage, operating duration, min and max power, and beginning and finish time slots. Energy profiles for all the system's appliances must be transferred to the centralized system. The application of game theory enables users to collaborate with minimal information sharing.

4 Scheduling of Energy Consumption

4.1 System Model

We examine a set α of a household apartment and designate the set of baseload, uninterruptible, and interruptible load-based equipment related to a building $a \in \alpha$ by $\beta_a = |\beta_a|$. Every piece of equipment has a distinct energy utilization profile with varying dynamics. The configuration of appliances is obtained in the equipment specification and measured empirically. The operation of equipment is made up of many uninterruptible sequential load periods. Symbol s_{bk}^t indicates the power of the equipment throughout loading stage k where $(k = (1, 2, \ldots, k_b)$ at a time slot $t \in \tau$, where $|\tau| = T$ indicates the subset of time periods. To convey the energy, s_{bk}^t are multiple factors that indicate the time period in hours. Actual and continuous energy components exist. In addition, we establish control variables $y_{bk}^t \in 0$ and 1 to signify whether or not such a load profile should be evaluated at the time for slot *t*. It is worth noting that while arranging the daily energy need, we consider the accessibility energy amount. Several strategies and procedures for rescheduling energy consumption in the event of a low energy supply are not in this article's scope.

The vector of daily usage is an appliance as $b \in \beta_a$ is written as follows:

$$R_b = \left[R_b^1, \ \ldots, \ R_b^t, \ \ldots, \ R_b^T\right] \tag{3}$$

Here R_b^t represents the required energy at the slot time t is calculated as:

$$R_b^t = \beta \sum_{k=1}^{k_b} y_{bk}^t s_{bk}^t \tag{4}$$

Further, add the additional judgment variable y and provide a x_{bk}^t as the binary variable to determine whether or not the phase load k of the equipment has been completed by slot time t. Whereas if stages load k of equipment has already been completed by time slot t than $x_{bk}^t = 1$; otherwise $x_{bk}^t = 0$. As a result, we have the following constraint:

$$x_b^t + y_b^t \le 1, \ \forall\{b, \ k, \ t\} \tag{5}$$

This constraint ensures both y_{bk} and x_{bk} cannot be changed to 1 at slot time t, as the three alternative scenarios are described in the following:

- k has already been completed, with $y_{bk}^t = 0$ and $x_{bk}^t = 1$.
- k is still active, therefore, $y_{bk}^t = 1$ and $x_{bk}^t = 0$.
- k has not started yet, thus $y_{bk}^t = 0$ and $x_{bk}^t = 0$.

Customers might select a start slot $s_b \in T$, and after that, the equipment works and ends at the slot $f_b \in T$ before the equipment finishes its job to satisfy them. $f_b \ge s_b + T_b$, whereby T_b is the time slots that are required to be completed for b's load profile. As a result, two restrictions are required:

$$\beta \sum\nolimits_{t \epsilon T_b} y_{bk}^t s_{bk}^t = E_b \tag{6}$$

and

$$y_b^t = 0, \ \forall \, t \in T \tag{7}$$

where E_b denotes the equipment's daily energy usage, and $T_b = \left[s_b, \ s_{b+1}, \ \ldots, \ f_{b-1}, \ f_b\right]$ denotes the collection of slots time among the beginning and end. Restriction Eqs. (6) and (7) secure that the equipment must start and complete its work at the specified times T_b, while leftover slots time $T, \ T_b$ must be left unoccupied T_b. The $s_b = 1$ and $f_b = T$ for loads of uninterruptible equipment.

Two limitations guarantee that uninterruptible equipment operation:

$$y_{bk}^{t-1} - y_{bk}^t \le x_{bk}^t, \ \forall \{b, \ k\}, \ \forall \, t = 2 \ to \ T, \tag{8}$$

and

$$x_{bk}^{t-1} \le x_{bk}^t, \ \forall \{b, \ k\}, \ \forall \, t = 2 \ to \ T \tag{9}$$

Whenever a stage k is executing at slot time $t-1$ (i.e., $y_{bk}^{t-1} = 1$), constraint Eq. (8) assures that it will either resume its t operations (i.e., $y_{bk}^t = 1$ and $x_{bk}^t = 0$) or complete ($y_{bk}^t = 0$ and $x_{bk}^t = 1$) at slot time t. The stage is not executing at $t-1$ (i.e.,, $y_{bk}^{t-1} = 0$), three possibilities exist at slot time t as follows:

- k has already been completed, with $y_{bk}^t = 0$ and $x_{bk}^t = 1$;
- k will start its execution with $y_{bk}^t = 1$ and $x_{bk}^t = 0$;
- k will be already in the waiting stage, implying that $y_{bk}^t = 0$ and $x_{bk}^t = 0$;

Condition 9 assures that if stage k is completed at slot period $t-1$ ($x_{bk}^{t-1}=1$), it could not be resumed execution, accordingly x_{bk}^{t} should be assigned to 1. Furthermore, if the stage is not completed during t ($x_{bk}^{t}=0$), it could not be completed at $t-1$, and x_{bk}^{t-1} is assigned to 0.

A load stage begins only after all previous steps have been completed to maintain the load stages of the processing sequence. We applied the additional restriction to ensure all these:

$$y_{bk}^{t} \leq x_{b(k-1)}^{t}, \ \ \forall \{b, \ t\}, \ \ \forall \, k = 2 \; to \; k_b \tag{10}$$

The price function $\mho_t(\ )$ yields the price of energy usage at slot time t. The overall quantity of energy consumed determines the cost of one kWh. During busy hours, the price does rise, and we suggest using a rising and strictly convex price function. Numerous piece-wise steps for linear function can be utilized to promote energy saving. Distributors provide electricity prices following government regulations. The same provider might make several deals and offers with varied 1 kWh pricing and subscription charges. The supplier communicates these prices, and the price function, to the edge agents.

4.2 Non-Cooperative Planning Game

To decrease delay and used energy, it is preferable to plan energy usage at the edge layer rather than the cloud layer, as previously stated. We merge the edge computing framework with a multi-agent system to apply a quasi-distributed energy usage work schedule. The modeling of components of the system by intelligent agents is represented in Fig. 1. Consumer appliances are supposed to be fitted with technology that allows them to communicate through the agent of buildings. Low-power ZigBee and Bluetooth technologies might link things within a residence. In contrast, PLC, Wi-Fi, and Ethernet technology could be used to interconnect edge and consumer agents within the building. These can connect to the cloud using fiber optics, 5G, or 4G services.

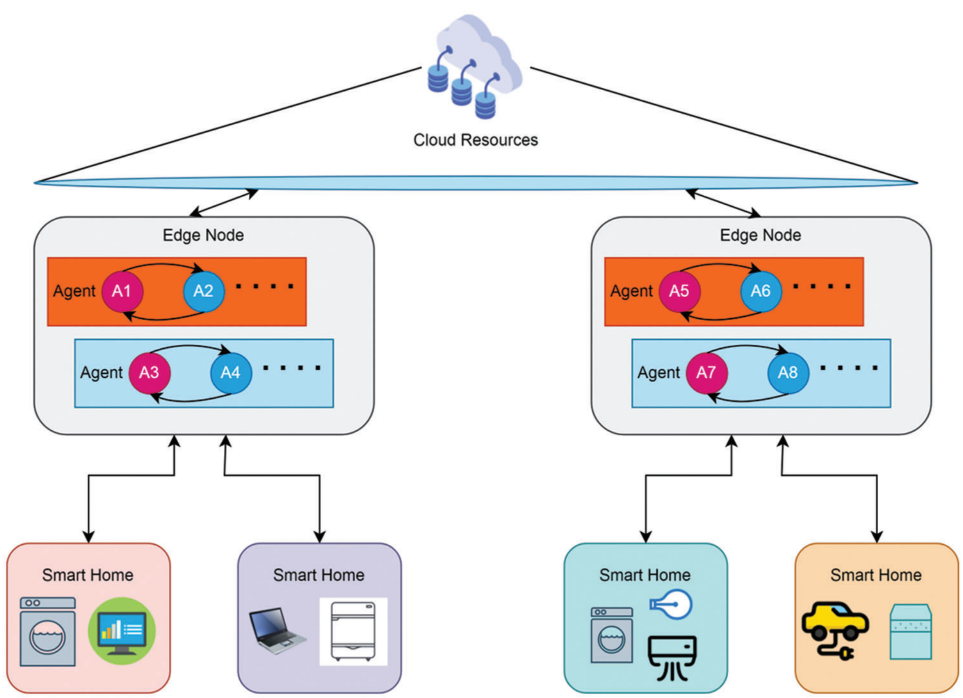

Figure 1: Scheduling of energy consumption using the multi-agent system-based edge architecture

With autonomous individual scheduling, the pricing method within this approach is based on overall energy consumption rather than individual demand. As a result, each appliance's schedule is determined by the schedules of all other appliances, reducing demand peaks and balancing energy use throughout the day. According to the proposed proposal, the subscribers should delegate the demand schedule to the edge agents. The following section will cover the assignment of the buildings to the edge nodes. To accomplish the best scheduling, the edge agents must collaborate. The set of edge nodes is represented by s $\varepsilon(E = |\varepsilon|)$, and the decision vector is redefined as $Y = (Y_1, \ldots, Y_e, \ldots, Y_E)$. Here, the consumption schedule vector Y_e is written as $Y_e = \left[y^t_{bj}\right](\forall_b \in \beta_a \wedge \alpha)$ allocated to e. The non-cooperative planning game is defined as follows:

- Edge agents are the players.
- The energy schedule Y_e is determined by each edge agent e.
- For each agent e, $p_e(Y_e;\ Y_{-e})$ is the payoff function.

$$p_e(Y_e;\ Y_{-e}) = \sum_{t \in T} \Omega_t \left(\beta \sum_{a \in \alpha} \sum_{b \in \beta_a} \sum\nolimits_{k=1}^{K_b} y^t_{bk} s^t_{bk} \right) \tag{11}$$

where $Y_e = (Y_1, \ldots, Y_{e+1}, \ldots, Y_E)$ is the vector representing containing all of the agents' schedules except e, and E is the count of edge agents.

Each edge agent strives to discover the optimal demand scheduling that shrinks the payout while working with different agents until the Nash equilibrium. The payout function $p_e(Y_e;\ Y_{-e})$ is strictly convex since the cost function is growing. This game belongs to the N-person game, and Nash equilibrium's existence and uniqueness are a direct outcome [24].

The Nash equilibrium is established, and no player can reduce their payoff function by adjusting its scheduling. The schedule forms the Nash equilibrium for such a game $Y^*_e,\ \forall_e \in E$ if and only if:

$$p_e\left(Y^*_e;\ Y^*_{-e}\right) \le p_e\left(Y^*_e;\ Y^*_{-e}\right),\ \forall_e \in E,\ Y_e \ge 0 \tag{12}$$

The optimal edge agent e schedule may be found by addressing the local optimization problem, given Y_{-e}.

$$S0:\ \min_{Y_e} p_e(Y_e;\ Y_{-e}) = \sum_{t \in T} \Omega_t \left(\beta \sum_{a \in \alpha} \sum_{b \in \beta_a} \sum\nolimits_{k=1}^{K_b} y^t_{bk} s^t_{bk} \right) \tag{13}$$

The issue related to the local, when the energy consumption schedule Y_e is for the sole variable for e.

To demonstrate this, we restructure the equation into the equivalent issue as follows:

$$S1:\ \min_{Y_e} p_e(Y_e;\ Y_{-e}) = \sum_{t \in T} \Omega_t \left(\beta \sum_{a \in \alpha} \sum_{b \in \beta_a} \sum\nolimits_{k=1}^{K_b} y^t_{bk} s^t_{bk} + \sum_{g \in \alpha / \alpha_e} \sum_{b \in \beta_a} d^t_b \right) \tag{14}$$

Here, α_e denotes the collection of buildings that have been allocated to e. The goal of the local issue is similar to the global issue Eq. (1). It is evident that e can resolve the case at the local level with IPM if it knows the total consumption scheduling D_e of all other nodes required to compute the 2nd term of Eq. (14) and the price function. The non-cooperative planning game is performed continuously in Algorithm 1. The edge agents run the algorithm in the sequence specified by a pre-defined list. The edge nodes reorganize this list when the cloud server initializes it. The first agent's e in the list solves the issue

Eq. (14) and calculate its schedule d_e in the first iteration by using it's genuine everyday consumption and a randomized D_{-e}.

It creates a global consumption scheduling D, sets it to d_e and passes it on to the next agents in the list queue. Depending on the incoming D, this agent g estimates its scheduling d_g, incorporates in the D. Further passes it on to the contiguous agent. These steps are repeated till every agent has decided on schedules of their own and has entered them into D. The final agent within the list is responsible for transferring the global schedule D to 'e'. In case 'e' discovers that D has changed, it rearranges the lists and delivers it to the new list heading along with the energy demand. Alternatively, it declares the end of the game and notifies each edge node's building of the final scheduling.

Algorithm 1: Non-cooperative planning game at edge tier.

Regulate Y_e using Interior Point Method (IPM);
Assign d_e to next agent;
Repetition
  obtain list and D;
  if 'e' == *first.list* **then**
    if D not changed **then**
      indicates *end of game*;
    end if
    updating D;
    rearrange lists;
    assigns *D&lists to first.list*
  end if
  $Y_e = IPM(D_{-e})$;
  if $Y_e < Y_e^{opt}$ **then** ▷*opt is used for term optimization*
    Updating Y_e^{opt}, D, and D_{-e};
  end if
  assign D and *next.lists;*
Until obtain *end of game*

The cost of energy is monotonically declining, and the edge agents successively upgrade their consumption plans. Additionally, because the cost could only take on positive values, it must drop to a positive fixed point as the number of repetitions goes to $+\infty$. The best solution of the game is identical to the game equilibrium, and the optimal solution of Y_e^{opt} is unique to Eq. (2).

The following section shall discuss choosing which edge device will schedule which building is dedicated to edge agents assignment.

4.3 Edge-Cloud Nodes Assignment

Here, we discussed a module for allocating edge nodes to help us schedule energy usage to minimize latency. In our view, optimizing customer energy consumption is insufficient; we also require optimizing the scheduling procedure. As a result, we considered balance among the nodes depending on their features and reduced the resources used by the edge devices. Additionally, we work to minimize scheduling delay and latency. To achieve the following three goals, we allocate edge nodes in the following ways:

- Reducing the overall schedule period and the number of edge nodes.
- Minimizing the overall amount of energy used by each edge node.
- Fair scheduling load distribution across the active edge devices.

4.4 Edge Node Selection Process

The edge nodes may address problems either in the clouds or in a distributive way. The following is how the centralized choice of edge nodes and the schedule of energy consumption work:

1. Building agents seek data and profiles about their customers' devices.
2. The building agents send the overall count of relevant devices to the edge node to which they are linked.
3. The edge nodes provide this knowledge to the cloud with attributes like distance, CPU, quality of connection, etc.
4. The cloud server resolves the issue, assigns a location to each edge agent, places the adversely impacted nodes into the list, and provides the judgment to the edge devices. The edge agents are put into a list randomly because the order has no bearing on the final schedule.
5. The edge agents relay the cloud server's decisions to the allocated building agents.
6. Those agents send information gathered from customers to the appropriate nodes.
7. Algorithm 1 is executed by the edge agents, and the schedule choice is sent to the buildings. After this, schedules are sent to the customers.

4.4.1 Energy Consumption Model

As edge nodes use energy to conduct the scheduled process and send and receive data, the power consumed depends on the node data size to process and the communication protocol used. The processed energy E_e^{proc} is determined by the type of edge node and amount of devices assigned by e. We may describe this as a β_e function:

$$E_e^{proc} = \varphi_e \beta_e \tag{15}$$

The function φ_e, which is specified by the nodes themselves, gives the predicted energy spent throughout the scheduled process through the node e. The communication energy E_e^{proc} contains energy dependent on the quantity of received and sent, node consumption features, connection quality, and the distances between e and another node.

4.4.2 Network Model

A centralized cloud server connects a group of edge nodes or devices ε $(E = |\varepsilon|)$ to form the network. The edge devices create a fully integrated network where each node is capable of wireless transmission with every other device. So, one edge node can directly connect with each building or block $(a \epsilon \gamma)$. A Boolean parameter $\beta_{ae} = 0$ is considered as indicating a, whether it can be directly connected with $e \varepsilon E$ or not. Here $\beta_{ae} = 1$ if a is connected to e otherwise $\beta_{ae} = 0$.

5 Performance Evaluation

To implement the proposed and existing solutions, we employed MATLAB and Simulink. The edge computing is performed using the appliances eight in numbers with varying usage patterns. The proposed technique is compared with the unscheduled and scheduled (HSA, EWA, and Hybrid) approach for the

RTP scheme mentioned in the article [25]. The activities are completed in 60, 30, and 5 min on these appliances in the edge-cloud environment. The performance of the proposed and existing schemes is tested based on the cost of energy consumption, PAR, and PKR. Moreover, the waiting time is also calculated to ensure the users' comfort. The fully connected graph is formed using 8 nodes and the IEEE 802.11n communication standard. The implementation is performed using an Intel Core i7-8750H CPU with 16 GB of RAM with Thermal Design Power (TDP) of 45 W, and we also consider the processing delay of the system.

In the cloud-edge environment, we took multiple houses, and each house had multiple appliances. Further, the appliances are categorized based on their usage pattern, like baseload, uninterruptible, and interruptible as described in Table 1. The proposed model can reduce electricity costs and PAR.

Table 1: Configuration of appliances

Category	Appliance	LOT (Hours)	Power (kWh)
Baseload	Lighting	16	1
Baseload	Refrigerator	24	2
Uninterruptible	Washing machine	2	2
Uninterruptible	Dryer	1	2.5
Uninterruptible	Electric vehicle	2	3
Interruptible	Dishwasher	2	3.5
Interruptible	LED Screen	2	1
Interruptible	Laptop	12	2

5.1 Scheduling Delay

The scheduling delay is increased as we increase the number of appliances in the Cloud, Fog, and Edge-Cloud environments. The Edge agent get the detail of various appliances of a particular zone and get the appliances in return to get their schedule. Our proposed model is compared with the [25] shown in Fig. 2, which already compared their techniques with the distributed approach [26]. The Edge-cloud's scheduling time is less than the cloud and fog-oriented ecosystems because the scheduler is closer to the appliances. As the number of appliances increases, the cloud scheduling time escalates because of communication overhead. The cloud does not back up the fog computing environment, which results in short processing power in terms of a large number of appliances in the area.

The optimal edge node assignment is shown in Fig. 3 concerning scheduling delay with a number of edge nodes and appliances. The proposed scheduling approach needs time to find the desired equilibrium because the edge nodes are weaker than fog and cloud. However, cloud support is used when a significant latency is reached. Many parameters need to evaluate before making the scheduling decision. Moreover, the communication time from edge nodes to the appliances is way less than fog and cloud computing.

5.2 Peak to Average Ratio (PAR)

The performance of the proposed model is compared with the unscheduled load, and the EHSA hybrid approach based on PAR is shown in Fig. 4. In the 24 slots in the day as per 60 min OTI, the peak hour load is 5 PM to 11 PM. Our proposed model can reduce the PAR value compared to existing techniques. Similarly, there are 48 slots in the 30 min OTI. The peak hour for the 30 min slot is from 9 AM to 5 PM. The hybrid technique is better than the unscheduled. However, the proposed model is superior in the 30 min OTI as well. In the 5 min OTI, there are 288 slots. The peak hours are considered from 6:15 AM to 7 PM. PAR values are also less compared to an unscheduled and hybrid approach in 5 min OTI. The low PAR value justifies the stability of the system. The proposed method also maintains the trade-off between the quality of service and cost.

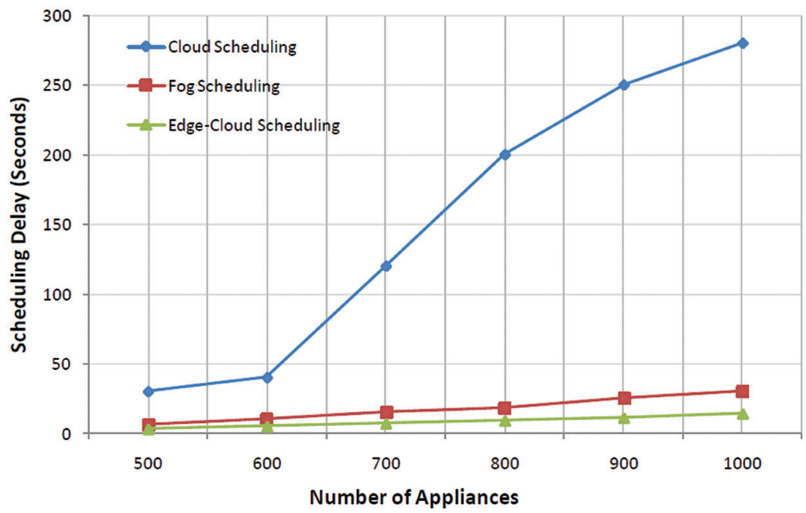

Figure 2: Comparison of a scheduling delay

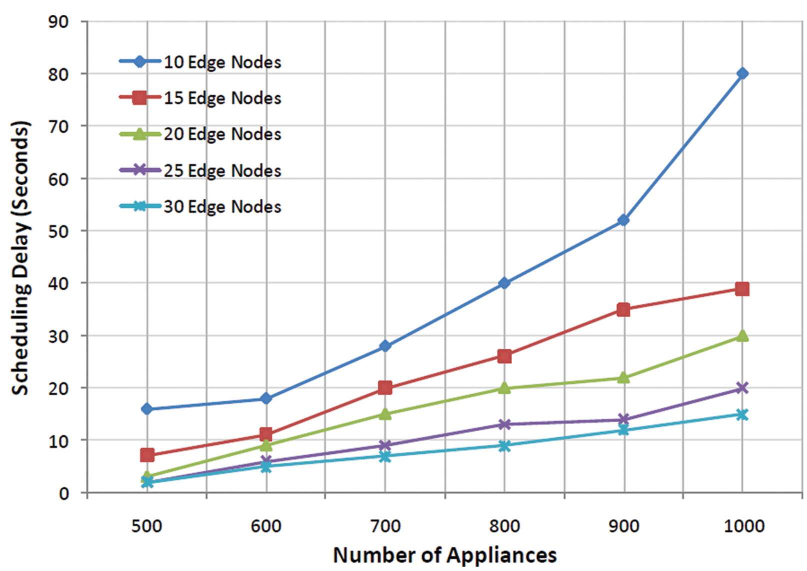

Figure 3: Comparison of scheduling delay with edge nodes

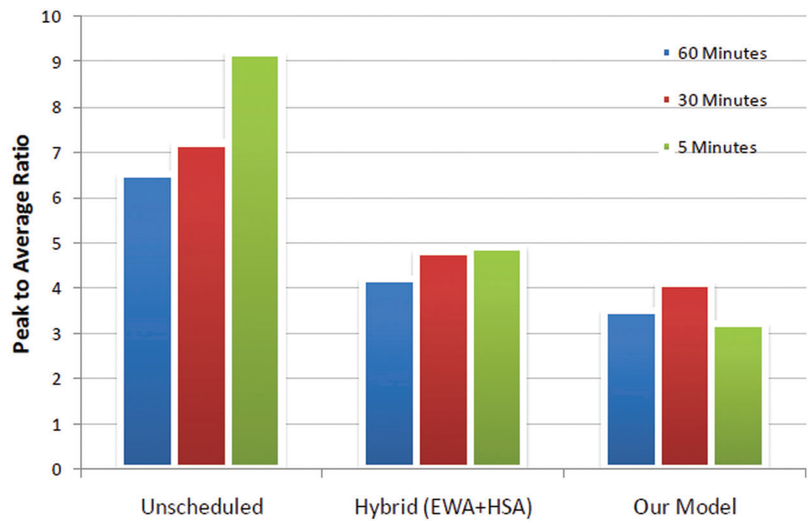

Figure 4: Comparison of PAR with edge nodes

5.3 Total Cost

The performance of the proposed model is compared with the unscheduled load, and the EHSA hybrid approach based on cost is shown in Fig. 5. In the 24 slots in the day as per 60 min OTI, the peak hour load is 5 PM to 11 PM. Our proposed model can reduce the cost of the PAR value compared to existing techniques. Similarly, there are 48 slots in the 30 min OTI. The peak hour for the 30 min slot is from 9 AM to 5 PM. The hybrid technique is better than the unscheduled; however, the proposed model is also superior in the 30 min OTI. In the 5 min OTI, there are 288 slots; the peak hours are considered from 6:15 AM to 7 PM. Cost is also less compared to an unscheduled and hybrid approach in 5 min OTI. The proposed method is more user-friendly than other techniques as scheduling decisions are processed locally, and in peak hours cloud can be used to mitigate the latency issues. The reason for the cost reduction is the load reduction in peak hours as per the category of appliances. The proposed system maintains the schedule and is on/off the appliances in peak hours. The significant latency is compromised to reduce the cost.

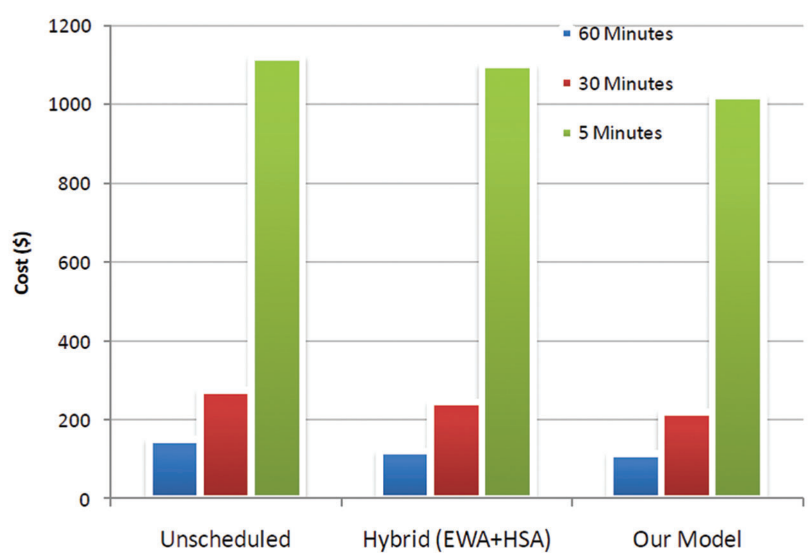

Figure 5: Comparison of cost with edge nodes

The performance evaluation of the proposed model has been performed on various existing scheduling techniques in the basics of scheduling delay, PAR, and cost. A different scenario has been considered by varying the number of appliances with other numbers of edge nodes. The trade-off between cost and quality of service has been observed. We effectively manage the peak hours to find a suitable schedule for the appliances.

6 Conclusion

In this paper, the edge nodes are deployed near smart homes to manage energy consumption. The non-cooperative games are applied to the scheduling process, which helps to reduce the total energy cost. Cloud computing is used to process the scheduling program to mitigate the fault in peak hours. The edge nodes can handle the latency issue. The fairness approach is applied to assign the edge nodes to the group of homes based on functional appliances. Eight types of appliances are considered in each home. The operation time interval (OTI) is regarded as 60, 30, and 5 min. The simulation results showed that the proposed system helps reduce the scheduling delay, PAR, and total cost for the same energy demand compared to existing techniques. The proposed approach gives better quality of service at less cost. The edge node selection method can be further improved with optimization techniques.

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