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Article

A Novel Energy Optimization System for Renewable Demand using Heuristics, Distributed Systems, and Machine Learning in a Smart City

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Abstract: Transportation, environmental conditions, quality of human life within smart cities, and system infrastructure have all needed practical and dependable smart solutions as urbanization has accelerated in recent years. In addition, the emerging Internet of Things (IoT) provides access to a plethora of cutting-edge, all-encompassing apps for smart cities, all of which contribute significantly to lowering energy consumption and other negative environmental impacts. For smart cities to meet the challenge of using less energy, the authors of this research article suggest planning and implementing an integrated power and heat architecture that puts renewable energy infrastructure and energy-storage infrastructure at the top of the list. To address these issues, we describe a smart proposed NEOSRD architecture that uses a distributed smart area domain to optimize renewable demand energy in a smart city across a wide area network. The energy requirements of desalination procedures are negligible when compared to the total local energy consumption and transportation, a feat accomplished by the proposed NEOSRD system. Here, the computational model shows how the established system is a valuable response to our problems and a cost-effective strategy for creating smarter structural elements that cut down on overall smart cities' energy costs.

Keywords: renewable energy, Internet of Thinks, renewable energy storage, smart city.

1. Introduction

There are many issues [1] that have arisen as a result of fast urbanization and financial development, and the smart city aims to solve or at least mitigate these issues by maximizing efficiency and effectiveness in areas such as energy production, waste management, and transportation. Multiple classifications of smart city developmental regions have appeared in recent literature [2], with the drawback of the power consumption priority being founded on the intelligent system framework. Smart cities [3], in general, have varied and abundant energy requirements [4], and they employ new methods in a systematic fashion, making full use of all available energy sources. The

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current smart systems architecture fails to handle energy consumption, but it does a good job of dealing with other issues, such as the use of renewable resources, increasing requirements, and the demand for power-efficient transportation models. Some models were developed in order to better inform customers about urban dynamics and the effects of renewable energy policies [6]. However, these strategies are often treated independently in the energy sector, leading to ineffective solutions [8] for smart city infrastructure. An integrated smart-city model [9] comprising all energy-related processes is highly desired to successfully satisfy the expanding energy needs of existing and future cities while maintaining the model's size and complexity. [10]

An electrical network may make better use of its grids and buildings by including energy storage technologies to perform tasks like lowering peak demand and balancing the load. Using the smart development system shown in Figure 1 as its foundation, conventional studies have tackled a number of massive energy-oriented activities [11]. This system's components include participation, inclusion, and cooperation. There are numerous links between the aforementioned domains and the energy system: Energy production ensures availability, distribution, and the usage of connection framework [12]. Furthermore, [13, 14], the major features for consumers that are accomplished depending on the energy panel infrastructure are the installation and transportation of energy modules.

In this piece, I'll be working toward two primary objectives. First, an understanding of such dynamics in the backdrop of power operations might be gained via the analysis of progress and trends by discovering synergies among various intervention domains. In addition, standard practices across a range of energy-related industries are analyzed from an operational and optimization standpoint. Another objective is to evaluate ongoing initiatives and software tools in order to propose methods for efficient power system modeling and maintenance, thus empowering consumers as well as decision-makers to construct sources of energy for smarter cities. In order to model them mathematically, they need the most important parts and growing bodies of knowledge, which are both part of these systems.

In order to maintain and permit the complexity of intricate systems in the area, interconnected and compatible systems are necessary due to the ongoing shift in the governance of these infrastructures in urban settings, which has resulted in the increasing development patterns of urban populations. Energy problems, especially in developing nations, are a prominent focus of study, and smart cities provide a promising environmental and technical solution. [15] Because more services may be provided thanks to improvements in information systems and infrastructure, municipal departments and facilities must adapt their operations accordingly. In addition, the upkeep of vital resources like energy and communication networks is greatly aided by the incorporation of technology standards, organizational needs, and integration criteria into the network's architecture. For a good infrastructure, network management systems must be strong, reliable, and able to work with other systems.

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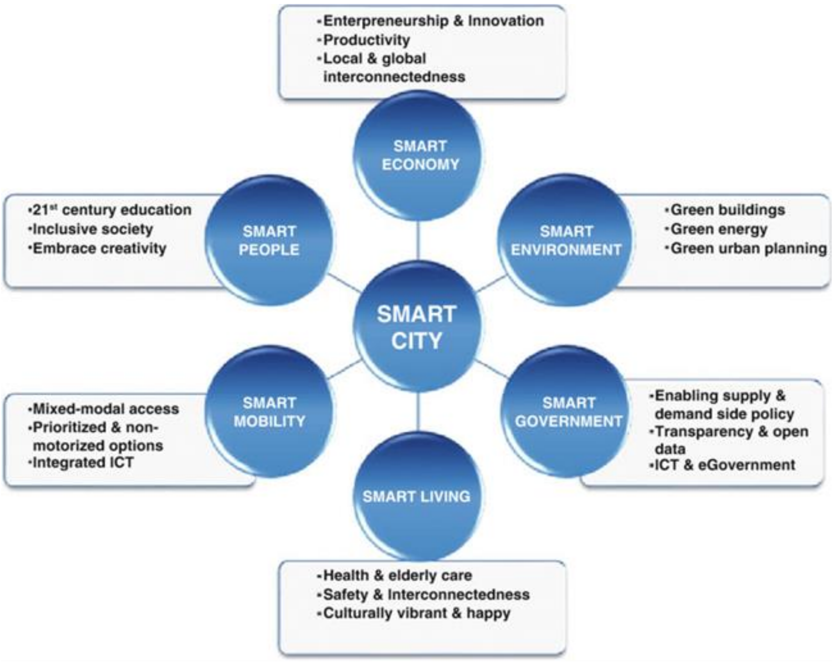

Figure 1: Smart City Model [23].

Figure 2: Smart city characteristics [24].

Many of the technologies that make up a smart city are shown and described using the smart route model in Figure 2. To name just a few, the primary domains of a given system include energy, water, transportation, building, and law and government. Some methods are discussed, as well as possible problems and drawbacks of smart city infrastructure. In this case, the exchange has affected energy control tactics used as RES well as ESS, particularly those aimed at optimising results for end users. The following illustrations depict power management systems and traditional methods based on different investigations.

2. Related Works

Rapid urbanisation, according to Baskar et al.[16], demands efficient energy systems for smart cities. Before presenting IoT devices in smart cities, the authors provide an introduction to power management in intelligent cities. Power harvesting and efficient

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solutions are examples of the first stage of energy management. Then, various approaches would be researched to learn how to store energy and make it more efficient for IoT use in smart cities. There have also been several submitted case studies that highlight the advantages of energy efficiency. The first case study looks at how putting equipment in smart home networks in a smart way could save money. The second use case looks at how to effectively set up specialised sources of energy in IoT end users and Smart cities.

A generalised demand-side management (DSM) framework was proposed by Ejaz et al.[17] to connect smart area networks to populated neighbourhoods. Also, issues relating to carrying numerous packs are formulated. Using integrated time models and inclination block rates, the model's results show that planned energy management approaches are used for energy prediction at a reasonable cost. The energy conservation processing unit centred on DSM conducts effectively managed energy control systems and energy regulation regulators, which results in lower electricity costs, a lower optimum-to-average percentage, and increased user comfort.

The workloads of the virtual servers determine the fog's energy usage. Several different architectures for clouds, fog, and mobile devices were proposed in this article. The clouds as well as the fog provide users with readily operable virtual computers. A meta-heuristic approach is suggested here to meet the different needs of cloud and fog VMs. The optimization algorithm (Genitic Algorithm) and the binary swarm optimization algorithm are both used in this method.

To promote the concept of smart cities across multiple continents [19], this offers a variety of suggestions, including but not limited to: urban planning; improved traffic management; network monitoring; public safety and health and supervision; security protocols; gunfire recognition; metres; and transit analysis. The Internet of Things was made possible thanks to smart buildings that provided users with access to low-cost IoT services. The authors considered business space convenience, accessibility, wellness, and energy efficiency. The writers considered energy over wireless links, especially as part of an IoT-based strategy, opens up new and exciting ways to completely change the way a wide range of devices work, as long as they meet the above requirements, which can be met naturally within IoT-based frameworks.

Several diagnostic manual approaches for lowering energy consumption (ECs) and peak-to-average ratios were developed by Ahuja et al. [20]. (PARs). Suburban energy consumption was recognised as a problem by the writers. To address this issue, we suggest a computational formula DSM-based technique for lowering PARs as well as ECs with little cost to the user in the form of waiting time. [21,22] Heuristic methods use the bacterial feeding optimization algorithm and the floral pollen algorithm. In contrast, a new optimization method was designed and tested for both standalone houses and multi-community "smart neighbourhoods," by merging the best features of the aforementioned current algorithms. Their constant use has to be weighed in terms of expected running times.

Several authors (SHU et al. This article presents the combined heat and power (CHP) architecture using a renewable energy system as well as an energy storage system (ESS) that aids in reducing the usage of energy in smart cities, as explained below.

3. Proposed NEOSRD Method

arious components have been developed based on quantitative analysis, estimates, and even crucial period response to create ESS strategies to equal energy requirements and load levelling. Methodologies and some of their possible drawbacks are discussed below. The energy control tactics that make use of ESS in this case have been affected by the exchange, particularly on the consumer side. Distribution system operators (DSOs) assist customers by using energy based on the energy prices incurred during peak times of system demand. Customers will have the option to use electricity at peak times, but ESS systems are designed to respond to demand and generate electricity at less expensive times. Since the DSO mechanism is also very effective, it is useful for such distribution network operators. This strategy is effective in industries where time-of-use (TU) is a key consideration. Nonetheless, it is vulnerable to the emergence of new peaks and is, thus, heavily reliant upon that duty plot rather than on other relevant devices.

The optimal power flow (OPF) structure lets you use direct and indirect estimation tools to improve pressure estimates. This makes it easier to include time-varying factors in the parameters of the ESS scheme and the structure of the plan as a whole.

Several studies implement a very sophisticated energy transition, with transport and regeneration infrastructures playing key roles. If the issue is to be reduced to a manageable size, and if the branch node will be employed to accomplish the desired solutions in order to meet the energy requirement, then the cost of the construction must be kept to a minimum.

This research article outlines a strategy whereby the fundamental concept has indeed been developed to optimise the total need profiles of an energy resource across a set of time intervals, thereby resolving the ESS scheduling problem. The approach allows for a variety of tactics to be used in order to satisfy full energy management and production targets while also achieving the appropriate energy pricing expectations.

A. Optimizing Energy Requirements by Formation Algorithm

If we assume a distribution conceptual model, then a simple network or creating time-varying power consumption is provided via multiple types of GCP above a time domain equaliser E = tm_1, tm_2, tm_3, tm_4, tm_5,... t_{mn}, where tm1 and tm2 form a consistent plot. Facilities like transformers, conveyor transmission compressors, load-restricted lines, and environmental factors all play a role in getting energy to this power grid or architecture. For a certain HT amount of time, tmi, the energy need, EDi, for the constrained source potential is calculated as follows:

$$HT_{ti} = ED_i tm_i \quad (1)$$

$$HT = \max(HT_{ti}) \quad (2)$$

The optimal solution may be found in the shortest amount of time, which is inferred to be related to the idealised limitation of the limiting source. For this purpose, the energy levels or period of time-outcome energy is denoted by tmi, and E_i with full energy excellence Ee and total EP_i operational efficiency and resource quality N_i stores it in it. The charging and operating needs of GCP system resources providing energy will not be compromised by the restrictions placed on the use of the E_i, as shown below.

$$HT_{ti} = \rho i_j \leq M \quad (3)$$

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where ϱ may be the value of Ee effectiveness, where stands for the energy coefficient's potency. Most of the Ee's output, which is capped at its process energy, was met by consumer demand. EP_i at regular periods of a period of length t_m, as shown in the following Equation (4).

$$\frac{i_m}{tm} \leq EP_i \quad (4)$$

When renewable energy technology is used in a CHP architecture, the total amount of energy released during an interval of a period that depends on the preceding time is M_k.

$$\sum_{k=1}^{N} M_k = Ee \quad (5)$$

Incorporating *m*, a time-dependent factor, into calculations of load as well as discharge rate in relation to energy values. Where *SE* appears to represent q separate energy load or release that will occur over the investment period. The problem may be mathematically realised as selecting some small subset SE of energy goals out of some much larger set ES of energy structures assuming that the range is k_1, k_2, k_3,….k_{es}. Therefore, the following conditions for Equation (6) hold:

$$M_{tm} + \sum_{i=1}^{k} \rho_i Yc_i \leq M\ r = 1,2,3 \ldots k. \quad (6)$$

To achieve the outcome and peak-demand-shaving goals, the developer must find a charged or discharged strategy that takes into account the energy needs of all the buildings using the ESS at each time period. According to the exceptionally heuristic and pre-set technique of constructing subsection amounts, multiple solutions will be achieved for the provided maximum quantity of pieces. In this case, we use different conditional approaches to set (SE) the energy (EN) using the numbers k_1, k_2,k_3,…k_n and generated (RG) parameters. Figure 3 shows how a 40-kWh capacity can be broken up into 10 separate 2-kWh squares or a mix of 2-kWh, 3-kWh, 6-kWh, and 7-kWh squares.

This is an important part of the optimal solution, which always requires coming up with a lot of potential solutions. By using the merging process indicated in Figure 4, the node executes the optimal heuristic method through a CHP architecture depending on the energy frameworks of renewable generation systems. The description, consolidated from the requirement phase and the energy efficiency improvement process for ESS collaboration, is another noteworthy piece of work.

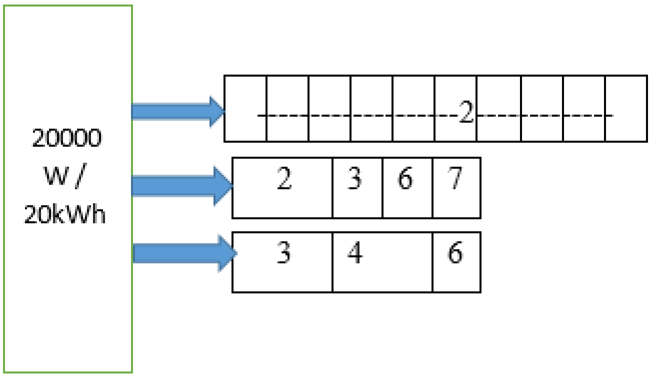

Figure 3: 2000w or 20 kWh Energy Storage System

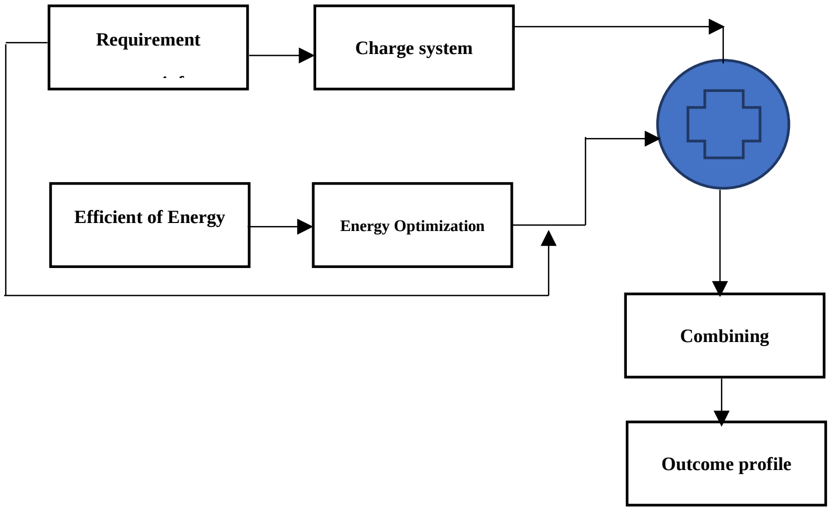

Figure 4: Proposed NEOSRD method process flow.

The amassed power is used at peak times or maybe after dark, when there isn't any directed power. Its ESS-based model has a set to which each battery may be attached. That's a two-for-one deal that demonstrates a broad variety of battery types being charged and discharged, leaving room for interpretation of their ultimate use. For each time interval, a binary parameter BP(tm) is assigned a value in the format shown below.

$$BP(tm) = \begin{Bmatrix} Charged & 1 \\ Didcharged & 0 \end{Bmatrix} \qquad (7)$$

B. Low Cost Energy Model

Energy tariffs on a daily or seasonal basis may be determined by a number of different regulatory frameworks. T threshold models for energy pricing are tailored to this time of day specifically, and are preprogramed in their entirety. CPP refers to a type of T that adjusts rates according to critical conditions. In this case, customers' electricity rates may continue to rise in line with normal inflation, reflecting the current cost of delivering electricity to the general public. T is used in all parts of the design, even the energy-dependent charges that are standard practise according to the IFR. The energy cost at each given time, denoted by the variable time tv, looks to be an a-linear function of the total energy need. The following equation gives an estimate of how much energy *TE* is needed to make all three products (μk + αk + βk) in the same amount of time.

$$TE = \mu_k + \alpha_k + \beta_k \qquad (8)$$

Using the IFR approach, the following equation is how power costs are determined:

$$\delta = \begin{Bmatrix} \delta_i & 0 \le TE \le TE_i \\ \delta_j & TE_i \le TE \le TE_j \\ \delta_k & TE_j < TE \end{Bmatrix} \qquad (9)$$

where a δ amount represents the proportion of total electricity costs attributable to usage. Power use levels were denoted by "TE_i" and "TE_j," whereas "δ_i," "δ_j," and "δ_k," represent respective prices for various nitty-gritty components. Depending on the degree of usage and other factors, balancing the need and the production of energy may be beneficial for either the network or the product. It shows the differences between the busiest and quietest times of day for every time period with an individual user. To compute this, you'll need to use the notation:

$$\delta = \frac{\max\,(TE_{(tm)})}{Tm^i \sum_{tm=i}^{Tm} TE} \qquad (10)$$

$$\delta_N = \frac{\max\,(TE_{(tm,N)})}{Tm^i \sum_{N=i}^{n}(\sum_{tm=i}^{Tm}(TE(tm,N)))} \qquad (11)$$

Algorithm 1 suggests that renters are under significant time pressure to get their tasks done in a short amount of time. Therefore, reducing processing times and costs is crucial to ensuring happy customers. As a result, it seems to be a kind of time-based trading that may save costs by optimising wait times and user payments in relation to how long each step of the process takes. The following equation shows how the math works out how long each piece of programmed devices δ has to wait.

$$\delta_a = \frac{\beta_a - \propto_b}{\varphi_a - \omega_a - \propto_b} \qquad (12)$$

The highest RES productivity is also a significant contributor to rising worldwide pollution. Every one of these formulations has as its optimization objective a procedure that may be represented as the following equation:

$$min \sum_{tm=1}^{48}\left(\vartheta_a \sum_{i=1}^{I}(TE_{(i,tm)} \times Y_{(i,tm)})\right) + \vartheta_b(\alpha_{(a,tm)}), \qquad (13)$$

$$\delta_{ed} \leq \vartheta_{ed} \leq \rho_{ed} \tag{14}$$

$$\delta_{sd} \leq \vartheta_{sd} \leq \rho_{sd} \tag{15}$$

Algorithm: The First Random Population Heuristic Method is:

Step 1: Set the default values for all variables.

Step 2: If N is the number of customers, then the number of transactions is equal to n.

Step 4: All a = A systems are equivalent.

Step 5: t = T openings to do a population that was assembled at random is a deliberate feature of the system's physical layout.

Step 6: Put the equation to the test in this context.

Step 7: Main work = FW

Step 8: If (PE (tm) (tm) and (FW (pe) FW (pe1) are both true, then

Step 9: Equals FW(pe) = FW(pe)

Step 10: The power is turned on and the system is operational Else

Step 11: Wait until traffic is light.

Step 12: if else

Step 13: fw(pe) = FW(pe– 1) .... if .... END .... for

Step 14: To begin a new population

Step 15: Select X and Y as the Parameters

Step 16: The Else-If Conditional, Number

Step 17: multiply at fw (x, y) ... End if

Step 18: Pop-Up Begins(PS, PN)

Step 19: End Procedure

Step 20: If high value of PE(tm) in every phase PE(tm) is higher

End: Algorithm

A special feature was implemented in order to maintain the convenience of the product under review while still decreasing electricity costs. In the objective function ∞_1, $\infty_2 \in i, j$ / ∞_1, $\infty_2 \in i$., the attributes i and j represent the relative importance of the various parts. Both negative and positive are possible, but only one will be shown. Our primary goal in this study is to decrease energy bills by making products more tolerable to end users. The observations of the mathematical framework reveal, as we will see in the findings and results discussion section, whether any model of power generation established contributes to reducing the overall difficulties but has been justified as an economically viable strategy that focuses on the construction of such intelligent network facilities under computational conditions.

4. Empirical Results and Discussion

Results are presented in Table 1 and Table 2, and visual representations are provided in Figures 6 to 8. The table below shows that while the number of squares increases, the amount of energy used in the release process also increases, which in turn increases the efficiency of the ESS.

A single GCP supplies energy to a power grid with fluctuating energy needs over a time circumpolar TZ consisting of N identical phases *{1, 2, …. n}* where TZ = tm_1, tm_2..., tm_n, and tm1 and tm_2 are the first and second epochs of a continuous graph with the same time *tm*. Figures 6 and 7 also show that this node or architecture gets its energy from a transformer, a conveyor transmitting expander, load-restricted connections, and environmental factors that are based on how much energy it needs.

Table 1: Summer time analysis of Characteristics and Study

(kW)	Base Case	Requirement response
Pm	1.75	2.87
Peak Requirement	1.98	2.76
Peak modification	-	0.15
Power	2.008	1.99

Table 2: Winder time analysis of Characteristics and Study

	Base Case	Requirement response
Peak Threshold (kW)	1.8	2.66
Peak Requirement (kW)	1.99	2.55
Peak difference	-	0.85
Power (kWh)	3.009	2.007

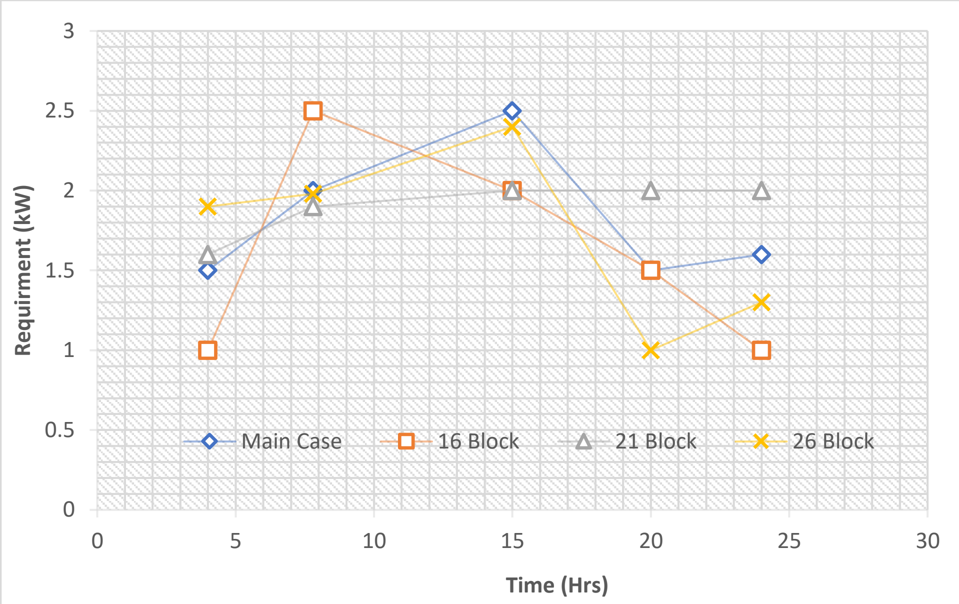

Figure 5: Summer time energy block requirements by ESS Response

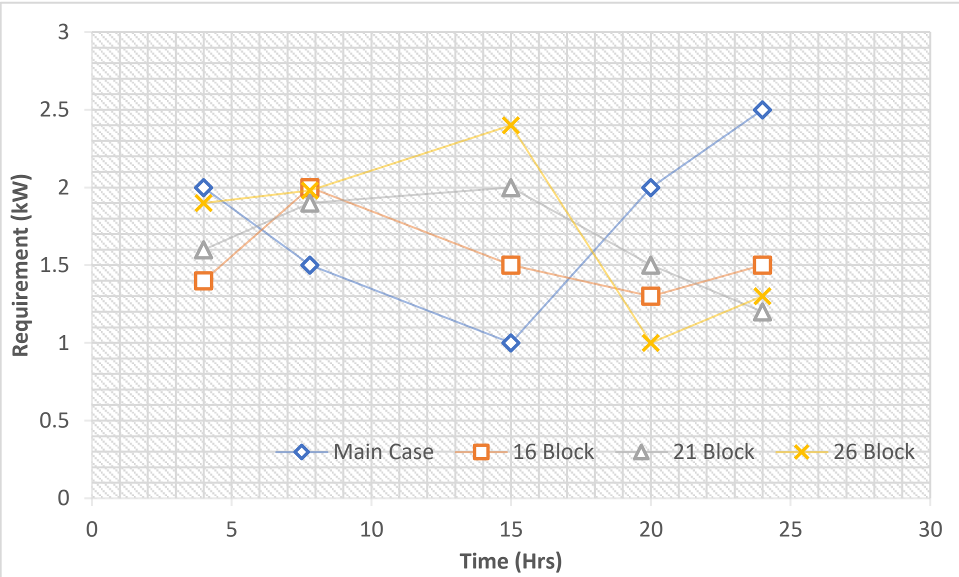

Figure 6: Winder time energy block requirements by ESS Response

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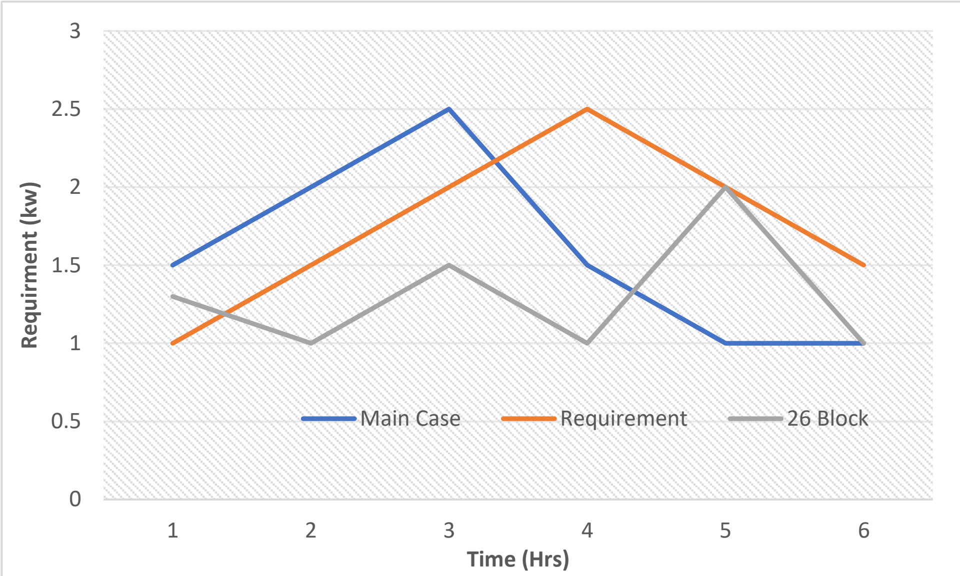

Figure 7: Winder and Summer Time Energy Requirements

TU pricing restrictions mean that lower charges for the year-round cost of energy are often reduced in the summer and winter months. The utilization-based taxes also mean that load-leveling would be indirect since interest payments will be shifted to times of the year when energy prices are lower.

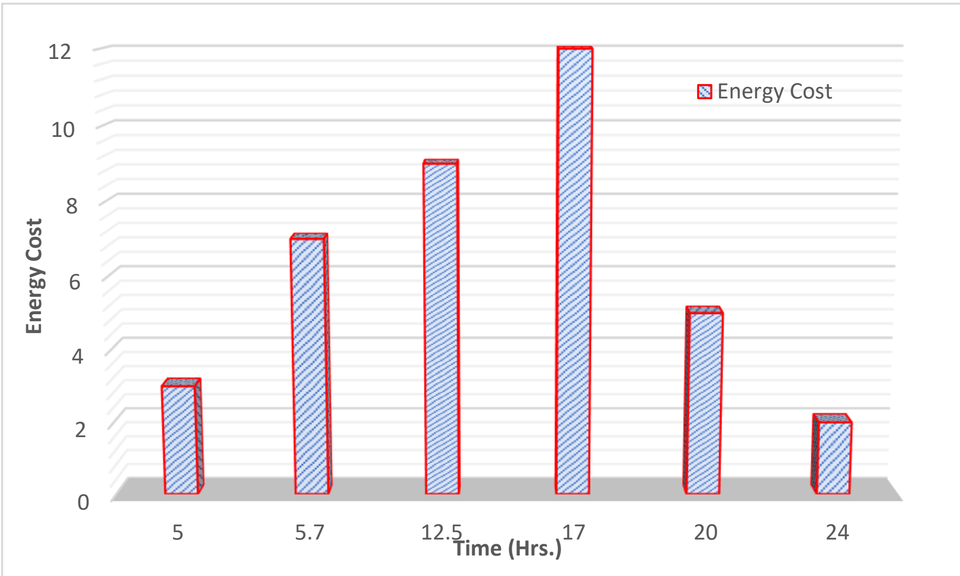

Figure 8: ESS for Time of Utilization System.

The location of a greater block of supplies in a given time that cannot be split up and disseminated to other various periods to lower energy requirements is a common cause of the average growth in these circumstances. These results indicate that in the basic scenario, peak consumption reductions, a straighter curve, and energy cost reductions may be realised whenever an ESS is distributed utilising the approach.

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Figures 5 and 6 are line graphs depicting summertime and wintertime demand phases, respectively. Installing a TU-based power storage system in a home to save money is hard because there aren't many limits on how much power you need, as shown in Figure 8.

Table 2. Simulation parameters by using the modified derivative algorithm.

Threshold Parameters	Parameter Values
Volume of People	600
Term selection	Wheel
Count	0.89
Mutation	0.32
Stopping Criteria	Max.
Max. Generation	1500

The development issues in DSO will be caused by the consumer benefits depending on the TU tariff. To meet the node's total demand, the network must be strengthened with more resources, such as a CHP architecture based on renewable energy sources to handle the increased peak energy consumption (RES). The power generation system utilises the patterns of energy bills, the sequence of power consumption, the degradation of the PAR, the degree of comfortability, and the optimum incorporation of RES, all of which are presented in Table 3 below, to determine the best course of action.

Based on Figure 9, each time slot during the day should have a power network backpack potential of approximately 20 kWh. The layer's batteries were seen as a potential renewable resource, and the batteries themselves were viewed as a potentially mobile way to integrate decentralised power generation. Power is generated using solar panels, which account for around half of the entire load supply. As can be seen in Figures 9 and 10, 1000w solar arrays installed in every smart city significantly alter the city's energy generation capacity in consideration of its fuel bills and the cost of its energy source. Figure 10 suggests remember that increasing overall energy consumption is preferable to RES in that it helps consumers reduce power costs. The findings demonstrate that consumers may reduce power use sufficiently and effectively by regulating their energy consumption. Figure 12 displays the daily decline in the standard energy charge [21, 22], as well as the daily, weekly, monthly, and yearly reductions in electricity costs for RES with energy usage. Therefore, the suggested approach employing NEOSRD is more trustworthy than existing methods.

Increased energy bills and increasing energy requirements that cause energy interruptions or stopping of power services are two key problems with the traditional electricity system. In this case, the power billing system has been updated to employ a TOU and

IFR combined model to educate customers and so reduce peak consumption. The ability of power generation in our context boosts the efficacy of such techniques, allowing utilities to meet customer demands and end users to lower energy prices.

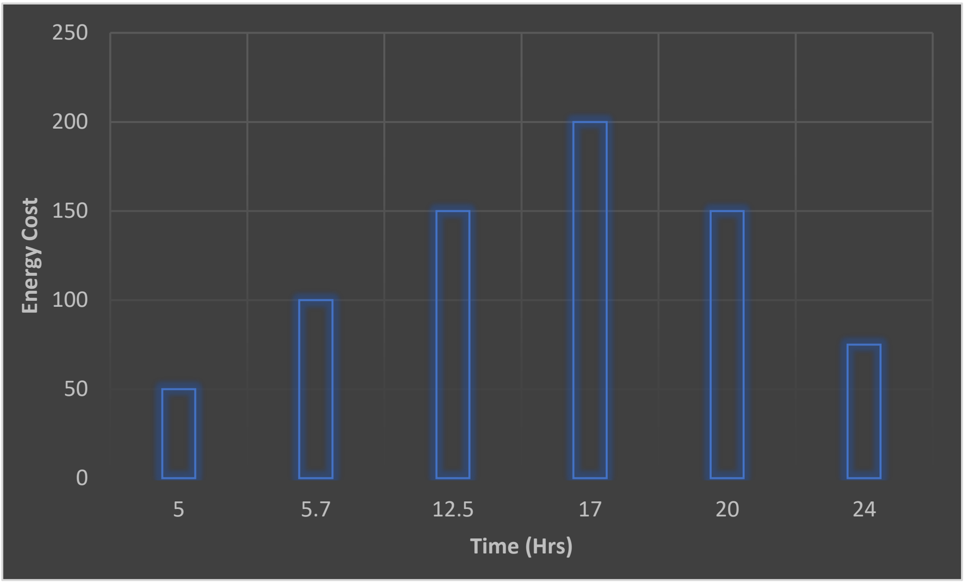

Figure 9: Electricity power intent

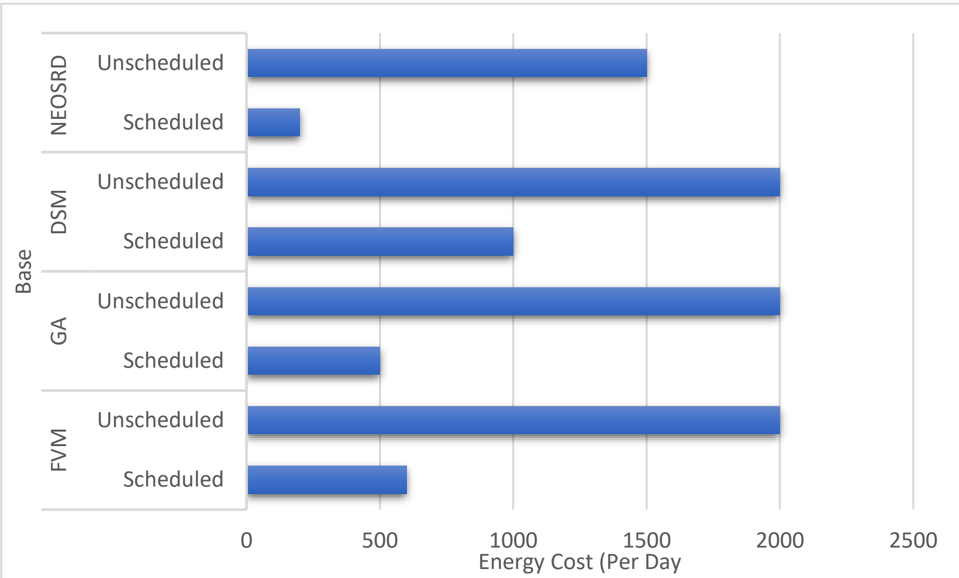

Figure 10: Reduction of Electricity Energy

A. Time Period of Waiting

There is a correlation between how much an appliance costs to run and how long it takes to be ready to use. Smart consumers may reduce their monthly power costs by following a power-optimal schedule for their equipment. Because of the uncertainty of demand in different price schemes, equipment's scheduled on and off times are not fixed in advance. It turns out that there is a countervailing link between the time saved and the amount of money saved on electricity. Time limitations on the goal functional allow the NEOSRD approach to provide a structure that maximises customer happiness and

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minimises energy costs. Figure 11 demonstrates that the energy expenditure is high for both low and intermediate waiting times, while Table 4 shows that higher efficiency in the waiting period ratio applies to every design.

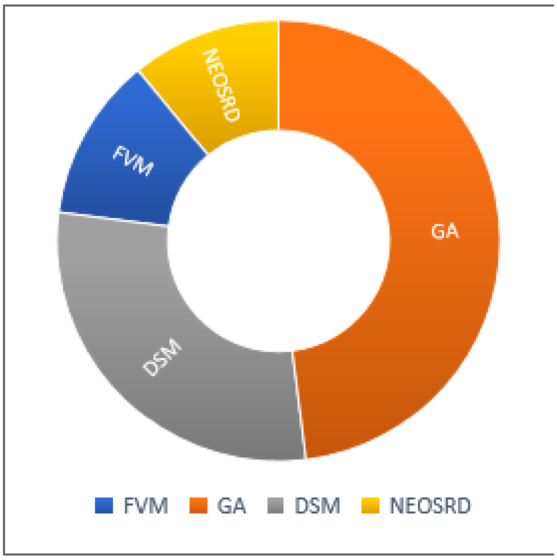

Figure 10: Existing and proposed system's energy consumption comparison

Table 4: Proposed system parameters evaluation

Volume of People	Generation (Max.)	Power (Max.)	Bill (Max.)	Bill / Day No Renewable Panel	Bill / Day Renewable Panel	Process Time
600	1100	15.84 16.87 19.26	70 72 74	$1.24x10^3$ $1.24x10^3$ $1.24x10^3$	$9.67x10^3$ $6.67x10^2$ $5.57x10^2$	3.12 2.1 1.6
1200	600	13.35 14.23 14.32	77 78 80	$1.24x10^3$ $1.24x10^3$ $1.24x10^3$	$4.37x10^2$ $6.76x10^2$ $8.67x10^2$	0.98 2.4 2.76
1800	200	13.54 16.87 14.34	68 79 85	$1.24x10^3$ $1.24x10^3$ $1.24x10^3$	$7.37x10^2$ $6.87x10^2$ $4.56x10^2$	2.6 2.4 0.96

The goal of the optimization procedure and the goal feature integrated into the algorithm is to delay the release of any device that needs to be improved. The vehicle scheduler will reschedule an appliance to a less expensive time of day if its peak power use falls outside of the effective energy window for that time of day. In addition, by disregarding the wait period element, optimal planning has indeed been achieved. It has

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been shown that our new way of doing things is more useful than the usual way of doing things.

5. Conclusions

In this research article, we examine how the idea of NEOSRD and its relevance in a modern city may assist in remedying the issues of power consumption brought on by fast urbanisation. These challenges were brought on because of rapid urbanisation, which is a result of rapid urbanisation. In particular, we investigate the many possible solutions to these problems. The optimization of algorithmic renewable energy needs for smart cities helps save high-priority resources such as communication and power infrastructure by influencing network architectural technology standards, organisational policies, and implemental parameters. This is one way that smart cities can benefit from algorithmic renewable energy needs optimization. Our method involves disseminating a smart urban area structure across a large network using a variety of optimization strategies to achieve more effective information translation in less processing time and with a low level of complexity. This is done in order to minimise the amount of work that needs to be done. In the not-too-distant future, there is a strategy to use learning approaches that will simplify the system.

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