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RESEARCH ARTICLE

Efficient Energy Management for Household: Optimization-Based Integration of Distributed Energy Resources in Smart Grid

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ABSTRACT Energy demand is increasing globally due to the growing human population and progressive lifestyle. The adequate use of available energy resources, including renewable, contributes to a country's economic sustainability and future development. Optimization–based energy management and cost minimization plays a significant role in overcoming energy crises in less developed countries. In this paper, an optimization–based dynamic energy management technique for smart grids is developed based on the integration of available renewable resources and variable consumer demand, distinctive to underdeveloped countries. Consumer demand is classified into fixed, flexible, and highly variable based on population characteristics. In this work, we developed a Dynamic Multiple Knapsack DMKNS algorithm, which automatically schedules energy provision to various users by optimally accounting for the available resources (Grid and Renewable). The proposed method provides a low-cost solution by maintaining a constant energy supply while preserving consumer comfort and grid stability. The simulation results with various intermittent availability of resources using MKNS show a saving up to 50% for a variable energy demand user. The proposed method is general and can also be applied to various underdeveloped regions with similar consumer demand and statistics.

INDEX TERMS Optimization-based energy management, dynamic multiple knapsack, energy storage, renewable energy system, smart grid.

I. INTRODUCTION

Over the last few decades, energy crisis and global warming have motivated the use and development of alternative, sustainable, and clean energy sources [1]. The use of these resources reduces the emission of carbon monoxide and other poisonous gases, which significantly improves the environment. Smart grid provides energy resource integration and management with optimal distribution and monitoring using two-way information exchange [2], [3]. In many underdeveloped countries, the use of renewable energy sources and their management and integration with the smart grid is still in the early stages of its development [4]. The lack of technology and planning in these countries causes under-utilization and sometimes wastage of these resources, leading to an energy crisis and excessive usage of fos-

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TABLE 1. User classification.

Class	Users	Energy Consumption
A	U_1 and U_2	Fixed
B	U_3^f , U_4^f and U_3^v and U_4^v	Flexible
C	U_5^v and U_6^v	Variable

TABLE 2. Comparison of Traditional Grid and Smart Grid.

Characteristics	Traditional Grid	Smart Grid
Technology	Electromechanical	Digital
Distribution	One-way	Two-way
Generation	Centralized	Distributed
Control	Limited	Pervasive
Customer Choices	fewer	Many
Restoration	Manual	Self-healing
Monitoring	Manual	Automatic

sil fuels. In addition, the exponential population growth in these underdeveloped countries also significantly increases the demand-supply gap. Recent research of forecasting consumer's electricity also predicts energy growth across different sectors with significant contributions coming from renewable energy sources [5]. Contrary to the traditional power grid, the smart grid allows demand-supply interaction by sharing utility and consumer data, thereby providing optimal cost-effective solutions [6]. A comparison of inherent features between traditional and smart grids indicating overall operational efficiency and optimization is given in Table 2.

Globally, the increasing energy demand and excessive use of non-renewable sources are of serious concern for underdeveloped countries [7]. The main sources of energy are dominated by traditional power systems, which are centralized and mainly dependent on petroleum, natural gas, and coal-based power plants [8]. This results in extensive use of fossil fuels for power generation, leading to a significant increase in CO2 emission. Renewable resources are widely used across the world to overcome energy demand and the use of fossil fuels. However, the intermittent nature of these resources in the form of biomass, waste, geothermal, hydro, solar, and wind often present integration challenges leading to severe under-utilization [9]. Consequently, this leads to reliability issues, which affects the grid's sustainability and resilience. In such cases, the smart grid responds by demand side management (DSM), which includes action taken to plan, implement, and monitor predefined activities that affect the consumer's electricity utilization patterns [10]. The adopted strategy in response to consumer data by DSM is usually a dynamic pricing pattern adapted by the smart grid to overcome and reduce the effect of intermittent demand for energy. Recent research suggested various pricing schemes to serve demand-side management expectations to deliver consumer-based cost-effective solutions [11]. The notable pricing schemes based on usage patterns and estimations are Real Time Pricing (RTP), Time of Use (TOU), and Critical Peak Pricing (CPP). These pricing schemes are real-time and based on demand response, with usually an estimated increase of 1.2% in electricity supply at 1% GDP growth.

TABLE 3. Comparison of proposed study with existing studies.

ESS and RES Integration	Cost reduction in peak hours	Reference
Yes	Partly	[16]
No	Partly	[17]
Yes	No	[18]
Yes	No	[19]
No	No	[20]
Yes	Partly	[21]
Yes	No	[22]
No	Partly	[23]
Yes	Partly	[24]
Yes	Partly	[25]
Yes	Partly	[26]
Yes	Partly	[27]
Yes	Partly	[28]
Yes	Maximum (50%)	Proposed study

This highlights the importance of a dynamic pricing scheme to address the continuous growth of electricity demand. Following subsections elaborate on real-time pricing algorithms and energy optimization techniques in smart grid.

The paper is divided into five Sections. Section II reviews the literature review. Materials and methods are presented in Section III. Results are discussed in Section IV, a brief discussion is made in Section V and the paper is finally concluded in Section VI.

II. LITERATURE REVIEW

Optimization techniques in energy management aim to the analysis of available consumer and utility data to make an informed decision, providing cost-effective solutions. Several optimization techniques are developed over a period of time to maximize usage of power assets with necessary renewable resources integration [12], [13], [14], [15]. Different techniques have already been implemented with various advantages and limitations.

In [16] a novel energy management scheme is presented in which an efficient model for smart home infrastructure is developed to minimize user electricity bills, optimize energy usage with the integration of renewable energy resources, and maximize user comfort. Simulation results showed that electricity bill is reduced with peak power management. A genetic algorithm was used and to validate results PSO and ASO can also be used. In [17] a fast randomized first-randomized first-order optimization system is offered for dynamic energy management. An ideal forecast problem was formulated by reducing the compeer's costs of the allied power utility, as a huge numeral of user's manageable devices arena compassed in the system. This model validated that existing energy resources can provide benefits for the economic operation of the power grid.

In [18] a single-leader-multiple-follower Stackelberg game (SLMFSG) among the auctioneer and residential users. An improved auction-based dual energy storage scheme is modeled among a number of domestic units and share facility controllers in a smart grid. In [19] power management and mechanism algorithms of microgrid by energy storage are conferred. In [20] a price-based demand response scheme was designed and implemented. Sequences of undeviating estimate models for the load forecast were presented, such as standard autoregressive (AR) and time-varying AR (TVAR). A mutual energy storage and load scheduling with renewable incorporation for real-time residential side energy management using the Lyapunov optimization technique is presented [21].

Similarly, a home energy management scheme using a genetic algorithm is presented in [22]. Particle Swarm Optimization (PSO) is a cloud-built optimization method, which is used for minimizing energy cost with the contribution of consumer's demand [23]. Contrary to the genetic algorithm, the PSO technique contains personal best as well as global best to get an overall finest solution. However, it primarily works with load-shifting techniques, so cannot be implemented without constraints. Recently, the Knapsack method of optimization is used to solve combinatorial problems [24]. It is applied, where an economical and productive solution to the scheduling problems is required. Experimental results demonstrated that the Knapsack method is effective in minimizing and bringing regularity to the users fluctuating energy pattern [26]. However, the method is cost-centered and often ignores user satisfaction. The optimization techniques alone can have limited effect, however, an effective smart grid system deployment needs resource integration and their optimal utilization. The need for integration of an energy storage system adds flexibility to the system, however, it also introduces new challenges by adding complexity of management and control [25].

A closed-loop pricing algorithm addressing the random demand of customers uses the deviation in prices caused by the variation between actual and desirable load [23]. The algorithm gains the advantage of both open and closed-loop schemes, however, it heavily relies on constant consumer feedback to adjust real-time pricing response. A recent energy management scheme based on an efficient model for smart home infrastructure minimizes the user bill and optimizes usage with the integration of renewable energy resources [6]. However, the scheme is primarily residential-based, with very restricted control and management. A new concept of micro-grid with energy storage is introduced to prioritize renewable energy resources by providing power to the load and efficiently managing battery discharging and overcharging [27]. However, excessive use of battery power and storage renders it unfeasible for large-scale commercial use.

The energy generation in most of underdeveloped countries predominantly uses fossil fuel, which is not environment-friendly [29], [30]. In addition, the increase in population in some of these countries has compelled the energy sector to make use of alternate sources. These sources of energy are mostly pollution-free and environment-friendly, however, due to their intermittent nature and lack of energy storage technologies, their efficiency is quite limited. The installation of any adopted Energy storage system (ESS) is usually very costly, requiring regular scheduled maintenance. However, despite the overwhelming cost, the advantage of a storage system in overcoming the intermittent nature of renewable energy resources adds much-needed stability to the grid. A study shows that a grid, with a storage capability of 10% to 1% of its generating capacity is considered to be more reliable and stable [28]. In [31] a critical look at dynamic multi-dimensional knapsack problem generation is presented. Similarly, the dynamic programming approach to solve real-world applications of the multi-Objective unbounded knapsack problem is presented in [32].

III. MATERIALS AND METHODS

The algorithm is based on solving Multiple Knapsack Problem (MKP), which dynamically minimizes the piece-wise cost function. DMKNS adds an additional constraint to the Knapsack problem, which automatically regulates energy consumption and cost variations. The MKP is the generalization of a single Knapsack Problem, where more constraints are added in the form of multiple objects to find the optimal solution.

In this work, we have developed a Dynamic Multiple KnapSack (DMKNS) algorithm. The major contributions in this work are as follows:

- Developed a Dynamic Multiple KnapSack algorithm, which automatically schedules the provision of energy to various users by optimally accounting for the available energy resources (Grid and Renewable).
- The proposed DMKNS algorithm provides a low-cost solution by maintaining a constant energy supply and at the same time preserving consumer comfort and grid stability.
- The intermittent availability of resources and energy demand is met by introducing piece-wise pricing, which dynamically provides a low-cost demand-specific solution.
- Simulation results of dynamic energy management scheduling using DMKNS shows a saving up to 50% for a variable energy demand user.
- The proposed method is general and can also be applied to various underdeveloped regions with similar consumer demand and statistics.

The next sub-sections, briefly discuss different classes of users. Note that in DMKNS, the users are classified based on their energy consumption, ranging from fixed to variable demand.

A. CLASS A (FIXED DEMAND)

The *Class A* consists of two users U_1 and U_2. They have fixed energy demand and may have the same or different power ratings. The energy consumption is fixed and a day-a-head demand needs to be provided to the grid. In return, the utility provides energy at the lowest possible rate using piece-wise pricing.

Some of the important abbreviations used in this Section are listed below.

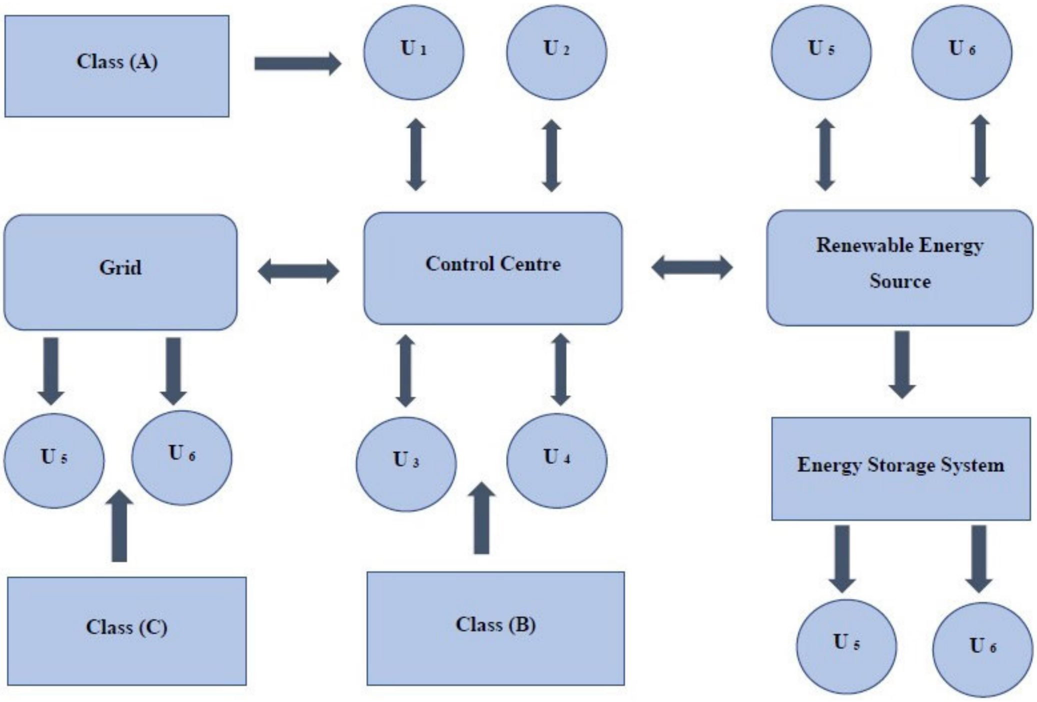

FIGURE 1. Schematic of the proposed DMKs scheme.

TABLE 4. Demand of fixed users U_1,U_2,U_3^f and U_4^f.

Hours	U_1 (KW)	U_2 (KW)	U_3^f (KW)	U_4^f (KW)
1:00 am	7	5	5	1
2:00 am	3	6	6	2
3:00 am	9	13	4	3
4:00am	13	14	4	4
5:00 am	11	8	4	2
6:00 am	7	11	5	6
7:00 am	5	9	2	2
8:00 am	4	11	1	6
9:00 am	15	0	2	3
10:00 am	10	1	4	3
11:00 am	4	15	6	6
12:00 pm	9	11	7	4
1:00 pm	5	10	3	4
2:00 pm	8	13	5	3
3:00 pm	5	15	3	6
4:00 pm	9	5	5	3
5:00 pm	6	4	3	5
6:00 pm	14	6	2	6
7:00 pm	8	8	2	7
8:00 pm	8	9	4	3
9:00 pm	4	4	3	1
10:00 pm	10	7	3	7
11:00 pm	7	9	5	4
12:00 am	11	9	7	2

B. CLASS B (FLEXIBLE DEMAND)

The *Class B* again consists of two users U_3 and U_4. They are further classified according to their demand as U_3^f, U_4^f and U_3^v, U_4^v. Note that the demand in this class is flexible, with U_3^f and U_4^f showing the behavior of U_3 and U_4 in fixed demand. Similarly, the U_3^v and U_4^v show their variable demand behavior. The utility will provide energy at the lowest possible rate, once responding to U_3 and U_4 fixed energy demand. The utility will give an option in case of variable energy demand to switch to fixed energy consumption to obtain the lowest rate. However, in case the users disagree, the energy will be provided at higher rates.

C. CLASS C (VARIABLE DEMAND)

The *Class C* also consists of two users U_5^v and U_6^v. Unlike *ClassA* and *ClassB*, these users have unpredictable and time-varying demand. As long as the demand is less than the supply, the utility will continue to provide energy from the grid at a slightly higher rate due to variable demand. However, when the demand is about to exceed the maximum capacity of the grid, the energy supply from the grid is automatically cut off. The energy is then provided by the renewable energy source integrated with the storage system. In this case, it is assumed that renewable sources attached to the battery storage system have enough energy to meet the excessive demand of the *Class C*. The Schematic of the proposed scheme is shown in Figure 1.

Figure 1 provides a visual representation of the proposed energy management scheme with a brief representation of multiple energy users, energy storage systems, renewable energy systems, and mainly the control unit which is automatically scheduling the overall system.Consumers are divided into three different classes, *Class A*,*Class B* and *Class C* along with multiple users. *Class A* has two users U_1 and U_2 and their energy consumption is fixed (i.e.) the utility has the knowledge of their energy demand day ahead. The demand of these users can vary in magnitude but will remain fixed in a specific time slot. The utility will provide energy to these users at the lowest possible rate as a reward. *Class*

B has two users U_3 and U_4 and their energy consumption is flexible. The utility will provide energy at the lowest possible rate, once responding to U_3 and U_4 fixed energy demand. The utility will give an option in case of variable energy demand to switch to fixed energy consumption to obtain the lowest rate. However, in case the users disagree, the energy will be provided at higher rates. Similarly *Class C* also consists of two users U_5^v and U_6^v. Unlike *ClassA* and *ClassB*, these users have unpredictable and time-varying demand. As long as the demand is less than the supply, the utility will continue to provide energy from the grid at a slightly higher rate due to variable demand. However, when the demand is about to exceed the maximum capacity of the grid, the energy supply from the grid is automatically cut off. A renewable energy storage system is shown in Figure 1. The energy is then provided by this renewable energy source. Similarly, in case of unavailability of energy from renewable energy systems, an energy storage system is integrated with the renewable energy system. A control center is also present to automatically schedule the variable energy demand by using an evolutionary algorithm.

In the mathematical preliminaries, we will first define various variables used in user scheduling in DMKs:

- The number of users is defined by "n" which corresponds to the number of objects in DMKs.
- The time slots variable "j" relates to the Knapsacks, with "m" as its maximum value. The prices of electricity in "j" slots are user dependent and can be fixed and variable.
- The total time required by any of the users to complete its task (i.e. 24 hours) is given by T_j^{req}.
- The cost function "$Cost_j$" is a piece-wise function that shows the cost of energy consumed in a given time slot "j". The system total capacity is represented by C_j.
- The amount of energy consumed by any user is denoted by E_i, which corresponds to the weight of the Knapsack. Whereas, "i" accounts for the time slots of energy consumed.

In order to represent the energy usage in a given time slot, let us define a Boolean integer variable Y_{ij} as:

$$Y_{ij} = \begin{cases} 1, & \text{Energy consumption in time slot } j \\ 0, & \text{No energy consumption in time slot } j \end{cases} \tag{1}$$

The linear objective function for cost minimization can now be defined as

$$min \sum_{i=1}^{n} E_i \sum_{j=1}^{m} Y_{ij} Cost_j \tag{2}$$

The integer variable Y_{ij} defining the energy usage is related to the amount of total energy consumed by each user as

$$\sum_{j=1}^{m} Y_{ij} = T_j^{req} \tag{3}$$

Note that "m'' defines the maximum number of time slots, which is incremented hourly. The total energy consumption in the proposed method is constrained by the maximum capacity (C_j) of the grid and can be mathematically expressed as:

$$\sum_{j=1}^{m} E_i Yi - j \leq C_j \tag{4}$$

The main focus of the DMKs algorithm is to meet the unpredictable and time-varying demand of *Class C* users. In order to accommodate these demands, let E_j^t be the total energy consumed by U_5^v and U_6^v users, when their total demand becomes greater than the maximum capacity (C_j). In this case, the capacity constraints change to:

$$\sum_{j=1}^{m} E_i Yi - j \leq C_j - E_j^t \tag{5}$$

In order to account for the excess energy generated by renewable energy, let E_j^r represent the excess renewable energy. Note that the constraint equation is further modified to account for these changes and can be written as:

$$\sum_{j=1}^{m} E_i Y_i - j \leq C_j - E_j^t + E_j^r \tag{6}$$

It is observed that (6) account for the case when the E_j^r exceeds the demand and is returned back to the grid to impact the overall cost of the scheme. The parameters used in the mathematical modeling and analysis of the proposed DMKs scheme are summarized in Table 1.

The derived mathematical expressions defining the scheme along with these parameters are used in the next section for the simulation and results.

IV. RESULTS

In this section, we present simulations and performance evaluation results of the proposed DMKs scheme with additional constraints of energy consumption and average cost under various availability conditions of energy sources and time slots. We are using the pie-wise concept of pricing in multiple time slots. It is important to note that the need and selection of multiple sacks are to account for variable prices in different time slots, which adds much-needed flexibility to a single knapsack and accommodates user comfort. The proposed scheme is valid for large-scale integration, however, without loss of generality, we consider only three classes with a maximum of two users in each class.

A. DEMAND OF Class A (FIXED), B (FLEXIBLE) AND C (VARIABLE)

The first classification in the simulation and analysis is the simple case of energy consumption by the fixed demand user i.e. *Class A* (U_1 and U_2). The grid provides them with energy at the lowest possible rate due to fixed demand. The demand data spread over the entire day, charged at a fixed rate of$2/kW is shown in 4. Note that the fixed demand of the

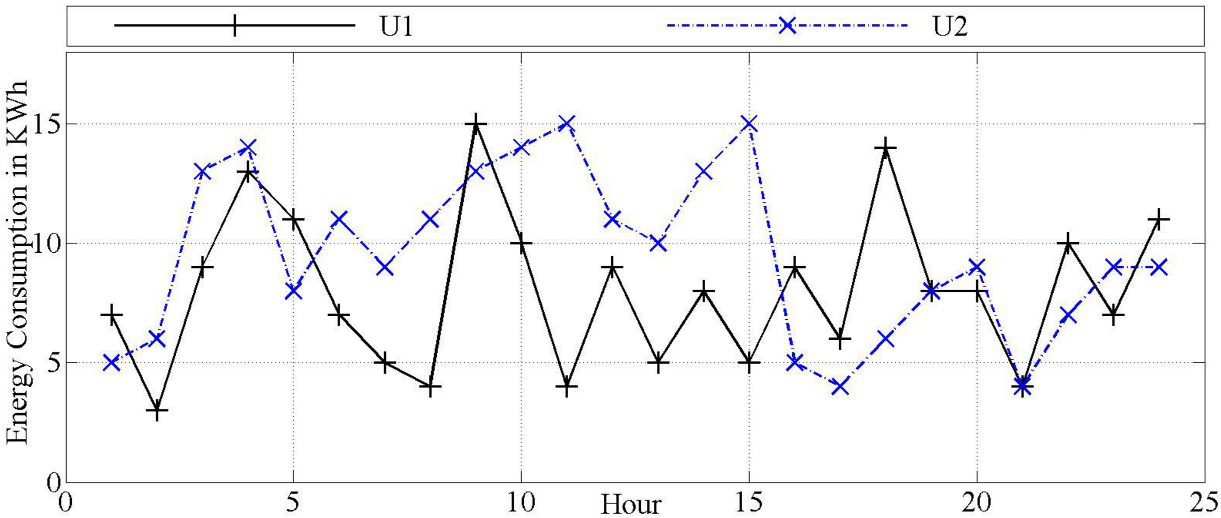

FIGURE 2. Energy fluctuation of U_1 and U_2 in terms of units consumed (KWh).

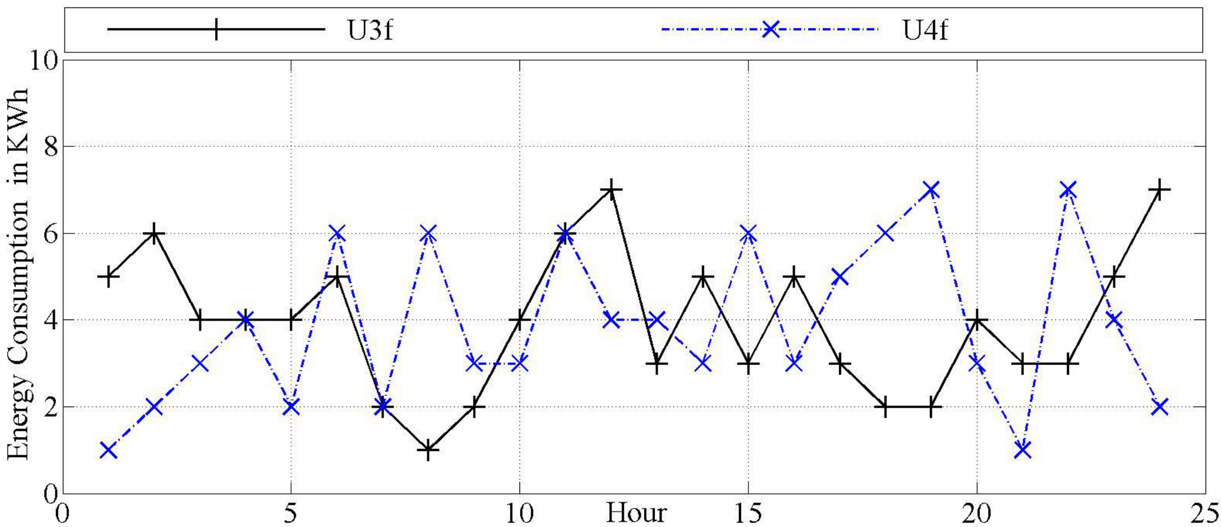

FIGURE 3. Energy fluctuation of U_3^f and U_4^f in terms of units consumed (KWh).

users follows a random demand model, where each temporal slot is uniformly distributed from 1:00 am to 12:00 am all-inclusive.

The energy usage of U_1 and U_2 giving details of random fluctuation in consumption is shown in Figure 2.

The user data along with its consumption shows an ideal case, where fixed demand places a predictable load on the grid allowing low prices at rates for the users.

Next are the *Class B* users, which are also known as flexible users U_3^f/U_3^v and U_4^f/U_4^v. They can switch their demand between fixed and variable. Note that the behavior of a fixed demand user is already discussed in the preceding paragraph in detail and also shown in Figure 3.

So without loss of generality, we will discuss variable users behaviour only i.e. U_3^v and U_4^v. The demand of these users is shown in Table 5. These users have variable energy demands throughout the day with added flexibility to their energy usage. In this case, the utility will provide energy comparatively at higher rates (i.e. $5/KW$) than the fixed energy users. The data of units consumed is plotted in Figure 4.

B. DEMAND OF Class C (VARIABLE USERS)

The next is the variable class users U_5^v and U_6^v. Note that the maximum energy allowed to all users in this class from the grid is 15 kW. In case of excessive energy consumption ($>$ 15 kW) by the users, the same can be drawn from the renewable energy source and energy storage system. In addition, note that the excess energy during the day is provided by renewable sources, and the same is drawn from the storage system at night. The demand of variable users (U_5^v and U_6^v) is shown in Table 6.

Energy consumption of of U_5^v and U_6^v is shown in Figure 5.

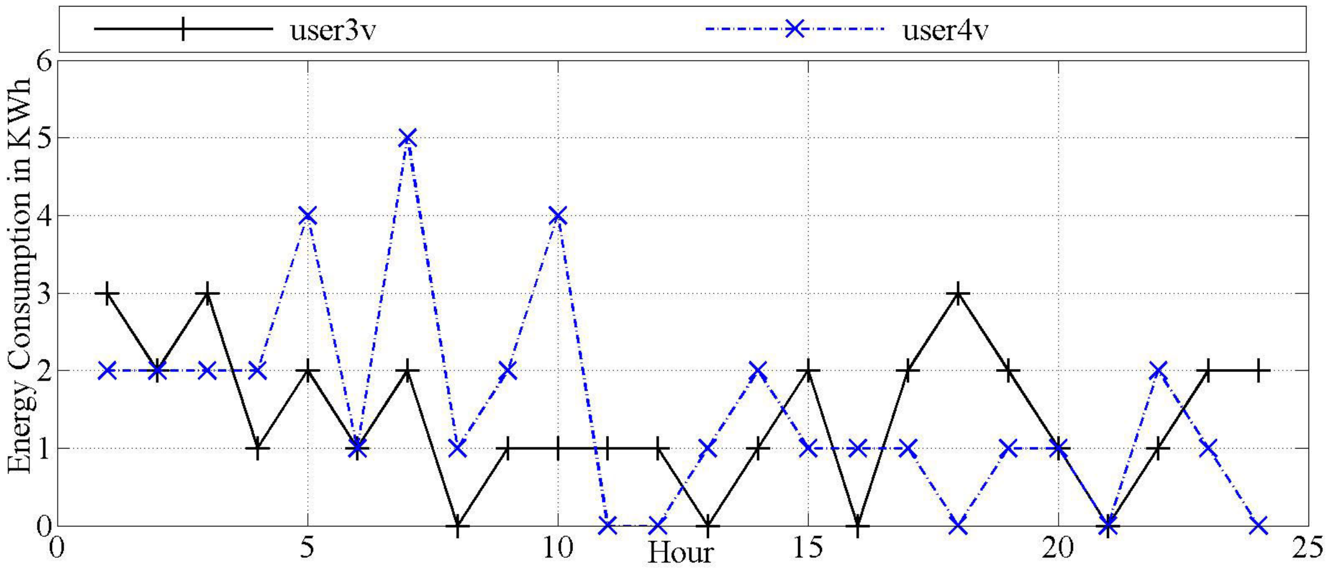

FIGURE 4. Energy fluctuation of U_3^v and U_4^v in terms of units consumed (KWh).

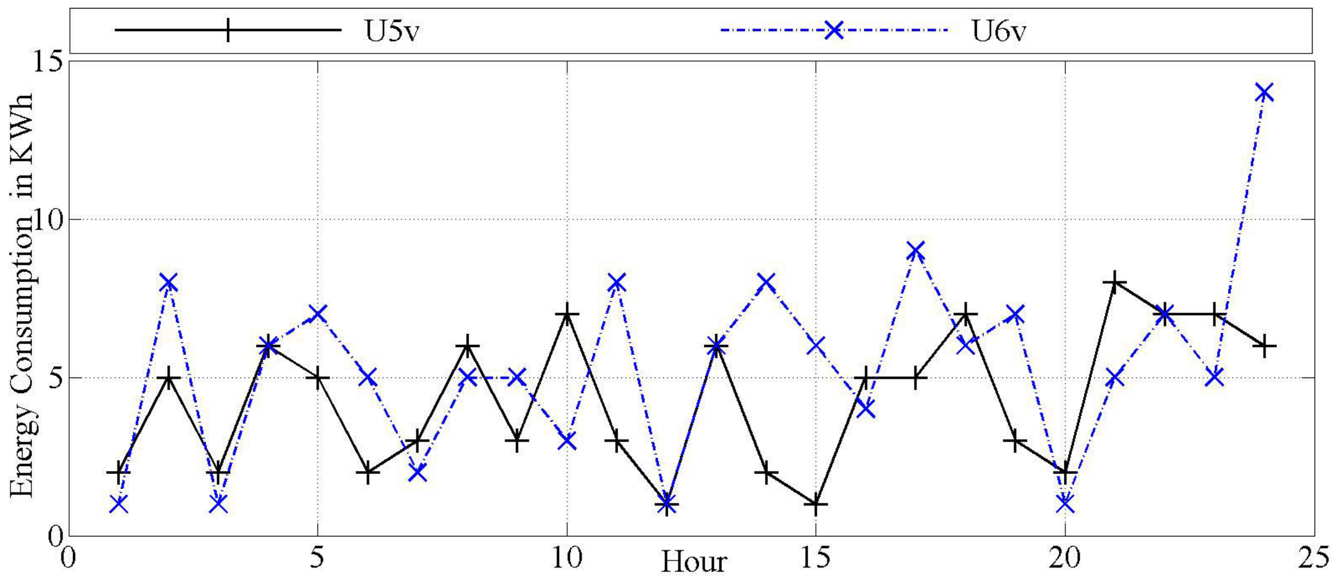

FIGURE 5. Energy fluctuation of U_5^v and U_6^v in terms of units consumed (KWh).

Similarly, the total energy consumption of all the users is shown in Figure 6.

The plotted results show that the majority of the variable users have an energy requirement greater than the total capacity of the grid. However, in some cases, the demand of these users is almost double the grid capacity (i.e. 30 kw for U_6^v).Therefore, an alternative is needed to overcome this problem in the form of *RES* and *EES*.

C. ENERGY CONSUMPTION OF U_5^v AND U_6^v FROM RENEWABLE AND ENERGY STORAGE SYSTEM

In this sub-section role of RES and *ESS* is briefly discussed. As long as the demand of variable users is within range of the maximum capacity of the grid (i.e.15 kw), the grid will continue to provide energy at the prescribed rates. As soon as the demand of any of the variable users is beyond the maximum capacity of the grid, *RES*, and *ESS* will schedule themselves to provide excess energy. A brief overview of energy consumption of U_5^v and U_6^v from renewable and energy storage systems is given in Table 7.

D. BILL CALCULATION FOR U_5^v AND U_6^v WITH AND WITHOUT RES AND ESS

In the bill calculations, the DMKs consider both of these variable users (U_5^v and U_6^v), and demand for electricity may exceed the maximum capacity of the grid (i.e. 15kW). If demand exceeds the limit, then the extra energy is provided by the *RES* and *ESS* using automated scheduling. In order to observe the significance of *RES* and *ESS* integration,

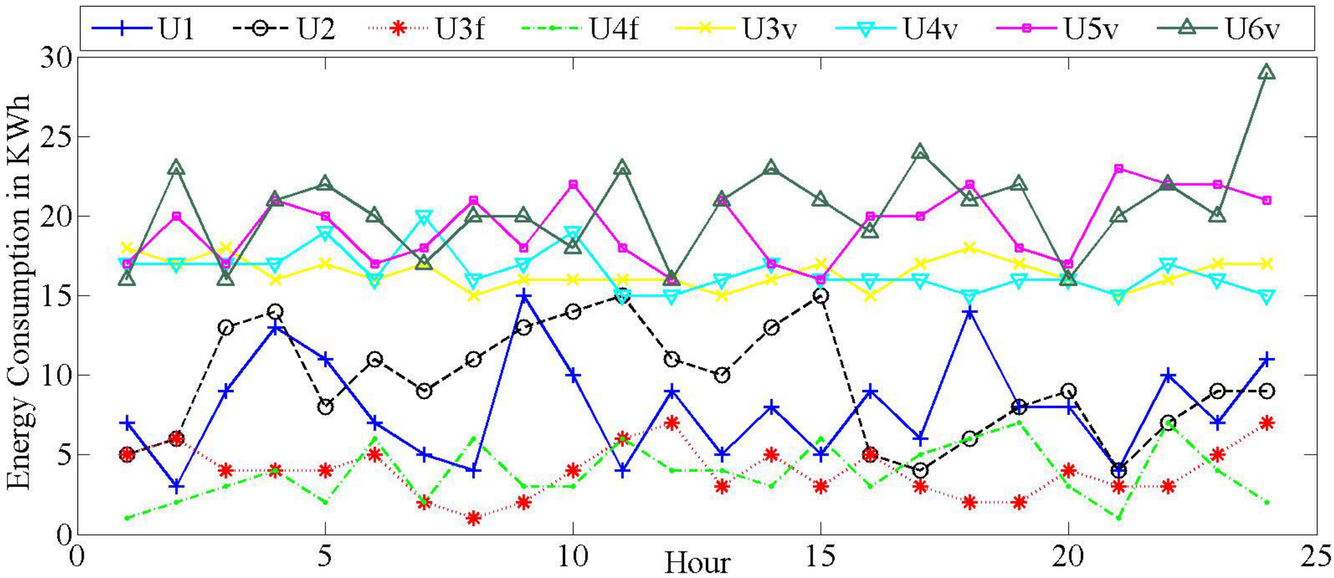

FIGURE 6. Total energy consumption of all users in terms of units consumed (KWh).

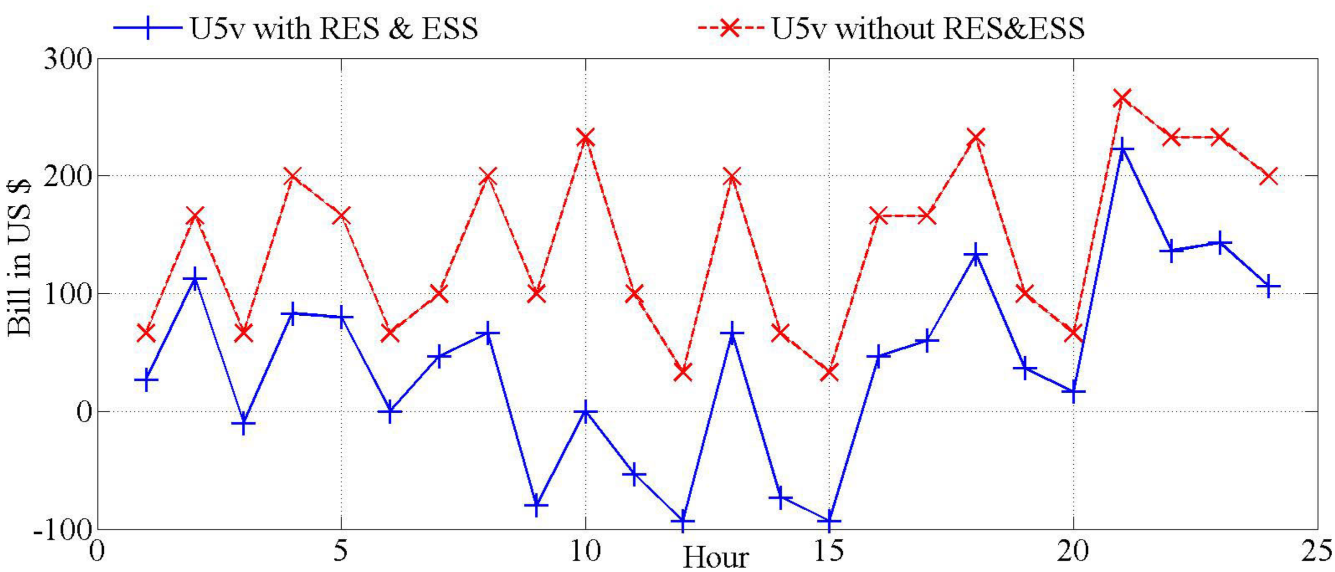

FIGURE 7. Comparison of bill for U_5^v with and without *RES* and *ESS*.

a comparison of Bill for U_5^v with and without *RES* and *ESS* is shown in Figure 7.

The results clearly show that for twenty-four hours, the bill for U_5^v without using *RES* and *ESS* is US$ 34.6. However, when *RES* and *ESS* are integrated, the bill is reduced to US$ 22.7. Similarly, the comparison of Bill for U_6^v with and without *RES* and *ESS* is shown in Figure 8.

Note that over a period of twenty-four hours, the bill of U_6^v without *RES* and *ESS* is US$ 43.2. However, when *RES* and *ESS* are integrated with the system, the bill reduces to US$ 15.9. The comparison of the two users i.e. U_5^v and U_6^v in Figure 7 and Figure 8 respectively, clearly shows dynamic energy management scheduling using DMKs results in providing low-cost solution even in the presence of intermittent availability of resources and demand. In Figure 7 and Figure 8 it can be clearly observed that in a few time slots, the value of the bill becomes negative which means that at that time user is not consuming energy from the grid, renewable and energy storage system rather it supplies surplus energy back to the grid.

A comparative analysis for both criteria (with and without *RES* and *ESS*) is illustrated in Table 8, which shows a saving of up to 50% for a variable user. In Table 8 Bill/day (US dollars) is presented for all the users. For U_1 and U_2, the cost of electricity over a period of 24 hours is 25.5 (US dollars) and 30.47 (US dollars) respectively. Similarly, U_3^f and U_4^f have 12.6 (US dollars) and 12.3 (US dollars) respectively. In order to account for the effect of renewable energy storage

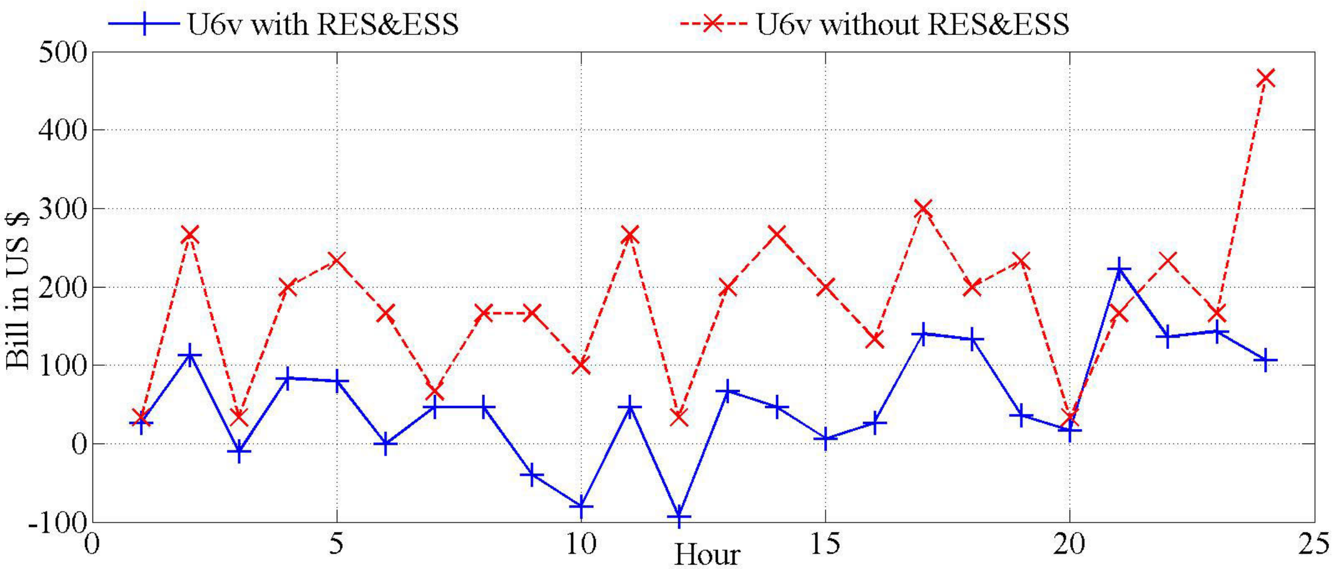

FIGURE 8. Comparison of bill for U_6^v with and without *RES* and *ESS*.

TABLE 5. Demand of variable users U_3^v and U_4^v.

Hours	U_3^v (KW)	U_4^v (KW)
1:00 am	3	2
2:00 am	2	2
3:00 am	3	2
4:00am	1	2
5:00 am	2	4
6:00 am	1	1
7:00 am	2	5
8:00 am	0	1
9:00 am	1	2
10:00 am	1	4
11:00 am	1	0
12:00 pm	1	0
1:00 pm	0	1
2:00 pm	1	2
3:00 pm	2	1
4:00 pm	0	1
5:00 pm	2	1
6:00 pm	3	0
7:00 pm	2	1
8:00 pm	1	1
9:00 pm	0	0
10:00 pm	1	2
11:00 pm	2	1
12:00 am	12	0

TABLE 6. Demand of variable users U_5^v and U_6^v.

Hours	U_5^v (KW)	U_6^v (KW)
1:00 am	2	1
2:00 am	5	8
3:00 am	2	1
4:00am	6	6
5:00 am	5	7
6:00 am	2	5
7:00 am	3	2
8:00 am	6	5
9:00 am	3	5
10:00 am	7	3
11:00 am	3	8
12:00 pm	1	1
1:00 pm	6	6
2:00 pm	2	8
3:00 pm	1	6
4:00 pm	5	4
5:00 pm	5	9
6:00 pm	7	6
7:00 pm	3	7
8:00 pm	2	1
9:00 pm	8	5
10:00 pm	7	7
11:00 pm	7	5
12:00 am	6	14

and energy storage system on the unit price of electricity for the highly variable users, it is evident from the results that for U_5^v (without *RES* and *ESS*) the Bill/day (US dollars) is 34.6 (US dollars), which is reduced to 22.7 (US dollars) by the integrating of *RES* and *ESS*. Similarly for U_6^v (without *RES* and *ESS*) the Bill/day is reduced to 15.9 (US dollars) from 43.2(without *RES* and *ESS*). In Table 8 Bill/day (US dollars) is presented for all the users. For U_1 and U_2, the cost of electricity over a period of 24 hours is 25.5 (US dollars) and 30.47 (US dollars) respectively. Similarly, U_3^f and U_4^f have 12.6 (US dollars) and 12.3 (US dollars) respectively. In order to account for the effect of renewable energy storage and energy storage system on the unit price of electricity for the highly variable users, it is evident from the results that for U_5^v (without *RES* and *ESS*) the Bill/day (US dollars) is 34.6 (US dollars), which is reduced to 22.7 (US dollars) by the integrating of *RES* and *ESS*. Similarly for U_6^v (without *RES* and *ESS*) the Bill/day is reduced to 15.9 (with *RES* and *ESS*) (US dollars) from 43.2(without *RES* and *ESS*). The impact of the decrease in per unit price of electricity is reduced to 50% by the integration of *RES* and *ESS* and managing the available resources by optimal scheduling.

From the above table is clear that adding *RES* and *ESS* has decreased the per unit price of electricity up to 50%.

TABLE 7. Demand of variable users (U_5^v and U_6^v) from grid,*RES* and *ESS* in kW.

Hours	U_5^v	U_6^v	RES	ESS
1:00 am	2	1	0	6
2:00 am	5	8	0	6
3:00 am	2	1	0	6
4:00 am	6	6	0	6
5:00 am	5	7	0	6
6:00 am	2	5	0	6
7:00 am	3	2	0	6
8:00 am	6	5	5	0
9:00 am	3	5	5	0
10:00 am	7	3	5	0
11:00 am	3	8	6	0
12:00 pm	1	1	6	0
1:00 pm	6	6	6	0
2:00 pm	2	8	7	0
3:00 pm	1	6	7	0
4:00 pm	5	4	7	0
5:00 pm	5	9	5	0
6:00 pm	7	6	0	6
7:00 pm	3	7	0	6
8:00 pm	2	1	0	6
9:00 pm	8	5	0	6
10:00 pm	7	7	0	6
11:00 pm	7	5	0	6
12:00 am	6	14	0	6

TABLE 8. Comparative analysis (with and without *RES* and *ESS*).

Users	Bill/day (US dollars)
U_1	25.5
U_2	30.47
U_3^f	12.6
U_4^f	12.3
U_5^v(without RES and ESS)	34.6
U_5^v(with RES and ESS)	22.7
U_6^v(without RES and ESS)	43.2
U_6^v(with RES and ESS)	15.9

V. DISCUSSION

The integration of *RES* and *ESS* has a dominant effect on the price of electricity consumed as well as the availability of electricity during peak hours. Similarly, the comfort of variable users is also maintained without imposing a penalty during peak hours. Thus DMKNs proved to be an efficient algorithm with multiple constraints.

Another consequence of using this technique is that the grid stability will not be disturbed in case of variation in the load on a large scale as the load will be automatically scheduled using maximum grid capacity as well as *RES* and *ESS*.It can be observed from the results that the per unit price of electricity has reduced to a great extent with the integration of *RES* and *ESS*.However, the constraints related to *ESS* are not discussed in detail, especially the capital cost and storage area for the *ESS*, which can be easily managed when this algorithm is implemented on a large commercial scale. The grid will continue to supply energy to various users on a piece-wise pricing concept as long as the maximum demand remains within the maximum grid capacity.

VI. CONCLUSION

In this paper, a dynamic energy management technique is developed based on the integration of available renewable resources and variable consumer demand, distinctive to underdeveloped countries. The work classifies consumer demand into fixed, flexible, and highly variable based on population characteristics. The developed optimization-based Dynamic Multiple KnapSack algorithm automatically schedules the provision of energy to various users by optimally accounting for the available energy resources. The proposed method provides a low-cost solution by maintaining a constant energy supply and at the same time preserves consumer comfort and grid stability. The final simulation results of dynamic energy management scheduling using the optimization-based Dynamic Multiple KnapSack algorithm shows a saving of up to 50% for a variable energy demand user. The proposed approach uses a method of integration, which is general and can also be applied to regions with similar consumer demand and statistics.

A. LIMITATIONS AND FUTURE WORK

There are a few limitations, which may generate future ideas and work. The optimization and practical implementation of DMKNS algorithm may require significant initial resources and infrastructure upgrades to support the integration of DERs and AI-based energy management. Similarly, the effectiveness of the system to some extent relies on weather conditions and other environmental factors, which may degrade the overall performance and affect the system's stability and reliability.

In future work, the following is suggested.

- The system can be further improved by integrating advanced AI techniques, such as deep learning or reinforcement learning, to enhance the accuracy and effectiveness of energy management.
- The system can be extended to support more complex energy management scenarios, such as multi-household or community-level energy management, to achieve greater energy efficiency and cost savings.

NOMENCLATURE

C_j	Total capacity of grid.
$Cost_j$	Cost function.
$DMKNS$	Dynamic Multiple Knapsack.
E_i	Total Energy consumed by any user from grid.
E_j^r	Excess renewable energy.
E_j^t	Total energy consumption by U_5^v and U_6^v.
EES	Energy storage system.
j	Time slot.
kW	Kilowatt.
RES	Renewable energy storage.
T_j^{req}	Total time.

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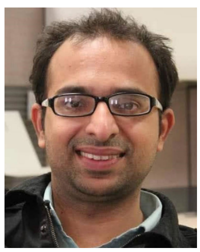

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