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On Reducing Energy Cost Consumption in Heterogeneous Cellular Networks using Optimal Time Constraint Algorithm

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Abstract:

The increasing data demand in recent years has resulted in a considerable rise in heterogeneous cellular network energy usage. Advances in heterogeneous cellular networks with renewable energy supplied from base stations offer the cellular communications sector interesting options. Rising energy consumption, fuelled by huge growth in user count as well as usage of data, has emerged as the most pressing challenge for operators in fulfilling cost-cutting and environmental-impact objectives. The use of minimum power relay stations or base stations in conventional microcells is intended to lower cellular network's total energy usage. We examine the reasons, difficulties, and techniques for addressing the energy cost reduction issue for such renewable heterogeneous networks in this paper. Because of the variety of renewable energy as well as mobile traffic, then the issue related to a reduction in energy cost necessitates both spatial and temporal resource allotment optimization. In this paper, we proposed a new technique for reducing the energy consumption cost using the optimal time constraint algorithmic approach. We demonstrate that the proposed method has time as well as space complexity. Experimental simulations on actual databases with synthetic costs are used to confirm the usefulness and efficacy of our method.

Keywords: Energy cost optimization, Heterogeneous Cellular Network, optimal time constraint algorithm, cellular communication.

I. INTRODUCTION

Because of the widespread use of bandwidth energy-consuming apps as well as mobile phones, cellular wireless networks have seen tremendous traffic rise necessitating the vast installation of base stations (BSs) with the significant rise in energy consumption. According to [1] BSs require a large quantity of energy in a cellular wireless network, around 65% to 85%. As a result, the mobile communications sector has made lowering the energy usage of BSs a major goal. In both academics, and business many strategies to minimize the BS's energy usage are being investigated [2–4]. A possible option is the heterogeneous cellular network (HetNet) [5] that comprises many kinds of BSs with varying transmission strengths and coverage regions. The high-density implementation of lower power tiny BSs within a huge macro cell characterizes the HetNet design. Smaller BSs are installed nearer to end customers, allowing for lower transmission power and better route loss circumstances.

In this paper, we look at how to reduce energy costs in a renewable heterogeneous cellular network using hybrid energy sources (HCN-HES). Figure 1 shows an illustrative network topology in which both picoBSs and macro are equipped with renewable power collecting instruments and on-grid electricity. In the following part, we'll go through the HCN-HES design problems. Renewable energy has a considerably lower 1 cost than on-grid electricity, and it is possibly available [6]. Not only does the traffic load allocation in an HCN-HES show temporal and geographical changes, but so does the renewable energy harvesting. As a result, the cost reduction issue necessitates temporal and geographical resource allotment optimization.

Figure 1: Heterogeneous Cellular Network (HCN).

Aside from social duty, there is a strong financial incentive to minimize energy use. In history, operators have prioritized technical advancements to quality-of-service (QoS) expectations, fulfill customer ability, and answer the insatiable desire for more broadband data. Moreover, the recent significant surge in energy costs has heightened the need for increasing communications energy efficacy. Power efficiency will undoubtedly become much more important in the future years. Furthermore, the public is concerned about the likelihood of radio-frequency (RF) power radiation from base stations as well as smart applications creating a health threat.

The cellular network in macro size is good at generating area covers for speech and data traffic at a lower speed, but it has limitations when it comes to offering large data rates for every area

unit. Increased receiving energy is required particularly for edge users of cells, to ensure an adequate SINR for effective communication. The growth in user count and the need for increased data rates are direct influences on macro-cell energy utilization.

The shortest path inquiry is a common issue in networking that has been thoroughly investigated in statistical graphs. Graphs, on the other hand, frequently change with time. The system namely European Traffic Message Channel (TMC) and Vehicle Information and Communication System (VICS) are considered as the transportation systems that may offer users contemporaneous traffic information. These transportation networking systems are based on time-based graphs, in which the travel time on a route fluctuates with time, bringing into consideration "rush hour." However, a road's toll cost is likewise a time-dependent algorithm. In the United Kingdom, there is a "Road pricing strategy" as well as "London congestion charge" to decrease traffic congestion as well as pollution [7].

Assume road network applications. Somebody has a meeting with her pals scheduled. The latest arrival time is t_1 , but she must get to her destination before t_2 . Each road throughout this network has two types of costs: journey time as well as toll price, most of that is based on time. It may be determined whether a path fulfills the time restriction or not based on the traveling time, that is, if someone can reach around time t_2 following way p . It's worth mentioning that there might be several routes from the supply source to the target which meet the time limit. As a result, finding an optimal approach with the lowest cost among all the pathways that fulfill the time restriction is critical.

The road network in the preceding illustration can be thought of as a huge graph G along with time data. In G , there are two types of costs for each edge (v_i, v_j) : $f_{i,j}(t)$ as well as $w_{i,j}(t)$. The duration cost $w_{i,j}(t)$ specifies how long it would consume to pass via an edge (v_i, v_j) : as well as the toll price $f_{i,j}(t)$ specifies how much it costs to travel via an edge (v_i, v_j) . All $w_{i,j}(t)$ as well as $f_{i,j}(t)$ are functionalities that are reliant on the edge's beginning terminal v_i arrival time t is (v_i, v_j) . These graphs are referred to as time-based graphs. In graphs based on time, the request for a cost-optimum path with a time restriction may be described as follows. Determine the optimal path p to v_e from v_s , fulfilling the underlying criteria: Provided a source v_s , a target v_e , the earlier arriving time t_d , as well as the recent arriving time t_a , discover an optimal path p to v_e from v_s , meeting the specified criteria: (1) After time t_d , taking path p starting from v_s , it is possible to reach v_e within time t_a ; as well as (2) path p consumes the lowest cost (toll price) of all the ways that meet the requirement (1).

The shortest path issue in time-based graphs has been studied extensively [8, 9]. Whenever the departing time from the supply source is picked from a user-defined beginning time interval, the majority of them are to identify an optimum path with the shortest traveling time to the target from the source. In these papers, each edge in a time-based graph is assumed to have just a single time function $w_{i,j}(t)$. Assuming the letter λ_i to represent the early arriving time at the vertex v_i . The below-mentioned expression may be used to determine λ_i :

$$\lambda_i = \min \left\{ \left(\lambda_j + w(v_j) \right) + w_{j,i} \left(\lambda_j + w(v_j) \right) \mid v_j \in N^-(v_i) \right\} \quad (1)$$

Here, $v_j \in N^-(v_i)$ denotes which v_j is an entering neighbor of v_i whereas $w(v_j)$ denotes the time having waited at v_j . The early arriving time at a vertex may be calculated using the early

arriving time at the vertices' approaching neighbors, according to this expression. This characteristic is used in all of these TDSP studies to find the smallest routes with the smallest trip time.

In the paper, section 2 includes the literature review related to the energy consumption cost in heterogeneous cellular networks. Section 3 encloses the proposed optimal time constraint algorithmic approach involved in reducing the cost of energy consumption. Section 4 includes the performance evaluation of the proposed algorithmic approach and finally, section 5 includes the conclusion.

II. LITERATURE REVIEW

From the perspective of smart grids, there seems to be a lot of study on lowering energy costs and emitting outputs at the data center [10]. Past approaches are centered on the development of contemporaneous energy management systems that minimize data center networking energy costs based on system constraints and taking into account quality of service (QoS) restrictions such as connection latency. These uncertainties are linked to stochastic variables such as contemporaneous pricing, data warehouse workloads as well as renewable energy supply. Under QoS restrictions, the predicted values of the attributes over time periods are used to describe this uncertainty. As a result, the issue formulations are predictable, as well as the energy costs are minimized utilizing technologies including linear programming (LP). Moreover, this may not always result in the greatest energy cost savings.

Reducing electricity prices [11–15], reducing energy usage [16, 17], and employing renewable sources of energy [18, 19] are some of the prior strategies for reducing energy expenses in the data center. The primary group of methods generally exploit the intelligent grid's temporal as well as particular fluctuations in power pricing to swap connectivity across data centers in order to decrease operating expenses. The second set of approaches seeks to minimize a data center networking's energy usage by utilizing cloud computing to minimize end-user energy usage. The influence of contemporaneous pricing is studied on the cloud transport networking infrastructure's operational costs and energy efficacy. To minimize emissions and operating expenses, the third category of approaches uses renewable energy acquired from local sources. The testbed namely the green star network (GSN) has been utilized to investigate the feasibility of using wind power to solar power to provide energy to the data centers.

To deal with the stochastic renewable production and workload arriving procedures, a stochastic optimization issue is proposed in [20]. Therefore, to tackle the problem, an online control technique dependent on Lyapunov optimization is presented. Mao et al. presented the Lyapunov optimization-based base station assignment and power control (LBAPC) method as a minimum complexity online solution to reduce the longer mean networking service cost in [21].

The major benefit of such an algorithmic approach is that it makes judgments based solely on immediate side input, independent of the need for channel transmission of information or energy harvesting procedures. For data center networks, a competitive match traffic sharing method is developed. Despite [22], the present study employs a rapid online optimization approach depending on the Lyapunov drift that effectively reduces system difficulty. They incorporate smart grid principles into the optimization formulations and utilize a QoS measurement for consumer happiness in the suggested restrictions, which is distinct from the

techniques. A similar Lyapunov optimization method is applied to base station allocation and energy regulation in a distinct setting.

Kanoulas et al offer an A* algorithm adaptation for the TDSP issue [23]. The primary concept is to calculate a reduced bound on the trip time from a supply source to target and then extend the path using this reduced constraint. The major issues with this A*-extended algorithmic approach are listed below. (1) To determine the lower bound, the above mentioned algorithmic approach must calculate the Euclidean distance among distinct two vertices as well as the top speed in roadways using the formula "distance speed." (2) The effectiveness of this technique is determined on the trip time evaluation's pruning power. Whenever the supply source and target in a graph are near to one other, then the approach is effective. In a big graph, it's tough to make such an estimate. The technique is unsatisfactory if the graph is big or the supply source is far apart from the target. (3) In the worst scenario, all routes from the supply source to the target are identified and preserved. The time, as well as space complexity of the algorithmic approach, grow exponentially with the GT size.

A more effective approach is presented for dealing with the TDSP issue [24]. There are two steps to this algorithmic approach: (1) time refinement as well as (2) path selection. The method modifies the earliest arriving time for each vertex in this way. The primary issue with the 2S method is that it must calculate the earliest arriving time expression, as well as a cost-optimal path containing sub-path, will be or not a path with optimal cost. The optimum path issue has been studied in an operational research field using the discrete-time paradigm [25, 26].

III. SYSTEM MODEL

(paper 1)The cost consumption of energy in BSs determines the majority of a cellular network's operational expense (OPEX). A customer could be in the covering regions of several BSs at the same time when HetNet is deployed. This gives users the option of selecting a BS with a lower transmission power while still meeting their service requirements. Moreover, with HCN-HCS, simply reducing overall power usage is insufficient; in some cases, using higher renewable energy is preferable due to its cheaper cost and reduced carbon footprint. Utilizing more conserved renewable energy as feasible in the current slot is not considered a smart approach, as recently founded renewable energy is unable to sufficiently meet traffic demands in the following slot. The proposed framework model is shown in Figure 2.

Figure 2: Efficient energy reduction system's framework.

Depending on the illustrated scenario, the energy cost is deduced for each BS is influenced not only by its related users, and yet also by the amount of renewable energy given to it. Thus, our goal is to discover a single user-BS connection matrix as well as an energy allocation vector that minimizes energy costs while still meeting network Quality-of-Service (QoS) criteria. The user connection matrix is $X = \{X_1, X_2, \dots, X_k\}$. The user connection at the k th time slot is denoted by X_k . In the k th time slot, the component $X_k(i, j)$ reflects the connection relationship among BS i as well as user j . The renewable energy allotment vector is denoted by $\vec{A} = (A_1, A_2, \dots, A_i, \dots, A_N)$. A_i is the BS i renewable energy allotment vector for every time slot. Furthermore, we utilize its constituent $A_{i,k}$ to indicate BS i energy allotment at the k th time slot, where $A_{i,k} \leq E_{i,k} + P_{i,k}^h \tau$. The stored energy of BS i initially of the k th time slot is $E_{i,k}$, as well as the length of every individual time slot, is denoted as τ . The energy collecting power of BS i during the k th time slot is $P_{i,k}^h$.

Let $\alpha_{i,k}$ be the functional indication for energy source being used:

$$\alpha_{i,k} = \begin{cases} 1, & A_{i,k} \geq P_{i,k}^{total} \tau \\ 0, & A_{i,k} < P_{i,k}^{total} \tau \end{cases} \quad (2)$$

$P_{i,k}^{total}$ is the total power consumed by BS i in the k th slot. The base station (BS) i is driven through energy in the k th time slot if $\alpha_{i,k} = 1$. The rest of the time, this BS is driven through on-grid electricity.

The unit cost of energy varies depending on the type of energy. μ and λ indicate the renewable energy as well as on-grid unit energy consumption costs, correspondingly. At the BS i in the k th time slot, the consumption cost of energy may be calculated using the formula,

$$J_{i,k} = \lambda(1 - \alpha_{i,k})P_{i,k}^{total} \tau + \mu\alpha_{i,k}P_{i,k}^{total} \tau \quad (3)$$

As a result, the overall energy cost savings problem may be expressed as a restricted optimization issue,

$$\min_{X, \vec{A}} J = \min_{X, \vec{A}} \sum_k \sum_i J_{i,k} \quad (4)$$

Depending on, (a) $P_{i,k} \leq P_i^{max}$

$$(b) \sum_i X_k(i, j) = 1$$

$$(c) X_k(i, j) \in \{0, 1\}$$

$$(d) A_{i,k} \leq E_{i,k} + P_{i,k}^h \tau$$

$$(e) \lambda > \mu \geq 0 \quad (5)$$

The maximal transmission power cost for every BS is the restriction (a). The restrictions (b) as well as (c) guarantee that every user is connected with just one BS. According to limitation (d), every BS's energy allotment unable to exceed the total of its conserved renewable energy as well as the quantity of power produced in the present time slot. The limitation (e) demonstrates how renewable energy has a considerably lower unit cost rather than on-grid electricity.

The overall energy cost is influenced by every BS's energy usage and also the energy source utilized in every time slot. The energy consumption of every BS is determined by that traffic load is distributed across multiple BSs in a single slot. The source energy is determined by every BS's energy usage as well as renewable energy storage. Renewable energy storage is linked to the charging procedure of each BS throughout time. As a result, the topic of minimizing energy costs offers significant problems for combined optimization in the temporal and spatial domains.

Spatial Traffic Balancing: Due to the significantly larger transmitting energy of macro BSs rather than pico BSs, in a heterogeneous network with smooth deployments of pico BSs inside the range of macro BSs, an imbalanced traffic load usage is generally achieved independent of any proper traffic balancing system in the spatial aspect. However, not just the energy consumption of every BS and also the accessible renewable energy must be considered in order to improve energy usage in HCN-HES. The accessible renewable energy between various BSs may display geographic variation within a regular time frame. In every slot, the consumption of energy between various BSs must be adjusted according to the allotted renewable energy of every HPBS to achieve the most of the renewable energy. The Base stations with higher renewable energy allotted are set aside to serve additional consumers while remaining within their capacity.

Temporal Renewable Energy Allocation: The renewable energy created in a 1-time slot was not utilized in subsequent time slots with every particular HPBS. because the amount of renewable energy obtainable in the 1-time slot is determined by the amount of renewable energy produced in that time slot as well as the amount of renewable energy leftover from prior slots, increased use of renewable energy in the present slot would then lead to a future shortage of renewable energy supply. Therefore, every HPBS's renewable energy allotment across multiple time slots must be managed in order to maximize its long-term performance. Although mobility traffic exhibits dynamic temporal and renewable energy output changes over time, both may be approximated from existing statistic data. A component like present renewable power production and consumption, estimates of future renewable energy harvesting as well as energy consumption are considered while solving the temporal renewable energy balance issue. Furthermore, the spatial traffic equalization across multiple BSs for every individual time slot is connected to the outcome of every HPBS's temporal renewable energy allotment.

Compute the Minimum Cost:

The reduction in energy consumption cost is achieved using the optimal time-constrained algorithmic approach from the source point v_s to the destination v_e . We calculate the latest arrival time λ_i for each vertex $v_i \in V$ in advance. Using the singular-source shortest path technique on G_T and the time cost $w_{i,j}$ on each edge, the lowest trip time to every vertex v_i starting from v_s may be calculated (v_i, v_j) . The aggregate of the early departure time t_d as well as the shortest time travel to v_i equals v_i latest arriving time λ_i . The singular-source shortest route algorithm has a temporal complexity of $O(n \log n + m)$.

The minimal destination value v_e of $g_e(t)$ is denoted by $g_e(t_e)$, wherein t_e is the time point when $g_e(t)$ is reduced. With a time restriction, $g_e(t_e)$ is the cheapest way to proceed between v_s to v_e . The goal is to estimate $g_e(t_e)$.

The algorithm shows the algorithmic approach for computing $g_e(t_e)$. T_i represents the time interval among the earliest arriving time v_i as well as the latest arriving time t_a for each vertex $v_i \in G_T$, i.e., $T_i = [\lambda_i, t_a]$. Through an iterative process, updating the algorithm $g_i(t)$ for each vertex $v_i \in G_T$. The processing time interval for $g_i(t)$ wherein the minimal value of $g_i(t)$ is discovered to keep updating $g_i(t)$ for every outgoing neighbor v_j of v_i is represented by S_i . S_i is modified as $[t_i, t_a]$ in every iteration, while $S_{i,j}$ is modified as $R_{i,j} = [t_i, t_a - w_{i,j}]$ for every leaving neighbor v_j of v_i . If $t \in T_i - S_i$, then T_i indicate the current lowest value $g_i(t)$. If $t_i \leq t_a - w_{i,j}$, it is apparent that T_i is likewise the current lowest value $g_i(t)$ for $t \in T_{i,j} - S_{i,j}$. It is worth noting that the present $g_i(t)$ is not best (or most accurate) atm-c-function. In the iterative process, $g_i(t)$ is updated using the algorithm until it reaches the correct value.

The source such as S_s , $g_s(t)$, and T_s are assigned as $S_s \leftarrow T_s$, $g_s(t) \leftarrow 0$, as well as $T_s \leftarrow 0$ to obtain the source v_s . For every arriving time period t , at the v_s point the cost is clearly 0. It indicates that for each $t \in [t_a, t_a]$, the atm-c-function $g_s(t)$ of v_s equalized to 0. $g_i(t)$, S_i , as well as T_i are assigned as $g_i(t) \leftarrow \infty$, $S_i \leftarrow \emptyset$, and $T_i \leftarrow \infty$ for the vertex with $v_i \neq v_s$.

In a time-based graph G_T , the vertices are maintained by the algorithmic approach further uses a priority queue Q . As per T_i , each and every vertex $v_i \in G_T$ are ordered in Q . Algorithmic approach dequeues the top vertex in Q with the smallest T_i over and over again. Since $T_s = 0$, the top vertex in Q is original versus. When target v_e is dequeued in the 1st time from Q , then the algorithm ends. It indicates that the cheapest route from point A to point B has been determined.

The algorithm initially from Q dequeues the top vertex, indicated as v_i , in each iterative process. For $t \in T_i - S_i$, i is the present $g_i(t)$ lowest value. Assuming t_i be the earliest moment in time at which $g_i(t) = T_i$. The present v_i atm-c-function is $g_i(t)$. S_i has been updated to $S_i \leftarrow [t_i, t_a]$. When $t_i \leq t_a - w_{i,j}$ for every outgoing neighbor v_j of v_i , then updating $g_j(t)$ for $t \in (R_{i,j} - S_{i,j}) \oplus w_{i,j}$. Simultaneously moment, T_j is changed. It's worth noting that if $g_i(t) = T_i$ for different assumptions, i.e., $g_i(t) = T_i$ for $t \in (t^a, t^b]$ it won't be able to locate the earliest point of time t_i . In this situation, t_i becomes t^a , while S_i becomes $(t_i, t_a]$. Assuming $[t^a, t^b]$ indicate the time period in which $g_i(t) = T_i$ and T_i represent the optimum or correct value atm-c-function $g_i(t)$ for the corresponding $t \in (t^a, t^b]$.

Algorithmic approach verifies if the processing time period matches the entire time interval, i.e., $S_i = T_i$, once updating $g_j(t)$ for every outgoing neighbor $v_j \in N^+(v_i)$. If $S_i = T_i$, v_i does not need to change $g_j(t)$ for each of v_i out coming neighbors v_j . Then, v_i is securely deleted from Q . When $S_i \neq T_i$, the algorithm computes the present $g_j(t)$ lowest value T_i for $t \in T_i - S_i$ and afterward enqueues v_i towards Q for subsequent processing. v_e is the $g_e(t)$ the minimal value for $t \in [\lambda_e, t_a]$ whenever the target v_e is dequeue for the 1st time from queue Q . As a result, Algorithm fails since T_e is the lowest cost from the supply source v_s to the target v_e with a time restriction.

The second stage is introduced to determine the best path p^* from supply source v_s still the target v_e and the optimum waiting time $w^*(v_i)$ for each vertex v_i including $cost(p^*) = g_e(t_e)$. The optimal path and optimal time algorithm for computing p^* and $w^*(v_i)$ for each $v_i \in p^*$. The basic principle in the iterative process is to locate the predecessor for each vertex $v_i \in p^*$ going backward from the target v_e to supply source v_s . Firstly, there is also a $v_i \leftarrow v_e$.

We identify the v_j predecessor of v_i in the optimum path p^* in alliteration. Assuming t_i represent the arriving time at v_i in path p^* , whereas $g_i(t_i)$ represent the cost of arriving at v_i in path p^* . Initializing t_e and $g_e(t_e)$ as the starting values for t_i and $g_i(t_i)$. Whether there would be a point time t_j , $t_j \leq t_i - w_{j,i}$ for every $v_j \in N^-(v_i)$, then

$$g_i(t_i) = g_j(t_j) + f_{j,i}(t_i - w_{j,i}) \quad (6)$$

The v_i antecedent as well as the at v_j arriving time in the path p^* are given as v_j and t_j . Since $g_i(t_i)$ is calculated by algorithmic approach using $g_j(t_j)$, include a predecessor v_j should exist. Thus, at v_j , the ideal waiting time would be:

$$w^*(v_j) = t_i - w_{j,i} - t_j \quad (7)$$

If supply source v_s is discovered as a predecessor, i.e., $v_i = v_s$, then the optimal path and waiting time algorithm ends. All of the vertices in p^* are identified as well as the optimum waiting time $w^*(v_i)$ for each vertex $v_i \in p^*$ is calculated.

ALGORITHM FOR ENERGY COST REDUCTION

Step 1: $T_s \leftarrow 0$; $g_s(t) \leftarrow 0$; $S_s \leftarrow T_s$; $v_i \leftarrow v_s$.

Step 2: Assuming Q as the priority queue that contains V at the start.

Step 3: while $v_i \neq v_e$ do

Step 4: Assuming t_i as the first point time where $g_i(t_i) = T_i$.

Step 5: $S_i \leftarrow [t_i, t_a]$

Step 6: for every individual $v_j \in N^+(v_i)$ do

Step 7: if $t_i \leq t_a - w_{i,j}$ then

Step 8: $R_{i,j} \leftarrow [t_i, t_a - w_{i,j}]$

Step 9: $g_{i \rightarrow j}(t) \leftarrow f_{i,j}(t - w_{i,j}) + T_i$ for $t \in (R_{i,j} - S_{i,j}) \oplus w_{i,j}$

Step 10: $S_{i,j} \leftarrow R_{i,j}$

Step 11: $g_j(t) \leftarrow \min\{g_j(t), g_{i \rightarrow j}(t) | t \in (R_{i,j} - S_{i,j}) \oplus w_{i,j}\}$

Step 12: $T_j \leftarrow \min\{g_j(t) | t \in T_j - S_j\}$

Step 13: If $S_i \neq T_i$ then

Step 14: $T_i \leftarrow \min\{g_i(t) | t \in T_j - S_j\}$

Step 15: $T_i \leftarrow \min\{g_i(t) | t \in T_i - S_i\}$

Step 16: enqueue (Q, v_i)

Step 17: $v_i \leftarrow dequeue(Q)$

Step 18: $g_e(t_e) \leftarrow T_e$

Step 19: $v_i(t) \leftarrow v_e$; $p^* \leftarrow \emptyset$; $g_i(t_i) \leftarrow g_e(t_e)$; $t_i \leftarrow t^*$

Step 20: While $v_i \neq v_s$ do

Step 21: for every individual $v_j \in N^-(v_i)$ do

Step 22: If $\exists t_j \leq t_i - w_{j,i}$, $g_i(t_i) = g_j(t_j) + f_{j,i}(t_i - w_{j,i})$ then

Step 23: $p^* \leftarrow p^* + v_j$; $w^*(v_i) \leftarrow t_i - w_{j,i} - t_j$

Step 24: $v_i \leftarrow v_j$; $t_i \leftarrow t_j$

Step 25: break

Step 26: return p^* and $w^*(v_i)$ for each $v_i \in p^*$

The regret function is dependent on a basic case study and comprises of exchanging fixed incoming packets in the optimum scheduling. Considering a job $r \in READY(R, t)$. When task r isn't scheduled (i.e., $r \text{ not belong to } \gamma$), the essential strategy is to reschedule $\gamma(t)$ rather than the job with the least weight in γ . The feeling of remorse grows.

$$\min(s \in [t, a(\gamma(t)) + d]) w(\gamma(s)) - w(r) \quad (8)$$

Since the replacement work has been withdrawn from r as well as $\gamma(t)$ is being considered in the plan. In the poor scenario, the $\gamma(t)$ is considered as replaced job whereas the $w(\gamma(t)) - w(r)$ is the regret. Initially, the regret function tries to swap $\gamma(t)$ and r whether task r is assigned at time t_r , wherein scenario the regret is zero. When it is not feasible, the function attempts to reschedule $\gamma(t)$ rather than the job with the lowest weight in γ . When $\gamma(t)$ is not possible to be reassigned, the regret function merely chooses the best available unscheduled task that can be assigned at t_r , as well as the regret, is now

$$w(\gamma(t)) - \max(u \in U_r) w(u) \quad (9)$$

Here, $U_r = \{j \in READY(R, t_r) | j \text{ not belong to } \gamma\}$

As job $\gamma(t)$ is no longer on the plan. Whether $\gamma(t)$ is reassigned at time s , thus the regret is resolved by choosing the best available unscheduled task that can be booked at a time t_r , as well as the regret has become

$$w(\gamma(s)) - \max(u \in U_{r,s}) w(u) \quad (10)$$

Here, $U_{r,s} = \{j \in READY(R, t_r) | j \text{ not belong to } \gamma \vee j = \gamma(s)\}$

The regret function requires $O(\max(d, |C|))$ time, which is sub-linear in $|J|$ as well as $|H|$ and insignificant. We can now demonstrate that it gives a 2-approximation.

At time t , the requesting set is represented as R and $r \in R$ represents a request which may be planned at t time. Considering γ^* as an optimum solution, i.e., $\gamma^* = OPTIMALSOLUTION(R, t)$ whereas in the case of γ_r as an optimum solution then $\gamma_r = OPTIMALSOLUTION(r, R, t)$ in which r is assigned at time t . Assume $\tilde{\gamma}_r$ as the solution produced through the regret function. We demonstrate this

$$\frac{w(\gamma_r)}{w(\tilde{\gamma}_r)} \leq 2 \quad (11)$$

The majority of the proof comprises of demonstrating whether another packet is available in γ^* with a weight of at minimum $w(l)$ for every lost packet l , offering everyone a 2-approximation assuming $w(\gamma_r) \leq w(\gamma^*)$. Initially, notice that the solution remains for $w(x) \leq w(r)$, because the regret function in the poor scenario merely loses packet x . As a result, we focus on $w(x) \geq w(r)$. When $x \in \tilde{\gamma}_r$, that is, whether the regret function exchanges x with some other packet y (scenario 1), the outcome remains the same because $w(y) \geq w(x)$. When x does not belong to $\tilde{\gamma}_r$ as well as x may be planned after time t , then indicates that a packet y occurs at these times which fulfill $w(y) \geq w(x)$, as well as the outcome is valid. The scenario with x is planned at time t . Therefore, r loss needs to be considered. The regret function is optimum if r not belong to γ^* else after time t , r will be in the optimal plan. Instead, a set of packets must be reasoned approximately. Indeed, $w(\gamma^*) = w(x) + w(r) + w(S)$, in which $S = \{p \in \gamma^* | p \neq x \& p \neq y\}$. $w(\tilde{\gamma}_r) \geq w(r) + w(S)$ is known as the regret function with loses packet x in the poor scenario. Lastly, $w(\gamma_r) = w(r) + w(Z)$, wherein Z is the number of packets that will be planned from time t . Because γ^* is optimum, we can deduce that $w(Z) \leq w(r) + w(S)$ as well as the outcome is.

IV. RESULT AND DISCUSSION

Depending on the renewable energy production paradigm as well as the mean predicted energy usage pattern, the proposed optimal time constraint algorithm obtains the renewable energy allotment vector to reduce energy cost for every BS throughout every time slot. We compute the energy cost of the initial time slot, and further include the succeeding slot to the allotment optimization repeatedly. The main concept is to make guarantee the energy cost of present slots is not higher than the prior slots. Whether it is not the situation, then the proposed algorithm will lower prior time slot allocations in order to assign the needed renewable energy to the present time slot.

It is typically challenging to acquire sufficient network data and synchronize between multiple BSs in heterogeneous cellular networks (HCNs). We next present a lower complex distributed UA method which allocates a biasing gain factor of the multiplicative channel b_i to every BS i in every slot, allowing for additional users to be transferred to the BS with adequate renewable energy allocation.

$$b_i = \begin{cases} 1 + \log_\gamma(\xi_i) & 0 < \xi_i \leq 1 \\ \gamma^{(\xi_i-1)} & \xi_i > 1 \end{cases} \quad (12)$$

Here, the energy drain ratio (EDR) is denoted as ξ_i , which is calculated by dividing the expected energy requirements by the renewable energy allotted, whereas $\gamma (0 < \gamma < 1)$ is the positive factor depending on the typical traffic load.

Table 1: Parameters and their value.

PARAMETERS	VALUE
The radius of macrocell	625 m
Each cell bandwidth	22 MHz

Maximum transmission power	Macro base station	47dBm
	Pico base station	32dBm
Static power	Macro base station	135 W
		14 W
Sleep power	Macro base station	76 W
		4.4 W
Slope dynamic power	Macro base station	4.8
		4.2
Path loss (km)	Macro user's cell	$129 + 38 \log(d)$
	Pico user's cell	$131 + 37 \log(d)$
The noise level in thermal power		-175dBm/Hz
User data demand		12Mbps
Time interval		625s

Every macrocell has a 2-tiered heterogeneous cellular network with seven macro cells as well as four Pico cells equally dispersed. Every BSs use on-grid along with renewable energy, with variable rates of renewable energy collection. The networking parameters and values are listed in Table 1. The temporal features of mobile traffic may be represented as two separate periods, according to the measurements record: the off-peak period and the peak time. The number of users is uniformly spread around an average value of forty users during the peak time, and ten users during the off-peak period. Moreover, mobile users are uniformly dispersed throughout the networks in the spatial section.

The conventional closest association method and the maximal renewable energy utilization (MREU) algorithm are used to evaluate our suggested approach. Figure 3 and Figure 4 illustrate the overall energy cost over the course of a single day. The energy produced during on-grid as well as renewable energy for unit prices are set at $\mu = 0$ and $\lambda=1$. The suggested methods use significantly less energy rather than another algorithmic approach, especially during peak periods. This is due to the suggested algorithms optimize renewable energy distribution in the temporal section based on statistical renewable energy consumption as well as mobile traffic patterns.

Figure 3: Total cost of energy for various periods of traffic.

Figure 4: Total Energy cost for Long Term Operation

On a range of seven class issues, Figure 5 shows the mean packet loss is considered as a function of possible optimizations count O for the multiple methodologies. It also calculates the best, a priori packet loss (O). The findings show the importance of stochastic data since algorithm E beats the clueless algorithms G, as well as LO, also closes the distance among them and the ideal result. It's worth noting since LO is not better than G, demonstrating the (common) pathology of over-optimizing. If a few optimizations are present (e.g., ≤ 15), the findings show that consensus beats E. For the limited improvements accessible, the increase is especially substantial. Whenever the number of possible optimization possibilities still delivers considerable gains against oblivious algorithms, the agreement is ruled by E. This is important because E is inconvenient for many issues involving time restrictions. The advantages of the proposed algorithm are obvious. The other algorithms, particularly consensus if there are only limited offline optimizations (high time restrictions) and expectancy since there are a significant number of improvements, are dominated by optimal time constraints algorithmic approach. Lastly, it's worth noting that the proposed algorithm delivers similar quality outcomes with fifty iterations when using ten offline optimizations. Because the mean number

of available demands at every time t is around 5, the experimental findings match the numerical simulations effectively.

Figure 5: Packet Scheduling in the OTC Algorithm.

V. CONCLUSION

We looked into the energy cost reduction in a forthcoming heterogeneous cellular network (HCN) in this study. Novel construction difficulties and technical difficulties have arisen as a result of the fact that mobile traffic and renewable energy display temporal and geographical dynamism in a network. We examined several current techniques and presented a novel resource allocation strategy to accomplish spatial traffic equalizing as well as temporal renewable energy equalizing. The optimal cost route with a time restriction is first defined. The optimal cost of the energy consumption path with respect to the time constraint is evaluated using the proposed optimum time constraint algorithmic approach. We demonstrate that perhaps the algorithm's time, as well as space complexity, are $O(kn \log n + mk)$ as well as $O((n + m)k)$. Lastly, we execute tests on actual databases to verify the efficacy and reliability of the proposed approach.

It offers a general architecture for online optimizing parameters as well as various variants, such as algorithms E, R, and C. Under functional and feasible considerations, the estimated quality loss for a maximum of $n|R|\Omega(\log(n|R|))$ offline optimizations of algorithmic approach E is $o(1)$, whereas algorithmic approach R seems to be a $p(1 + o(1))$ -approximation until its inherent regret function is a as well as requires a maximum of $n\Omega(\log(n|R|))$ offline optimizations. Simulation findings show that the suggested system is more successful than two peer techniques in regards to cost reduction, packet planning, as well as numerous vehicles routing independent time windows, confirming the theoretical conclusions. It demonstrates the

importance of stochastic data and also the practical utility of algorithmic approaches R and C under time restrictions.

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