AI/ML-Based Sensing-Assisted Energy-Efficient Communications in Next-Gen Cellular Networks

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***Abstract*—5G networks promise to transform our technology experience by delivering ultra-high speeds and low latency, enabling applications like Augmented Reality (AR) and Connected Autonomous Vehicles (CAVs). However, 5G's higher frequencies reduce its range and lead to performance inconsistencies, especially for users on the move. Moreover, the energy consumption of 5G is significantly higher than its predecessor, 4G, raising sustainability concerns. In this paper, we explore a solution that combines the strengths of Integrated Sensing and Communication (ISAC) with the advanced analytics capabilities of the Network Data Analytics Function (NWDAF) in 5G networks. We leverage two new functions, Sensing Service Function (SSF) and Energy Efficiency Control Function (EECF), designed to work together to make smarter, more energy-efficient network decisions. By optimizing base station downlink transmit power, our approach not only reduces energy consumption but also carefully balances the trade-offs between latency and energy efficiency. Our findings suggest a promising path toward a greener and more reliable future for 5G and beyond networks.**

I. Introduction

The latest generation of cellular networks, 5G, offers ultra-high bandwidth and ultra-low latency, far surpassing the performance of 4G LTE, via a combination of PHY layer innovations such as higher modulation schemes, beamforming, (massive) MIMO, and wider channels. Such high data rates, combined with low latency, hold the promise to finally support *latency-critical* applications such as Augment Reality (AR), Mixed Reality (XR), Connected Autonomous Vehicles (CAVs), and the Metaverse, which demand ultra-high network bandwidth and low network latency to support offloading of compute-intensive tasks to the edge cloud.

However, 5G's higher frequency bands reduce its range making it difficult to achieve the same widespread coverage as LTE and causing high network performance fluctuations for users on the move. In addition, recent studies [1], [2] have shown 5G networks, with such high speed innovations, to be extremely power-hungry, consuming $3\times$ more energy as compared to their predecessor 4G LTE. Energy bills account for 90% of the operational expenditure (OPEX), with approximately 80-90% of the energy consumption originating from the Base Station side. With the ever increasing demand for high-speed, resilient, and ubiquitous connectivity, it is imperative to reduce the overall energy consumption to march towards a *greener* future. Hence, naturally, the question that comes up is "can we make 5G and beyond 5G communications fast, reliable, and energy efficient?"

The next-generation of mobile cellular networks is highly anticipated to leverage both sensing and communication technologies in an amalgamated fashion to achieve faster and more reliable communication [3]. Integrated Sensing and Communication (ISAC) is a unified system that shares the sensing and communication resources throughout the network. ISAC use cases are categorized into sensing assisted communication (SAC) and communication assisted sensing (CAS) [4], [5]. ISAC has the potential to enhance localization methods, map the physical world, and predict blockages/mobility so that the network can proactively make decisions to facilitate better communication. Additionally, from 3GPP Rel. 17, Network Data Analytics Function (NWDAF) was introduced to provide a standardized AI/ML based functionality in 5G core network. NWDAF collects input data from various data providers across different network domains (RAN, Core, Application, and OAM), generates Analytics (statistics and predictions), and deliver these insights to analytics consumers inside the network [6], [7].

Exploiting the above two facets of next-generation cellular networks, we propose a solution that leverages sensing assisted communications aspect of the ISAC alongside AI/ML functionality of NWDAF to generate sensing analytics which can assist energy-efficient and performance-optimized network decisions. In line with latest Rel. 19 3GPP discussions, we consider two new network functions (NF): SSF (Sensing Service Function), and EECF (Energy Efficiency Control Function) which provide the NWDAF with sensing and energy consumption related parameters to generate relevant analytics for all users in the network. We also formulate an optimization problem which takes sensing and energy related analytics parameter as input and optimizes BS power consumption while taking into consideration of performance related constraints. We evaluate the performance of the proposed optimization based problem via extensive simulations and show that the proposed solution can reduce energy consumption.

The rest of the paper is organized as follows: §II provides a high level overview of the overall system structure, describing the functions of SSF, EECF and NWDAF in context to our work. In §III, we introduce the communication model used, the sensing parameters to be measured, sensing analytics to be generated, energy parameters to be calculated and finally formulate the optimization problem. §IV presents simulation results, followed by concluding remarks in §V.

II. System Model

In this section, we present the high-level architecture of our system model shown in Fig. 1. The system comprises two

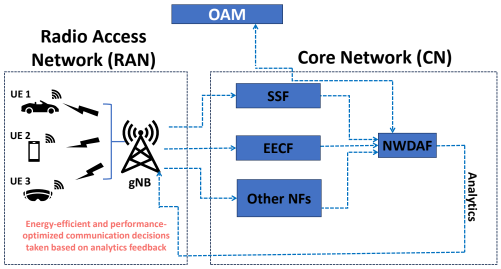


Fig. 1: High-level system architecture.

network domains: the Radio Access Network (RAN) and the Core Network (CN). The RAN consists of a base station (BS) and multiple user equipments (UEs). Each UE or user operates different types of applications at a given time instant having different Quality of Services (QoS) requirements. The CN, serving as the heart of the 5G network, provides connectivity to the BS and eventually the end-users by orchestrating essential functions and interaction via the use of different network functions that help in authentication, security, session management, traffic aggregation from end devices, etc.

We assume that the BS is equipped with different sensors to collect various environment-related and UE-related data and relay that information to the CN. A novel aspect of this work is to exploit sensing parameters and corresponding analytics to gauge the communication medium and augment it with network energy-consumption related parameters such that the BS can leverage this information to make energy-efficient communication decisions. We consider two new NFs inside the CN: Sensing Service Function (SSF) and Energy Efficiency Control Function (EECF), which are expected to be standardized by 3GPP. The SSF aggregates all the sensing data measurements from the BS, caculates sensing data parameters and forwards them to the NWDAF. NWDAF generates sensing Analytics based on sensing parameters provided by SSF and provides it to different network consumers; consumers of such analytics can be other NFs, the operations, administration, and management (OAM) layer, RAN or third-party entities. Similarly, the EECF is designed to calculate per-UE energy data and feed it to the NWDAF for the generation of energy-related analytics. In addition, existing NFs such as Session Management Function (SMF) will provide information about UE-specific traffic patterns and QoS requirements to the NWDAF to generate the relevant performance-related analytics. NWDAF provides sensing and energy related analytics to the BS, assisting it in making energy-efficient optimization based decisions while taking the performance related analytics into consideration.

III. Problem Formulation

With growing diverse types of applications, i.e, XR, video streaming, industrial transportation, etc, it is imperative for cellular networks to classify and prioritize the flows for different traffic classes accordingly to facilitate better communication eventually leading to better QoE (Quality of Experience). Current 5G architecture has the ability to distinguish and manage traffic flows with different Quality of Service (QoS) requirements [8]. The 5G QoS Identifier (5QI) represents specific QoS class assigned to the flow, defining the quality characteristics and service level agreement associated with it. QoS flow is further categorized into guaranteed bit rate (GBR) and non-guaranteed bit rate (Non-GBR). Non-GBR flows are best effort delivery flows, not having any specific data rate requirements. However, GBR flows include delay-critical resource types and depending on the class of traffic, each GBR flow has parameters such as packet delay budget (PDB) and packet error rate (PER) to define the requirements associated with the QoS flow. In 5G, the QoS flow represents the lowest level of granularity for a traffic flow and each PDU session can have a maximum of two QoS flows [8].

In this work, we assume each UE has one active PDU session at a particular time instant with one GBR QoS flow. The the high-level architecture of our system is defined as follows: The RAN consists of one base station (BS) and N users, indexed as $u = 1, 2, ..., N$. This network offers M different types of applications indexed as $a = 1, 2, ..., M$ where T_a is the latency requirement (e.g., delay budget) per packet per application a. Denote $\gamma_{u,a}$ as the binary variable to indicate the association of user u to application type a. Here, $\gamma_{u,a} = 1$ if the association occurs, and $\gamma_{u,a} = 0$ otherwise, and $0 \leq \sum_a \gamma_{u,a} \leq 1$. Let's assume each application is assigned to a different Quality of Service flow (QoS). Assume R_u is the total DL data rate of user u. L_a is the average number of bits per packet to be transmitted from the server to the user in downlink direction for application type a. Each user has an energy credit available at a granularity of per-day and energy credit per day for user u is denoted by EC_u^D.

Communication model: We assume that each BS is equipped with ISAC capabilities, capable of sensing the channel between the BS and the UE. At a given time, the BS transmits ISAC signal y. Due to the presence of reflectors, y contains multiple non-line-of-sight (NLoS) signals. Reflectors can include low-flying aircrafts, vehicles traveling on the road, as well as buildings and long-standing facilities that serve as fixed reflectors. These fixed reflectors can be easily filtered and eliminated by the BS through observation over a period of time. Once the BS obtains perception information, it is shared with the SSF to be also forwarded to the NWDAF.

Each BS operates on OFDMA and has K physical resource blocks (PRBs) of B kHz bandwidth. The BS DL transmit power for user u is P_u. If the channel between the BS and user u is given by $H_{BS,u}$, the noise spectral density is σ, the number of PRBs allocated to user as K_u, then the downlink rate of user u is:

$$R_u = BK_u log_2(1 + (P_u H_{BS,u}/BK_u\sigma)) \tag{1}$$

TABLE I: Summary of Notations

Notations	Definitions
E_u^{E2E}	End-to-end energy consumption per user
$E_{u,a}^{CN}$	Core network energy consumption per QoS flow per user
T	Time window
P_u	Downlink transmit power per user
L_a	Average number of bits per packet to be transmitted from the server to the user in downlink direction for application
R_u	Total downlink data rate per user allocated to an application per time window
$T_{a,u}^{Core}$	Average core network latency per application per user
T_a	Delay budget per packet per application
ζ_u	Indicator from NWDAF showing if ϕ_{LOS}^u is higher than threshold
ϵ_u	Indicator from NWDAF showing if user violates daily energy credit
d' and d''	Different latency downgrading coefficients

where,

$$H_{BS,u} = \sum_{l=1}^{L} h_{BS,u,l} \tag{2}$$

such that,

$$h_{BS,u,l} = \alpha_{BS,u,l} e^{-j2\pi f_0 \tau_{BS,u,l}} e^{j2\pi T_x v_{BS,u,l}} a(\phi_{BS,u,l}, \theta_{BS,u,l}) \tag{3}$$

containing one line-of-sight (LoS) path and $L-1$ non-line of sight channel paths generated by the multiple reflectors from the environment. $e^{-j2\pi f_0 \tau_{BS,u,l}}$ represents the phase shift caused by delay, $\tau_{BS,u,l}$ represents the propagation delay, f_0 represents the frequency of the signal, $e^{j2\pi T_x v_{BS,u,l}}$ represents the Doppler frequency shift, T_x is the sampling frequency, $v_{BS,u,l}$ is the Doppler parameter, $\alpha_{BS,u,l}$ is the fading coefficient, and $a(\phi_{BS,u,l}, \theta_{BS,u,l})$ is the vector coefficient of the channel, which includes the information of the channel's transmission, reflection, and incident angles [9].

Sensing components: Sensing data of the network includes sensing measurements data (e.g., doppler frequency), sensing parameters (e.g., probability of line-of-sight) and sensing analytics. Sensing parameters are calculated at SSF based on the sensing data measurements received from RAN and NWDAF generates sensing analytics based on the sensing parameters received from SSF. Let's assume for a set of sensing paramters 1,...,p, the NWDAF generates $\phi_u^1, \phi_u^2, \phi_u^3, ..., \phi_u^p$ such that ϕ_u^j is the probability that sensing parameter j of user u is within a range of interest t_u^j.

In this work, we consider the probability of line-of-sight (LoS) as the sensing parameter of interest such that probability of LoS for a user in a time slot is calculated as the number of time instances that the user is in LoS condition divided by total number of LoS measurement instances performed during that time slot. NWDAF generates the probability of LoS analytics as the amount of time that the probability of LoS is within a range of interest. Note that the proposed system model is generic in terms of the number and type of sensing parameters that can be incorporated. There have been numerous methods in the research literature exploiting signal statistics such as the mean excess and root mean square (RMS) delay spreads, maximum amplitude, rise time, and phase shift information, to accurately identify LoS channels [10]. Others exploit the Ricean K factor (larger implying LoS, smaller implying NLoS) and power-angle spectrum (PAS), which contains angular information of channels, to identify LoS channels [11]. Finally, repeated received signal strength (RSS) patterns over the multi-path components of a channel can be leveraged to determine if a channel is LoS or not [12].

Energy components: EECF can calculate network and UE energy consumption in different granularity (e.g., per UE, per applicstion, per QoS flow, per PDU session, and etc) based on the input received from other NFs. Here, we assume EECF calculates the $E_{u,a}^{CN}$ as the average core energy consumption per user per QoS flow for a given time window based on QoS flow, session and UE information received from SMF and AMF. Note that a one-to-one mapping between QoS flow and application is assumed, i.e., there is one QoS flow or application per user. Then, the total energy consumption per user per time window is calculated as follows:

$$E_{\mathrm{u}}^{E2E} = \sum_a \gamma_{u,a} E_{u,a}^{CN} + T P_u \tag{4}$$

where Pu is the downlink transmit power of BS for user u.

NWDAF can also get energy credit information for each user from subscription data and generate energy consumption violation alerts based on the energy credits.

Optimization Problem. We assume a time-slotted system where the optimization problem run at the beginning of a time window. We formulate a mixed-integer non-linear programming (MINLP) problem **OP** where the objective is to minimize the total network energy consumption, while taking into consideration of the packet delay budget per application.

$$\min_{P_u} \sum_u E_u^{E2E}, \tag{5}$$

s.t.

$$\gamma_{u,a}(L_a/R_u + T_{a,u}^{Core}) \ \leq$$

$$\zeta_u \epsilon_u d_u'' T_a + (1-\zeta_u)\epsilon_u d_u' T_a + (1-\epsilon_u) T_a, \tag{6}$$

$$0 \leq P_u \leq P_{max}, \forall u \in N, \tag{7}$$

$$P_u \in R^+, \forall u \in N, \tag{8}$$

where Eq. (6) enforces the delay budget constraint per application. ϵ_u is the indicator from NWDAF stating if a user has violated their daily energy credit where $\epsilon_u = 1$ means the user violated the daily energy credit. Once an user's daily energy credit is violated, our system employs a latency

TABLE II: Simulation Parameters

Parameter	Value
Users	40
Frequency	2.4 GHz
Channel bandwidth per PRB	180 kHz
$Pmax$	43 dBm
Probability of LoS threshold	0.7
Avg. bits per packet	208 Kb - 2240 Kb
Avg. latency deadline	0.03 s - 0.225 s
Avg. core network latency	0.002 s
Time window (T)	5 mins

downgrading mechanism to increase the delay budget (increase the latency deadline of the applications), thereby reducing the transmission power required to meet the delay budget. Moreover, let ζ_u be the indicator from NWDAF stating whether the probability of LoS of user u is higher than a threshold where $\zeta_u = 1$ indicates the case when the probability of LoS of user u is higher than a threshold. Let d' and d'' be defined as two latency downgrading coefficients. We use d' coefficient to increase the latency requirements (downgrade QoS) for those users having $\zeta_u = 0$, i.e., users with poor channel conditions. On the other hand, d'' coefficient is leveraged to increase the latency requirement for users with good channel conditions. Eq. (7) also ensures that P_u does not exceed the maximum downlink transmit power. Moreover, Eq. (8) enforces real value constraints. The following summerizes the sequence of events:

1) The SSF collects the sensing data from the BS, calculates sensing parameters and forwards them to NWDAF. NWDAF generates sensing analytics and provides them as an input to the optimization problem.
2) Similarly, the EECF collects energy related data, calculates per user per application energy consumption and forwards them to the NWDAF.
3) The NWDAF provides the sensing analytics, energy analytics, and QoS analytics to the optimization problem in every time window T.
4) Them optimization problem determines the optimal P_u that minimizes E_u^{E2E}.

IV. Simulation Results and Analysis

In this section, we present the simulation results of our proposed optimization framework. We use Python's scipy library to implement the optimization framework **OP** and use Sequential Least Squares Programming (SLSP) to solve the optimization problem. The simulation parameters used for this work are shown in Table. II.

In the simulations, the time window (T) is set to 5 mins, meaning the optimization is run every 5 mins to determine the optimal average downlink tx power per user which would be the power at which the BS will communicate with an user for the next 5 mins. In reality, the channel conditions can fluctuate in a matter of seconds and an ideal solution is to run the optimization framework every second to fetch an optimial downlink tx power. However, running an optimization

TABLE III: Different cases showing values of d' and d''

Case	Scenario (d'>d'')	Scenario (d'<d'')
1	d'= 1.5, d'' = 1.05	d'= 1.05, d'' = 1.5
2	d'= 1.5, d'' = 1.4	d'= 1.4, d'' = 1.5

framework every second is not feasible in practical and hence we consider running our optimization every 5 min, using average values for the input parameters. To test the efficacy of our method, we run our optimization framework every 2 s (2 s is the 3GPP defined default 5QI averaging window for GBR QoS flows [8]) with different L_a value ranges having different standard deviations. Then, we run the same simulation with time window set to 5 mins, considering average L_a values.

Fig. 2 shows the total E2E energy consumption as a function of time for one example 5 mins time window T, with two cases: (a) optimization is run every 2 second in a 5-min window, and (b) optimization is run once in a 5-min window. We observe, for both low and high standard deviation of L_a values, our system that is run every 5 mins, is able to optimize the downlink tx power and thereby minimize the energy accurately with respect to the 2-second fluctuations.

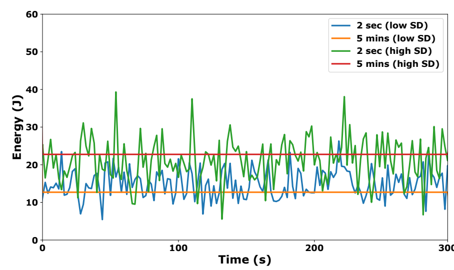
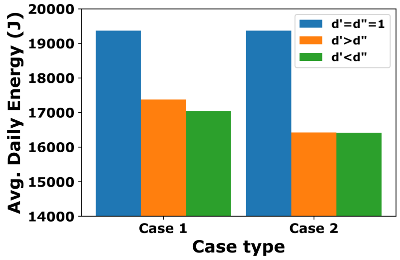


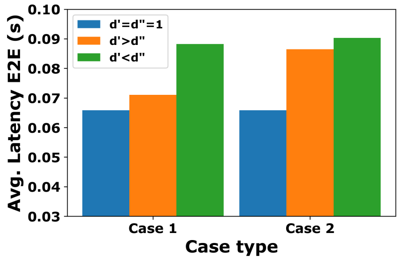
Fig. 2: Energy consumption comparison for different optimization time windows (T).

We compare the performance of our proposed solution against a baseline condition where $d' = d'' = 1$, meaning the users are not penalized when they violate the daily energy credit. For our proposed solution, we further break it down into two parts: (Scenario a): $d' > d$", where a higher latency downgrade coefficient is applied to the users with poor channel conditions ($\zeta = 0$), and (Scenario b): $d' < d''$, where a lower latency downgrade coefficient is applied to the users with poor channel conditions. Furthermore, we choose two different cases where the d' and d'' values are different. Table. III shows the values of d' and d'' values for the two cases. Case 1 suggests a comparatively less aggressive latency downgrade factor compared to Case 2.

Fig. 3a shows the average daily end-to-end energy consumption across all users, comparing the baseline scenario against our proposed solution. We observe, for both cases, the energy consumption of our proposed solution is lower than the baseline scenario. The drop is more pronounced for case 2 where we used a higher latency downgrading coefficient, reducing the energy aggressively. As a result, we see in Fig. 3b the latency in case 2 for our proposed solution is higher than the one in case 1 due to the aggresive reduction of energy by increasing



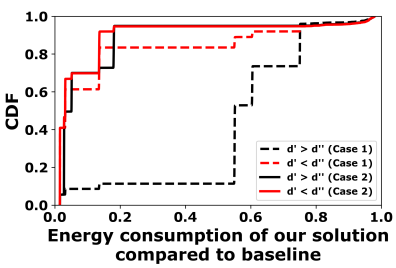
(a) Daily energy.



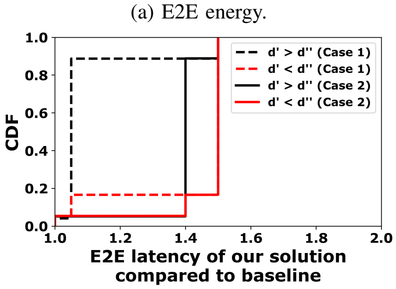
(b) E2E latency.

Fig. 3: Overall comparison of avg. daily energy and latency.

the latency deadlines of the applications. To further understand



(a) E2E energy.

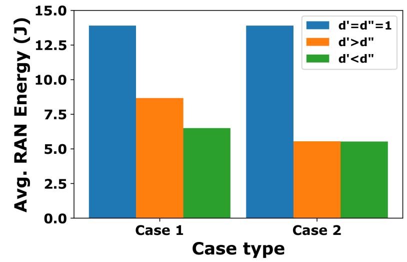


(b) E2E latency.

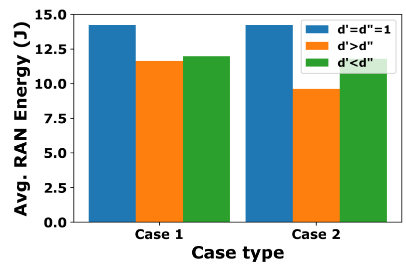
Fig. 4: Per-user E2E energy and latency comparison.

the trade-off between the energy consumption and latency using our proposed system, we show the per user percentage in reduction and increase in E2E energy consumption and latency in Fig. 4. Fig. 4a shows that around 95% of the times for case 2, where the system aggressively tries to downgrade the latency deadline, the energy consumption drops to 0.2 times the baseline. Consequently we notice that the median latency for case 2 is high (1.4-1.5 % of the baseline). Interestingly the increase in latency is not proportional to the decrease in the energy, showing the efficacy of our proposed approach.

On the other hand, for case 1, we see different patterns for the two scenarios. For $d' < d''$, around 80% of the times the energy consumption is very low (<0.2) and the rest of the times it drops to 0.6-0.9% of the baseline. In the scenario, where $d' > d''$, 80% of the times, the energy becomes > 0.5 times the baseline. In general, for case 1, where the reduction in energy is lower compared to case 2, we see that our system still tries to make a significant effort to lower the energy consumption, i.e., 0.6 times the baseline energy consumption on average.



(a) $> 50\%$ users with $\zeta = 1$.



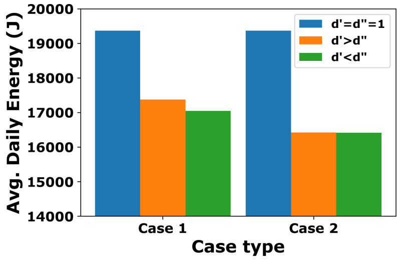
(b) $< 50\%$ users with $\zeta = 1$.

Fig. 5: Comparison of RAN energy consumption for varying percentage of users with $\zeta = 1$.

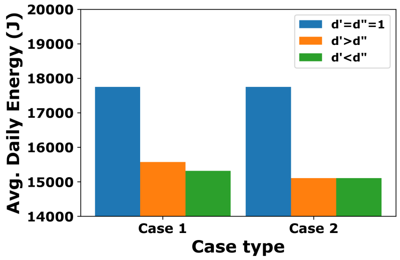
Interestingly, in Fig. 3a, we see that the energy consumption is lower in both the cases for the scenario $d' < d''$. This suggests that users with poor channel conditions are penalized comparatively lesser than users with good channel conditions, on average. We found the reason for such results depends on the distribution of ζ in the network. Remember, in Eq.6, if ζ is 1, d'' downgrade coefficient is used and d' otherwise. So, if a large percentage of users in a network, have $\zeta = 1$, on average, having a higher d'' will reduce energy consumption more for users with good channel conditions.

To test our hypothesis, we ran the simulation, with varying percentage of users having $\zeta = 1$. Fig. 5 compares the RAN latency when $> 50\%$ of users in a network have $\zeta = 1$ vs. when $< 50\%$ of users in a network have $\zeta = 1$. Fig. 5b clearly illustrates that when majority of the users in the network have poor channel conditions, the impact of $d' > d''$ in lowering the average energy consumption is higher. Again for case 2, the energy is lower due to higher d' and d'' value, which increases the latency deadline aggressively.

Up till now, we ran our simulations with a fixed daily energy credit which was kept to a same value for all users. Now, we look into the impact of varying the daily energy credit limit.



(a) Fixed energy credit.



(b) Varying energy credit.

Fig. 6: Avg. daily energy consumption comparison for varying energy credit threshold among different users

We ran the simulation by setting the daily energy credit limit to 3 distinct values: daily energy credit same as/lower than/higher than the fixed daily energy credit limit. Fig. 6 compares the overall daily energy consumption for the fixed energy credit simulations against the per-user varying energy credit simulations. In general, we observe similar trends for both types of experiments, with our proposed system consuming lower energy than the baseline. For the varying energy credit limit (Fig, 6b), we see the energy consumption is slightly lower than the fixed energy credit scenario. This stems from the fact that for some users having lower energy credit limit, our system starts reducing the energy per iteration much faster than the scenario where the limit was higher, thereby reducing the overall average energy consumption.

Overall, we observe that our proposed approach reduces energy consumption considerably compared to the baseline scenario. The reduction in energy can vary from being 0.1-0.9 times the energy consumption of the baseline scenario depending on different values of d' and d'' values. Consequently, our solution increases the average latency of the users with a maximum of 1.6 times the baseline latency. However, the increase in latency is not proportional to the energy reduction. Further, our analysis shows the interplay between the channel condition of the users and the energy reduction, and also how energy consumption is impacted when multiple users have varying energy credit limits.

V. Conclusion

This work advances the integration of sensing and AI/ML (Analytics) to improve energy efficiency in 5G networks. We have proposed a novel approach that reduces network energy consumption by combining sensing parameters of ISAC, AI/ML capability of NWDAF in 5G core, and energy parameters calculated by Energy Efficiency Control Function (EECF). Specifically, we identified a sensing parameter and its related analytics which can assist energy minimization decisions in the network. Our approach, which optimizes base station downlink transmit power, achieved significant energy savings ranging from 0.1 to 0.9 times the energy consumption of a baseline scenario while resulting in a maximum increase in latency of up to 1.6 times. This trade-off highlights the effective balance our solution strikes between reducing energy consumption and managing latency. Additionally, our analysis demonstrated how different channel conditions and varying energy credit limits impact overall energy savings and network performance. The findings validate the potential of our solution to enhance energy efficiency while maintaining manageable latency levels. Future research should explore additional sensing parameters and optimization strategies to further refine these trade-offs and adapt to the evolving demands of next-generation mobile networks.

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