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A serious gaming approach for optimization of energy allocation in CubeSats

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Abstract
Energy consumption remains an open challenge in aerial systems such as CubeSats and therefore optimization of its allocation is a top priority for maximizing operational capacity. Our research review reveals a plethora of approaches for optimization of energy allocation and all achieving varying degrees of success and not without any compromises. In this paper, we exploit the use of serious gaming in a novel energy allocation algorithm that aims at minimizing energy consumption to maximize the utilities of both CubeSats and terrestrial sensors. To demonstrate this, we use Stackelberg for serious gaming and standalone topology for CubeSat configuration. The experimental results show that the use of a Stackelberg game approach for optimization has led to reduction in the required transmission energy in sensors, an improved link performance between the CubeSat and ground sensors, and an increase in network lifetime and performance without resorting into sensor power enhancements or other external power sources. The overall average operational capacity improvement predictions range between 22 to 27% across all performance indicators of energy efficiency across RF chains of link budgets.

Keywords Serious gaming · Optimization · Energy allocation · Energy consumption · Cubesat · Aerial model · Wireless connectivity

1 Introduction

Serious gaming is an alternative testbed for testing complex decision-making in numerous subject areas through simulation and analysis of decision-making processes. The use of rewards, which are incentives based on performance, and the user interactions that follow

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inform on the choice of actions. Serious gaming techniques are increasingly applied widely for data analytics by retrieving valuable information from complex large data sets that support generating smart decision. The learning and training concepts rely on discovering data patterns and those data elements that when adapted may change the data patterns. This is driven by the competition as it unfolds during interaction and helps support decision making and performance optimization, despite the continuous challenge of measuring the learning impact of competition [8, 9, 28].

Serious gaming is regularly used to examine the behavior of rational and strategic decision-makers by considering possible equilibriums in conflict-of-interest situations and then providing appropriate mechanisms for enabling cooperation between two or more players. Stackelberg, and Nash Equilibrium are prime examples of the use of hierarchical serious gaming in observing the sequential interactions among players foe the purpose of making strategic decisions across many applications. Observing different attributes and behaviors among players during interactions enables these serious gaming methods to seek optimum decision-making solution(s) [7, 12, 17]. Serious gaming has been applied successfully for smart decision making to enhance performance across a wide range of applications ranging from education to healthcare, to manufacturing and energy allocation is among these. Optimization of energy allocation will prolong network terminal lifetime and which in turn will help with sustaining the system performance, especially of wireless systems. This requires optimization of channel modeling and use of the limited transmission energy resources [6, 32].

Satellite systems including Cubesat are crucial in global wireless communication systems, due to their soft deployment, high frequency bands, wide coverage footprint, and line-of-sight connectivity. Yet, despite the advancement of Cubesat technology, energy allocation and consumption remain an open challenge that reportedly affect performance and/or operational lifetime. CubeSats use solar cells to convert solar light to electricity that is stored in rechargeable lithium batteries that are an energy source during an eclipse as well as during peak load times. Moreover, the energy subsystem in Cubesat is responsible for storing, distributing, and controlling the spacecraft's electrical energy. The efficiency of the Cubesat solar cells may be affected, for instance, by the radiation intensity of the sun, and the incident angle at which the sunlight strikes the cells [5, 23, 26].

Motivated by the open challenge of energy consumption, the overall aim of this paper is to apply serious gaming in optimizing energy allocation in a Cubesat. Section 2 reviews related work in support of the design and concludes by highlighting the specific research gaps that motivate our proposed contribution. Section 3 presents the design of our proposed model that deploys serious gaming into the underlying communication infrastructure. Section 4 evaluates our proposed model and presents a first proof-of-concept. Section 5 concludes.

2 Related research review

This section reviews related research works whose optimization approach includes the use of serious gaming and their target is energy allocation in aerial systems. For ensuring consistency and keep within the scope, a primary and a secondary set of criteria have been used to source and review the related works; the primary criteria include the use of optimization, the *network* configuration, and the vehicle type whereas the secondary criteria include propagation path loss, altitude, and coverage range. The section concludes with a summary of our findings and whose purpose is to bring to the fore research gaps which serve to motivate our own work.

[16] introduces a study on green UAV communications for 6G that also includes a review of various optimization techniques for power consumption includes serious gaming. The authors suggest a set of optimization parameters, i.e., UAV trajectory, configuration, and link budget, for efficient energy allocation. [22] proposes a resource allocation scheme for satellite networks based on the bargaining model of a two-player resource allocation game theory approach. Their simulation shows reasonable results in relation to time and throughput for their application area of emergency service provision. The proposed solution requires bit energy over power density.

[11] utilises Nash Equilibrium in a power allocation strategy for cognitive satellite networks. The results in relation to bit error rate (BER), and signal-to-noise ratio (SNR) suggest an acceptable level of performance. However, as the proposed technique has been deployed in only a specific scenario, scalability is an issue to be resolved. [31] introduces power allocation for inter-satellite links for which a utility function is designed and optimized with Nash Equilibrium using signal-to-interference and noise ratio (SINR), utility values, and transmission power as the performance indicators. The results suggest improvements in power resource reservation.

[18] considers a Stackelberg model for managing interference in a multibeam satellite system that helps with power allocation and consumption. The results prove that the proposed game model can adjust the price of interference to achieve a trade-off between intercell interference and operating profit. [34] presents a two-layer Stackelberg equilibrium to allocate power and computation resources among users while satisfying the quality of service (QoS) constraints and utility price. In response to the resource allocation problem the authors aim at maximizing the utility between operator and users, which leads to energy minimization. The Stackelberg equilibrium achieves optimal pricing.

[33] optimizes satellite transmission energy allocation at a 1000 km altitude applying empirically different weight factors. The results show improvement in energy allocation. However, satellite energy use, transponder state and service requirements need further consideration. [30] uses a Lyapunov optimization approach for energy efficiency over multibeam satellite downlinks. This helps with optimal control of a dynamical system for queueing networks. The results on energy efficiency show noticeable improvements, but with some delay trade-off.

[20] considers Artificial Intelligence (AI) approaches for satellite power allocation. The approaches include genetic algorithms, simulated annealing, particle swarm, and deep reinforcement learning for multibeam management to maintain robustness and fair power consumption. The results vary across different approaches with noticeable trad-offs. The approaches do not find a global optimum, only local optima. Therefore, they offer no guarantee of good performance when user behaviour changes. [10] uses deep reinforcement learning to optimize power allocation for high throughput satellites. The results focus on time and throughput management for maintaining power not for dynamic power allocation.

[24] presents a mathematical integer programming (IP) formulation for task scheduling and energy management of CubeSats. The proposed model mainly focuses on maximizing the number of tasks of a CubeSat while maintaining low energy consumption. The results of the proposed model suggest an optimal energy effective scheduling plan, allowing the best possible use of available energy resources while ensuring quality of service (QoS). [25] proposes a model that focuses on energy efficiency for Unmanned Aerial Vehicle (UAV) using Exact Potential Games (EPG) and Nash Equilibrium. The model seeks a compromise between coverage deployment and energy consumption. The results confirm the success of the proposed approach and confirm the reliability of the proposed model. However, modifying the frequency band results in interference.

[29] proposes a cooperative joint cooperative beam association and power allocation scheme in LEO Satellites using many-to-many a match game-based beam association (MGBA) algorithm and a successive convex approximation (SCA) power allocation (SPA) algorithm. The results show that the proposed MGBA-SPA scheme outperforms other contrast schemes.

2.1 Research motivation and proposed contribution

Table 1 summarises the findings from our review of the literature separating between issues that are being addressed and those that are not, hence, creating gaps that motivate further research work, including ours. Our proposed contribution not only aims to address on-going challenges, but it also offers added value. Optimizing energy allocation in CubeSats is scarcely reported in the literature and currently lacking consideration of a serious gaming approach. Therefore, a key difference between the proposed contribution and what is reported in the literature is, primarily, the novel energy allocation approach that aims at joint minimization energy consumption to maximize utilities for both Cubesat and terrestrial sensors using a Stackelberg game approach. This noticeable shift from mainstream approaches promises smart decisions and achieving the objective of efficient energy allocation. This requires making multiple decisions to minimize energy consumption, i.e., from fair transmission to maximization of feasible sleep time, to optimization of convergence range, to adjustment of cluster size and to node selection.

3 Proposed model

Figure 1 shows a bird's-eye-view of the proposed model that uses Stackelberg serious gaming for optimizing energy allocation on a Cubesat. A proof-of-concept implementation verifies.

Wireless communications between a Cubesat and all its terrestrial nodes, whether mobile or stationary, is challenging as this involves managing a potentially large number of terrestrial nodes connected to the Cubesat whilst in orbit. Introducing node clustering and a head node would help with managing the number of nodes that are directly communicating at any given time with the Cubesat. A cluster head will have the responsibility of data transmission directly to the Cubesat, which reduces the probability of data collision between nodes and in turn would lead to better energy consumption. The cluster size and the number of nodes in each cluster can be pre-set to ensure energy allocation fairness. Cluster allocation considers criteria, such as energy level consumption, number of neighbor nodes, and harvested energy levels. This approach can help with maximizing network lifetime and achieving energy dissipation load balancing utilization in respective clusters.

Figure 1 depicts two segments [2, 13], the space segment with its Cubesat and payloads, and the ground segment with its ground control station that is linked to the Cubesat with a RF control link that supports all Cubesat operational functions and aerial navigation. The Cubesat serves K randomly distributed sensors on the ground via the RF links, and this can be optimized using Stackelberg serious gaming. Sensing the link margin data depends on a set of parameters including path loss, transmitter power, Multiple Input Multiple Output (MIMO) antenna gain, frequency band, and bandwidth. Data links are established between cluster heads and ground sensors. Stackelberg comes into play to prioritise access and optimize the overall network utility and energy allocation for the Cubesat. Guaranteeing a fair energy allocation

Table 1 Related research against the proposed contribution

Ref	Aerial Type	Configuration	Optimization Approach	Issues Resolved	Issues Persisting
[22]	Satellite	Stand alone	Two-player game	Propagation delay	bit energy/power density
[11]	Satellite	Stand alone	Nash	RF allocation	Scalability, no power data
[31]	Satellite	Network	Nash	Inter-satellite links	Complexity
[18]	Satellite	Stand alone	Stackelberg	Interference	Transmit power fixed/limited
[34]	Satellite	Integrated	Stackelberg	QoS/utility price	Utility price/evolution speed trade-off
[33]	Satellite	Bus	Empirical	Link capacity	Complexity, low performance
[30]	Satellite	Stand alone	Lyapunov optimal	Data traffic	Delay trade-off
[20]	Satellite	Stand alone	AI	High throughput	Inflexible, local optima
[10]	Satellite	Stand alone	DRL	High throughput	Sporadic higher energy
[24]	Cubesat	Stand alone	IP formulation	Task and energy plan	Broad time units
[25]	UAV	Mesh	EPG and Nash	Coverage	RF band set, interference
[29]	Satellite	Stand alone	MGBA-SPA	Coop beam, power plan	Complexity
Model	Cubesat	Stand Alone	Stackelberg	Fair transmission, cluster size adjustment, convergence range optimization, node selection, feasible sleep time maximization	

requires multi-optimization decisions on fair transmission, feasible sleep time maximization, convergence range optimization, cluster size adjustment and node selection.

Estimating a Cubesat link margin is heavily dependent on various parameters that effect the free space link from the Cubesat to the sensors on the ground. Thus, we have considered the Carrier to Noise ratio (C/N) in Eqs. 1 and 2, and the bit energy per noise density ratio (E_b/N_0) in Eq. 3. These parameters are widely considered as quality indicators of a satellite communication channel, from which a fuller range of link budget parameters can be drawn, e.g., throughput, Signal to Interference Noise Ratio (SINR), Received Signal Strength (RSS), coverage range, [1, 4, 5].

$$(C/N)_T = P_t + G_C + G_S - (\frac{4\pi d}{\lambda^2}) - F - 10\log_{10}\left(KT_0B\right) - L \tag{1}$$

$$d\ [km] = 2\ E_r\ [\cos^{-1}\left(\frac{E_r}{E_r + h_t} \times \cos(\theta)\right) - \theta] \tag{2}$$

$$E_b/N_0 = \left(\frac{C}{N}\right)_T \times (\frac{Bw}{R_b}) \tag{3}$$

$$RSS = P_t + G_C + G_S - P_L - L \tag{4}$$

$$Th = B \times \log\,(1 + \frac{RSS}{N + I}) \tag{5}$$

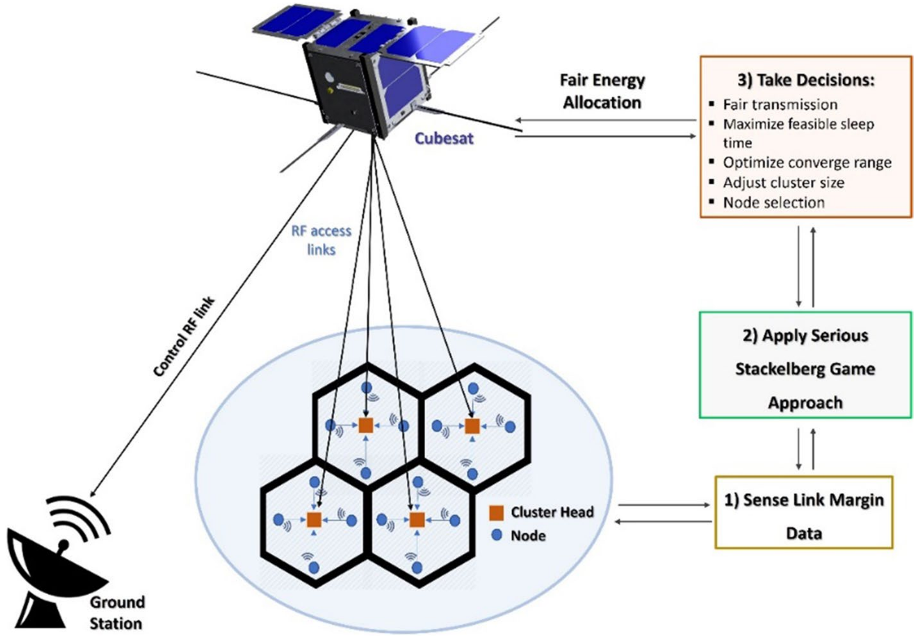


Fig. 1 A conceptual framework of the proposed model

where P_t indicates transmission power, G_C indicates CubeSat antenna gain, G_S indicates ground station antenna gain, d indicates distance from the Cubesat to earth station and/or ground sensors, λ indicates wavelength, a fraction of speed of light to frequency. d is calculated with consideration of the elevation angle θ, which is vital in satellite wireless communication systems for achieving better LoS connectivity, L refers to losses, E_r indicates the earth radius (6,371 km), h_t indicates the Cubesat altitude, F indicates the receiver noise figure, K indicates the Boltzmann's constant (1.38.10–23 Ws/K), T_0 indicates the absolute temperature (290 K), B indicates the receiver noise bandwidth, N indicates the Noise figure, I indicates interference, Bw indicates the required bandwidth (MHz), R_b indicates data bit rate, and Th refers to predicted throughput in (Mb/s).

Efficient and fair energy allocation is vital in maximizing the usage of shared resources like bandwidth, which in turn can benefit both transmitter and receivers. An optimization model with serious gaming may optimize priority-based access and overall network utility. The aim of this paper is to use Stackelberg as the serious gaming approach in achieving that. With serious gaming, the learning concept and strategies can be developed based on real conditions or data from predicted results. With the proposed model the Cubesat, acting as the leader, sets the interference prices to the terrestrial sensors, acting as the supporters, including both the cluster heads and cluster nodes. The Cubesat, although affected by the cost of interference, focuses on maximizing its utility from interference returns. The terrestrial sensors focus on maximizing their utilities per unit of power consumption. Hence, Stackelberg aims at obtaining the optimal prices for Cubesat and optimal transmission powers for terrestrial sensors. The formulation of the serious Stackelberg game approach is mathematically expressed in Eqs. (6) to (17) [15, 32].

The Cubesat can transmit data at a particular level of energy P_P, while terrestrial sensors transmit at a variable energy P_i, thus the SINR at receivers is as in Eq. (6). The energy allocation price problem is formulated as a two-stage Stackelberg serious game with the Cubesat being the leader and the N terrestrial sensors being the followers. The sensors chose their own transmission energy according to the interference energy price p_i set by the Cubesat. Hence, the Cubesat aims to maximize its utility by forcing a charge for interference I_{ik} produced by the terrestrial sensors by consideration of the interference effects on the overall utility as in Eq. (7).

$$\gamma_i\ (P_i) = \frac{P_i\ g_i\ h_i}{\sum_{k=1}^{N}\ Pp^{I_{ik}} + \sigma^2} \tag{6}$$

$$U_{cubesat}\left(p_i, P\right) = \sum_{i=1}^{N}\left\{p_i\ I_i\left(P_i\right) - \alpha\ I_i\left(P_i\right)\right\} \tag{7}$$

where g_i refers to channel energy gain between a cluster head and one of its nodes, h_i refers to channel energy gain between a Cubesat and a cluster head, K refers to the number of terrestrial sensors. Channel energy gains are distributed using additive white Gaussian noise and variance σ^2, where α refers to the conversion factor of a Cubesat's economic loss per unit of interference produced by sensors, $I_i\left(P_i\right)$ refers to the interference between a cluster head and its nodes, P denotes the vector of energy allocation for all sensors.

In the serious game, the Cubesat seeks to achieve optimal utility through its interference price (objective O1), this is expressed as in Eq. (8), whereas terrestrial sensors aim at maximizing their utility through receiving optimal allocated energy (objective O2) this is expressed as in Eq. (9). Both objectives are pursued without any degradation of the quality of service for transmission of large data packets with the lowest transmission delay possible.

$$O1\ :\ \max_{p_i \geq 0}\ U_{cubesat}\left(p_i, P\right) \tag{8}$$

$$\begin{gathered} O2\ :\ \max_{p_i \geq 0}\ U_{ti}\left(P_i, p\right) \\ s.t. E\left[W_i\right] \leq T_i \end{gathered} \tag{9}$$

where W_i refers to time where a sensor is waiting in a queue for packets to be transmitted, $E\left[W_i\right]$ refers to service time, T_i refers to delay constraint which is converted into a transmission rate constraint as in Eqs. (10) and (11). O2 is solved in a non-cooperative game G to maximize utilities as in Eq. (12).

$$R_i \geq \varphi\ (T_i,\ \upsilon_i,\ Z) \tag{10}$$

$$R_i = \log_2(1 + \gamma_i\left(P_i\right)) \tag{11}$$

$$G = \left\{\Omega\left\{P_i\right\}_{i\in\Omega,}\ \{U_i\left(P_i,\ p\right)\}\ _{i\in\Omega}\right\} \tag{12}$$

where R_i refers to transmission rate,υ_i refers to packet arrival rate of terrestrial sensors, Z refers to packet size, and Ω to a set of terrestrial sensors $\{1, 2, \ldots\ldots k\}$.

Equations (13) to (17) present a Stackelberg equilibrium which aims at finding the fractional structure of the terrestrial sensors' objective function and convert it into an equivalent parametric programming problem.

$$U_{cubesat}(p^*, P^*) \geq U_{cubesat}\left(p_i, P^*\right) \tag{13}$$

$$U_{ti}\left(P_i^*, p^*\right) \geq U_{ti}\left(P_i, p^*\right) \tag{14}$$

$$\begin{aligned} &O3 : \max_{p_i \geq 0} U_{ti}\left(P_i, p_i\right) \\ &s.t. R_i \geq R_{th} \end{aligned} \tag{15}$$

$$R_{th} = \varphi(T_i, \upsilon_i, Z) \tag{16}$$

$$U_{ti}\left(P_i,\ p_i\right) = \xi_i \log_2\left(1 + \gamma_i\left(P_i\right)\right) - p_i I_i(P_i) - q_i(P_c + P_i) \tag{17}$$

where p^* and P^* refer to optimal solution of objectives O1 and O2 respectively, thus $p^*$and P^* refer to the point of the Stackelberg equilibrium. p^* represents the optimal strategy of the Cubesat, whereas P^* refers to the optimal power of the terrestrial sensors. ξ refers to a conversion factor to represent the economic gain of terrestrial sensors, $I_i(P_i)$ refers to the interference that terrestrial sensors will experience from the Cubesat under the interference price p_i, P_c refers to the additional circuit power consumption of sensors through transmission, and q_i refers to the searching function for the optimum solution.

A feasible sleep strategy is introduced to minimize energy consumption and in turn extend the lifetime of wireless sensors. To enable that, sensor nodes switch between two modes: active and sleep. Sensor nodes observing the feasible sleep strategy help with balancing energy consumption by switching between active and sleep modes so that not all sensor nodes are active at any given moment. This is formulated as in Eqs. (18) to (20).

$$FS = \left\{N, K\left\{u_i\right\}\right\} \tag{18}$$

$$u_i\left(s_i, s_{-i}\right) = U_i\left(s_i, s_{-i}\right) - C_i\left(s_i, s_{-i}\right) \tag{19}$$

$$U_i\left(s_i, s_{-i}\right) = R * P \tag{20}$$

where u_i denote the utility function of the i^{th} player, N and K denote respectively the player and their strategic space in the wireless sensors network, s_i denotes the mode of the i^{th} sensor node, s_{-i} denotes the mode of all other nodes, $U_i\left(s_i, s_{-i}\right)$ and $C_i\left(s_i, s_{-i}\right)$ denote respectively the revenue and cost functions of the i^{th} sensor node, R and P denote respectively the reward and probability of a sensor node sending successfully a data packet to the next sensor node. The probability of s_i being either in active or sleeping mode is 1 and 0 respectively.

Optimization of transmission energy P_i^* using Stackelberg serious gaming is formulated in Eqs. (21) to (27) [19, 21], with the Cubesat interference price set in consideration of utility $\max U_{MBS}$ and bandwidth.

$$\frac{\partial U_{ti}}{\partial P_i} = \frac{\xi_i}{\ln 2} \times \frac{g_i}{G_i + P_i g_i} - p_i h_i - q_i = 0 \tag{21}$$

$$P_i^* = \frac{\xi_i}{\ln 2\ (p_i h_i + q_i)} - \frac{G_i}{g_i} \tag{22}$$

$$\max\ U_{MBS} = \sum_{i=1}^{N} p_i\ P_i h_i - \sum_{i=1}^{N} \alpha_i\ P_i h_i \tag{23}$$

$$p_i^* = p_i^*\ (G_i) \tag{24}$$

$$p_i = Z_i\left(p_i\right) = -\frac{P_i}{\partial P_i / \partial p_i} + \alpha_i \tag{25}$$

$$p = \left[Z\left(p_1\right),\ Z\left(p_2\right) \dots,\ Z\left(p_N\right)\right]^T \tag{26}$$

$$p(t+1) = Z(p(t)) \tag{27}$$

where Z(p) refers to the interference price competition constraints, p(t + 1) refers to the updated process price.

Achieving optimal or fair transmission energy allocation helps the Cubesat to make relevant decisions such as adjusting the cluster sizes, optimizing the convergence ranges, node selection, and maximizing feasible sleep time, which in turn helps guaranteeing a fair energy allocation. Figure 2 shows the interactions among players and with the utility, Cubesat, during game play where each player represents a cluster head, P_N is the energy demand of players and determining K and M will maximize energy reduction. Algorithm 1 is our energy allocation approach using Stackelberg serious gaming.

4 Simulation results and discussion

We have used MATLAB's CubeSat blockset simulation library, as shown on Fig. 3, to simulate, visualize and analyse the Cubesat link margin. The data is used as input to our model. Figure 4 illustrates early predictions of the Cubesat's link margin using GUI plots. These plots present a general overview of the Cubesat communication performance based on indicators such as PL and power consumption, which in turn help with observing the likely effect of likely improvement before deploying any serious gaming.

Figure 5 shows the Cubesat and cluster head utilities after Stackelberg deployment. Maximizing utilities per unit power of consumption helps in sustaining a reliable connection with Cubesat, thus enabling Internet of Everything (IoE) communications with ground sensors. Sharing the transmission spectrum will undoubtably cause interference.

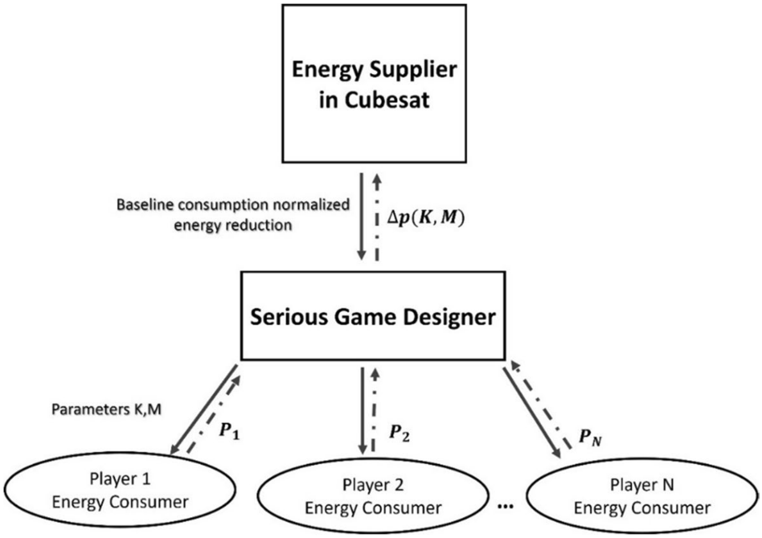


Fig. 2 Interactions among players and with the utility, Cubesat, during game play

```
Intilaization: g, h, l, ξ, N, σ, P_c, P_P, α, δ, a, and b
Traning:
While |F(q)|> σ do
        Use equations (15) and (22) to calculate the optimal p* and P*
        While |p(k) -p(k-1)| > δ or |P(k) -P(k-1)| > δ do
                Revise p(k)and P(k)based on equations (15) and (22)
                K=k+1
                end While
        if F(a).F(q)≥ 0 then a=q else b=q end if
        q=(a+b)/2
end While
```

Algorithm 1 Energy allocation using Stackelberg serious gaming

The Cubesat objective is to maximize use of its utility by imposing a monetary charge for the interference caused by cluster heads whilst considering the effect of interference on the utility. Figure 5 reveals that as the weight assigned to interference rises so does the utility benefit. In contrast, increases in throughput affect utility use which in turn causes higher power consumption.

Figure 6 presents the evaluation of the performance of the proposed power allocation scheme, both Stackelberg (Cubesat) utility and price, against the Quality of Service (QoS) threshold. This is a vital performance indictor as it reveals the optimal interference prices and power consumption. The Fig. 6 reveals a clear pattern of pricing and utilities

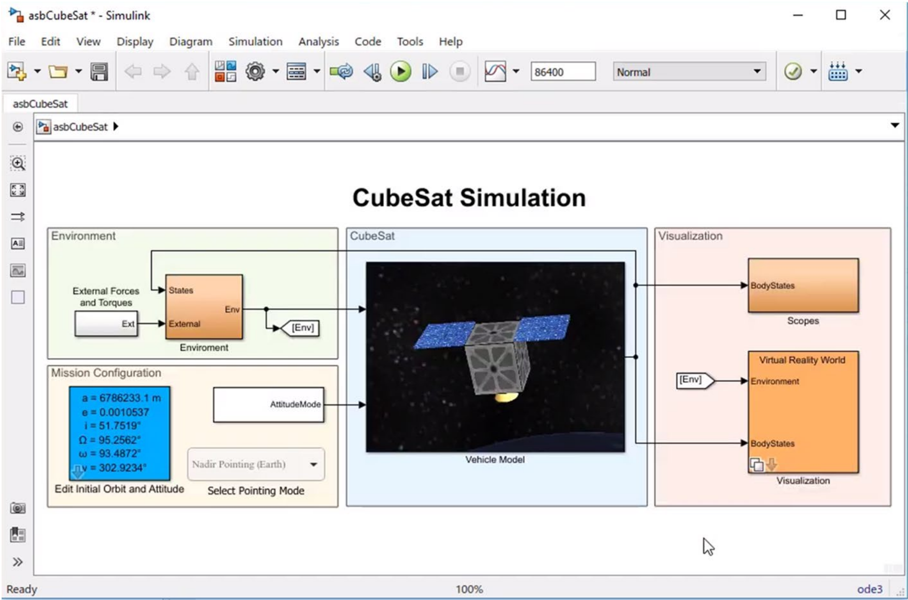


Fig. 3 CubeSat Blockset in MATLAB

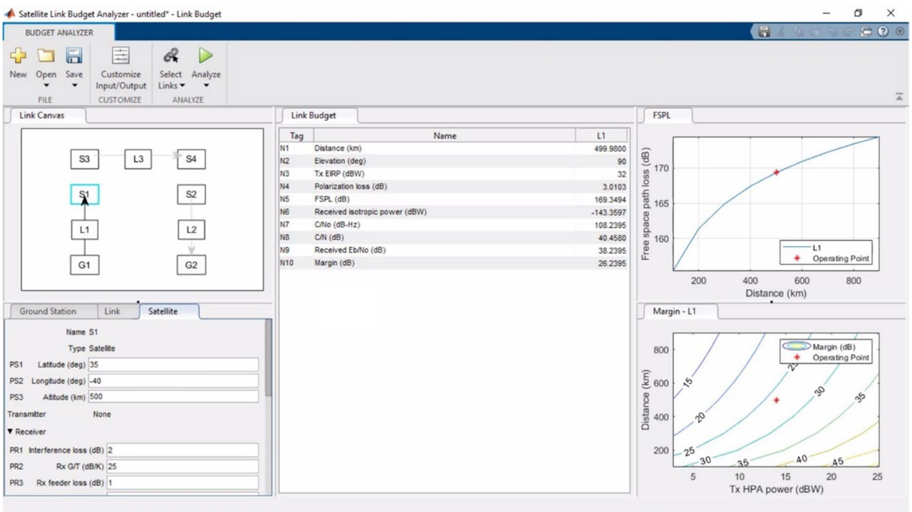


Fig. 4 Link margin results of the Cubesat prior to deploying serious gaming

equilibrium with increasing QoS threshold which in turn suggests that the proposed power allocation scheme presents a noticeable improvement in power-saving.

Guaranteeing fair energy allocation and thus fair transmission, an RF chain of MIMO antennas is introduced, and its number optimized, which not only enhances energy efficiency, but also yields the best data-rate performance, as Fig. 7 demonstrates. The RF

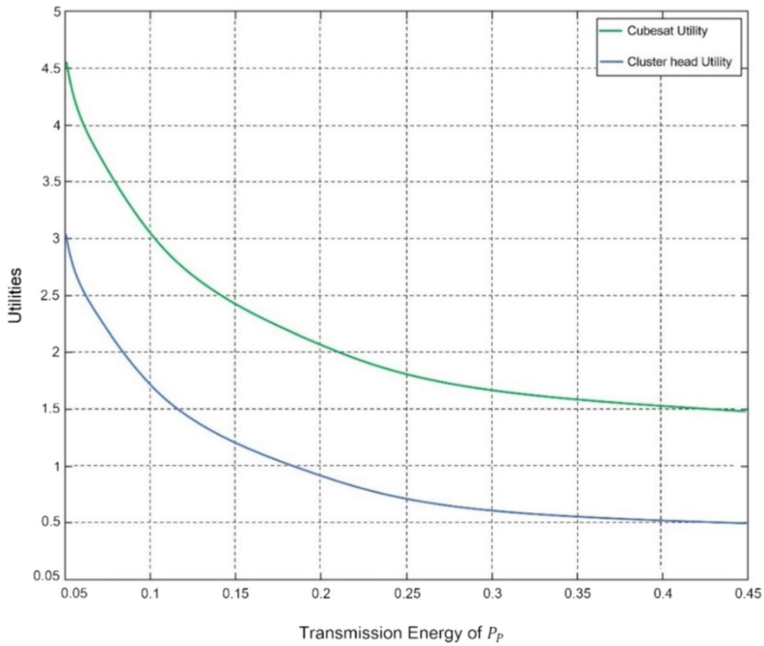


Fig. 5 Cubesat and cluster head utilities after serious gaming deployment

chain enables grouping of sensors together into clusters before selecting cluster heads. The Figure shows the rise in energy efficiency arising from the use of RF chains for clustering of sensors.

The non-optimized wireless channels suffer the effects of high path loss and fading, and sensor battery lifetime degradation. The predicted results of the link budget parameters between the Cubesat and ground sensors, including RSS and Th, are linked with two main QoS performance indicators: the Eb/No of Eq. (3), and the bit error rate (BER) of Eq. (28),

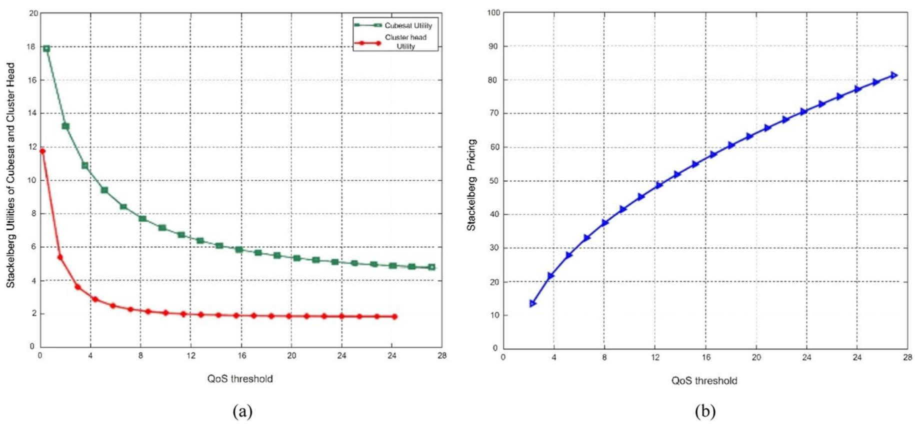


Fig. 6 Stackelberg utility (**a**) and price (**b**) against QoS threshold

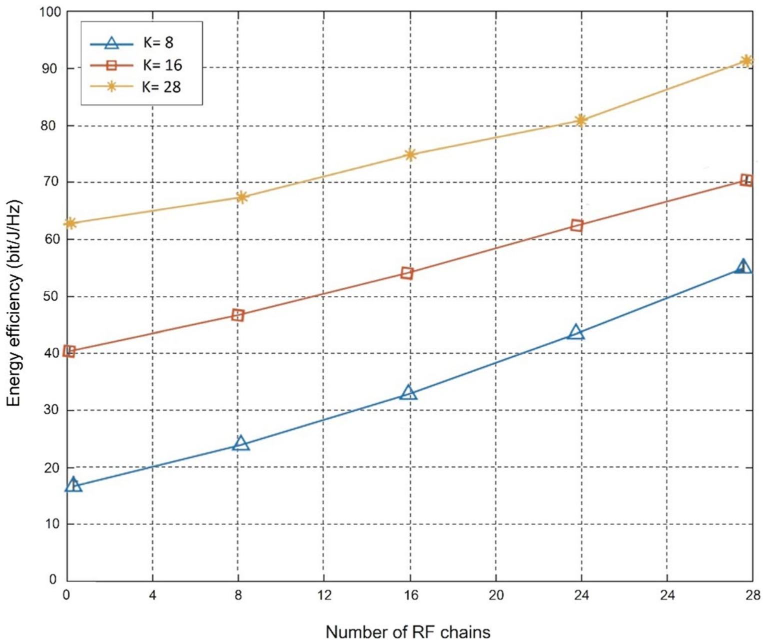


Fig. 7 Energy efficiency of the proposed approach in relation to RF chains

where $erfc$ is a complementary error function that describes the cumulative probability curve of Gaussian distribution.

$$\mathrm{BER} = \frac{1}{2}\mathrm{erf\ c}\sqrt{\frac{E_b}{N_0}} \tag{28}$$

Figures 8 and 9 show the predicted results of the RSS and Th link budget parameters between the Cubesat and ground sensors at a distance range between 400 and 800 km; firstly, non-optimized, i.e., prior to applying serious gaming and, secondly, optimized, after applying the proposed approach. Both RSS and Th show an increase with distance and shadowing effects, with their values floating within an acceptable average. After applying the proposed serious gaming approach, the predicted results of both RSS and Th shows an increase of 27% on average. This suggests that optimization of energy consumption is possible without resorting to sensor power enhancements or external power sources.

Figure 10 shows the Eb/No performance before and after applying the proposed serious gaming approach at the lowest BER achieved of $1x10^{-6}$ using the "Semilogy" function in MATLAB. The best link performance is the one that allows for the lowest possible BER with the lowest possible Eb/No, i.e., after applying the proposed serious gaming approach. This prescribes a robust channel, where a low error rate is achieved without requiring a high transmission power. The overall predictions of these two QoS indicators reveal reasonable improvements. This may lead to a reduction in the required transmission energy from sensors and an improved link performance between Cubesat and ground sensors, thus, increasing network lifetime and performance. The predicted Eb/No performance, after applying the proposed serious gaming approach, shows an increase of 21% on average in relation to non-optimized predictions. Once again this

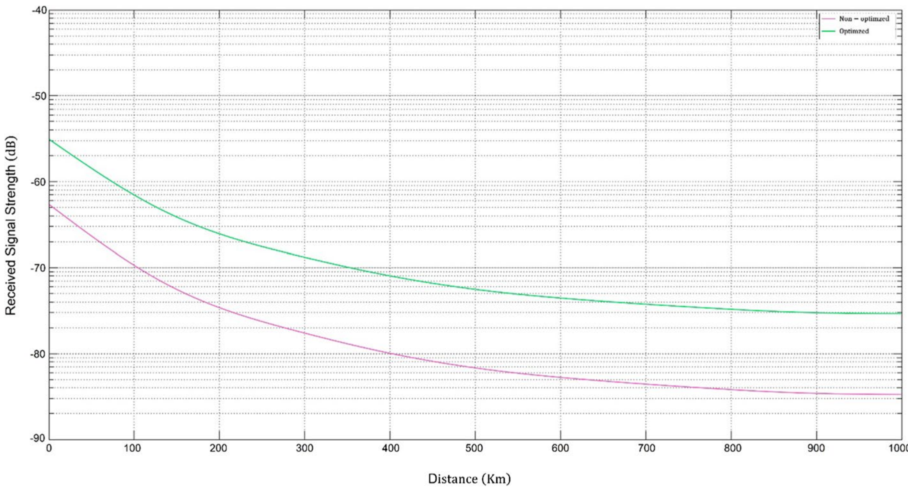


Fig. 8 RSS predictions before and after applying the proposed serious gaming approach

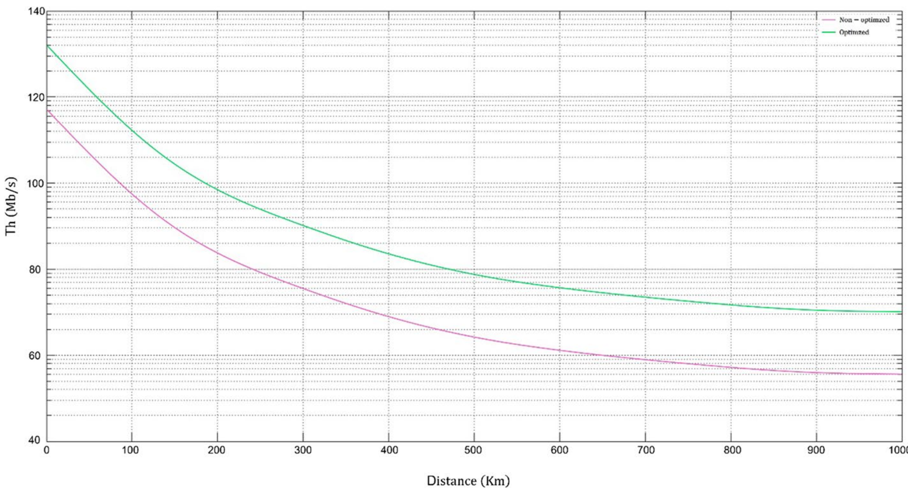


Fig. 9 Th predictions before and after applying the proposed serious gaming approach

supports the conclusion that energy consumption optimization is possible without having to resort to sensor power enhancements or external power sources. This may lead to a reduction in the required transmission energy from sensors and an improved link performance between Cubesat and ground sensors, thus, increasing network lifetime and performance. Most importantly, this improvement yields to optimization of energy consumption without using sensor power enhancements or external power sources. After applying the Stackelberg gaming approach, the Eb/No performance has improved by an average of 21% in comparison to non-optimized predictions. This is a noticeable improvement that results in fair transmission between nodes and clusters. Figure 11

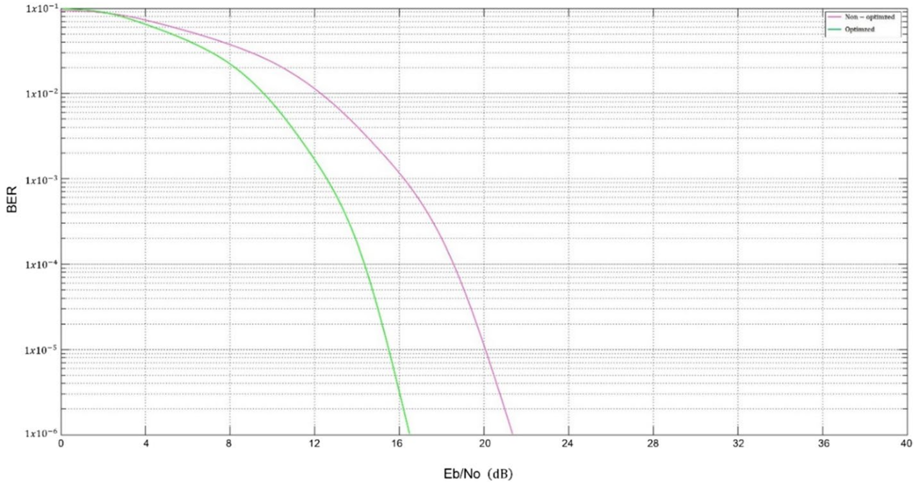


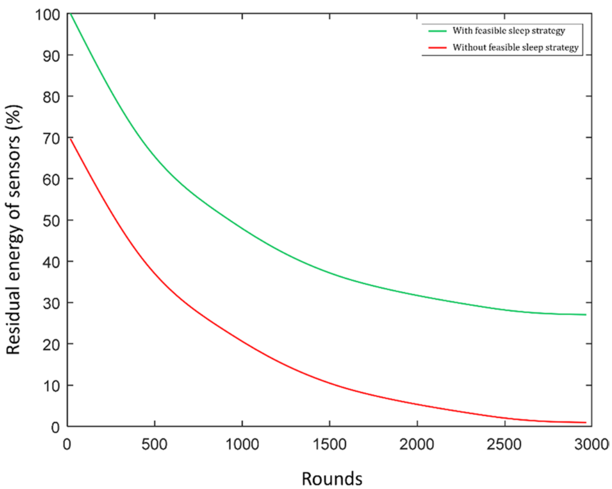
Fig. 10 Eb/No performance at the lowest BER predictions

shows the residual energy of wireless sensors at their lowest levels, with a feasible sleep strategy.

4.1 First proof-of-concept

Figure 12 shows a bird's-eye view of a first proof-of-concept IoT space-to-ground system for smart farming primarily aimed at crop irrigation and water management. The space part comprises of the CubeSat with its payloads and a transceiver module, which is responsible for collecting data from a wireless server gateway and then transmitting it to the cloud for storage and predictive analysis. The ground part comprises of wireless sensors collecting data on soil moisture, air humidity, air temperature, and water levels, and a cluster head

Fig. 11 Feasible sleep strategy for sensor nodes



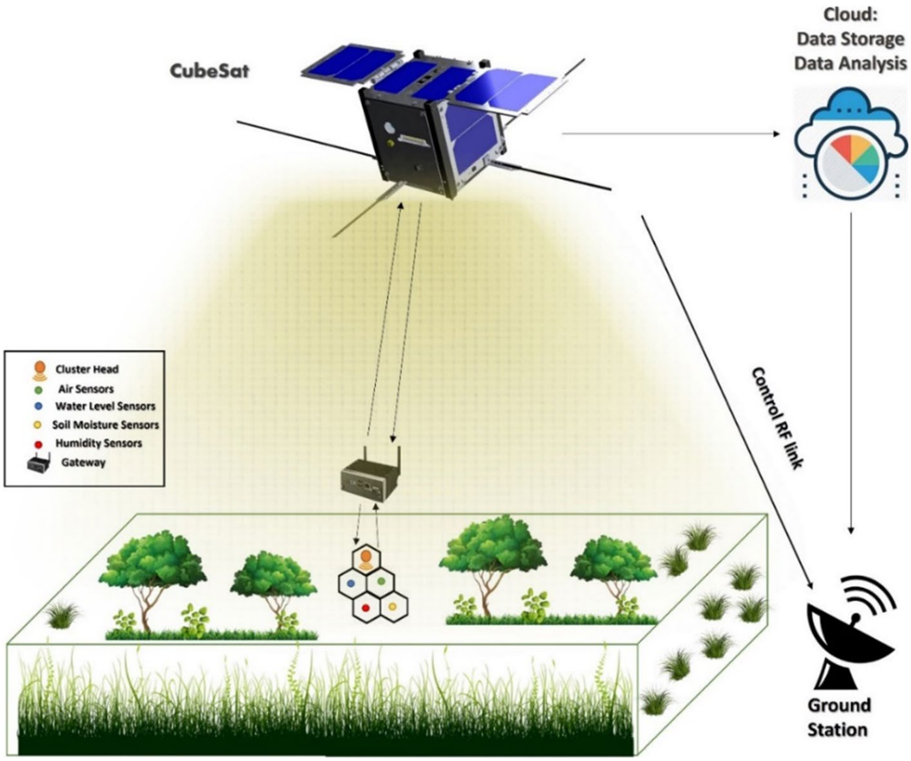


Fig. 12 The proof-of-concept IoT space-to-ground system

and a gateway to manage the communication process. The wireless sensors on the ground use the Message Queuing Telemetry Transport (MQTT) protocol to transmit their data to the CubeSat for real-time edge processing. Figure 13 shows a Blynk IoT platform dashboard depicting real-time data values. Figure 14 displays the python code used for extracting the sensed data for evaluation and validation of the link quality between the CubeSat and the ground sensors before and after Stackelberg.

Figure 15 visualizes the performance of a 5G Wi-Fi Module using a set of key performance indicators that includes coverage, capacity, access point, security, signal level, interference, noise. The focus is on RSSI and signal coverage levels, as they help measure the performance of the communication link between the CubeSat and ground sensors. The RSS shows reasonable average floats between -81 and -85dBm, and maximum data rates between 130 and 135Mbps. Figure 16 visualizes the performance of the 5G Wi-Fi Module after Stackelberg and this shows improvements between 10 and 15% for RSSI, which is an acceptable level for power consumption.

To calculate performance Eb/No and BER are used as per Eqs. (28) to (32) [3, 14, 27].

Fig. 13 Blynk IoT platform dashboard that shows edge-processed sensor data

$$\frac{E_b}{N_0} = \frac{C}{N} + 10 \log BW - 10 \log R_b \quad (29)$$

$$\frac{C}{N} = EIRP - P_L - A_R + \left(\frac{G}{T}\right) - 10 \log \frac{KBw}{0.001} \quad (30)$$

$$EIRP = P_t + G_t + G_r - L \quad (31)$$

$$\frac{G}{T} = G_r - 10 \log T \quad (32)$$

where EIRP is Effective Isotropic Radiated Power, C/N is carrier power, BW is bandwidth, R_b is data rate, P_t is transmission power , G_t and G_r is transmission and receiver antenna gains respectively, L is connector and cable loss, A_R is rain and atmospheric gas attenuations, K is Boltzmann's constant, G/T is the ratio of the receiver antenna gain to the system noise temperature in dB, T is affective temperature, and ERFC of (28) is a complementary error function that defines the cumulative probability curve.

Figure 17 compares predicted BER and Eb/No values for power consumption before and after Stackelberg. Pre-Stackelberg BER achieves 1×10^{-5} whereas post-Stackelberg achieves improved performance of an average of 5 dB which suggests a channel with low error rates that utilizes minimum transmission power. Furthermore, post-Stackelberg,

```python
        while (moisture < thresh):
            grovepi.digitalWrite(motor,1)
    else:
        grovepi.digitalWrite(motor,0)


dht_sensor = 4
light_sensor = 0
moisture_sensor = 1
motor = 3

grovepi.pinMode(motor, "OUTPUT")
grovepi.pinMode(dht_sensor, "INPUT")
grovepi.pinMode(light_sensor, "INPUT")
grovepi.pinMode(moisture_sensor, "INPUT")

initTime = time.time()

while True:
    motor_state = firebase.get('/iot-garden-monitoring-system', 'motor_state')
    update = firebase.get('/iot-garden-monitoring-system', 'update')
    pi_state = firebase.get('/iot-garden-monitoring-system', 'pi_state')

    print("received data", time.time() - initTime)
    initTime = time.time()

    if (pi_state == unicode("0")):
        grovepi.digitalWrite(motor,0)
        break

    [temp,humidity] = grovepi.dht(dht_sensor, 0)
    light = grovepi.analogRead(light_sensor)
    moisture = grovepi.analogRead(moisture_sensor)

    light = 100*light/1023
    moisture = 100 - (100*moisture/1023)

    print("temp = ", temp)
    print("humidity = ", humidity)
```
Ln: 32 Col: 0

Fig. 14 Python code for extracting sensed data

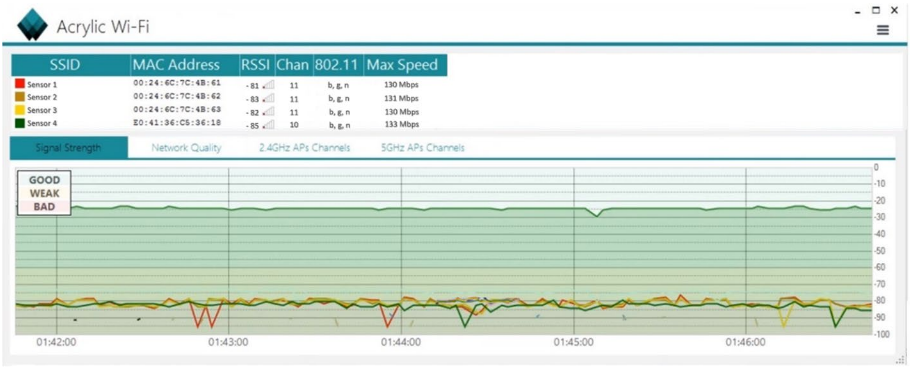


Fig. 15 RSSI and signal coverage levels

maximum capacity is achieved without increasing transmission power between the CubeSat and ground gateway, and average power consumption records an improvement of 15%.

5 Concluding discussion and future work

This work presents the use of Stackelberg serious gaming for energy allocation between a Cubesat and ground sensors, which on the one hand minimizes energy consumption and, on the other hand, maximizes the transfer of utilities from Cubesat to terrestrial sensors.

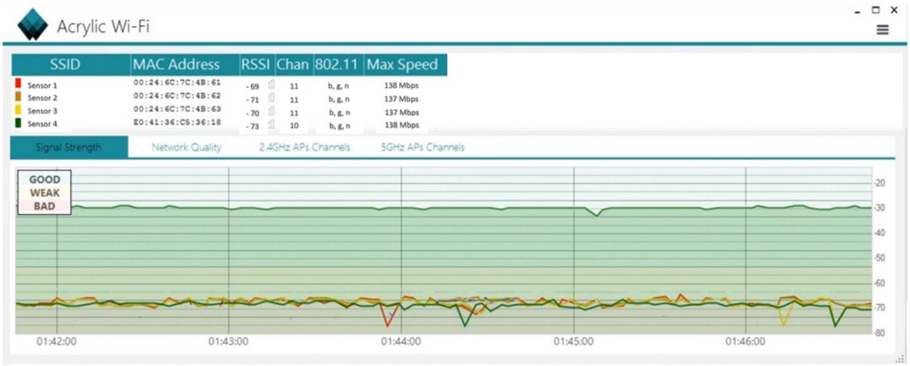


Fig. 16 RSSI and signal coverage levels after Stackelberg

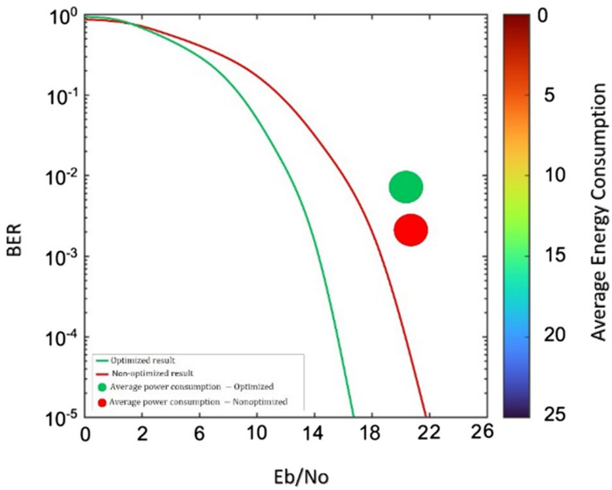


Fig. 17 BER and Eb/No for power consumption before and after Stackelberg

The use of Stackelberg aims at prioritizing access and optimizing the overall network utility and solving the problem of energy allocation. This supports making a set of decisions to guarantee fair energy allocation: fair transmission, feasible sleep time maximization, convergence range optimization, cluster size adjustment, and node selection. The predicted results not only suggest a reduction in the required sensor transmission energy and an improved link performance between a Cubesat and its ground sensors but also an increase in network performance and battery lifetime without the use of sensor power enhancements or external power sources. Overall, the performance indicators suggest improvements ranging between 22 and 27% on average across all performance indicators in comparison to non-optimized predictions.

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Data availability All data generated or analysed during this study are included in this article.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

References

1. Alharbi G et al (2022) Design and Study of a Miniaturized Millimeter Wave Array Antenna for Wireless Body Area Network. Int J Antennas Propag 2022:1–25. https://doi.org/10.1155/2022/1736377
2. Almalki FA (2019) Comparative and QoS Performance Analysis of Terrestrial-aerial Platforms-satellites Systems for Temporary Events. Int J Comput Netw Commun 11(6):111–133. https://doi.org/10.5121/ijcnc.2019.11607
3. Almalki FA, Angelides MC (2019) A machine learning approach to evolving an optimal propagation model for last mile connectivity using low altitude platforms. Comput Commun 142–143:9–33. https://doi.org/10.1016/j.comcom.2019.04.001
4. Almalki FA, Angelides MC (2022) Autonomous flying IoT: A synergy of machine learning, digital elevation, and 3D structure change detection. Comput Commun 190:154–165. https://doi.org/10.1016/j.comcom.2022.03.022
5. Almalki F, Ben Othman S (2021) Predicting Joint Effects on CubeSats to Enhance Internet of Things in GCC Region Using Artificial Neural Network. Mob Inf Syst 2021:1–16. https://doi.org/10.1155/2021/1827155
6. AlSkaif T, Guerrero Zapata M, Bellalta B (2015) Game theory for energy efficiency in Wireless Sensor Networks: Latest trends. J Netw Comput Appl 54:33–61. https://doi.org/10.1016/j.jnca.2015.03.011
7. Angelides MC, Sofokleous AA (2012) A game approach to optimization of bandwidth allocation using MPEG-7 and MPEG-21. Multimed Tools Appl 62(1):287–309. https://doi.org/10.1007/s11042-011-0981-0
8. Bennaceur J, Ahmadi H, Souhi S (2021) Game-Theoretical Approaches for Service Provisioning in Network Virtualization: Survey, Taxonomies and Open Challenges. Telecom 2(3):232–254. https://doi.org/10.3390/telecom2030016
9. Charilas D, Panagopoulos A (2010) A survey on game theory applications in wireless networks. Comput Netw 54(18):3421–3430. https://doi.org/10.1016/j.comnet.2010.06.020
10. Dai N, Zhou D, Sheng M, Li J (2021) Deep Reinforcement Learning Based Power Allocation for High Throughput Satellites, IEEE 94th Vehicular Technology Conference (VTC2021-Fall), Norman, OK, USA, pp. 1–5. https://doi.org/10.1109/VTC2021-Fall52928.2021.9625395
11. Del Re E, Gorni G, Ronga L, Suffritti R (2009) A power allocation strategy using Game Theory in Cognitive Radio networks. International Conference on Game Theory for Networks, Istanbul, Turkey, pp. 117–123. https://doi.org/10.1109/GAMENETS.2009.5137392
12. Erol Ö, BaşaranFilik Ü (2022) A Stackelberg game approach for energy sharing management of a microgrid providing flexibility to entities. Appl Energy 316:118944. https://doi.org/10.1016/j.apenergy.2022.118944
13. Essid C et al (2022) New MIMO Antenna with Filtration for the Future Multiuser Systems in Satellite Communications. Wirel Commun Mob Comput 2022:1–12. https://doi.org/10.1155/2022/1040333
14. Essid C, Abdelhamid C, Almalki FA, Ali O, Sakli H (2022) New MIMO Antenna with Filtration for the Future Multiuser Systems in Satellite Communications. Wireless Communications and Mobile Computing 2022:e1040333. https://doi.org/10.1155/2022/1040333
15. Fernandez-Cerero D, Fernandez-Montes A, Jakobik A, Kolodziej J (2018) Stackelberg game-based models in energy-aware cloud scheduling. In: Proceedings of 32nd European Conference on Modeling and Simulation, Wilhelmshaven, Germany (ECMS 2018). Edited by: Lars Nolle, Alexandra Burger,

Christoph Tholen, Jens Werner, Jens Wellhausen. European Council for Modeling and Simulation. https://doi.org/10.7148/2018-0460
16. Jiang X, Sheng M, Zhao N, Xing C, Lu W, Wang X (2021) Green UAV communications for 6G: A survey. Chin J Aeronaut 35(9):19–34. https://doi.org/10.1016/j.cja.2021.04.025
17. Li X et al (2022) Secure Spectrum-Energy Efficiency Tradeoff Based on Stackelberg Game in A Two-way Relay Cognitive Satellite Terrestrial Network. IEEE Wirel Commun Lett. 1–1. https://doi.org/10.1109/lwc.2022.3172129
18. Li F, Lam K, Liu X, Wang J, Zhao K, Wang L (2018) Joint Pricing and Power Allocation for Multibeam Satellite Systems With Dynamic Game Model. IEEE Trans Veh Technol 67(3):2398–2408. https://doi.org/10.1109/tvt.2017.2771770
19. Liu B, Xu H, Zhou X (2018) Stackelberg Dynamic Game-Based Resource Allocation in Threat Defense for Internet of Things. Sensors 18(11):4074. https://doi.org/10.3390/s18114074
20. Luis JJG, Pachler N, Guerster M, del Portillo I, Crawley E, Cameron B (2020) Artificial Intelligence Algorithms for Power Allocation in High Throughput Satellites: A Comparison, 2020 IEEE Aerospace Conference, Big Sky, MT, USA. https://doi.org/10.1109/aero47225.2020.9172682
21. Papaioannou TG, Hatzi V, Koutsopoulos I (2014) Optimal design of serious games for demand side management, IEEE International Conference on Smart Grid Communications (SmartGridComm), Venice, Italy, pp. 800–805. https://doi.org/10.1109/SmartGridComm.2014.7007746
22. Petraki D, Anastasopoulos M, Chen Hsiao-Hwa, Cottis P (2009) Distributed Resource Allocation for Delay-Sensitive Services in Satellite Networks Using Game Theory. IEEE Trans Comput Intell AI Games 1(2):134–144. https://doi.org/10.1109/tciaig.2009.2027693
23. Radi MA, Adnan Ahmed M, Hassan MM, Ghenai C (2022) Performance Analysis, Parametric Study, and Optimization of CubeSat Solar Power System for Ship Tracking of Marine Traffic. Advances in Science and Engineering Technology International Conferences (ASET) pp. 1–6. https://doi.org/10.1109/ASET53988.2022.9735123
24. Rigo CA, Seman LO, Camponogara E, Morsch Filho E, Bezerra EA (2021) Task scheduling for optimal power management and quality-of-service assurance in CubeSats. Acta Astronautica 179:550–560. https://doi.org/10.1016/j.actaastro.2020.11.016
25. Ruan L et al (2018) Energy-efficient multi-UAV coverage deployment in UAV networks: A game-theoretic framework. China Commun 15(10):194–209. https://doi.org/10.1109/cc.2018.8485481
26. Saeed N, Elzanaty A, Almorad H, Dahrouj H, Al-Naffouri T, Alouini M (2020) CubeSat Communications: Recent Advances and Future Challenges. IEEE Commun Surv Tutorials 22(3):1839–1862. https://doi.org/10.1109/comst.2020.2990499
27. Salh A et al (2022) Low Computational Complexity for Optimizing Energy Efficiency in mm-wave Hybrid Precoding System for 5G. IEEE Access 10:4714–4727. https://doi.org/10.1109/ACCESS.2021.3139338
28. Sun Z et al (2021) Applications of Game Theory in Vehicular Networks: A Survey. IEEE Commun Surv Tutorials 23(4):2660–2710. https://doi.org/10.1109/comst.2021.3108466
29. Tong J et al (2022) Cooperative Beam Association and Power Allocation in UD-LEO Satellite Communication Networks: A Spectrum Sharing Manner. Electronics 11(3):299. https://doi.org/10.3390/electronics11030299
30. Wang K, Wang S (2020) Energy Efficiency and Delay Trade-off over Multi-beam Satellite Downlinks, IEEE International Conference on Communication, Networks and Satellite (Comnetsat), Batam, Indonesia, pp. 188–193. https://doi.org/10.1109/Comnetsat50391.2020.9328949
31. Zhang H, Li Q, Zhang Y, Li X (2021) Game Theory Based Power Allocation Method for Inter-satellite Links in LEO/MEO Two-layered Satellite Networks, IEEE/CIC International Conference on Communications in China (ICCC), Xiamen, China, pp. 398–403. https://doi.org/10.1109/ICCC52777.2021.9580385
32. Zhang E, Yin S, Ma H (2019) Stackelberg Game-Based Power Allocation for V2X Communications. Sensors 20(1):58. https://doi.org/10.3390/s20010058
33. Zhang Q, Zhai H, Gao Z (2020) On-board Transmitting Power Allocation in Satellite Communication System, IEEE 20th International Conference on Communication Technology (ICCT), Nanning, China, pp. 622–626. https://doi.org/10.1109/ICCT50939.2020.9295825
34. Zhu X, Jiang C, Kuang L, Zhao Z, Guo S (2020) Two-Layer Game Based Resource Allocation in Cloud Based Integrated Terrestrial-Satellite Networks. IEEE Trans Cogn Commun Netw 6(2):509–522. https://doi.org/10.1109/tccn.2020.2981016