Use Case of Agentic AI and IoT in 6G Networks for P2P Energy Trading in Smart Grids

Kelvin Anoh, Benard Kipchumba, Ogheneovo Okpako, Augustine Ikpehai, Kennedy C. Okafor and Sabita Maharjan

***Abstract*—Artificial intelligence (AI) and Machine Learning (ML) will play significant roles in 6G networks and beyond, making them intelligent, self-organising, and cost-effective. Network servers will house AI algorithms just like the application servers. 6G networks will be user-centric, leveraging the Internet of Things (IoT) to transform critical infrastructure into smart infrastructure. This study presents a notable use case of AI and IoT for 6G networks, specifically in coordinating peer-to-peer (P2P) energy trading within virtual microgrids (VMGs) of smart grids. The study deploys IoT technologies at the network edge to connect and collect energy trading data from P2P energy prosumers. The model also includes AI agents configured within the mobile edge computing (MEC) servers at the next-generation Node-B (gNB) of the 6G radio access network to adjust the cell size of VMGs, thereby enabling the discovery of more P2P energy prosumers. Results show that deploying AI agents in the 6G networks can minimise the operational expenditure (OPEX) of network operators and energy trading costs for consumers, while maximising the utility of energy prosumers.**

***Index Terms*—Artificial Intelligence, Agentic AI, IoT, 6G Networks, Smart Grid, Peer-to-Peer Energy Trading.**

I. Introduction

In the timeline of wireless communication standards, new standards emerge approximately every ten years [1]. Thus, the sixth-generation (6G) network standard will emerge in approximately 5 years. It will be complex, intelligent, self-organising, self-optimising and cost-effective. While 5G networks are service-oriented, 6G networks will be more user-centric [2]. These requirements mean that the 6G network will incorporate a range of technologies, such as artificial intelligence (AI) and machine learning (ML) in the radio access networks (RAN) [3]. 6G network will deploy Internet of Things (IoT) technologies (e.g., SigFox, Weightless, LoRaWAN, Ingemu, NB-IoT, etc.) to complement the standard, for example, in blind spots and remote areas.

Among other IoT technologies, Long-Range Wide-Area Network (LoRaWAN) is attractive due to its low power consumption, low data rate, long range (or wide coverage), and scalable coverage [4]. It achieves adaptive coverage by switching spreading factors (SFs) via its adaptive data rate (ADR) feature, thereby balancing data rate, coverage, and power consumption [5]. Recently, there has been growing interest in modifying the SF switching method to improve the efficiency of the LoRaWAN network. In the literature, three methods for dynamic allocation of SF are identified: using artificial intelligence, ADR, decentralised SF and channel detection [4]. This study explores the performance of an IoT network with AI-based dynamic SF switching and the user experience in such a network.

Consider users in a smart grid, one of the key challenges is how to cost-effectively provide flexible, scalable connectivity for energy prosumers in remote hard-to-reach areas and blind spots with abundant renewable energy. By implementing network slicing in the LoRaWAN radio access network, the recent 6G-LoRaGRAN project [6], which integrated 6G and LoRaWAN, offers a promising pathway to overcome this challenge.

With this approach, dedicated LoRaWAN slices with distinct SFs can be created for different numbers of prosumers and dynamically allocated using AI agents. This allows LoRAWAN to vary cluster sizes by switching between SF7 and SF12, conserving energy on underutilised LoRAWAN nodes.

The use of AI in switching SF based on signal quality (e.g., signal-to-noise ratio (SNR), received signal strength indicator (RSSI), and data rate) can be performed at the network server to meet the expectations of 6G networks. In Rel-18, for example, 3GPP introduced AI/ML in the 5G-NR RAN [3]. In Rel-19, the 3GPP RAN3 working group is investigating AI for network (AI4Net) and network for AI (Net4AI). AI4Net is a reactive process that boosts network performance and management using AI, whereas Net4AI is proactive, utilising wireless networks to enhance AI/ML services [3]. AI/ML will be used to enhance privacy and security in infrastructure and user communications, and in optimising 6G networks [2]. In 6G networks, agentic AI will be configured in the RAN, typically network server [3]. In mobile applications, integrating AI into LoRaWAN IoT networks reduces packet loss by 28% [7]. In static IoT applications (e.g., smart metering in smart grids), switching SF with AI/ML minimises packet loss by 32%. With AI/ML, the battery life of LoRaWAN can be extended [8], which aligns with the AI4Net paradigm in the 3GPP 6G standard [3].

In this study, our main contributions are:

- modelling of a use case-based 6G network for intelligent, self-optimising and cost-effective P2P market;
- adaptive LoRaWAN IoT network that can adjust its coverage size autonomously based on AI/ML;
- integration of agentic AI and IoT technologies into smart grids to enhance user experience via dynamic allocation of telecom resources and maximising network user utility.

As AI agents collect data from network servers, agentic AI perform dynamic network coordination to optimise coverage by computing the suitable SF. Results show that this new approach enhances the user experience. In the remaining sections of this study, the system model is presented in Section II, the results are discussed in Section III, and the conclusion follows.

II. System Model

In a P2P energy trading network, a LoRaWAN IoT network connects LoRaWAN nodes (prosumers) to a LoRaWAN gateway as shown in Figure 1. Using WiFi, Ethernet (midhaul) and cellular

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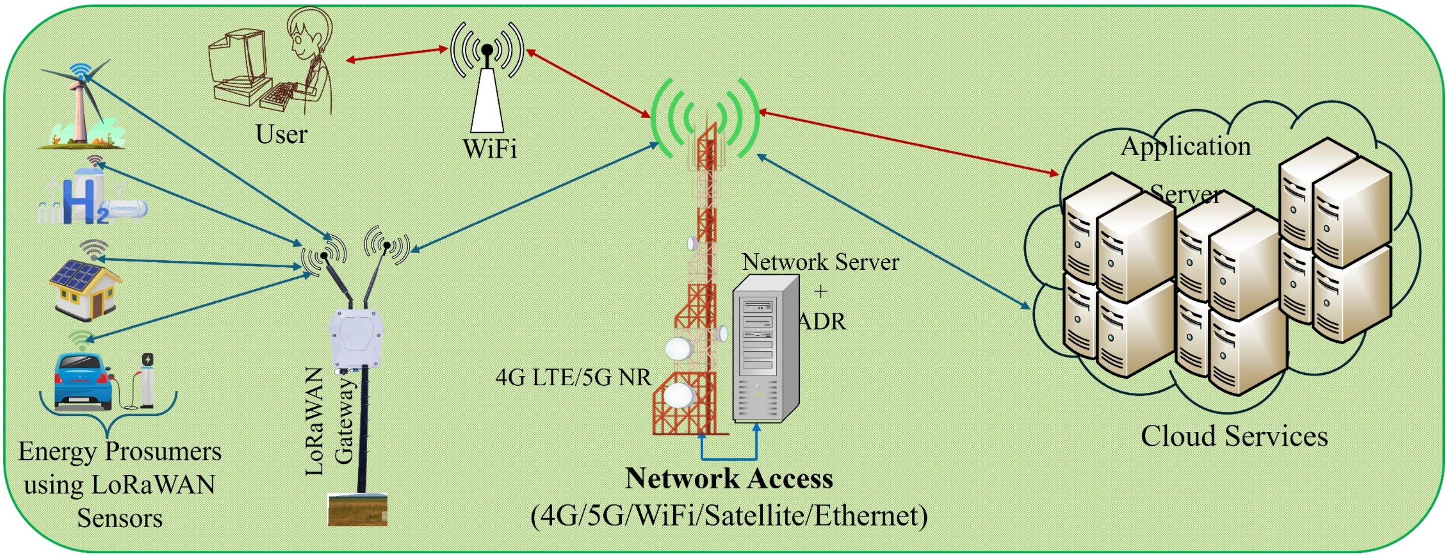

Figure 1: Present LoRaWAN network architecture showing energy prosumer connected to the LoRaWAN gateway using LoRaWAN sensors.

or satellite communication service (backhaul), the LoRaWAN gateway interconnects to the network server and application servers. This study envisions an energy trading network based on the 6G network that deploys AI agents in the RAN and agentic AI in the core. The RAN of the 6G network embodies a mobile edge computing (MEC) server at the next-generation Node-B (gNB) as shown in Figure 2. AI agents are configured in the MEC server to coordinate prosumer traffic via an IoT gateway and communicate with the agentic AI system in the cloud. Traffic data collected from the users is used by the AI agents to infer the node density within each cell. Based on AI/ML, RSSI and SNR can be used to predict LoRaWAN coverage [8]. Each energy prosumer has a LoRaWAN wireless sensor that connects to the gNB via the IoT gateway. Thus, the LoRaWAN IoT network complements the 6G network. Although not suitable for high data rate applications, LoRaWAN is ideal for smart grid applications. Currently, switching the coverage radius in LoRaWAN using SF is achieved by ADR located in the network server [4].

To redesign the network for an intelligent operation, the adaptive deployment of SF can be performed using an AI agent in the network server based on received signal quality (e.g., SNR and RSSI) [8]. The proposed model in Figure 2 considers a connectivity that uses a 6G network (Plane 2) as the backhaul to the Internet (Plane 3), deployed to serve the energy trading market (Plane 1) in order to minimise electrical power losses, minimise energy cost, reduce emissions and operational expenditure (OPEX). In terms of communication resources, the model intends to minimise telecom resources and OPEX. AI agents are configured within each network (shown as MEC server in Figure 2) to coordinate an energy trading cluster [9]. This study investigates an AI-based telecom network overlaid on top of power networks, making it a smart power network. When the number of prosumers changes, the network autonomously reconfigures, switching off some cells (Plane 4), reducing energy cost for prosumers and telecom OPEX.

A. *Model Formulation*

The model considers a smart grid of energy prosumers that are physically connected to trade their excess energy generation or storage, $\{x_i\}_{i=1}^{n_p}$, at time t, where n_p is the number of prosumers. From [10], the utility received by the prosumer is given by

$$U(e_i) = \sum_{i\in n_p} w_i \log_e(e_i+\gamma) + \sum_{j\in n_c}\sum_{i\in n_p}(E_i^{\text{gen}}-e_i)p_j \qquad (1)$$

where w_i is the willingness of prosumer i to consume $e_i \in E_i^{\text{gen}}$, E_i^{gen} is the total energy generated, p_j is the price paid by prosumer j for $(E_i^{\text{gen}}-e_i)$ units of energy bought, n_c is the number of consumers and $\gamma > 0$ is a constant introduced to limit $\log_e(\cdot)$ from reaching $-\infty$ when $e_i = 0$. Here, $u_i(e_i) = w_i \log_e(e_i+\gamma)$ is the utility derived from self-consumption and $r_i(E_i^{\text{gen}}, e_i) = \sum_{j\in n_c}(E_i^{\text{gen}}-e_i)p_j$ is the revenue received by i from their n_c customers. It is important to clarify that all the extra energy $(E_i^{gen}-e_i)$ declared by prosumer i does not usually reach prosumer j due to losses. In that case, it is effective to denote

$$x_i = E_i^{gen} - e_i - \chi_i(E_i^{gen}-e_i) \qquad (2)$$

$$= E_i^{gen} - e_i - \epsilon_i, \qquad i = 1,\cdots,n_p \qquad (3)$$

where $\epsilon_i = \chi_i(E_i^{\text{gen}}-e_i)$ is the power loss during transmission and χ_i = loss coefficient. The uncertainty due to weather conditions will cause the renewable energy generating system to underperform, reducing the capacity factor of the renewable energy system and, as such, contributing to uncertainty and variability in the amount of x_i declared by prosumer i.

In [11], the utility of a consumer was expressed as

$$u_j(x_i) = w_j \log_e(\sum_{i\in n_p} x_i + \gamma), \qquad j = 1,\cdots,n_c \qquad (4)$$

where w_j is the willingness of the consumer to make a payment. In [12], the model (4) was described as the surplus that consumers seek to maximise as follows:

$$\bar{U}(x_i) = \sum_{j\in n_c} u_j(x_i) - p_j\Big(\sum_{i\in n_p} x_i\Big). \qquad (5)$$

From [11], energy price has a non-linear model of the form [13]:

$$p_j = f\Big(\sum_{i\in n_p} x_i\Big) = a x_i^2 + b x_i, \qquad j = 1,\cdots,n_c \qquad (6)$$

where a and b are constants. If the prosumer sells a larger volume, then a will be negative, reflecting market saturation. The consumer aims to minimise the cost of purchasing $\sum_{i\in n_p} x_i$ units so as to

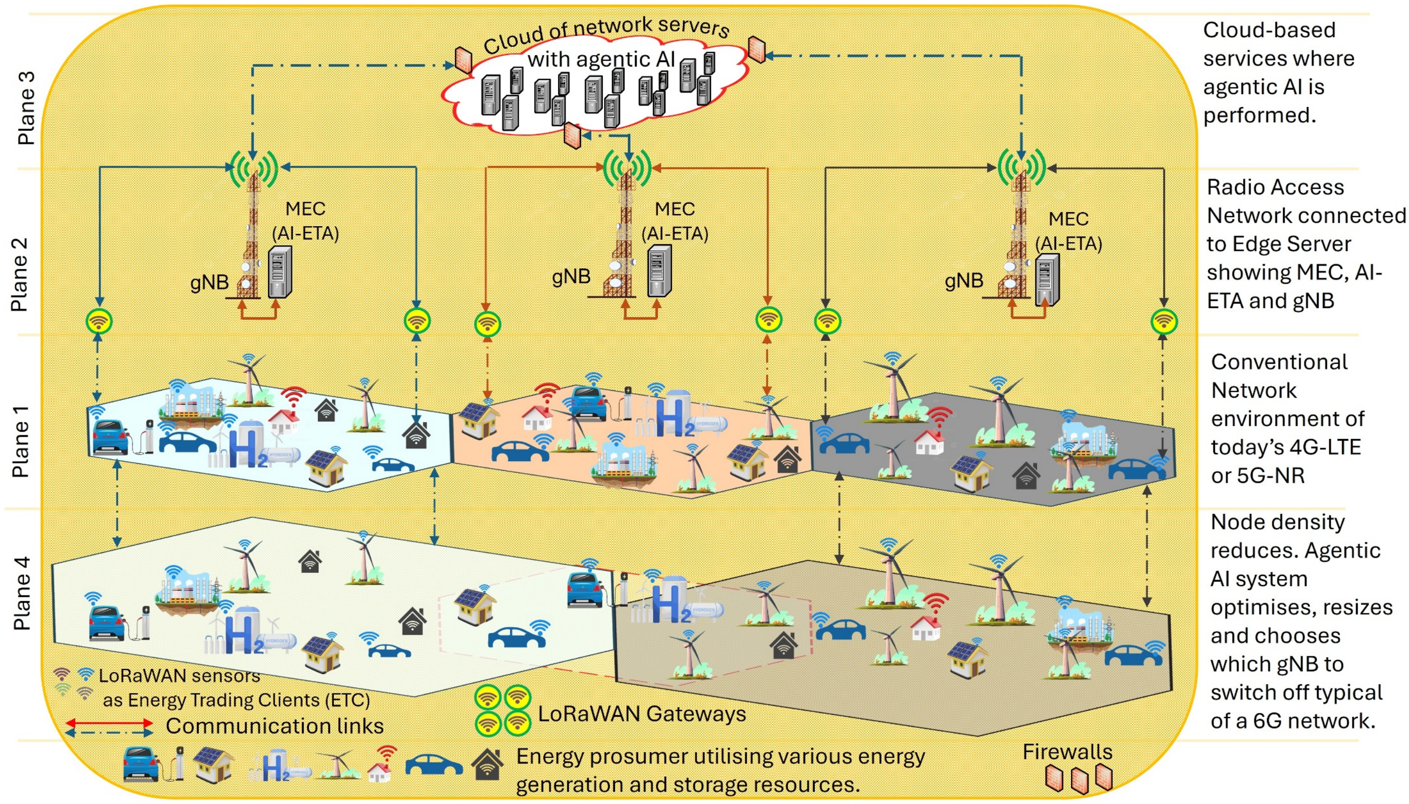

Figure 2: Proposed 6G-enabled P2P energy trading network, with agentic AI orchestration of LoRAWAN resources and adaptive coverage.

maximise problem (5) of its energy needs that satisfies

$$\sum_{i\in n_p} x_i \geq \sum_{j\in n_c} \mathcal{E}_j^{\min}, \qquad j = 1, \cdots, n_c \tag{7}$$

where $\mathcal{E}_j^{\min}$ is the minimum load that prosumer j wishes to satisfy. Each LoRaWAN network uses its SF to optimise its power consumption, data rate and coverage, of radius expressed as

$$r_m = \left(\frac{c}{4\pi f}\right)^{2/\mu} \cdot \sqrt[\mu]{\frac{2^{\mathrm{SF}} P_t}{\rho \xi k_B B_w \Theta}}, \quad \begin{array}{l} m = 1, \cdots, \mathcal{M}, \\ \mathrm{SF} \in \{7, 8, \cdots, 12\} \end{array} \tag{8}$$

where μ is the path-loss exponent, $c = 3 \times 10^8 \mathrm{ms}^{-1}$, $f \in \{868, 915\}$ MHz (Europe), $P_t = 14$ dBm, ρ is the desired SNR, $\xi = 6$ dB is noise figure, $B_w \in \{125, 250, 500\}$ kHz is the bandwidth, Θ is the temperature and $\mathcal{M}$ is the number of VMGs. The AI agents perform optimisation to dynamically assign suitable telecommunications resources to the active energy prosumer within each trading interval.

Since p_j in (6) is nonlinear, the energy cost part in (1) and (5) can be expressed as

$$\mathcal{C}_j(x_i, r_m) = p_j\Big(\sum_{i\in n_p} x_i\Big) \tag{9a}$$

$$= \underbrace{\alpha_j \sum_{i\in n_p} x_i^2 + \beta_j \sum_{i\in n_p} x_i}_{\text{generation cost}} + \underbrace{\zeta_j \sum_{i\in n_p} x_i d_i}_{\text{transmission cost}} \tag{9b}$$

$$= \alpha_j \sum_{i\in n_p} x_i^2 + \vartheta_j \sum_{i\in n_p} x_i d_i \qquad j = 1, \cdots, n_c \tag{9c}$$

where $\vartheta_j = \beta_j + \zeta_j$, ζ_j is the transmission fee and d_i is the separation distance between a prosumer and consumer. Note that

$$d_i \leq 2r_m \tag{10}$$

which implies that the distance separating any two prosumers is no more than the diameter of the m^{th} VMG.

B. *Agentic AI and AI Agents in the 6G Network*

AI agents are the building blocks of an agentic AI system [14], [15]. They can be implemented using convolutional neural networks, deep neural networks, k-nearest neighbors (k-NN), Decision Tree Classifier (DTC), Random Forest (RF), Multinomial Logistic Regression (MLR) algorithms [7], [8], [14] or any other machine learning model to determine the SF and node density at m^{th} VMG based on the traffic density received within a trading period. Each AI agent receives about 50 packets per day from $n = n_c + n_p$ prosumers (i.e. $50 \times n$) [16]. As a multi-agent system [15], [17], the agentic AI system autonomously determines and assigns the number of prosumers to each VMG. Unlike [18], TinyML and reinforcement learning can be implemented in the network server of a 6G network (e.g., MEC server) to adjust the SF based on energy trading characteristics in Figure 2. The role of the AI agent is to process the local information of a VMG (e.g., the prosumer node density in the area) and assign suitable SF to cover the prosumers. Since energy prosumers and renewable energy are not always available, AI agents must be able to coordinate and assign suitable network coverage to active prosumers [7], [18] while optimising the number of LoRaWAN gateways (and gNBs) available at each energy trading period.

In that case, an agentic AI system, located in the cloud (e.g., application server of a 6G network), would coordinate the assignment of network resources to the energy prosumers. For example, a) the agentic AI system performs piecewise optimisation to find the optimal number of cells that can cover/serve the active prosumers (as shown in Algorithm 1); b) agentic AI system determines SF and sends instructions to AI agents (specifically, ADRs) in each MEC server to assign the corresponding SF based on Algorithm 2. From such architecture, the proposed 6G network utilises a multi-agent system (MAS) [15], [17] to realise an intelligent network that self-organises and self-optimises, thereby reducing OPEX for telecoms operators, minimising energy losses for power networks, lowering energy costs for energy traders, and achieving autonomy. Since the proposed model uses one agent per LoRaWAN gateway, agents cannot engage in anticompetitive behaviour, such as agent collusion. However, to enhance security, trust and mitigate anticompetitive behaviour, blockchain can be incorporated to authenticate AI agents and prosumers [19].

Each user (prosumer) solves the following optimisation:

$$\mathbf{P1}: \quad \max_{e_i,d_j} U(e_i,d_j) = \sum_{i\in n_p} u_i(e_i) + \sum_{j\in n_c} \mathcal{C}_j(x_i,d_j) \tag{11a}$$

$$\text{subject to}: \quad 0 \le x_i < E_i^{\text{gen}} \tag{11b}$$

$$0 \le d_i \le 2r_m \tag{11c}$$

where $\mathcal{C}_j(x_i,d_j) = \big(-\sum_{i\in n_p} x_i^2\alpha_j + \sum_{i\in n_p} x_i d_j \vartheta_j\big)$. In the prosumer case, note that the term α_j in (9c) and (11) is negative to capture market saturation, i.e., falling price as the prosumer sells a larger amount of energy. Such a condition leads to a form of diminishing returns. For the consumer, the energy buyer is interested in maximising its utility by solving problem:

$$\mathbf{P2}: \max_{x_i,d_i} \bar{U}(x_i,d_i) = \sum_{i\in n_p} u_j(x_i) - \sum_{i\in n_p} \mathcal{C}_i(x_i,d_i) \tag{12a}$$

$$\text{subject to}: \quad x_i \ge 0 \tag{12b}$$

$$0 \le d_i \le 2r_m \tag{12c}$$

$$\sum_{i\in n_p} x_i \ge \sum_{j\in n_c} \mathcal{E}_j^{\min} \tag{12d}$$

where $\mathcal{C}_i(x_i,d_i) = \big(\sum_{j\in n_c} x_i^2\alpha_j + \sum_{j\in n_c} x_i\vartheta_j d_i\big)$. Note that $\mathcal{C}_j(x_i,d_j) \neq \mathcal{C}_i(x_i,d_i)$. The agentic AI uses the node density information presented by each AI agent to reconfigure the number of VMGs within the area since the agentic AI system is equipped with a global knowledge of the trading area.

Clearly, both problems **P1** and **P2** can be solved using $fmincon()$ command in MATLAB. This study investigates three conditions: near ($d_j = 0.1 \times 2r_m$), far ($d_j = 2r_m$) and optimal ($d_j = d_j^\star$) distances such that $d_j^{\text{near}} \le d_j^\star \le d_j^{\text{far}}$. Since $\alpha_j < 0$ to ensure diminishing returns, it is easy to show that

$$\frac{\partial^2 U_i(e_i)}{\partial e_i^2} = -\sum_{i\in n_p} \frac{w_i}{(e_i+\gamma)^2} + 2\sum_{j\in n_c}\alpha_j < 0 \tag{13}$$

which implies that the utility models remain concave. By this convention, it is easy to determine the optimal energy sold, x_i, or consumed, e_i.

III. Results and Discussions

A. Single Prosumer with Single Customer

Consider a UK setting involving residential and non-residential energy prosumers. An average UK family consumes 7.5 kWh of electricity per day [20], [21] and each 1 kWh of electricity costs £0.64 (64 pence) [20]. This study also adapts the parameters used in [10] and [9] to investigate the utilities of the prosumer and consumer given E_i^{gen}, e_i, x_i and $d_j^\star$. When the energy cost model is linear as in (1) and (5) with $n_p = n_c = 1$, for example, the results in Figure 3 are similar to those reported in [10] and [9], demonstrating the conventional law of diminishing returns for both the prosumer and the consumer, as expected. The prosumer enjoys an increasing utility at low self-consumption e_i, suggesting that the $\log_e(\cdot)$ dominates. Beyond $e_i = 10$ kWh, the utility of the prosumer decreases, showing that the linear revenue function dominates. This value, $e_i = 10$ kWh, is approximately similar to the average energy consumption (e.g., electricity) of an average UK family as reported by the British Gas company [20]. Comparing the individual utilities of prosumers and consumers, it can be observed that prosumers achieve higher utility due to the revenue they receive from consumers. The maximum utility is observed when at the optimal consumption, $x_i^\star$ for the consumer (or $e_i^\star$ in the case of the prosumer), and can be found when the marginal utility $\frac{w_j}{x_i+\gamma}$ equals the marginal cost p_j. This is found by taking the first derivative of (1) and setting the result to zero, i.e., $\frac{\partial U_i}{\partial e_i} = 0$ (or $\frac{\partial U_j}{\partial x_i} = 0$ in the case of consumer). Note that if $u_i(e_i) < r_i(E_i^{\text{gen}}, e_i)$, then utility will be negative.

Algorithm 1: Algorithm for optimising the virtual cluster size of P2P Energy by the agentic AI system

Input: $\{n | n = n_c + n_p\} > 0$
Output: $\{\text{SF} \mid d_i\} \le 2r_m$
$n_c \leftarrow define$;
$n_p \leftarrow define$;
$\text{SF} \leftarrow \{7, 8, \cdots, 12\}$;
$n_k^{\text{SF}} \leftarrow define$; /* node threshold per SF */
$k \leftarrow \{1, \cdots, |\text{SF}|\}$; /* index of SF */
for $m \leftarrow 1$ **to** $\mathcal{M}$ **do**
  $E_1 = \text{randn}(1, n_c)$; /* consumersdata */
  $Pr_1 = \text{randi}([0\ 1], \text{size}(E_1))$; /* probability */
  $E_1 = E_1 .* Pr_1$; /* consumer data */
  $E_2 = \text{randn}(1, n_p)$; /* producer data */
  $Pr_2 = \text{randi}([0\ 1], \text{size}(E_2))$; /* probability */
  $E_2 = E_2 .* Pr_2$; /* producer data */
  $n_{ic} = \text{nnz}(E_1)$; /* #consumers */
  $n_{ip} = \text{nnz}(E_2)$; /* #producers */
  $n(m) = \text{sum}(n_{ic}, n_{ip})$; /* #prosumers */
  while $n(m) > 0$ **do**
    if $n_5^{\text{SF}} < n(m) \le n_6^{\text{SF}}$ **then**
      $\text{SF} \leftarrow 12$;
      $U_i(x_i^\star, d_i^\star) \leftarrow u_i(e_i) + \mathcal{C}_j(x_i^\star, p_j^\star, d_i^\star)$; /* prosumer utility */
      $U_j(x_i^\star, d_i^\star) \leftarrow u_j(x_i^\star) - \mathcal{C}_i(x_i^\star, p_j)$; /* consumer utility */
    else
      if $n_4^{\text{SF}} < n(m) \le n_5^{\text{SF}}$ **then**
        $\text{SF} \leftarrow 11$;
        ⋮
      else
        if $\cdots < n(m) \le \cdots$ **then**
          ⋮
        else
          $\text{SF} \leftarrow 7$;
          ⋮
        end
      end
    end
  end
end

Algorithm 2: Algorithm for optimising the virtual cluster size of P2P Energy network by the agentic AI system with an insufficient number of prosumers per VMG

```
Input: {n | n = n_c + n_p} > 0
Output: {SF | d_i} ≤ 2r_m
n_c ← define;
n_p ← define;
SF ← {7, 8, ··· , 12};
n_k^SF ← define;        /* node threshold per SF */
k ← {1, ··· , |SF|};    /* index of SF */
for m ← 1 to M do       /* loop m agents */
    E_1 = randi([0 m̂], 1, n_c) ;    /* consumers' data/packets transmitted showing it is active */
    E_2 = randi([0 m̂], 1, n_p) ;    /* produers' data/packets transmitted showing it is active */
    n_ic = nnz(E_1);          /* #consumers */
    n_ip = nnz(E_2);          /* #producers */
    n(m) = sum(n_ic, n_ip);   /* #prosumers */
    while n(m) > 0 do
        if n_5^SF < n^(m) + n^(m+1) ≤ n_6^SF then
            SF ← 12;
            ETA_(m) ← SF ;   /* Assign SF to ETA with higher node density */
            U_i(x_i*, d_i*) ← u_i(e_i) + C_j(x_i*, p_j*, d_i*)
            U_j(x_i*, d_i*) ← u_j(x_i*) − C_i(x_i*, p_j*, d_i*)
        else
            if n_4^SF < n^(m) + n^(m+1) ≤ n_5^SF then
                SF ← 11;
                ETA_(m) ← SF;
                ⋮
            else
                if ··· < n^(m) + n^(m+1) ≤ ··· then
                    ⋮
                else
                    SF ← 7;
                    ETA_(m) ← SF;
                    ⋮
                end
            end
        end
    end
end
```

B. Utility of Prosumer and effect of Distance

Considering the linear distance model, prosumer selling x_i units of energy at SF12 should receive higher revenue and consequently higher utility than in any other SF. For each SF, consider three conditions: near ($d_j = 0.1 \times 2r_m$), far ($d_j = 2r_m$) and optimal ($d_j = d_j^\star$) distances such that $d_j^{\text{near}} \leq d_j^\star \leq d_j^{\text{far}}$. Prosumers trading with energy consumers at far distances receive higher revenue due to the increasing distance, as shown in Figure 4. Similarly, for each SF prosumers selling energy to consumers at the maximum distance in a cell, $d_j = 2r_m$, receive higher revenue and consequently higher utility than selling within the same SF (or cell) at a nearer distance, $d_j = 0.1 \times 2r_m$.

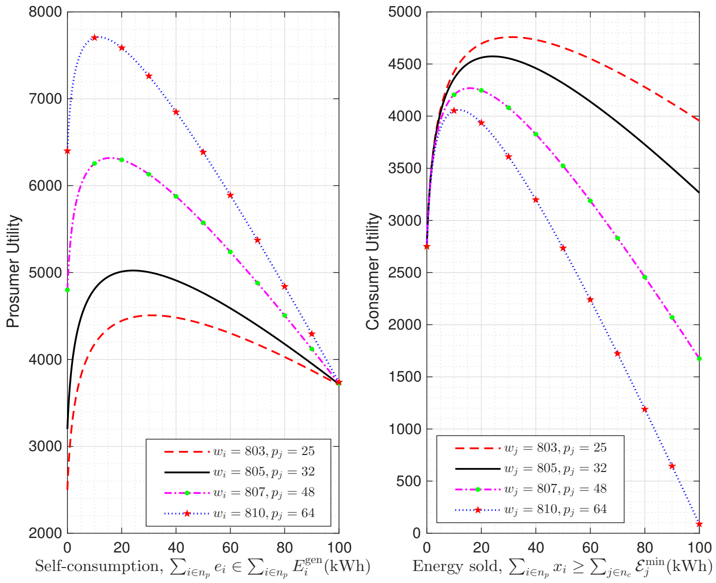

Figure 3: Utilities of prosumer and consumer based on e_i and x_i, respectively.

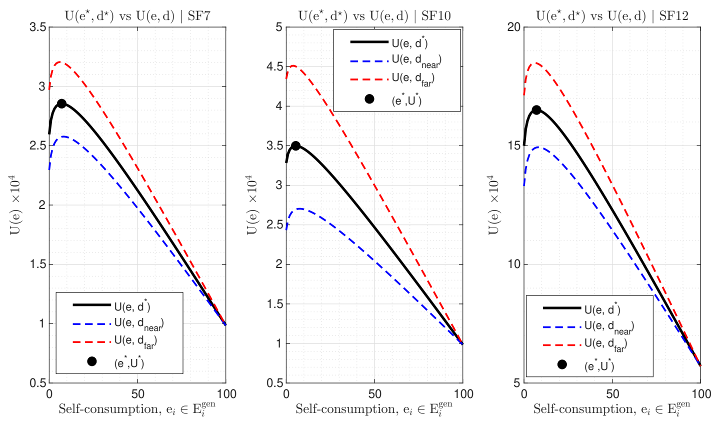

Figure 4: Comparison of prosumer utility at near, far and optimal trading distances

C. Penalty Model to Discourage Distant Energy Trading

From the (9c), (11a) and (12a), prosumers receive higher revenue for selling x_i at SF12 than at any other SF. Such practices pose a challenge to sustainability frameworks, including local energy trading and sharing, Net Zero, embedded generation and the United Nations Sustainable Development Goals. To solve the problem, a penalty should be introduced to discourage prosumers from trading at farther distances, such as

$$\mathcal{C}_j(x_i, d_j) = \sum_{i\in n_p} x_i^2 \alpha_j + \sum_{i\in n_p} x_i d_j \vartheta_j - \sum_{i\in n_p} \lambda_i x_i^p \left(\frac{d_j}{2r_m}\right)^q \quad (14)$$

where $\lambda_i > 0$, $p < 0$ and $q < 0$ are penalty parameters. Note that for any SF, $d_j \leq 2r_m$, which is the maximum distance separating any two prosumers. Solving for the optimal distance in (14) yields

$$d_j^\star = \left[\frac{2r_m \vartheta_j}{\lambda_i q}\right]^{\frac{1}{q-1}} x_i^{\frac{1-p}{q-1}}, \qquad d_j^\star \in [0,\ 2r_m]. \quad (15)$$

Considering the excess energy units used in [9], Figure 5 shows that the energy sold decreases as the distance increases, and thus, the revenue received also decreases, encouraging local energy trading, embedded generation, and other similar initiatives.

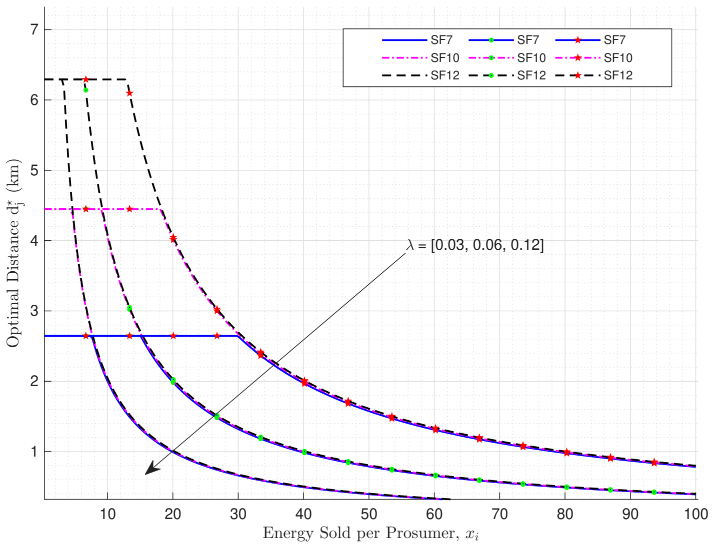

Figure 5: Tradeoff between energy sold and distance for different SFs

IV. Conclusion

Since 3GPP has demonstrated in Release 18 that artificial intelligence and machine learning will play a key role in future radio access networks of wireless communication standards, such as 6G networks, this study proposes possible use cases of the standard. For example, Internet of Things technologies will be used to complement 6G networks, serving blind spots and last-mile connections. Artificial intelligence and machine learning will be integrated into the network server, just as they are included in the application server. This study presents a notable use case of artificial intelligence and machine learning within the network and application servers to optimise the operation of IoT technologies for peer-to-peer energy trading prosumers formed into virtual clusters. Using LoRaWAN IoT technology as an example, agentic AI is proposed to adjust the LoRaWAN cell size by autonomously switching its spreading factor, while AI agents are deployed at the network edges to coordinate traffic characteristics within each energy trading area. Results showed that using agentic AI, IoT and AI agents framework, 6G network will support peer-to-peer energy trading in which more energy are sold to nearer neighbours than farther ones. Idle gNBs can be switched off, saving operational expenditures for network operators. These observations favour modern sustainability frameworks, such as Net Zero, Clean Power 2030, the United Nations Sustainable Development Goals, embedded energy generation, and local energy trading.

References

[1] K. Anoh, C. H. See, Y. Dama, R. A. Abd-Alhameed, and S. Keates, “6G Wireless Communication Systems: Applications, Opportunities and Challenges,” *Future Internet*, vol. 14, no. 12, p. 379, 2022.

[2] S. F. Drampalou, D. Uzunidis, A. Vetsos, N. I. Miridakis, and P. Karkazis, “A user-centric perspective of 6g networks: A survey,” *IEEE Access*, vol. 12, pp. 190 255–190 294, 2024.

[3] G. C. Yin Gao, Angelo Centonza, “AI/ML for NG-RAN & 5G-Advanced towards 6G,” Aug. 2025, retrieved 06 Sept. 2025. [Online]. Available: https://www.3gpp.org/technologies/ai-ml-ngran

[4] C. Aliagas, R. Pueyo Centelles, R. Meseguer, P. Millán, and C. Molina, “Dynamic selection and detection of spreading factors and channels for end-node devices of lora networks,” *Electronics*, vol. 14, no. 17, p. 3341, 2025.

[5] Q. Zhou, K. Zheng, L. Hou, J. Xing, and R. Xu, “Design and implementation of open LoRa for IoT,” *IEEE Access*, vol. 7, pp. 100 649–100 657, 2019.

[6] N. Chinchilla-Romero, J. Navarro-Ortiz, F. Delgado-Ferro, and J. M. Lopez-Soler, “6g-loragran: A testbed for researching lorawan and 5g integration,” in *2025 IEEE Wireless Communications and Networking Conference (WCNC)*, 2025, pp. 1–7.

[7] A. Farhad and J.-Y. Pyun, “AI-ERA: Artificial Intelligence-Empowered Resource Allocation for LoRa-Enabled IoT Applications,” *IEEE Transactions on Industrial Informatics*, vol. 19, no. 12, pp. 11 640–11 652, 2023.

[8] A. Prakash, N. Choudhury, A. Hazarika, and A. Gorrela, “Effective Feature Selection for Predicting Spreading Factor with ML in Large LoRaWAN-based Mobile IoT Networks,” in *2025 National Conference on Communications (NCC)*. IEEE, 2025, pp. 1–6.

[9] K. Anoh, S. Maharjan, A. Ikpehai *et al.*, “Energy Peer-to-Peer Trading in Virtual Microgrids in Smart Grids: A Game-Theoretic Approach,” *IEEE Trans. Smart Grid*, vol. 11, no. 2, pp. 1264–1275, 2020.

[10] W. Tushar, B. Chai, C. Yuen, D. B. Smith, K. L. Wood, Z. Yang, and H. V. Poor, “Three-party energy management with distributed energy resources in smart grid,” *IEEE Transactions on Industrial Electronics*, vol. 62, no. 4, pp. 2487–2498, 2014.

[11] Z. Fan, “Distributed demand response and user adaptation in smart grids,” in *12th IFIP/IEEE International Symposium on Integrated Network Management (IM 2011) and Workshops*. IEEE, 2011, pp. 726–729.

[12] T. Yamazaki, H. Takano, H. Asano, and T. Nguyen-Duc, “Theoretical study on demand-side management to reduce imbalance between electricity supply and demand,” *Discover Applied Sciences*, vol. 6, no. 10, p. 506, 2024.

[13] A. Milacic, “A simplified model of quadratic cost function for thermal generators,” in *Proceedings of the 23rd International DAAAM Symposium 2012*, 2012.

[14] A. K. Pati, “Agentic AI: A Comprehensive Survey of Technologies, Applications, and Societal Implications,” *IEEE Access*, 2025.

[15] P. A. Olujimi, P. A. Owolawi, R. C. Mogase, and E. V. Wyk, “Agentic AI frameworks in SMMEs: A systematic literature review of ecosystemic interconnected agents,” *AI*, vol. 6, no. 6, p. 123, 2025.

[16] D. Vukobratovic, D. Bajovic, K. Anoh, and B. Adebisi, “Distributed energy trading via cellular internet of things and mobile edge computing,” in *ICC 2019 - IEEE Intl. Conf. Commun.*, May 2019.

[17] A. Sales Mendes, D. M. Jiménez-Bravo, M. Navarro-Cáceres, V. Reis Quietinho Leithardt, and G. Villarrubia González, “Multi-agent approach using LoRaWAN devices: An airport case study,” *Electronics*, vol. 9, no. 9, p. 1430, 2020.

[18] M. Ali Lodhi, X. Sun, K. Mahmood, A. Lodhi, Y. Park, and M. Hussain, “AI-Enhanced Resource Allocation for LPWAN-Based LoRaWAN:A Hybrid TinyML and Deep Learning Approach,” *IEEE Internet of Things Journal*, vol. 12, no. 14, pp. 28 950–28 963, 2025.

[19] O. Jogunola, M. Hammoudeh, B. Adebisi, and K. Anoh, “Demonstrating blockchain-enabled peer-to-peer energy trading and sharing,” in *2019 IEEE Canadian conference of electrical and computer engineering (CCECE)*, 2019, pp. 1–4.

[20] S. Wood, “What is the average energy bill in Great Britain?” Aug. 2025, retrieved 18 Sept. 2025. [Online]. Available: https://www.britishgas.co.uk/energy/guides/average-bill.html#caveat

[21] “Average gas and electricity usage,” retrieved 20 Sept. 2025. [Online]. Available: https://www.ofgem.gov.uk/information-consumers/energy-advice-households/average-gas-and-electricity-use-explained