# DNN aided PSO based-scheme for a Secure Energy Efficiency Maximization in a cooperative NOMA system with a non-linear EH

Carla E. Garcia
Department of Electrical, Electronic and Computer Engineering
University of Ulsan
Ulsan, South Korea
carli.garcia27@hotmail.com

Mario R. Camana
Department of Electrical, Electronic and Computer Engineering
University of Ulsan
Ulsan, South Korea
mario_camana@hotmail.com

Insoo Koo
Department of Electrical, Electronic and Computer Engineering
University of Ulsan
Ulsan, South Korea
iskoo@ulsan.ac.kr *(corresponding author)*

***Abstract*— Physical layer security is an emerging security area to tackle wireless security communications issues and complement conventional encryption-based techniques. Thus, we propose a novel scheme based on swarm intelligence optimization technique and a deep neural network (DNN) for maximizing the secrecy energy efficiency (SEE) in a cooperative relaying underlay cognitive radio- and non-orthogonal multiple access (NOMA) system with a non-linear energy harvesting user which is exposed to multiple eavesdroppers. Satisfactorily, simulation results show that the proposed particle swarm optimization (PSO)-DNN framework achieves close performance to that of the optimal solutions, with a meaningful reduction in computation complexity.

**Keywords—** ***physical layer security, non-orthogonal multiple access (NOMA), deep neural network (DNN), particle swarm optimization (PSO), secrecy energy efficiency (SEE).***

## I. INTRODUCTION

Cooperative communications integrated by the promising non-orthogonal multiple access (NOMA) technique and cognitive radio (CR) technology have been investigated as potential solutions for 5G and beyond wireless networks. Particularly, NOMA provides fairness by exploiting the power domain to transmit the messages according to the user's channel strength. Thus, more transmission power is delivered to users' messages that have lower channel strength while lower transmission power is assigned to users' messages that have stronger channel conditions. Moreover, NOMA performs superposition coding (SC) coding at the transmitter side and successive interference cancelation (SIC) at the receivers to decode the messages of the weaker users. Furthermore, CR serves unlicensed users while preventing interference and congestion with licensed ones to enhance the use of the radio frequency (RF) spectrum.

Although NOMA and CR provide benefits in terms of spectrum and energy efficiency. Security still remains a critical concern in wireless networks due to the signals transmitted among nodes can be intercepted in the shared and open wireless environment. Therefore, research on physical layer security (PLS) has become an alternative approach to complement traditional cryptographic-based techniques by affording an additional protection layer. The basic idea of PLS is to take advantage of the physical properties of the channel to ensure the information against eavesdroppers. In the literature, the cooperative communications aided PLS technique has played a significant role in wireless security enhancements [1-3]. In this sense, a smart resource allocation scheme is an innovative and useful strategy in cooperative networks to reduce computational complexity while providing wireless communications security. Different machine learning-based techniques have been investigated to solve resource assignment problems in NOMA networks [4-6]. Particularly, several applications rely on supervised classification learning. For instance, in [7], the authors proposed to solve the relay selection problem based on feed-forward neural networks (FFNN). In [8], the authors utilized the deep neural network (DNN) to solve the power allocation problems in a cooperative NOMA network where the near user acts as a relay under the presence of one eavesdropper.

None of the cooperative systems studied above consider secrecy energy efficiency (SEE) maximization nor CR technology. In addition, a non-linear energy harvesting (EH) user entails significant contributions to solving the spectrum scarcity issue and improving energy efficiency.

Our aim is to provide a low computational complexity solution that maximizes the SEE in a cooperative CR NOMA system with a non-linear EH under the presence of multiple eavesdroppers. Therefore, we propose a DNN aided PSO scheme that reduces the computational time and optimizes the SEE.

The main contributions of this paper are summarized as follows.

- We investigate the SEE maximization in a cooperative relaying CR-NOMA network with a non-linear EH to prevent various eavesdroppers' wiretaps. Therefore, we formulate the non-convex SEE optimization problem as a bilevel optimization problem subject to the constraints that satisfy the quality-of-service (QoS) requirements of the secondary users, primary users, EH user, and the maximum transmission power at the secondary base station (SB) and the relay.
- We design an innovative secure scheme based on swarm intelligence and machine learning techniques. Particularly, the outer optimization problem is solved by the DNN to select the optimal relay. The inner problem takes the outcome of the DNN to solve the power allocation problem by utilizing the PSO technique.
- Simulation results show that the proposed DNN aided PSO achieves a near-optimal performance with much lower complexity compared with an exhaustive search (ES)-PSO-based scheme. Moreover, simulation results validate the superior performance of NOMA over the conventional OMA scheme. In addition, we analyze the effect of non-linearity and linearity on the SE of the proposed scheme.

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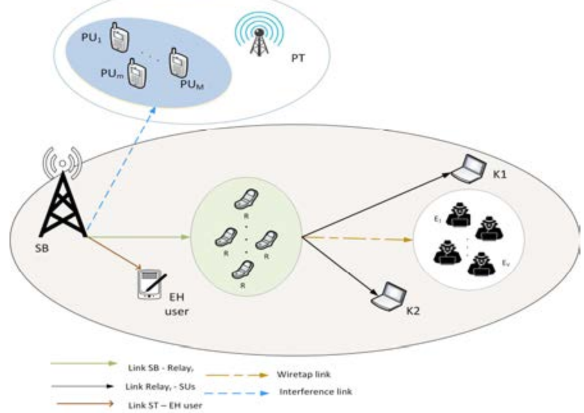

Fig. 1. Cooperative CR-NOMA system with a non-linear EH user.

## II. System Model

In this paper, we propose a collaborative relaying CR-NOMA system as shown in Fig. 1, which is integrated by a SB, a non-linear EH user, two secondary intended users denoted as K1 and K2, and R relays. The proposed system is exposed to the presence of multiple eavesdroppers ( $E_v$ ), where all nodes are equipped with a single antenna. We consider that SB–R–K1 link is considerably longer than the SB–R–K2 link. Thus, SB–K1 link can support a lower QoS than SB–K2 [9].

Moreover, there is no direct link between the SB and the secondary user. Therefore, the proposed network is aided by an intermediate decode and forward (DF) node. The node or relay is selected from the R relays and is denoted by $r$. The transmission is performed in two phases. In Phase 1, the SB conveys the messages $k_1$ and $k_2$ belong to the secondary users K1 and K2, respectively, to the relay. Meanwhile, the EH user stored the RF energy by receiving the superimposed RF signals of the secondary users K1 and K2 through an antenna. Then, the node, $r$, decodes $k_1$ by treating $k_2$ as interference and executes SIC to decode $k_2$ . In Phase 2, the node $r$ transmits the superimposed signal composed of $k_1$ and $k_2$ to the secondary users K1 and K2.

### A. Phase 1. Direct Transmission

During this stage, the SB conveys the signal, $k = k_1 w_2 + k_2 w_2$, where $k_1, k_2 \in \mathbb{C}$ are the independent and identically distributed (*i.i.d.*) information bearing messages for user 1 and user 2, respectively. The power of the transmitted symbol is normalized, i.e., $E\left(|k_1|^2\right) = E\left(|k_2|^2\right) = E\left(|k_3|^2\right) = 1$, and $w_1$, and $w_2$ are the corresponding transmit power variables. Accordingly, the received signal at relay $r$ can be given by

$$y_r = h_r\left(\sqrt{w_1}k_1 + \sqrt{w_2}k_2\right) + n_r, \qquad (1)$$

where $h_r$ is the channel coefficient between the SB and relay $r$, while $n_r \sim CN\left(0, \sigma_r^2\right)$ is the additive Gaussian noise with zero mean and $\sigma_r^2$ variance.

The relay $r$ first decodes the message $k_1$ by treating the message $k_2$ as noise, and then performs SIC to decode $k_2$ . Consequently, the received signal-to-interference-plus-noise ratio (SINR) for K1, and the signal-to-noise ratio (SNR) for K2 at node, $r$, can be described by (2) and (3), respectively:

$$SINR_{k_1}^r = \frac{|h_r|^2 w_1}{|h_r|^2 w_2 + \sigma_r^2}, \qquad (2)$$

$$SNR_{k_1}^r = \frac{|h_r|^2 w_2}{\sigma_r^2}. \qquad (3)$$

Based on (2) and (3), the rate of the far-user data and the near-user data at the node $r$ are formulated by (4) and (5), respectively.

$$\gamma_{K1} = \frac{1}{2}\log_2\left(1 + \frac{|h_r|^2 w_1}{|h_r|^2 w_2 + \sigma_r^2}\right), \qquad (4)$$

$$\gamma_{K2} = \frac{1}{2}\log_2\left(1 + \frac{|h_r|^2 w_2}{\sigma_r^2}\right). \qquad (5)$$

Moreover, (6) and (7) are the requirements to satisfy that the node $r$ can successfully decode the messages $k_1$ and $k_2$ [13], as follows:

$$\frac{1}{2}\log_2\left(1 + \frac{|h_r|^2 w_1}{|h_r|^2 w_2 + \sigma_r^2}\right) \geq \psi_1 \qquad (6)$$

$$\frac{1}{2}\log_2\left(1 + \frac{|h_r|^2 w_2}{\sigma_r^2}\right) \geq \psi_2, \qquad (7)$$

where $\psi_1$ and $\psi_2$ are the target data rate for the secondary users K1 and K2, respectively.

The consider non-linear EH user is modeled according to [10], and can be formulated as follows:

$$EH_{user} = \frac{1}{2}\frac{\psi - L\Omega}{1 - \Omega}, \qquad (8)$$

where $\Omega = \frac{1}{1 + \exp(ab)}$ and $\psi = \frac{L}{1 + \exp\left(-a\left(p_{\mathrm{int}} - b\right)\right)}$, $p_{\mathrm{int}}$ denotes the input power. In this case, $p_{\mathrm{int}} = |h_{se}|^2\left(w_1 + w_2\right)$, where $h_{se}$ is the channel coefficient from the SB to the EH user. $L$ is a constant that set the maximum harvested power at EH receiver when the EH circuit is saturated. Parameters $a$ and $b$ are constants depending on the detailed circuit specifications, for example capacitance, resistance and diode turn-on voltage. We consider the values adopted in [10] which are given by $L = 3.9mW$, $a = 1500$, and $b = 0.0022$.

### B. Phase 2. Relay Transmission

In this phase, we consider that node $r$ can decode both signals, then, users $Ki, i \in \{1,2\}$ receives the following signal:

$$y_{r,Ki} = f_{r,Ki}\left(\sum_{j=1}^{2}\sqrt{w_{r,Kj}}k_j\right) + n_{Ki}, i \in \{1,2\}, \qquad (9)$$

where $f_{r,Ki}$ is the channel coefficient between relay $r$ and the secondary user $Ki, i \in \{1,2\}$. The power allocation assigned to the secondary users K1 and K2 from the relay are denoted as $w_{r,K1}$ and $w_{r,K2}$, respectively. $n_{Ki} \sim CN\left(0,\sigma^2_{Ki}\right)$ denotes the additive Gaussian noise at K1 and K2.

The SINR at K1 to decodes its message $k_1$ considers the interference caused by the secondary user K2 and can be described as follows:

$$\mathrm{SINR}_{r,K1} = \frac{\left|f_{r,K1}\right|^2 w_{r,K1}}{\left|f_{r,K1}\right|^2 w_{r,K2} + \sigma^2_{K1}}. \tag{10}$$

Due to NOMA principle, the SNR of secondary user K2 to decode its message can be describe as:

$$\mathrm{SINR}_{r,K1} = \frac{\left|f_{r,K2}\right|^2 w_{r,K2}}{\sigma^2_{K2}}. \tag{11}$$

Consequently, the rate of the far-user data at K1 and K2 can be described as (12) and (13), respectively.

$$\gamma_{k_1,rK1} = \frac{1}{2}\log_2\left(1+\frac{\left|f_{r,K1}\right|^2 w_{r,K1}}{\left|f_{r,K1}\right|^2 w_{r,K2} + \sigma^2_{K1}}\right), \tag{12}$$

$$\gamma_{k_1,rK2} = \frac{1}{2}\log_2\left(1+\frac{\left|f_{r,K2}\right|^2 w_{r,K1}}{\left|f_{r,K2}\right|^2 w_{r,K2} + \sigma^2_{K2}}\right). \tag{13}$$

Moreover, the rate of the strong-user data at K2 can be expressed as

$$\gamma_{k_2,rK2} = \frac{1}{2}\log_2\left(1+\frac{\left|f_{r,K2}\right|^2 w_{r,K2}}{\sigma^2_{K2}}\right). \tag{14}$$

We investigate the challenging scenario where the eavesdroppers have a powerful detection capability to receive $k_1$ without being jammed by $k_2$, and vice versa. Hence, the rate of K1 and K2 secondary users' data at the eavesdropper can be expressed as

$$\gamma_E^{Ki} = \frac{1}{2}\log_2\left(1+\mathrm{SNR}_{ev}^{Ki}\right), i \in \{1,2\}, \tag{15}$$

where $\mathrm{SNR}_{ev}^{Ki} = \max\limits_{v\in\{1,2,\ldots V\}} \frac{w_{r,Ki}\left|g_{r,E_v}\right|^2}{\sigma^2_{E_v}}$, $g_{r,E_v}$ is the channel coefficient between node $r$ and eavesdropper $v$, and $\sigma^2_{E_v}$ represents the variance in the additive Gaussian noise at the eavesdropper.

The achievable data rate for secondary user K1 should satisfy the minimum rate at the relay, secondary user K1 and K2 since the node $r$ performs the DF protocol and K2 employs SIC to decode the message $k_1$, while secondary user K1 decodes its message by treating $k_2$ as noise.

$$\gamma_{k_1,\min} = \min\left(\gamma_{k_1,rK1}, \gamma_{k_1,rK2}, \gamma_{K1}\right). \tag{16}$$

Similarly, to the achievable data rate for secondary user K1, to the achievable data rate for K2 should meet the minimum rate at the relay, and secondary user K2, as follows:

$$\gamma_{k_2,\min} = \min\left(\gamma_{k_2,rK2}, \gamma_{K2}\right). \tag{17}$$

Accordingly, the secrecy rates of secondary user K1 and K2 can be expressed as (18) and (19), respectively:

$$\gamma_{\sec,K1} = \left[\gamma_{k_1,\min} - \gamma_E^{K1}\right]^+. \tag{18}$$

$$\gamma_{\sec,K2} = \left[\gamma_{k_2,\min} - \gamma_E^{K2}\right]^+, \tag{19}$$

where $[x]^+ = \max(0,x)$.

## III. Problem Formulation

The SEE of the proposed NOMA-enable cooperative CR system is defined as the ratio of total secrecy rate to power consumption in both phases. Then, we first propose to solve the SEE optimization problem by applying the PSO scheme to generate the dataset with the best values of power allocation variables to train the DNN algorithm by optimizing the weights of the network that allows obtaining the maximum SEE. Meanwhile, the relay selection problem is performed in an exhaustive search manner which entails high computational complexity. Therefore, the problem for the SEE maximization is formulated as a bilevel optimization problem, as given below:

$$\max_{\{r\}}\left(h(r) = \max_{w_1,w_2,\{w_{r,K1},w_{r,K2}\}} \frac{\gamma_{\sec,K1}+\gamma_{\sec,K2}}{\frac{1}{2}\left(w_1+w_2+p_{c1}+w_{r,M1}+w_{r,M2}+p_{c2}\right)}\right) \tag{20a}$$

subject to:

$$\text{C1: } \gamma_{k_1,\min} \geq \Phi_1, \tag{20b}$$

$$\text{C2: } \gamma_{k_2,\min} \geq \Phi_2, \tag{20c}$$

$$\text{C3: } w_1 + w_2 \leq P_{ST}^{\max}, \tag{20d}$$

$$\text{C4: } w_{r,K1} + w_{r,K2} \leq P_r^{\max}, \tag{20e}$$

$$\text{C5: } EH_{user} \geq \xi, \tag{20f}$$

where $h(r)$ represents the inner part of the optimization problem according to the lower-level variables. The lower-level variables are the power allocation variables: $w_1$, $w_2$, $w_{r,K1}$, $w_{r,K2}$. Meanwhile, $r$ is the upper-level variable of the outer part of the optimization problem (20). Moreover, $p_{c1}$ and $p_{c2}$ are the constant circuit power for or transmitting signal processing in phase 1 and phase 2, respectively.

Since we applied the underlay CR network, (21) and (22) are the constraints to prevent the transmission power at the SB and the relay, respectively, interfere with the primary network.

$$P_{SB}^{\max} = \min\left\{\frac{Int_{SB}^{\max}}{\max\limits_{m\in\phi_m}\left|h_{sm}\right|^2}, P_{SB}\right\}, \tag{21}$$

where $Int_{SB}^{\max}$ is the threshold to limit the interference power at the PUs from the SB, $\phi_m$ is the set of PUs, the maximum power at the ST is denoted by $P_{SB}$, and the channel coefficient from the SB to the $PU_m$ is denoted as $h_{sk}$; and

$$P_r^{\max} = \min\left\{\frac{Int_r^{\max}}{\max\limits_{m\in\phi_m}\left|h_{rm}\right|^2}, P_r\right\}, \tag{22}$$

where $Int_r^{\max}$ is the threshold to limit the interference power at the PUs from the relay $r$, the maximum power at the relay $r$ is denoted by $P_r$, and the channel coefficient from relay $r$ to the $PU_m$ is denoted by $h_{rm}$.

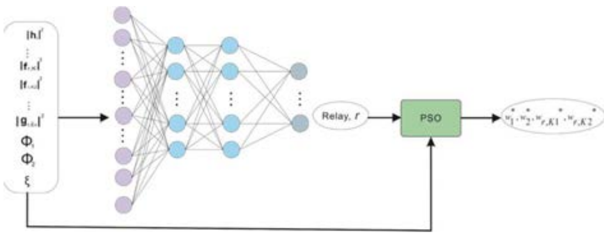


Fig. 2. General overview of the proposed DNN+PSO based scheme.

## IV. PROPOSED DNN AIDED PSO BASED-SCHEME

In this paper, we construct a DNN-based scheme to solve the relay selection problem in (20). In particular, the relay that achieves the highest SEE is selected by the DNN. Fig. 2 shows the framework of the proposed method which consists of two main modules: a DNN, and a PSO module to solve problem (20).

### *A. DNN module*

The proposed DNN module [11] is composed of an input layer, four hidden layers, and an output layer, as shown in Fig. 2. The input of the DNN involves the channel from the SB to the relay, the channels from the relay to the secondary users, the target data rate values, and the minimum target value required by the EH user. The number of neurons per hidden layer is 100,50,100,50, respectively. We used tanh activation function, stochastic gradient descent as a solver, the learning rate is set to 0.001 and the batch size is set to 128.

### *B. PSO module*

The second module is the PSO algorithm [12], [13] which utilizes the relay selected by the DNN to optimize the power allocation to the secondary users. To this end, PSO searches for the global solution by iteratively updating its position and velocities.

In this paper, the best performance is achieved by the maximum value of the SEE, and the following vector contains the $n$-th particle's position composed of 4 elements as follows:

$$\mathbf{x}_n = \left\{x_{w_1,k}, x_{w_2,k}, x_{w_{r,K1},k}, x_{w_{r,K2},k}\right\}, \tag{23}$$

where $n = 1,2,...,N_P$, $N_p$ represents the number of particles in the swarm, $x_{w_1,k}, x_{w_2,k}, x_{w_{r,K1},k}$ and $x_{w_{r,K2},k}$ are the particle's position of the transmission power variables $w_1, w_2, w_{r,K1}$, and $w_{r,K2}$, respectively. Moreover, the maximum and minimum power levels of each power allocation variable are stablished to define the limits of the search space for each particle's position. Hence, the limits of the search space for each power allocation variable $w_1, w_2, w_{r,M1}$, and $w_{r,M2}$, are $\left(0, P_{ST}^{\max}\right]$, $\left(0, P_{ST}^{\max}\right]$, $\left(0, P_{r}^{\max}\right]$, and $\left(0, P_{r}^{\max}\right]$.

Furthermore, we utilize a penalty method based on [3] to deal with the proposed constrained optimization problem (20). Then, the fitness function is defined as follows:

$$F\left(w_1, w_2, w_{r,K1\min}, w_{r,K2\min}\right) = \begin{cases} \dfrac{\gamma_{\sec,K1} + \gamma_{\sec,K2}}{\frac{1}{2}\left(w_1 + w_2 + p_{c1} + w_{r,K1} + w_{r,K2} + p_{c2}\right)} & \text{if } z_i \le 0, \forall_i \\ f_{\min} - \partial_r \sum_{i=1}^{5} Q_i \max\left(z_i, 0\right), & \text{otherwise,} \end{cases} \tag{24}$$

where $f_{\min}$ is the lowest value of the SEE in the population, $\partial_r = \sqrt{t}$ is the penalty value at the iteration $t$, of the PSO algorithm and the penalty parameter of the $i$-th constraint is denoted by $0 \le Q_i \le 1$. Moreover, from the constraints of problem (20) for the $r$-th selected relay node, we obtain $z_1 = \Phi_1 - \gamma_{k_1,\min}$, $z_2 = \Phi_2 - \gamma_{k_2,\min}$, $z_3 = w_1 + w_2 - P_{ST}^{\max}$, $z_4 = w_{r,K1} + w_{r,K2} - P_r^{\max}$, and $z_5 = \xi - EH_{user}$. The function $\max\left(z_i, 0\right)$ also lets us consider the values of the constraints that are not met.

In Table I, the proposed low complexity solution is described to maximize the SEE for the problem (20). The input parameters of PSO belong to the maximum iteration number, the inertia weight for velocity update, the cognitive and social parameters, denoted as $Ite_{\max}$, $s_v$, $c_1$, and $c_2$, respectively. In addition, $N_p$ and the limits of the search space $\left(0, P_{ST}^{\max}\right]$, $\left(0, P_{ST}^{\max}\right]$, $\left(0, P_{r}^{\max}\right]$, and $\left(0, P_{r}^{\max}\right]$ are part of the input parameters. Then, the velocity of each $n$-th particle in each $t$ iteration is updated according to the relative positions of the individual local best position $\mathbf{pb}_n$ and $\mathbf{g_b}$, as follows:

$$v_{w1,n}^{t+1} = s_v^t v_{w1,n}^t + u_1 c_1\left(pb_{w1,n} - x_{w1,n}^t\right) + u_2 c_2\left(gb_{w1} - x_{w1,n}^t\right) \tag{25}$$

$$v_{w2,n}^{t+1} = s_v^t v_{w2,n}^t + u_1 c_1\left(pb_{w2,n} - x_{w2,n}^t\right) + u_2 c_2\left(gb_{w2} - x_{w2,n}^t\right) \tag{26}$$

$$v_{w_{r,K1},n}^{t+1} = s_v^t v_{w_{r,K1}n}^t + u_1 c_1\left(pb_{w_{r,K1},n} - x_{w_{r,K1},n}^t\right) + u_2 c_2\left(gb_{w_{r,M1}} - x_{w_{r,K1},n}^t\right) \tag{27}$$

$$v_{w_{r,K2},n}^{t+1} = s_v^t v_{w_{r,K2}n}^t + u_1 c_1\left(pb_{w_{r,K2},n} - x_{w_{r,K2},n}^t\right) + u_2 c_2\left(gb_{w_{r,K2}} - x_{w_{r,K2},n}^t\right) \tag{28}$$

where $u_1$ and $u_2$ are random numbers between 0 and 1.

Once the velocity is updated, the $n$-th particle's position update is values, as follows:

$$x_{w1,n}^{t+1} = x_{w1,n}^t + v_{w1,n}^{t+1}, \tag{29}$$

$$x_{w2,n}^{t+1} = x_{w2,n}^t + v_{w2,n}^{t+1}, \tag{30}$$

$$x_{w_{r,K1},n}^{t+1} = x_{w_{r,K1},n}^t + v_{w_{r,K1},n}^{t+1}, \tag{31}$$

$$x_{w_{r,K2},n}^{t+1} = x_{w_{r,K2},n}^t + v_{w_{r,K2},n}^{t+1}, \tag{32}$$

Note that before applying the machine learning algorithm, the relay selection is performed in an exhaustive search manner. Therefore, the best candidate relay node is that one achieves the maximum SEE among all the possible relays in the network, according to the outcomes of the $\mathbf{g_b}$ values. In addition, the computational complexity of the PSO-based method depends on $Ite_{\max}$, and $N_p$, i.e., $\mathcal{O}\left(Ite_{\max} N_p\right)$ [3].

## V. SIMULATION RESULTS

We used MATLAB and Python software to perform the simulation results.

In the considered cooperative CR-NOMA network, the channel coefficients are modeled as $h_r : CN\left(0, d_{SB-r}^{-pa}\right)$, $f_{r,M1} : CN\left(0, d_{r-K1}^{-pa}\right)$, $f_{r,K2} : CN\left(0, d_{r-K2}^{-pa}\right)$, $h_{se} : CN\left(0, d_{SB-EHuser}^{-pa}\right)$, $g_{r,E_v} : CN\left(0, d_{r-E_v}^{-pa}\right)$,

TABLE I. DNN+PSO SCHEME TO SOLVE PROBLEM (20).

1: Input: Set the network parameters of the system and selected relay $r^*$ by the DNN.

2: Initialize $SEE_{\max} = 0$.

3: Establish the parameters of PSO.

4: Initialize the iteration count $t = 1$.

5: Initialize the values of the $n$-th particle's position.

$$\mathbf{x}^{(t)} = \left\{ \left( x_{w1,n}^{(t)}, x_{w2,n}^{(t)}, x_{w_{r,K1},n}^{(t)}, x_{w_{r,K2},n}^{(t)} \right) \right\}, \forall n.$$

6: Initialize the initial values of the $n$-th particle's velocities.

$$\mathbf{v}^{(t)} = \left( \mathbf{v}_{n,w_1}^{(t)}, \mathbf{v}_{n,w_2}^{(t)}, \mathbf{v}_{n,w_{r,K1}}^{(t)}, \mathbf{v}_{n,w_{r,K2}}^{(t)} \right)$$

7: Compute the maximum objective function $SEE\left(\mathbf{x}_n^t\right), \forall n$, in (20) for each $n$-th particle.

8: Establish the initial best particles' positions $\forall m: \mathbf{pb}_n = \mathbf{x}_n^{(t)}$, that achieved the best yield so far.

9: From among all the particles, set the initial $\mathbf{gb}$.

$$\mathbf{gb} = \underset{1 \le n \le N_p}{\arg\max}\ SEE\left(\mathbf{x}_n^{(t)}\right).$$

10: Iteration count $t = t + 1$.

11: **For** each particle $n$ **do**

12: From (25), (26), (27), and (28), update the particles' velocities.

13: From (29), (30), (31), and (32), update the particles' positions.

14: Update the best $\mathbf{pb}_n$.

**if** $SEE\left(\mathbf{x}_n^t\right) > SEE\left(\mathbf{pb}_n\right)$ **then**

$\mathbf{pb}_n = \mathbf{x}_n^{(t)}$

**end if**

15: Update $\mathbf{gb}$, $\forall n$.

**if** $SEE\left(\mathbf{x}_n^t\right) > SEE\left(\mathbf{gb}\right)$ **then**

$\mathbf{gb} = \mathbf{x}_n^{(t)}$

**end if**

16: **end for**

17: **if** $t < Ite_{\max}$, **then**

$t = t + 1$ and go to $\rightarrow$ step 11

**else**

go to $\rightarrow$ step 18

**end if**

18: **End PSO:** for the relay $r^*$ the optimal power allocation values are $\left\{ w_1^*, w_2^*, w_{r,K1}^*, w_{r,K2}^* \right\} =$ **best_gb** to acquire the highest value of SEE in (20).

$h_{sm} : CN\left(0, d_{SB-PU_m}^{-pa}\right)$, and $h_{rm} : CN\left(0, d_{r-PU_m}^{-pa}\right)$, where $d_{a-b}$ denotes the distance between node $a$ and $b$, and $pa$ is the path-loss exponent, $pa = 4$. In addition, we set the noise variance as follows: $\sigma_{K1}^2 = \sigma_{K2}^2 = \sigma_r^2 = \sigma_{E_v}^2 = -80$ dBm, and $P_{SB}^{\max} = P_r^{\max} = P_{\max} = 30$dBm.

The coordinates of the nodes are set to be $SB = (0,50), K1 = (100,50), K2 = (70,42), R_1 = (50,54)$, $R_2 = (50,50), R_3 = (50,46), R_4 = (50,42), PU_1 = (75,59)$, $PU_2 = (25,59), PU_3 = (50,37), EHuser = (9,46)$. The network is $100\text{m} \times 60\text{m}$. The results are averaged over several channel realizations. The simulation parameters of PSO are set to be $N_p = 30$, $Ite_{\max} = 300$, $s_v = 0.7$, $c_1 = 1.494$, and $c_2 = 1.494$. Moreover, the total dataset contains 57600 samples, which is split into 80% for the training dataset and 20% for testing.

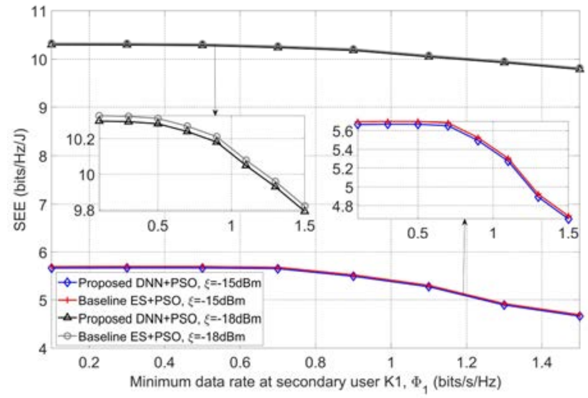


Fig. 3. SEE performance between the proposed DNN+PSO and the baseline ES+PSO scheme.

Fig. 3 illustrates the SEE versus the minimum rate at secondary user $K1$ when the minimum data rate at secondary user is equal to $\Phi_2 = 0.5$ bps/Hz/s, and the energy required at the EH user is equal to $\xi = -15$ dBm and $\xi = -18$ dBm. From Fig. 3, we can observe that the proposed DNN-PSO achieves a near-optimal performance to that of the ES-PSO scheme. ES+PSO method is an iterative algorithm that requires solving PSO a total of times equal to the number of relays available in the network such that select one that achieves the highest SEE. Therefore, the DNN scheme is utilized instead of the ES as an efficient strategy to reduce the computational complexity. It is worth highlighting that the true label of the DNN is obtained by ES. ES exhaustively finds all the possible solutions and selects the best one that reaches the highest SEE. Furthermore, the computation time required by the standard ES+PSO and DNN+PSO framework is 4.2s and 1.3s, respectively. Therefore, the proposed DNN-PSO-based solution provides less computational time and overcomes the conventional ES+PSO method. Moreover, Fig 3 shows that the SEE decreases as de minimum data rate and EH requirement increase. This is because more power needs to be allocated to satisfy the requirements of the secondary and EH users and the power consumption is inversely proportional to the SEE. Accordingly, it reduces the SEE.

Fig. 4 shows the effect from linearity of EH on SEE in the proposed cooperative relaying CR-NOMA system when the minimum data rate at secondary user is equal to $\Phi_2 = 0.5$ bps/Hz/s, and the energy required at the EH user is equal to $\xi = -15$ dBm and $\xi = -18$ dBm. Fig. 4 validates that the cooperative CR-NOMA system with the non-linear EH user achieves lower SEE than that obtained by the ideal linear EH user. This is because the ideal case assumes that the user can harvest all the power of the incoming signal. However, the non-linear EH considers a more realistic scenario that includes circuit specifications that reduce the SEE performance.

Fig. 5 shows the SEE comparative performance between the proposed CR-NOMA scheme and the conventional CR-OMA baseline scheme for the target rate of $\Phi_2 = 0.5$ and the EH requirement of $\xi = -18$ dBm and $\xi = -20$ dBm. We

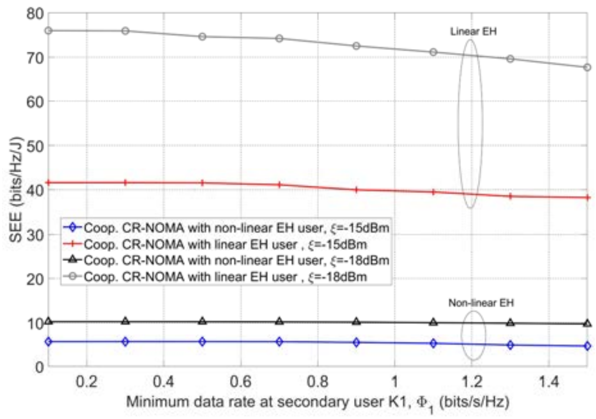


Fig. 4. SEE performance between the proposed cooperative CR-NOMA with non-linear EH user and the cooperative CR-NOMA with linear EH user scheme.

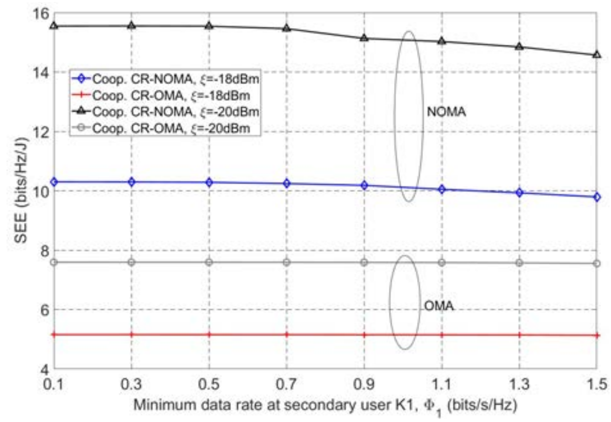


Fig. 5. SEE performance between the proposed cooperative CR-NOMA with non-linear EH user and the conventional cooperative CR-OMA with non-linear EH user scheme.

observe that the NOMA scheme overcomes the OMA method since NOMA efficiently uses the spectrum and power resources. Particularly, NOMA allows to simultaneously transmit information to both users in the same frequency band.

## VI. Conclusion

In the proposed paper, we design a novel artificial intelligence-based solution composed of the PSO-based technique and a DNN to enhance the wireless security communication in collaborative relaying CR-NOMA system in the challenging presence of several eavesdroppers. In addition, we consider the practical design of a non-linear EH user. Accordingly, the proposed DNN+PSO-based solution maximizes the SEE of the network while satisfying the QoS requirements of all nodes in the network. Satisfactorily, numerical results show that the proposed PSO-DNN framework can achieve a performance close to the optimal solutions given by the PSO and ES method, with significantly lower complexity. Furthermore, simulation results verify that the proposed scheme achieves higher SEE performance than the OMA benchmark.

## References

[1] L. Lv, J. Chen, Q. Ni, Z. Ding and H. Jiang, “Cognitive Non-Orthogonal Multiple Access with Cooperative Relaying: A New Wireless Frontier for 5G Spectrum Sharing,” IEEE Communications Magazine, vol. 56, no. 4, pp. 188–195, April 2018.

[2] D.-T. Do, M.-S. Van Nguyen, T.-A. Hoang, and M. Voznak, “NOMA Assisted Multiple Access Scheme for IoT Deployment: Relay Selection Model and Secrecy Performance Improvement,” Sensors, vol. 19, no. 3, p. 736, Feb. 2019.

[3] C. E. Garcia, M. R. Camana, and I. Koo, “Relay selection and power allocation for secrecy sum rate maximization in underlying cognitive radio with cooperative relaying NOMA,” Neurocomputing, vol. 452, pp. 756–767, Sep. 2021.

[4] U. Uyoata, J. Mwangama, and R. Adeogun, “Relaying in the Internet of Things (IoT): A Survey,” IEEE Access, vol. 9, pp. 132675–132704, 2021.

[5] T.-V. Nguyen, T.-N. Tran, K. Shim, T. Huynh-The, and B. An, “A Deep-Neural-Network-Based Relay Selection Scheme in Wireless-Powered Cognitive IoT Networks,” IEEE Internet of Things Journal, vol. 8, no. 9, pp. 7423–7436, May 2021.

[6] T.-H. Vu, T.-V. Nguyen, and S. Kim, “Cooperative NOMA-Enabled SWIPT IoT Networks with Imperfect SIC: Performance Analysis and Deep Learning Evaluation,” IEEE Internet of Things Journal, pp. 1–1, 2021.

[7] M. A. Salem, A. B. Abd.Aziz, H. F. Al-Selwi, M. Y. B. Alias, T. Kim Geok, A. Mahmud, and A. S. Bin-Ghoot, “Machine Learning-Based Node Selection for Cooperative Non-Orthogonal Multi-Access System Under Physical Layer Security,” Dec. 2019.

[8] F. Jameel, W. U. Khan, Z. Chang, T. Ristaniemi, and J. Liu, “Secrecy Analysis and Learning-Based Optimization of Cooperative NOMA SWIPT Systems,” 2019 IEEE International Conference on Communications Workshops (ICC Workshops), May 2019.

[9] Huynh, T.-P.; Ngoc Son, P.; Voznak, M. Secrecy Performance of Underlay Cooperative Cognitive Network Using Non-Orthogonal Multiple Access with Opportunistic Relay Selection. Symmetry 2019, 11, 385.

[10] K. Xiong, B. Wang, and K. J. R. Liu, ‘‘Rate-energy region of SWIPT for MIMO broadcasting under nonlinear energy harvesting model,’’ IEEE Trans. Wireless Commun., vol. 16, no. 8, pp. 5147–5161, Aug. 2017. [24] R. Sahay and C. G. Brinton, "Robust Subject-Independent P300 Waveform Classification via Signal Pre-processing and Deep Learning," in IEEE Access, doi: 10.1109/ACCESS.2021.3089998.

[11] R. Sahay and C. G. Brinton, "Robust Subject-Independent P300 Waveform Classification via Signal Pre-processing and Deep Learning," in IEEE Access, doi: 10.1109/ACCESS.2021.3089998.

[12] M. O. Okwu and L. K. Tartibu, Metaheuristic Optimization: NatureInspired Algorithms Swarm and Computational Intelligence, Theory and Applications, vol. 927. Cham, Switzerland: Springer, 2020.

[13] C. E. García, M. R. Camana and I. Koo, "Low-Complexity PSO-Based Resource Allocation Scheme for Cooperative Non-Linear SWIPT-Enabled NOMA," in IEEE Access, vol. 10, pp. 34207-34220, 2022, doi: 10.1109/ACCESS.2022.3162838.