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RESEARCH ON NAVIGATIONAL OPTIMIZATION OF MOBILE ROBOT THROUGH ENHANCING QUALITY OF COMMUNICATION AND APPLICATION OF DEEP REINFORCEMENT LEARNING ALGORITHM

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INTRODUCTION

1. Rasionale of the dissertation

To meet societal demands, the number of mobile robots in factories has been increasing significantly. Concurrently, the presence of Internet of Things (IoT) devices in these factories is also rising. This situation leads to challenges related to sharing workspace among robots, between robots and other devices, and between robots and humans. For effective operation, mobile robots in factories must not only complete their navigation tasks but also exchange information with other devices, such as central control stations, other robots in multi-robot systems, or other wireless devices to ensure effective management and operation of the entire factory. Hence, integrating wireless communication into mobile robots is a practical solution. In this scenario, mobile robots serve as components of the IoT system, helping to reduce computational energy consumption and address communication issues within the factory. To ensure that robots complete their tasks while maintaining reliable communication with the system, optimizing the trajectory of mobile robots in a wireless communication environment within the factory is crucial. Therefore, the researcher has chosen the topic ***"Research on navigational optimization of mobile robot through enhancing quality of communication and application of deep reinforcement learning algorithm"***.

2. Research Objective

- Study of Models and Algorithms for Optimizing Network Systems to Enhance Communication Quality for Mobile Robot Operations.

- Development of Trajectory Optimization Algorithms to Minimize Energy Consumption for Mobile Robots Operating in Ideal Communication Environments.

- Development of Navigation Systems for Mobile Robots Combining Trajectory Optimization with Wireless Communication and System Energy Consumption Minimization.

- Simulation, Verification, and Evaluation of the Effectiveness of Proposed Algorithms and System Models.

3. Research scope

Theoretical Aspects:

- Conduct a comprehensive review of mobile robots operating in communication environments, including the current state of research both domestically and internationally, to derive suitable research directions for the dissertation.

- Research and propose models and algorithms for network optimization to expand coverage and improve wireless communication quality within the factory.

- Formulate the trajectory optimization problem for robots within a factory to minimize energy consumption under ideal communication conditions, and develop algorithms to solve this problem.

- Research and propose a navigation system for mobile robots in environments where communication conditions are not guaranteed.

- Formulate the trajectory optimization problem for robots within a factory to minimize energy consumption in environments with unreliable communication, and develop algorithms to solve this problem.

- Utilize optimization tools to perform simulations.

Experimental Aspects:

- Develop simulations to validate the effectiveness of models and algorithms for optimizing wireless communication networks that support mobile robot operations.

- Develop simulations to validate trajectory optimization algorithms for mobile robots in ideal communication environments.

- Develop simulations to validate trajectory optimization algorithms for mobile robots in environments with unreliable communication.

Chapter 1. OVERVIEW OF path planning FOR MOBILE ROBOTS IN FACTORIES

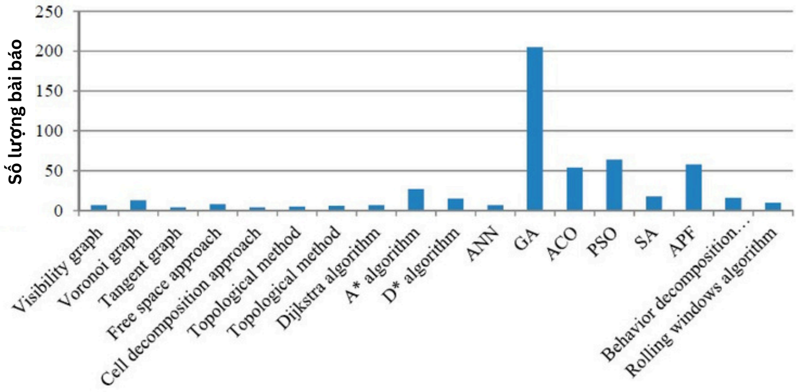


Figure 1.2: The number of research studies on path planning for robots based on data from Engineering Village [2].

1.1. The path planning problem for mobile robot

For decades, the field of robotics has garnered significant attention, continually evolving and profoundly impacting human life [12]. In modern factories, mobile robots with flexible movement capabilities play a crucial role in industrial applications such as material handling and supporting key stages in production lines [13]. As a result, mobile robots have attracted considerable interest from researchers and businesses both domestically and internationally.

Generally, the motion control structure of a mobile robot can be divided into three stages: Localization and Path Planning, Trajectory Tracking, and Motor Control. The motion control of mobile robots involves two main issues: path planning and the design of trajectory tracking controllers. This dissertation focuses on the path planning problem for mobile robots. This area has been extensively researched over the decades, with numerous algorithms proposed, as summarized in Figure 1.2 [2].

1.2. Mobile robots and wireless communication

According to [25], mobile robots can currently be classified into two types: Autonomous Mobile Robots (AMR) and Connected Mobile

Robots (CMR). Equipped with sensors and computational resources, AMRs are capable of performing their tasks independently. The complexity arises when AMRs face the challenge of requiring large memory, substantial computational resources, and the ability to execute complex Artificial Intelligence (AI) algorithms for difficult tasks. Additionally, as the number of robots in factories increases, along with other IoT devices, the devices within the factory will operate in a shared workspace. In such scenarios, robots must coordinate with each other to form multi-robot systems or swarm robots to achieve high efficiency in performing tasks within the factory. Therefore, a connected robot system provides an effective solution, while also alleviating the memory and computational resource burdens for each robot.

However, wireless communication in factories serving mobile robots faces significant challenges, including the emergence of dead zones and an inability to meet the reliability and latency requirements of factory applications. Consequently, to achieve sustainable throughput growth for wireless networks in factories supporting mobile robot operations, with low cost, complexity, and energy consumption, the development of new technologies along with network optimization is an urgent issue.

1.3. State of research in Vietnam and abroad

1.3.1. State of research in Vietnam

In Vietnam, path planning for robots has been and continues to be a focus in both industry and research. In industry, most robots in factories currently operate with predefined trajectories. Robots are guided by magnetic strips placed on the floor, QR codes on the floor, or other navigation tools. However, research is still striving with the hope that robots will have the capability to make optimal decisions for tasks autonomously [26-31].

1.3.2. State of research in abroad

The problem of path planning for mobile robots

To ensure that robots do not collide with obstacles during movement, previous research on path planning for robots has proposed various algorithms for different application scenarios. By dividing the continuous space into a grid with finite points, efficient path planning algorithms, including Dijkstra's, A*, and D*, have been developed to find the shortest path between two points in both static and dynamic environments [32].

An optimal trajectory can significantly reduce the energy required by the robot. However, the trajectory optimization problem aimed at minimizing energy consumption for robots is challenging because it is a non-convex optimization problem. Authors [39-45] have proposed various solutions for minimizing energy for robots.

Studies [46-48] propose using Deep Reinforcement Learning (DRL) techniques for pathfinding in environments that are either unknown or partially known.

Integration of wireless communication for mobile robots

Many authors have focused on integrating communication for robot systems. Publications [49-50] have proposed solutions for optimizing the system. Additionally, publications [4-6] and [51] focus on using Intelligent Reflecting Surfaces (IRS) to enhance wireless communication quality in factory environments, aiming to create an adjustable radio environment as shown in Figure 1.5.

1.4. Research direction of the dissertation

Based on the issues related to optimizing systems for mobile robot operations, this dissertation will investigate three problems. The first is to study models and algorithms to enhance wireless communication quality in factories supporting mobile robot operations. Once the issue of wireless communication quality is addressed, assuming that all points during the robot's movement meet communication speed constraints, the communication environment is considered ideal. The second problem is to research path planning algorithms for mobile robots

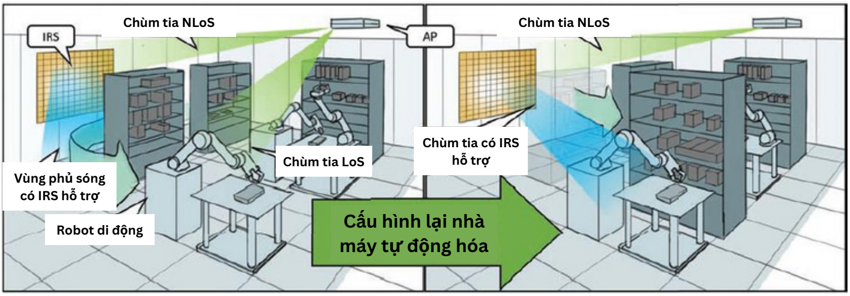


Figure 1.5: IRS helps adjust coverage areas corresponding to changes in the factory layout. [4]

in an ideal communication environment. In practice, achieving an ideal communication environment is challenging. Therefore, the third problem is to study navigation systems for robots in environments with unreliable communication.

1.5. Conclusion of Chapter 1

Chapter 1 has outlined the challenges of trajectory planning for mobile robots in wireless communication environments within factories. Through a review of related studies both domestically and internationally, the doctoral candidate has identified a research direction. These topics will be elaborated upon in the following chapters of the dissertation.

The contributions of Chapter 1 are published in works CT4 and CT5.

Chapter 2. ENHANCING WIRELESS COMMUNICATION QUALITY FOR MOBILE ROBOT IN FACTORIES

2.1. The problem of optimizing wireless communication performance in factories

In a factory environment, in addition to mobile robots, there are many other devices connected to the network, such as laptops, tablets, mobile phones, wireless sensors, Bluetooth devices, and various other communication devices. One challenge is how to allow multiple devices to share the resources of a network system while still meeting the requirements for the operation of each device. This is the first challenge for wireless communication systems in factories. Furthermore, in a factory environment, there are many devices, machinery, and walls, creating many areas within the factory that do not receive wireless communication signals, known as dead zones.

This is the second challenge when using wireless communication in factories. To address the first issue, measures need to be taken to optimize the performance of the wireless communication network in the factory. However, network optimization issues can only be feasible if the signal coverage in the factory is consistently ensured, meaning the second challenge mentioned must be addressed. Recently, a new concept of Intelligent Reflecting Surface (IRS) or Reconfigurable Intelligent Surface has been introduced in wireless communication research [56] as a solution to the dead zone problem. IRSs can create a programmable wireless network environment.

2.2. System model

The dissertation proposes a network system model integrating data communication and energy harvesting combined with IRS-supported D2D network, named DED2D (integrated data and energy network and D2D communication coexistence system). Specifically, the main network includes a base station (BS) and mobile robots requiring information IUs (Information Users), as well as wireless sensors requiring energy EUs (Energy harvested Users), with D2D communication devices sharing resources with the main network. The system model is illustrated in Figure 2.3.

2.2.1. Signal received at mobile robots

2.2.2. Signal received at wireless sensors

2.2.3. Signal received at D2D receivers

2.2.4. Optimization problem

The dissertation investigates an optimization problem combining the optimization of i) beamforming for information transmission to mobile robots, ii) beamforming for energy transmission to wireless sensors, iii) time-sharing ratio of the TFIET system, iv) transmission power of D2D transmitters, and v) reflection coefficient of IRS. The goal is to maximize the minimum throughput of mobile robots while ensuring the energy harvesting requirements of EUs and the D2D communication rate threshold. Therefore, the optimization problem is described mathematically as follows:

$$
\begin{aligned}
&\max_{\bar{\mathbf{w}},\bar{\mathbf{v}},\mathbf{p},\tau=(t_i,t_e)\in\mathbb{R}^2_+,\bar{\boldsymbol{\theta}}} f(\bar{\mathbf{w}},\bar{\mathbf{v}},\mathbf{p},\tau,\bar{\boldsymbol{\theta}}) \\
&\triangleq \min_{d_i\in\mathcal{U}_I} t_i R_{t_i,d_i}(\bar{\mathbf{w}},\mathbf{p},\bar{\boldsymbol{\theta}}) && (2.8a)\\
\text{s.t.}\quad & (2.1),\\
& t_e\rho E_{t_e,e_j}(\bar{\mathbf{v}},\mathbf{p},\bar{\boldsymbol{\theta}}) \geq e_{min}, \forall e_j\in\mathcal{U}_E, && (2.8b)\\
& t_i R_{t_i,k}(\bar{\mathbf{w}},\mathbf{p},\bar{\boldsymbol{\theta}}) + t_e R_{t_e,k}(\bar{\mathbf{v}},\mathbf{p},\bar{\boldsymbol{\theta}}) \geq R_{k,min}, \forall k\in\mathcal{K}, && (2.8c)\\
& t_i + t_e \leq 1, && (2.8d)\\
& t_i \sum_{d_i\in\mathcal{U}_I} \|\bar{\mathbf{w}}_{d_i}\|^2 + t_e \sum_{e_j\in\mathcal{U}_E} \|\bar{\mathbf{v}}_{e_j}\|^2 \leq P_{B,max}, && (2.8e)\\
& \|\bar{\mathbf{w}}_{d_i}\|^2 \leq P_{B,max}; \|\bar{\mathbf{v}}_{e_j}\|^2 \leq P_{B,max}, && (2.8f)\\
& p_k \leq P_{k,max}, \forall k\in\mathcal{K}, && (2.8g)
\end{aligned}
$$

where the parameters and constraints are described in detail in the dissertation.

2.3. Optimization algorithm

This section presents the method for approximating the objective function and non-convex constraints in problem (2.8) into two convex optimization problems (2.23) and (2.37). Algorithm 1 details the steps to find the optimal solution of the original problem (2.8) by iteratively solving the approximation problem until the algorithm converges. The obtained solution is proven to be convergent.

2.4. Orthogonal time allocation scenatio

In Section 2.3, the dissertation focuses on the DED2D system with IRS support, where D2D transmitting devices send signals during the periods when the BS transmits information and energy. The N-OTA scenario helps increase bandwidth utilization but also increases interference to the network elements. This section examines the DED2D system with IRS support and orthogonal time allocation (OTA) between the time for receiving information by mobile robots, energy harvesting by wireless sensors, and D2D communication. Specifically, in a time slot, the BS allocates separate time intervals for information transmission, energy transmission, and D2D communication. This way, there will be no interference from D2D communication to the main network, but the time allocated for information and energy transmission from the BS will be reduced. Therefore, it is interesting to discuss the performance of the N-OTA and OTA scenarios in the simulation results section.

The optimization problem in the OTA scenario is similar to (1),

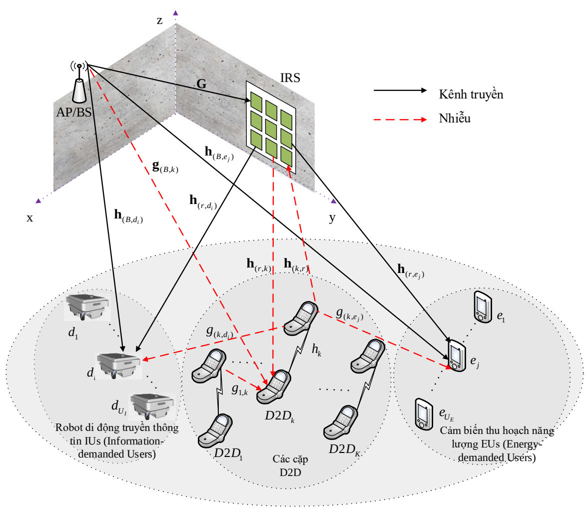


Figure 2.3: IRS-aided DED2D network.

where t_d is the time portion for D2D communication, i.e., $\tau = (t_i, t_e, t_d)$. Mathematically, the optimization problem is described as follows:

$$\max_{\bar{\mathbf{w}},\bar{\mathbf{v}},\mathbf{p},\tau=(t_i,t_e,t_d)\in\mathbb{R}^3_+,\bar{\boldsymbol{\theta}}} f(\bar{\mathbf{w}},\bar{\mathbf{v}},\mathbf{p},\tau,\bar{\boldsymbol{\theta}}) \triangleq \min_{d_i\in\mathcal{U}_I} t_i\widetilde{R}_{t_i,d_i}(\bar{\mathbf{w}},\bar{\boldsymbol{\theta}}) \quad (2.40a)$$

$$\begin{aligned}
\text{s.t.}\quad & (2.1), \\
& t_e\rho\widetilde{E}_{t_e,e_j}(\bar{\mathbf{v}},\bar{\boldsymbol{\theta}}) \geq e_{min}, \forall e_j \in \mathcal{U}_E, && (2.40b)\\
& t_d\widetilde{R}_{t_d,k}(\mathbf{p},\bar{\boldsymbol{\theta}}) \geq R_{k,min}, \forall k \in \mathcal{K}, && (2.40c)\\
& t_i + t_e + t_d \leq 1, && (2.40d)\\
& t_i \sum_{d_i\in\mathcal{U}_I} \|\bar{\mathbf{w}}_{d_i}\|^2 + t_e \sum_{e_j\in\mathcal{U}_E} \|\bar{\mathbf{v}}_{e_j}\|^2 \leq P_{B,max}(1-t_d), && (2.40e)\\
& \|\bar{\mathbf{w}}_{d_i}\|^2 \leq P_{B,max}, \|\bar{\mathbf{v}}_{e_j}\|^2 \leq P_{B,max}, && (2.40f)\\
& t_d p_k \leq P_{k,max}, \forall k \in \mathcal{K}. && (2.40g)
\end{aligned}$$

Next, the dissertation presents the method for approximating the objective function and non-convex constraints in problem (2.40) into two convex optimization problems (2.48) and (2.55). Algorithm 1 details the steps to find the optimal solution of the original problem (2.8) by iteratively solving the approximation problem until the algorithm converges. The obtained solution is proven to be convergent.

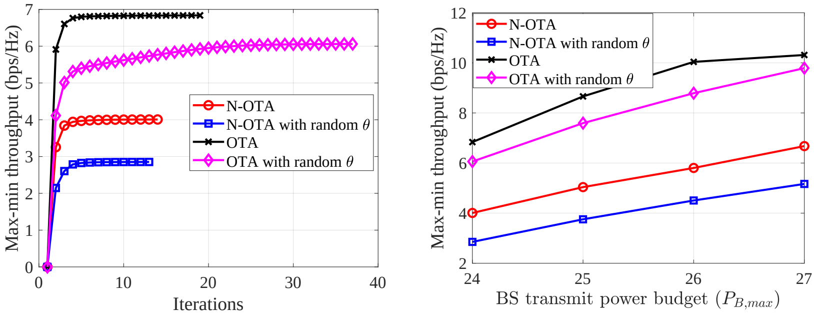
2.5. Evaluation of the model and algorithm

The simulation parameters are detailed in the dissertation and Table 2.1. The simulation results from Figures 2.4 to 2.6 demonstrate the effectiveness of the proposed model and algorithms.

2.6. Conclusion of chapter 2

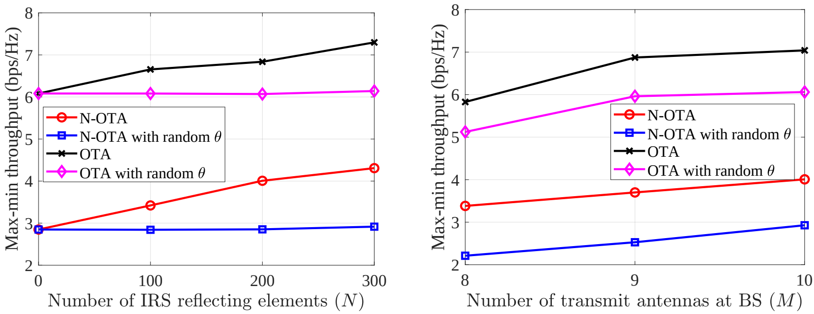
Chapter 2 presents the proposed model and algorithm for optimizing network systems in urban and industrial environments to support the operations of special devices, particularly for mobile robots.

The content of Chapter 2 is published in work CT1. Work CT1 presents a proposal for a DED2D wireless network model and an optimization algorithm that allows mobile robots to communicate,



(a) (b)

Figure 2.4: a) Convergence of the algorithms b) Data throughput changes with the BS's budget power $P_{B,max}$.



(a) (b)

Figure 2.6 : Throughput achieved with a) the number of IRS elements and b) the number of antennas at the BS.

wireless sensors to harvest energy, and devices using direct communication methods in a factory to share the same network bandwidth while still achieving effective communication for each type of device.

Chapter 3. OPTIMAL TRAJECTORY ALGORITHM FOR MOBILE ROBOT IN IDEAL COMMUNICATION SCENARIO

3.1. Convex optimization

3.2. Developing an optimal trajectory algorithm for mobile

robot

3.2.1. Objective and constraints of the optimization problem

The trajectory found is expected to move to the destination with the shortest travel distance. Assume the robot operates in an industrial environment, where the number of obstacles is represented by a set $\mathcal{M}$. Without loss of generality, assume that all obstacles are circular in shape.

3.2.2. Trajectory optimization algorithm

The optimization problem was formulated as

$$\min_{\mathbf{q}} J \tag{3.24a}$$

$$\text{s.t. } \mathbf{q}(1) = \mathbf{q}_s, \tag{3.24b}$$

$$\|\mathbf{q}(k+1) - \mathbf{q}(k)\| \leq \tau v_{\max}, \forall k \in (1, h), \tag{3.24c}$$

$$\|\mathbf{q}(k) - \mathbf{q}_m^O\| \geq d_m^r, \forall t \in (1, h), m \in (1, M), \tag{3.24d}$$

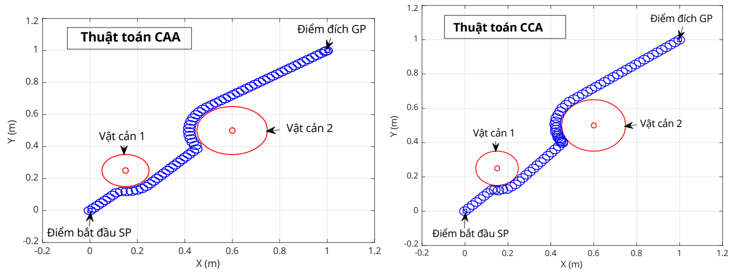
where constraint (3.24b) is the Start Point (SP), constraint (3.24c) is the velocity limit of the robot, and (3.24d) are the obstacle avoidance constraints. This problem is non-convex because constraint (3.24d) is non-convex. Therefore, a convex approximation algorithm is presented to approximate problem (3.24) into a convex problem for solution.

Algorithm 1 outlines the general approach for finding the optimal trajectory for the robot, known as the Convex Approximation Algorithm (CAA).

3.2.3. Results evaluation

This section presents the simulation results that validate the effectiveness of the proposed algorithm. The simulations were conducted using MATLAB, and the convex optimization problem was solved using the CVX package along with the Mosek 9.1.9 solver. For comparison, the dissertation introduces a calculation algorithm based on the robot's kinematic equations, known as the Conventional Computing Algorithm

(CAA). The simulation results shown in Figure 3.2 demonstrate the effectiveness of the proposed algorithm.



(a) (b)

Figure 3.2: Optimal trajectory of the robot with (a) CAA algorithm and (b) CCA algorithm.

3.3. Developing an algorithm for minimizing energy consumption

In this section, the dissertation focuses on the objective function of energy consumption of the robot. Specifically, it addresses the trajectory optimization problem for the robot with the goal of minimizing energy consumption.

3.3.1. Modeling energy consumption of mobile robot

The total energy consumption of the robot can be expressed as follows:

$$E = \frac{1}{2}\sum_{d=0}^{D-1} m\left(\frac{|\mathbf{q}_{d+1} - \mathbf{q}_d|}{\tau}\right)^2 + 2\mu m g \sum_{d=0}^{D-1} |\mathbf{q}_{d+1} - \mathbf{q}_d| + P_s(D-1)\tau, \tag{3.36}$$

where, m the mass of the robot, g is the gravitational acceleration, and μ is the coefficient of sliding friction depending on the surface type of the robot's operating environment, P_s is the system's source voltage, D is the number of discretization steps, $d \in [0, D]$ represents the time steps, $\mathbf{Q} = [\mathbf{q}_0, \mathbf{q}_1, \ldots, \mathbf{q}_D]$, và $\bar{\mathbf{v}} = [v_1, v_2, \ldots, v_D]$ are the trajectory and corresponding velocities at the discrete time steps, respectively, and τ is the duration of each step.

3.3.2. Collision avoidance constraints

In the robot's working environment, we assume that obstacles are polygonal with H edges. Specifically, suppose there is a set $\mathcal{M}$ of obstacles in the robot's working environment.

3.3.3. Algorithm for optimizing energy consumption for mobile robot

In general, we can design a trajectory for the robot to minimize the total travel distance, thereby reducing the kinetic energy consumed by the robot. However, it is essential to ensure that no collisions occur during the robot's movement. Additionally, we can reduce the duration of each movement step to decrease energy consumption on the computer, electronic circuits, and sensors. However, this requires the robot to move faster, which may exceed the robot's capabilities. Therefore, in this section, the dissertation formulates the problem of minimizing the robot's energy consumption by optimizing both the trajectory and the duration of each movement step while still ensuring collision avoidance requirements.

The algorithm for finding the optimal trajectory with the objective of minimizing energy in the presence of static obstacles is outlined in Algorithm 6. This algorithm is named OSOW (Optimal Static Obstacle Workspace) to indicate that it solves the trajectory optimization problem for robots in environments with only static obstacles.

3.3.4. Optimization problem in the ccenario with dynamic obstacles

In this section, the dissertation focuses on the scenario where dynamic obstacles appear during the robot's movement. Specifically, for static obstacles, the assumptions remain unchanged from the previous section. Firstly, based on the information about static obstacles, the robot will calculate the optimal trajectory using Algorithm 3, which is Algorithm OSOW, solving problem (3.43). Subsequently, the robot will move according to this trajectory. This trajectory, denoted as $\mathbf{Q} = [\mathbf{q}_0, \mathbf{q}_1, \ldots, \mathbf{q}_D]$, is called the global trajectory. During the robot's movement, at step $i \in [0, D]$, suppose the robot detects $\mathcal{N}_i = \{1, \ldots, N_i\}$ moving obstacles (MOs). Each moving obstacle (MO) is assumed to be circular in shape. Specifically, the robot observes that an MO n_i has a center at $\mathbf{q}^O_{n,i} = (x^O_{n,i}, y^O_{n,i})$ moving with velocity $\bar{\mathbf{v}}_{n_i} = (v_{nx_i}, v_{ny_i})$. To avoid collisions, the next movement trajectory of the robot $\mathbf{q}_{i,d_i} = (x_{i,d_i}, y_{i,d_i})$ vi $d_i \in [0, D_i]$ is the number of steps required to avoid N_i moving obstacles. Let vt cn. Gi $\mathbf{Q}_i = [\mathbf{q}_{i,0}, \mathbf{q}_{i,1}, \ldots, \mathbf{q}_{i,D_i}]$, và $\bar{\mathbf{v}}_i = [v_{i,1}, v_{i,2}, \ldots, v_{i,D_i}]$ be the sets of positions and velocities for the robot during the avoidance of obstacles. Accordingly, $\mathbf{Q}_i$ is called the local trajectory. Thus, the collision avoidance conditions are described as follows:

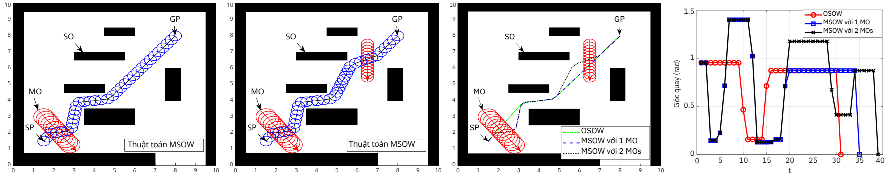
$$\|\mathbf{q}_{i,d_i} - \mathbf{q}^O_{n,d_i}\| \geq r^O_{n,i} + d_r + \delta, \forall n \in \mathcal{N}, d_i \in [0, D_i], \tag{3.49}$$

where $r^O_{n,i}$ is the radius of obstacle n, and $\mathbf{q}^O_{n,d_i} = (x^O_{n,d_i}, y^O_{n,d_i})$ is the position of obstacle n at step d_i. The energy consumption minimization problem for the robot in the dynamic obstacle avoidance scenario will include additional dynamic obstacle avoidance constraints (3.49).

As mentioned above, the robot will follow the local trajectory, $\mathbf{Q}_i$, to avoid dynamic obstacles, and then return to the global trajectory $\mathbf{Q}$, to move towards the destination. Therefore, the overall algorithm for the path planning problem for a robot in an environment with both static obstacles (SOs) and moving obstacles (MOs) is presented in Algorithm 7. This algorithm is named Algorithm MSOW, which stands for the algorithm for path planning in environments containing both Moving and Static Obstacles in the robot's Workspace.

3.3.5. Results evaluation

This section presents the simulation results for the proposed algorithms. The simulation results demonstrate the effectiveness of the proposed algorithms.



(a) (b) (c) (d)

Figure 3.6: Optimal trajectory of the robot for minimizing energy consumption with (a) MSOW scenario with 1 MO (b) MSOW scenario with 2 MOs (c) all three scenarios and (d) Rotation angle of the robot corresponds to the optimal trajectories.

3.4. Conclusion of Chapter 3

The main contributions of Chapter 3 are as follows:

- Proposed the CAA algorithm to solve the optimal trajectory problem for mobile robots in an ideal communication environment.

- Proposed the OSOW and MSOW algorithms to address the path planning problem aimed at minimizing energy consumption for static and dynamic obstacles, respectively.

The contributions of Chapter 3 are published in works CT2 and CT3. Work CT2 presents algorithms based on convex optimization for path planning of robots in a factory environment with dynamic and static obstacles to minimize the robot's energy consumption. Work CT3 presents algorithms based on convex optimization for path planning in a factory environment to minimize the robot's travel distance.

Chapter 4. TRAJECTORY OPTIMIZATION ALGORITHM FOR MOBILE ROBOT IN STAR-IRS-ASSISTED COMMUNICATION NETWORK

4.1. System Model for mobile robot navigation with STAR-IRS

4.1.1. STAR-IRS

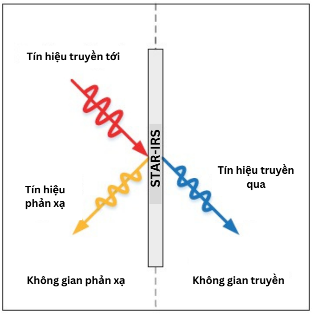


Figure 4.1: STAR-IRS. [7]

A new concept of IRS is STAR-IRS (Simultaneously Transmitting and Reflecting IRS). Specifically, as shown in Figure 4.1, a signal can reach a STAR-IRS element from both directions of the surface. A portion of the signal is reflected into the same side of the space as the incoming signal, called the reflection space, while the remaining portion is transmitted to the opposite side of the incoming signal, referred to as the transmission space.

4.1.2. System Model for Navigation of Mobile Robots in a Wireless Communication Environment

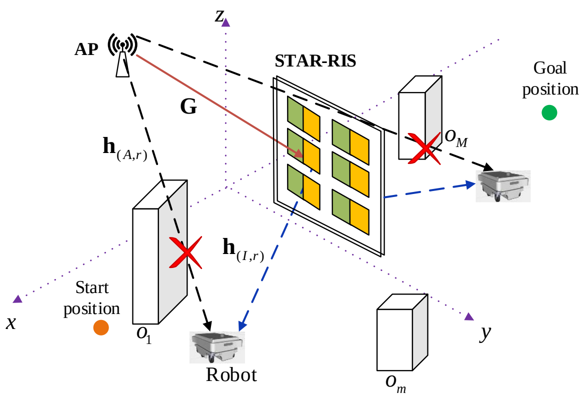


Figure 4.3: Illustration of the robot navigation system in a house with STAR-IRS-assisted communication.

In this section, PhD student first introduces the robot navigation system in a house where the communication system is supported by

STAR-IRS. Specifically, STAR-IRS operates in ES mode, as illustrated in Figure 4.3. The dissertation focuses on the model of the navigation system for a robot in a house, including an AP with one antenna and a mobile robot equipped with an antenna. Due to the complex environment in future smart factories, the robot may encounter obstacles, and the direct channels between the AP and the mobile robot might be unstable or even blocked. To address this issue, the dissertation proposes a STAR-IRS-supported communication system consisting of N signal transmission and reflection elements, with the set of STAR-IRS elements denoted as $\mathcal{N} = \{1, \ldots, N\}$. For installation, STAR-IRS can be mounted on the ceiling of the factory to provide high-quality transmission channels between the AP and the robot throughout the entire 360^0 space around the IRS. Let T be the robot's travel time. For simplicity, T is divided into L time steps δ, i.e., $T = L\delta$.

4.1.3. Signal model

The signal received by the robot is modeled as follows:

$$y_l^c = (h_{A,r}(\mathbf{q}_l) + \mathbf{h}_{(I,r)}^H(\mathbf{q}_l)\bar{\mathbf{\Theta}}_l^c\mathbf{g})\sqrt{p_l}s_l + n_l, \tag{4.10}$$

where, $c \in \{r, t\}$, p_l is the transmission power from the AP to the robot, s_l is the signal transmitted to the robot, and $n_l \sim \mathcal{CN}(0, 1)$ is the additive white Gaussian noise at the robot with an average power of σ^2 at time slot l. Then the SINR at the robot is

$$\zeta_l^c = \frac{|h_{A,r}(\mathbf{q}_l) + \mathbf{h}_{(I,r)}^H(\mathbf{q}_l)\bar{\mathbf{\Theta}}_l^c\mathbf{g}|^2 p_l}{\sigma^2}. \tag{4.11}$$

Therefore, the communication rate achieved at the robot is

$$R_l^c = \log_2\Big(1 + \frac{|h_{A,r}(\mathbf{q}_l) + \mathbf{h}_{(I,r)}^H(\mathbf{q}_l)\bar{\mathbf{\Theta}}_l^c\mathbf{g}|^2 p_l}{\sigma^2}\Big). \tag{4.12}$$

4.1.4. The optimal navigation problem for mobile robot

The energy consumption of the system includes the energy consumed by the robot, denoted as E_R which is described in Chapter 3, and the energy consumed by the AP, denoted as $E_A = \sum_{l=1}^{L} p_l \delta$. Let $\mathbf{Q} = [\mathbf{q}_1, \mathbf{q}_2, \ldots, \mathbf{q}_L]$ be the trajectory of the robot and $\mathbf{p} = [p_1, p_2, \ldots, p_L]$ be the transmission power from the AP to the robot corresponding to that trajectory. Let γ be the minimum communication rate at the robot and $p^{\max}$ be the maximum transmission power of the AP. The trajectory optimization problem for the robot aims to minimize the system's energy consumption and is formulated as follows:

$$\min_{\mathbf{Q},\mathbf{p},\bar{\boldsymbol{\Theta}}^c} W_1 E_R + W_2 E_A \tag{4.21a}$$

$$\text{s.t.} \quad (4.3), (4.4), (4.5),$$

$$R_l^c \geq \gamma, \forall l \in \mathcal{L}, \tag{4.21b}$$

$$T \leq T^{\max}, \tag{4.21c}$$

$$p_l \leq p^{\max}, \forall l \in \mathcal{L}, \tag{4.21d}$$

$$\phi_{l,n}^c = \frac{\xi \pi}{2^{b-1}}, \xi \in \{0, 1, \ldots, 2^b - 1\}, \forall n \in \mathcal{N}, l \in \mathcal{L}, \tag{4.21e}$$

where W_1 and W_2 are the weights for the objective function corresponding to the energy consumption by the robot and the AP, respectively.

The optimization problem described is non-convex and therefore quite difficult to solve. Consequently, a method based on deep reinforcement learning techniques will be proposed and presented below.

4.2. Markov Decision Process Model

4.2.1. Reinforcement Learning

4.2.2. MDP model for navigation problem

The problem of path planning for a mobile robot can be described as an optimization problem defined by $< \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R} >$, where $\mathcal{S}$ is the state space, $\mathcal{A}$ is the action space, $\mathcal{P}$ is the state transition probability function, and $\mathcal{R}$ is the reward function.

State Space

Action space

Reward function

4.3. Deep Reinforcement Learning Algorithm

4.3.1 Advantage Actor-Critic

4.3.2 Proximal Policy Optimization

4.3.3 Convergence and complexity of actor-critic-based algorithm

4.4 Performance Evaluation

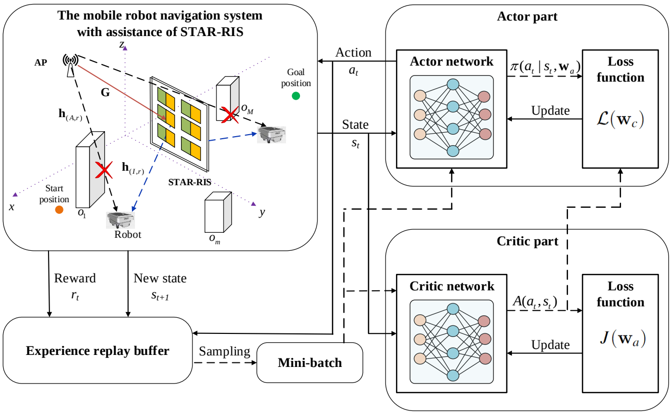


Figure 4.6: Resource management framework based on the A2C model.

Figure 4.6 illustrates the PPO algorithm applied to the path planning problem for a mobile robot in a factory. Specifically, Algorithm 8 shows the steps of the PPO algorithm for optimally combining system parameters, robot motion trajectory, and communication rate.

4.4 Evaluating the effectiveness of the model and navigation algorithm for mobile robot

For comparison purposes, the dissertation focuses on the following algorithms:

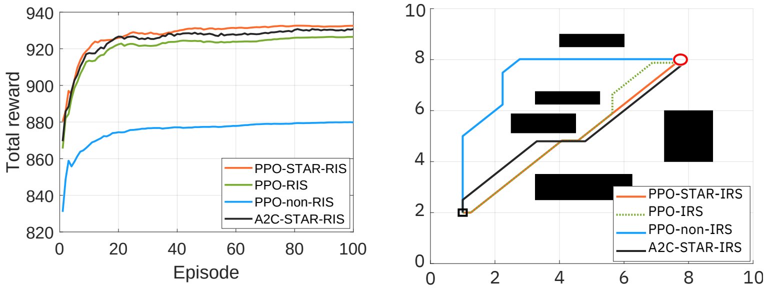
- **PPO-STAR-IRS:** This algorithm is based on DRL that is described in Section 4.3.2 (shown in Algorithm 8).

- **A2C-STAR-IRS:** This is A2C (Advantage Actor Critic) algorithm that applied for mobile robot navigation that is assisted by STAR-IRS. A2C-STAR-IRS is similar to PPO-STAR-IRS with the objective function without $\texttt{clip}(\underline{p}_t(\theta), 1-\epsilon, 1+\epsilon)$.

- **PPO-IRS:** This uses the DRL similar to the PPO-STAR-IRS algorithm, but the passive RIS is used rather than the STAR-IRS.

- **PPO-non-IRS:** This uses the DRL similar to the PPO-STAR-IRS algorithm, but no RIS is used to assist the mobile robot.

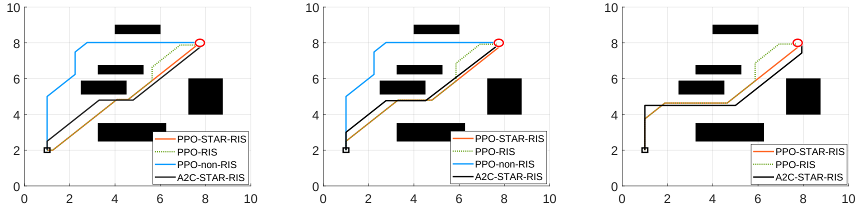
Observing from Figure 4.8, it is seen that all algorithms converge to stable reward values after approximately 50 episodes. Notably, the PPO-STAR-IRS algorithm outperforms the A2C-STAR-IRS, PPO-IRS, and PPO-non-IRS algorithms in terms of total reward. Overall, the system supported by STAR-IRS demonstrates superior trajectory effectiveness. Specifically, using the PPO-based algorithm yields better results than A2C.



(a) (b)

Figure 4.8: (a) Convergence of the algorithms and (b) Optimal trajectory obtained by the algorithms.

Next, the dissertation considers the impact of the communication rate threshold requirement on the robot's optimal trajectory. As shown in Figure 4.9, as the communication rate requirement increases, the robot needs to find a way to meet that requirement. This leads to a longer trajectory for the robot. This difference is highlighted in Figs.



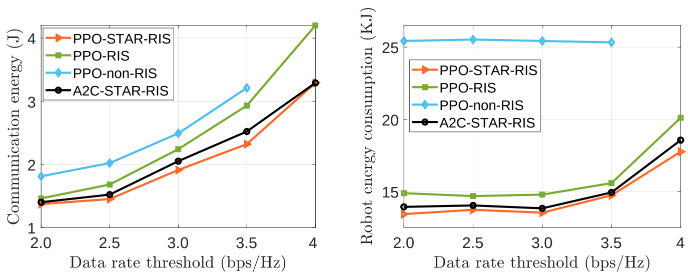
(a) $\bar{\gamma} = 2.5$bps/Hz (b) $\bar{\gamma} = 3.5$bps/Hz (c) $\bar{\gamma} = 4$bps/Hz

Figure 4.9: The impact of the communication rate threshold requirement on the optimal trajectory of the mobile robot.

4.9(a), (b), and (c).

It is noteworthy that when the communication rate threshold requirement increases to a certain level (4.0 bps/Hz), the system without IRS support fails to find any path that meets the requirement. Additionally, in all scenarios, the trajectory obtained by PPO-STAR-IRS is always the shortest, while the trajectory obtained by PPO-non-IRS is always the longest.

Figures 4.10(a) and (b) respectively show the impact of the communication rate threshold on communication energy and energy consumed by the robot.



(a) (b)

Figure 4.10: The impact of the communication rate threshold on (a) communication energy and (b) energy consumed by the robot.

Next, the dissertation evaluates the impact of the phase shift quantization bit number, the number of elements of STAR-IRS, and maximum transmit power on the STAR-IRS-assisted navigation system for the mobile robot. The results are presented in Figs 4.11, 4.12, 4.13, and 4.14 in the dissertation.

4.5. Conclusion of chapter 4

The main contributions of Chapter 4 are as follows:

- Propose a system model for robot navigation in a factory environment with STAR-IRS support.

- Propose the PPO-STAR-IRS algorithm to solve the path planning problem for minimizing energy consumption for the robot in a STAR-IRS supported communication environment.

The contributions of Chapter 4 are published in works CT6 and CT7. Work CT6 presents the proposal of a navigation model for robots in a wireless communication environment supported by STAR-IRS, and subsequently proposes an optimization algorithm based on DRL techniques to minimize the robot's travel distance. CT7 develops an optimization algorithm for the navigation system of robots in a STAR-IRS supported communication environment to minimize system energy consumption.

CONCLUSION

The dissertation has achieved its goal of researching and proposing a network model and optimization algorithm for network systems used in factories, thereby proposing a navigation system for robots to minimize energy consumption for mobile robots and the system in both ideal communication environments and environments supported by STAR-IRS. Additionally, the dissertation has simulated and evaluated the proposed algorithms and system models.

MAIN CONTRIBUTIONS OF THE DISSERTATION

1. Proposed DED2D network model with IRS support and the OTA and N-OTA optimization algorithms aim to enhance communication quality for supporting the operation of mobile robots.

This system is proposed based on research into the benefits that IRS brings to wireless communication systems. This system has not been previously proposed worldwide. Specifically, integrating information and energy communication systems with D2D communication in the same frequency band, along with the proposed algorithms, not only enhances communication quality for mobile robots but also supports wireless sensors in energy harvesting, contributing to the sustainability of the system.

2. Proposed to use the OSOW and MSOW algorithms for optimal trajectory planning of mobile robots in an ideal communication environment, and the PPO-STAR-IRS algorithm for energy optimization of mobile robots in a communication environment supported by STAR-IRS.

The OSOW and MSOW algorithms are based on approximating the objective function and constraints to convert the problem into a convex optimization problem. Simulation results have identified the optimal trajectory that allows the robot to reach its destination with minimal energy consumption. The PPO-STAR-IRS algorithm, based on DRL techniques, has effectively addressed the dynamic problem with time-varying trajectories and channels. Simulation results demonstrate the effectiveness of the proposed model and algorithm.

Additionally, during the course of the dissertation, the research has been published in reputable national and international conferences and journals.

LIST OF THE PUBLICATIONS RELATED TO THE DISSERTATION

1. N. T. T. Van, H. T. Nguyen, N. C. Luong, N. M. Tien, D. Niyato, and D. I. Kim, “Intelligence Reflecting Surface-Aided Integrated Data and Energy Networking Coexisting D2D Communications,” IEEE Trans. Wirel. Commun., pp. 1–1, 2022, doi: 10.1109/TWC.2022.3181822.
2. N. T. T. Van, N. M. Tien, N. C. Luong, and H. T. K. Duyen, “Energy consumption minimization for autonomous mobile robot: A convex approximation approach,” Journal of Robotics and Control (JRC), vol. 4, no. 3,pp. 403–412, 2023, doi: 10.18196/jrc.v4i3.17509.
3. N. T. T. Van, N. Manh Tien, H. T. K. Duyen, N. M. Cuong, and D. H. Duân, “A Convex Approximation Method to Optimize Trajectory for AGV Robot Motion Planning,” in Proceedings of the sixth Vietnam international conference andExhibition on Control and Automation VCCA-2021; ISBN 978-604-95-0875-2.
4. N. T. T. Van, N. Manh Tien, N. M. Cuong, H. T. K. Duyen, B. T. T. Ha, and B. V. Tuan, “Building SLAM system and Intelligent Navigation for Autonomous Mobile Robot base on ROS,” in Proceedings of the sixth Vietnam international conference and Exhibition on Control and Automation, VCCA-2021; ISBN 978-604-95-0875-2.
5. N. T. T. Van, N. M. Tien, N. M. Cuong, H. T. K. Duyen, and N. D. Duy, "Constructing an Intelligent Navigation System for Autonomous Mobile Robot Based on Deep Reinforcement Learning". Cham: Springer International Publishing, 2021, pp. 251–261. [Online]. Available: https://doi.org/10.1007/978-3-030-76620-7_22.
6. N. T. T. Van, N. M. Tien, N. C. Luong, and L. M. Khoi, “Simultaneously Transmitting And Reflecting (STAR) IRS Enhanced Mobile Robot Path Planning: A Reinforcement Learning based Approach,” in Proceedings of the seventh Vietnam international conference and Exhibition on Control and Automation, VCCA-2024; ISBN 978-604-937-357-2.
7. N. T. T. Van, N. C. Luong, H. Le Hung, N. T. Hoa and N. M. Tien, "Minimizing Energy Consumption in Mobile Robotics with STAR-RIS in Smart Factories," *2024 Tenth International Conference on Communications and Electronics (ICCE)*, Danang, Vietnam, 2024, pp. 741-746, doi: 10.1109/ICCE62051.2024.10634674.