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# Smart Implementation of Industrial Internet of Things Using Embedded Mechatronic System

Abdelhamid Zaidi, Ismail Keshta, Zatin Gupta, Prachi Pundhir, Tripti Pandey, Praveen Kumar Rai, Mohammad Shabaz, and Mukesh Soni



AQ1 ***Abstract*—In Industry 4.0, integrating Industrial Internet of Things (IIoT) and smart manufacturing is crucial for high-quality, efficient, and cost-effective production. However, the performance of IIoT systems can be hindered by unevenly distributed edge service providers (ESPs). To tackle this challenge, we propose an optimized embedded system for edge intelligence and smart manufacturing, leveraging digital twin (DT) technology. Our approach employs a DT-assisted alliance game resource optimization strategy to jointly optimize multidimensional resource allocation, including bandwidth, computing, and caching resources, while considering constraints like maximum delay. The optimization problem maximizes edge terminal utility and ESP utility, transformed into a convex optimization problem with linear constraints. An approximate optimal solution is obtained through an alternating iterative method. Simulation results demonstrate significant enhancements in resource utilization efficiency compared to baseline schemes like Nash equilibrium and large coalition. The proposed scheme is ideal for large-scale edge intelligence and smart manufacturing systems, with benefits increasing alongside the number of ESPs.**

***Index Terms*—Digital twin (DT), edge intelligence, embedded system, Industrial Internet of Things (IIoT), smart manufacturing.**

## I. Introduction

The INDUSTRIAL Internet of Things (IIoT) is revolutionizing the manufacturing industry by enabling the collection and analysis of vast amounts of data, leading to more efficient processes and increased productivity. Embedded systems are at the heart of this transformation, providing the intelligence needed to make sense of the data and take action based on the insights gained. The rise of edge intelligence in IIoT systems is paving the way for deep data mining and collaborative computing, creating a new ecology of industrial production [1]. The application of IoT in mechatronics involves integrating sensors and communication technologies into mechanical systems to enable remote monitoring, data collection, and real-time control. This convergence enhances predictive maintenance, efficiency optimization, and overall system performance. The role of embedded systems in mechatronics is crucial, as they serve as the "brains" of interconnected mechanical and electronic components, enabling real-time control, data processing, and communication for enhanced functionality and automation. Additionally, addressing the challenges and opportunities posed by deep learning applications in drug development, while incorporating the security concerns of edge intelligence, digital twins (DTs), and federated learning, would further enrich the manuscript's content.

With the integration of edge intelligence systems into 5G/6G, artificial intelligence, and other technologies, emerging applications, such as AR/VR rendering [2] and AI model training [3], are becoming increasingly prevalent. These applications require intensive computing tasks and are sensitive to delays, making sensing data a crucial component of IIoT edge intelligence. As a result, research on edge intelligence is divided into two main areas: 1) the optimization of edge resource configuration and 2) the design of intelligent algorithms.

While traditional static configuration optimization methods have some specific effects, the dynamic changes of user service requirements and edge device (ED) resource distribution in IIoT edge intelligent systems are difficult to predict [4]. This makes it challenging to adopt existing edge resource allocation strategies directly. Related research is mainly carried out through optimization theory, DT, and other technical routes to address this issue. This letter explores a fascinating topic and comprehensively addresses various aspects. However, I suggest that the authors consider adding more details to enhance the manuscript.

Optimization theory research encourages resource cooperation by promoting joint optimization of edge resources through cooperative game models, improving their utility and overall resource utilization [5], [6]. DTs are considered a practical approach to solving the dynamic resource optimization of IIoT systems because of their real-time, full life-cycle monitoring and high-fidelity simulation characteristics [7], [8], [9]. However, these works focus on the dynamics and collaborative optimization of EDs and the competitive relationship among them. The optimization of edge resources needs to consider the impact of EDs on edge service provider

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(ESP) alliance resources, and the satisfaction of support and task offloading services should reflect the selection effect on the results of ESP resource cooperation behavior. The virtual space, responsible for monitoring and simulating dynamic network changes, plays a pivotal role. This space undergoes real-time updates to reflect evolving network conditions.

This letter proposes a DT-assisted edge intelligent resource association optimization scheme to address the challenge, considering the dynamic nature of application service demand and resources on both ED and ESP sides. The scheme integrates DT technology into the industrial edge intelligent system, encompassing factors like task offloading, transmission power, computational complexity, delay constraints, and resource limits. It formulates a utility maximization multiobjective optimization problem accounting for user satisfaction, revenue distribution, and energy costs. Additionally, this letter explores the emergence of deep data mining and collaborative computing, which shape a novel ecosystem for industrial production.

This letter discusses how the integration of IIoT and smart manufacturing enables the collection and analysis of extensive data, leading to enhanced efficiency and productivity (Introduction). It highlights the role of embedded systems and edge intelligence in processing this data to make informed decisions for process optimization.

To optimize the ESP resource combination, improve system resource utilization, and maximize the utility of ESP alliance players, this letter proposes a DT-assisted distributed dynamic coalition game (DT-assisted, Distributed and Dynamic Coalition Game, 3DCG) resource allocation algorithm. The algorithm constructs a transferable utility (TU) vibrant coalition game model and embeds alternate iterations.

## II. Related Work

In several fields, including edge intelligence, DTs, federated learning, blockchain, Industry 4.0, the IoT, and deep learning, the rapid growth of technology has created new opportunities and difficulties. A thorough grasp of these subjects can be obtained from a literature review that includes pertinent studies and shines light on recent developments. This letter explores traditional static configuration optimization methods and their limited effects, highlighting challenges posed by dynamic changes in user service requirements.

This letter delves into the composition of the physical space comprising distributed EDs, ESPs, and cloud computing centers (CCs).

The integration of federated learning, blockchain, and DT technologies into edge intelligence and industrial IoT networks has been the subject of studies by Lu et al. [1], [2], which also propose low-latency and communication-efficient techniques to improve network performance and resource optimization. Bécue et al. [3] and Al Ja'afreh et al. [4] focused on the use of AI in industrial processes and the integration of IoT with software-defined networks as they study the promise and difficulties of Industry 4.0, artificial intelligence, and cyber risks. The impact of Industry 4.0 on South Africa is examined by Dhamija et al. [5], while the opportunities and difficulties presented by deep learning applications in drug development are highlighted by Askr et al. [6].

As a result, research on edge intelligence is divided into two main areas: 1) the optimization of edge resource configuration and 2) the design of intelligent algorithms.

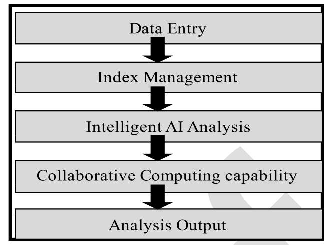


Fig. 1. Edge intelligent system model assisted by DTs.

This complexity encouraging the innovation and promoting workable solutions. The development of edge intelligence, DTs, federated learning, and related fields depends on filling these research gaps.

## III. Edge Intelligent System Model Assisted by Digital Twin

This letter considers the application scenarios of intelligent monitoring of industrial production lines. It proposes a DT-assisted edge brilliant system model, as shown in Fig. 1, which is mainly composed of two parts: 1) physical space and 2) virtual space.

The physical space consists of distributed EDs, ESPs, and cloud CCs. EDs host intelligent applications and analyze local sensor data to respond to user service requests. ESPs have the computing power and provide EDs with task offloading and resource support services. CC is composed of cloud servers with rich computing and communication capabilities. A collaborative optimization scheme is used to dynamically optimize ESP's offloading decision, transmission bandwidth, and computing resource allocation to match the resource requirements of different edge intelligent applications. The virtual space monitors and simulates dynamic network changes in real time by establishing an accurate mapping of ED service requests and ESP resource status. Virtual-real space mapping connects physical and virtual spaces to optimize task offloading and resource scheduling strategies.

## IV. Formulations of the Coalition Game Problem

This letter aims to provide reliable task offloading service support for edge intelligent applications on the ED side through ESP resource cooperation. This letter delves into the optimization problem that aims to maximize both edge terminal utility and ESP utility, transforming it into a convex optimization problem with linear constraints. We use a dynamic alliance game framework to model ESP task offloading and resources to obtain an ESP resource cooperation strategy that adapts to environmental changes. The synergy problem is described as a coalition game model with TU. To this end, this letter gives the following related definitions.

*Definition 1 (TU):* The alliance game of mobile utility can be defined as a triplet $(N, P, U)$. Among them, $N$ is the ESP player set, $P$ is the set of ESP alliances, and $U$ is the actual number of natural utility functions represented by the function. It can be assigned to the players in the partnership in some way and is called the alliance utility.

*Definition 2 (Alliance Partition):* Alliance partition $P = \{G1, G2, \ldots, Gk, \ldots, GK\}$ and $k, k' \in K$, there are $Gk, Gk' \subseteq N$ and $Gk \cap Gk' = \emptyset$.

The mobile utility alliance game proposed in this letter can be formulated as an optimization problem to maximize alliance utility under various ESP resources and task offload delay constraints. For industrial edge intelligence scenarios, a logarithmic user satisfaction function is used and task offloading energy consumption to construct the revenue part and cost part of the ESP alliance and player utility function. Therefore, in the time slot $t$, the utility function of any alliance Gk$\subseteq N$ is expressed as

$$U^t_{G_k} = a\log\left(1 + \sum_{i\in G_k} w^t_i\right) - \xi E^t_{G_k,\mathrm{tr}}. \tag{1}$$

Among them, a represents the satisfaction factor of the user to the task offloading service, and $\xi$ is the weight coefficient for determining the energy consumption compensation of EDj. Equation (4) quantifies the total utility obtained by the ESP alliance Gk after considering the benefits and costs of resource cooperation. The first term represents the income of the partnership Gk for providing task offloading services for edge intelligent applications on the EDj side, which depends on the impact of the total task offloading amount of the ESP in Gk on user satisfaction; the second term represents Gk's compensation for EDj communication transmission energy consumption, It is used to measure the communication cost caused by ESP cooperation sharing bandwidth resources. In addition, the utility function has a similar simplified form for any ESP that works independently (that is, $|Gk| = 1$).

Considering that the resource cooperation between ESPs only occurs within several disjoint confederations, we examine any coalition and formulate an optimization problem to jointly optimize the bandwidth resources of the ESPs in the union Gk within each time slot span $t$ The allocation of $B^t_{G_k}$ and computing resources $F^t_{G_k}$, as well as the unloading and scheduling strategy of the task amount $W^t_{G_k}$, maximize the utility $U^t_{G_k}$ of the alliance Gk. Considering the constraints of idle bandwidth resources on the ESP side, cache resource reserves, and application service delays on the ED side, formulate the main optimization Problem P1 is developed as follows:

$$P1:\ \max_{w^t_i, b^t_i} U^t_{G_k} \tag{2}$$

$$\text{s. t. } 0 \le b^t_i \le b^t_{i,\max} \tag{2a}$$

$$\sum_{i\in G_k} b^t_i \le B^t_{\max} \tag{2b}$$

$$0 \le w^t_i \le c^t_{i,\max} \tag{2c}$$

$$\sum_{i\in G_k} w^t_i \le w^t_j \tag{2d}$$

$$T^t_{i,\mathrm{tr}} \le \tau^t_j. \tag{2e}$$

Constraints (2a) and (2b) are bandwidth allocation constraints, which indicate that the bandwidth resource contribution of any ESP is not only limited by individual idle bandwidth resources but also needs to consider the total occupancy of the alliance Gk spectrum resources to avoid the occurrence of signal loss during ESP task offloading interference. Constraint (2c) is a cache resource constraint, which ensures that the task offload received by each ESP will not because data overflow because it exceeds the limit of its idle cache resources. Constraint (2d) means that the total task offload of ESPs in the alliance Gk is not exceed the total task amount of the application service request initiated by the current EDj. Finally, constraint (2e) indicates that the task offloading service provided by the alliance Gk must meet the delay requirement of the application service request.

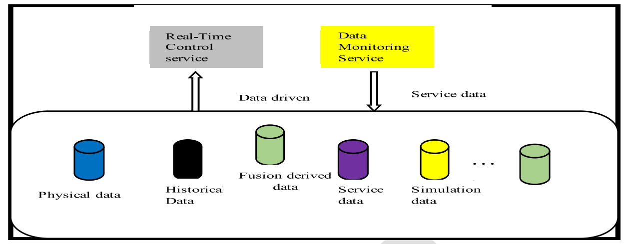


Fig. 2. Structural framework of the DT system.

According to the above optimization problem formulation, we can determine the maximum utility of any alliance in time slot $t$ through joint optimization. However, the motivation and premise of ESP cooperation are to improve its utility by sharing idle resources. In addition, the resource contribution of ESP is given by the corresponding energy consumption cost is cost, which needs to be adequately compensated. To this end, we measure the contribution of ESP to the alliance utility $U^t_{G_k}$ in the TU alliance game by weighted average and determine the income part of its utility based on this. In addition, consider the utility function of ESPi in the time slot $t$ can be expressed as follows:

$$u^t_i = \frac{w^t_i}{\sum_{i\in G_k} w^t_i} - \zeta E^t_{i,cp}. \tag{3}$$

Among them, $\zeta$ is the weight coefficient of ESPi to calculate the energy consumption cost. Considering the constraints of ESPi's computing resources in the time slot $t$ and the total delay of task execution, the suboptimization problem P2 is formulated as

$$P2:\ \max_{f^t_i} u^t_{i,G_k} \tag{4}$$

$$\text{s.t. } 0 \le f^t_i \le f^t_{i,\max} \tag{4a}$$

$$T^t_{i,cp} \le \tau^t_j - T^t_{i,\mathrm{tr}}. \tag{4b}$$

Constraint (4a) is an ESP computing resource constraint, which means that ESP can choose to execute tasks or turn off sleep and cannot overclock during task execution. Constraint (4b) is a delay constraint, which means that the alliance Gk task offloads the maximum transmission and computing delay and must not—the maximum tolerable delay in time slot $t$ exceeding EDj.

## V. Problem Transformations and Solution

This section first transforms the multiobjective nonlinear constrained optimization problem in Section III into a single-objective linear constrained optimization problem; then, a DT-assisted distributed dynamic alliance game resource allocation algorithm based on Pareto optimal rules is formulated; finally, the stability and convergence of the proposed scheme provide rigorous theoretical analysis and proof. The Structural framework of the DT system is shown in Fig. 2.

In the suboptimization problem P2, since the variable $w^t_i$ has been determined in the main optimization problem P1, the calculation energy consumption will gradually decrease with the decrease of the decision variable $f^t_i$ so that the value of the objective function continues to increase. Therefore, when satisfying the calculation under the condition of extension constraints, ESP will try to reduce the contribution of computing resources; that is, the rules (4a) and (4b) are combined into

$$\frac{e_j^t w_i^t}{\tau_j^t - T_{i,\mathrm{tr}}^t} \le f_i^t \le f_{i,\max}^t. \tag{5}$$

For any ESPi, if $(e_j^t w_i^t/[\tau_{j,\max}^t - T_{i,\mathrm{tr}}^t]) \le f_{i,\max}^t$, max, the optimal computing resource contribution is $f_i^{t*} = ([e_j^t w_i^t]/[\tau_{j,\max}^t - T_{i,\mathrm{tr}}^t])$; like $([e_j^t w_i^t]/[\tau_{j,\max}^t - T_{i,\mathrm{tr}}^t]) > f_{i,\max}^t, f_i^{t*} = f_{i,\max}^t$. Therefore, formula (5) can be further simplified as follows:

$$w_i^t \le \frac{\tau_{j,\max}^t}{\left(\frac{1}{b_{i,\max}^t \log\left(1+\frac{\left|g_{ij}^t\right|^2 p_{j,\mathrm{tr}}^t}{\sigma^2}\right)} + \frac{e_j^t}{f_{i,\max}^t}\right)}. \tag{6}$$

In addition, the constraint condition (5) in P1 is transformed into a linear representation $w_i^t \le \tau_{j,\max}^t b_i^t \log(1 + [|g_{ij}^t|^2 p_{j,\mathrm{tr}}^t]/\sigma^2)$. After the above derivation process, P1 and P2 are combined and expressed as an optimization problem P3

$$P3: \max_{w_i^t, b_i^t} U_{G_k}^t \tag{7}$$

$$\text{s.t. } 0 \le b_i^t \le b_{i,\max}^t \tag{7a}$$

$$\sum_{i \in G_k} b_i^t \le B_{\max}^t \tag{7b}$$

$$0 \le w_i^t \le c_{i,\max}^t \tag{7c}$$

$$\sum_{i \in G_k} \omega_i^t \le \omega_j^t \tag{7d}$$

$$w_i^t \le \tau_{j,\max}^t b_i^t \log\left(1 + \frac{\left|g_{ij}^t\right|^2 p_{j,\mathrm{tr}}^t}{\sigma^2}\right) \tag{7e}$$

$$w_i^t \le \frac{\tau_{j,\max}^t}{\left(\frac{1}{b_i^t \log\left(1+\frac{\left|g_{ij}^t\right|^2 p_{j,\mathrm{tr}}^t}{\sigma^2}\right)} + \frac{e_j^t}{f_{i,\max}^t}\right)}. \tag{7f}$$

For real-time monitoring of IIoT networks, CC continuously collects DT models of ED and ESP to capture network details, including device locations, service requests, resource availability, and constraints. DT processes this to update the network state space $S$, containing data like application requests, wireless rates, resource limits, and usage. Thus, $s(t)$ $S$ summarizes edge services, transmission rates, bandwidth, computing, storage, and constraints

$$s(t) = \left\{DT_{ED_j}^t, R_j^t, B_{N,\max}^t, F_{N,\max}^t, C_{N,\max}^t, Env^t\right\}. \tag{8}$$

$R_j^t = [R_{1j}^t, R_{2j}^t, \ldots, R_{Nj}^t]$ represents the wireless data transmission rate vector between ED and ESP, $B_{N,\max}^t = [b_{1,\max}^t, b_{2,\max}^t, \ldots, b_{n,\max}^t]$ is the bandwidth resource of ESP Vector, $F_{N,\max}^t = [f_{1,\max}^t, f_{2,\max}^t, \ldots, f_{n,\max}^t]$. The environmental resource constraint is the cache resource vector, $\mathrm{Env}^t = B_{\max}^t$.

This letter proposes a DT-assisted distributed dynamic alliance game 3DCG resource allocation algorithm for the decision-making module of CC. The algorithm follows the Pareto order based on preference relationships and the rules of merging and splitting, and includes three stages: 1) network state initialization; 2) task offloading based on the alliance game; and 3) resource allocation. In the process, ESP coalitions maximize their utility through merging or splitting operations.

TABLE I
SIMULATION PARAMETER SETTINGS

| System Parameter | Value Setting |
|---|---|
| The total amount of tasks requested by edge intelligent application services/MB | [10,20] |
| Computational complexity of edge intelligent application service request task/(cycle/bit) | [50,200] |
| Edge intelligent application service request maximum tolerable delay/ms | [50,500] |
| Maximum transmission power of edge terminal/mW | [50,100] |
| Edge service provider maximum bandwidth resources/MHz | [1,5] |
| Edge service provider maximum computing resources/GHz | [4,10] |
| Edge service provider maximum cache resources/MB | [1,2] |
| Edge service provider chip computing energy consumption coefficient /W/(cycle/s)3 | [1,2.5] |
| Maximum multiplexing bandwidth/MHz | 16 |
| Noise power/dBm | -110 |

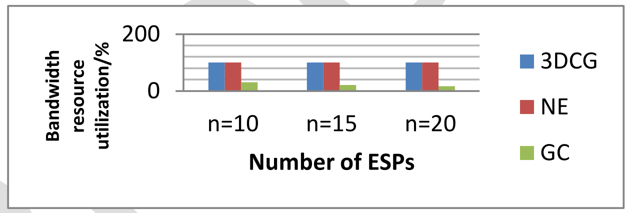


Fig. 3. Utilization rate of bandwidth resources.

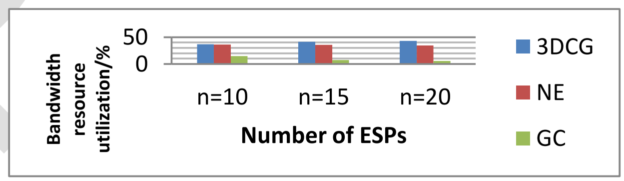


Fig. 4. Utilization rate of computing resources.

## VI. SIMULATION RESULTS AND ANALYSIS

To verify the impact of the DT-assisted edge intelligent resource joint optimization scheme proposed in this letter on the utilization of ESP resources, this letter builds a numerical simulation environment based on the MATLAB platform and CVX optimizer to analyze and evaluate the performance of the proposed scheme. For industrial the simulation case of intelligent monitoring of the production line considers an industrial edge smart system with $N = 10$ ESPs, adopts the channel model of Rayleigh fading, and all physical entities are randomly deployed in a rectangular area of 1 km×1 km. The value range of simulation parameters refers to IIoT, DTs and edge intelligence-related literature [7], [10], [12] as listed in Table I. AQ4

This study initially tests the proposed scheme for optimizing resource allocation and system resource utilization. Figs. 3–5 compares three resource optimization methodologies to show how ESP scale $n$ changes affect bandwidth, compute, and cache resource use. NE and GC are benchmarking schemes. All strategies in this research can increase resource utilization in any ESP player set scale under the following conditions. The NE scheme's compute and storage resource utilization falls linearly and the GC scheme's three resource utilization decreases

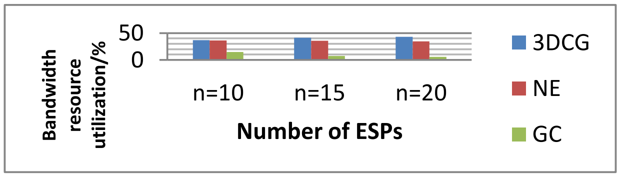


Fig. 5. Utilization rate of cache resources.

exponentially as the ESP player set scale expands. Trend. Unlike the baseline scheme, this scheme's bandwidth resources always reach full utilization, whereas computation and storage resource utilization increase linearly with ESPs. The scheme's performance advantage is most apparent when the ESP player is $n = 20$. Compared to the NE and GC schemes, its computing resource utilization is 22% and 721% higher, and its cache resource utilization is 24% and 710% higher. This letter's scheme is better for large-scale edge intelligent systems.

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## VII. Conclusion

This letter introduces a DT-enabled dynamic alliance game resource allocation algorithm for ESP resources in smart manufacturing. The approach enhances resource utilization, particularly in large-scale scenarios, using embedded system-based IoT. While reliant on real-time data, future work could integrate AI predictions for resource demand and explore novel opportunities and challenges in embedded system-based IoT. This study underscores embedded system-based IoT's significance in facilitating DT-assisted resource optimization, advancing smart manufacturing.

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