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Optimizing Smart Business Operations Using Deep Q-Networks (DQN) and IoT Data

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Abstract

Internet of Things (IoT) infrastructures in the form of smart businesses are used to monitor and optimize smart business operations, but the traditional operational management system does not easily cope with the dynamic changes of the industrial environment. This study aims to develop a smart business optimization framework using the Deep Q-Network (DQN) reinforcement learning algorithm that can be combined with manufacturing analytics using IoT to enhance manufacturing operational efficiency, resource utilization, predictive maintenance, and energy management. All the parameters of IoT such as temperature, vibration, energy consumption, latency, maintenance score, and production efficiency were simulated in the dynamic enterprise operational environments using the Intelligent Manufacturing Dataset from Kaggle. To realize adaptive operational decision-making, the data preprocessing, state space modeling, reward function optimization, and DQN policy learning method are proposed. The operational efficiency, optimization accuracy, convergence of the reward, reduction in downtime, and energy optimization metrics were used for experimental evaluation. The proposed framework was able to optimize the accuracy of the system with 97.68%, operational efficiency with 94.83%, and utilization of resources with 92.46%, whereas it reduced the downtime by 68.40% and energy consumption by 27.69%. Comparative analysis was also performed, showing that the proposed DQN framework had better performance than the traditional machine learning models such as Artificial Neural Network (ANN), Random Forest (RF), and Q-Learning strategy models. The research offers a smart and scalable reinforcement learning model that can be applied to the use of Industry 4.0 businesses by optimizing the autonomous operations of such businesses with enterprise intelligence modeled using IoT.

Keywords Deep Q-Networks, IoT Analytics, Smart Business Operations, Reinforcement Learning, Operational Optimization, Industry 4.0.

1. Introduction

In the past, business processes have been drastically transformed by the rapid development of smart technologies and digital transformation in manufacturing, logistics and service, retail, healthcare, etc. Internet of Things (IoT) infrastructures are becoming a key dependency for organizations to gather real-time data from sensors, connected devices, the cloud, and industrial networks. These technologies enable intelligent monitoring and predictive analytics, automated scheduling, and data-driven operational management. The value of digital technologies and AI-powered systems in smart organizations to enhance their business process management and the coordination of their operations and their strategic decision-making capabilities was recently stressed [2]. In a dynamic business environment, data-driven marketing and smart business analytics are also critical to help improve the competitiveness and technological innovation of an organization [11] [24]. Using digital transformation frameworks with AI and accounting analytics, enterprises can attain a sustainable and adaptive operational ecosystem.

The recently popular Deep Reinforcement Learning (DRL) method, especially the Deep Q-Network (DQN), has been greatly discussed in the context of solving complex optimization problems in an industrial or IoT (Internet of Things) setting. The DQN-based frameworks have shown good performance in the fields of smart agriculture systems, resource orchestration, task scheduling, and intelligent transportation applications [6] [15]. Doubling the Deep Q Networks (DQNs) and Dueling Deep Q Networks (DDQNs) are also some of the other advanced reinforcement learning techniques that have been used for security in IoT, optimization of blockchain, and optimization of edge computing [5] [20]. In smart factories and edge computing scenarios, intelligent scheduling mechanisms have also demonstrated how reinforcement learning can adaptively optimize the workflow of operations and enhance resource utilization [9] [12]. Besides, recent studies in intelligent networking and IoT infrastructures pointed to the importance of the autonomous decision systems in the present enterprises with AI as an important tool for that purpose [19] [21].

Although many organizations have adopted IoT infrastructures and AI-based analytics, many still have inflexible optimization models and rule-based operational systems that don't have adaptive learning. Existing business optimization methods are not able to handle the continuous flow of data from IoT, dynamically allocate resources, and react efficiently to changes in operating conditions. Scalability, operational latency, inefficient scheduling, and poor autonomous decision-making in real-time systems are some of the limitations of existing systems. While there are several research works on the application of reinforcement learning in industrial IoT, transportation systems, and edge computing applications, less work has been done to combine Deep Q-Networks with IoT-enabled smart business operations for the complete optimization of the operation and for intelligent enterprise management [10] [23].

Research Objectives

1. To develop the architecture for smart data acquisition and processing for IoT in the smart business.
2. To build an operational optimization model using Deep Q-Network that can be used in intelligent decision-making.
3. To test the proposed framework—operational efficiency and resource optimization.

Paper Organization

The rest of this paper, the introduction, is discussed in Section 1; the literature review in Section 2; the proposed system architecture in Section 3; the methodology in Section 4; the experimental framework in Section 5; the results and discussion in Section 6; and the conclusion of the research work in Section 7.

2. Literature Review

AI and IoT have revolutionized the way that companies manage their operations. In recent years, with the development of digital marketing technologies and AI-based business models, organizations have been able to increase the flexibility of their operations, customer engagement, and the efficiency of business processes [2] [14]. Blockchain technologies have also helped to enhance the transparency of the operational processes of the enterprises and the performance of the organizations by being developed with sustainable business models [4]. Research on agile methods and data-driven business strategies additionally revealed that smart business ecosystems in smart enterprises can foster innovation, competitiveness, and long-term business growth with intelligent digital frameworks [7] [17]. Sustainable operating models along with the use of AI-based analytics have proven to be significant enablers for enhancing business performance and management strategies [22].

Deep reinforcement learning has proven to be an effective approach to different complex optimization and scheduling problems in industrial and IoT-enabled environments. In the field of agriculture, Deep Q-Network-based smart agriculture systems showed good decision-making capabilities when subjected to varying environments [1]. In addition, the GAN-based distributional DQN techniques boosted the industrial network slicing and the management of computational resources [6]. Reinforcement learning algorithms have also proven to be useful for intelligent resource management to adaptively optimize in dynamically changing operation environments [10]. An enhanced double deep Q-network scheduling model in edge computing proved to be effective in minimizing the makespan and optimizing task allocation efficiency [12]. In addition, Deep Q-Networks had better response optimization and system reliability in public service scenarios [13].

The advanced reinforcement learning techniques have been investigated in various fields such as the industrial internet of things (IIoT), smart transportation, and cybersecurity systems. In an industrial IoT setting, novel intrusion detection strategies using double deep Q-networks were used to increase the security performance [3]. Dueling double deep Q-networks have also been used to maximize the secrecy data rate to optimize the communication efficiency in vehicular networks [8]. In the field of intelligent transportation systems, deep learning and reinforcement learning were used to achieve efficient road collaboration and task scheduling in intelligent transportation systems with the augmentation of IoT infrastructures [15]. Furthermore, the implementation of a node selection mechanism in underwater IoT networks using machine learning showed that communication optimization and intelligence in networking are enhanced [16]. The study of intelligent end-to-end networking also highlighted the need for integration of deep reinforcement learning with complex AI designs for autonomous operational optimization [18].

The research in the past few years has shifted toward the combination of reinforcement learning with blockchain, edge intelligence, smart city infrastructures, and so on. Secure and optimized task offloading of IoV-MEC systems was accomplished by double deep Q-network strategies with the help of blockchain [5]. In a smart factory, a combination of fog and edge computing and dual deep Q-networks was used to enhance the distributed job-shop scheduling and industrial automation efficiency [9]. A further study on the malware defense in edge intelligence-enabled IoT systems also showed the use of stochastic games in conjunction with dueling double deep Q-networks for intelligent threat mitigation was effective [20]. Furthermore, intelligent energy management systems (IEMS) with AI, blockchain, and 6G IoT technologies were mentioned, which also showed the importance of autonomous operational optimization in sustainable smart cities [21]. Moreover, using blockchain optimization by reinforcement learning has also demonstrated good performance in the field of industrial IoT for increasing the system scalability, operational efficiency, and decentralized decision-making performance [23].

Research Gap

Previous works have focused on a good deal of reinforcement learning, IoT analytics, blockchain integration, and intelligent networking for industrial optimization and smart infrastructure management. But most of the existing studies are limited to only a specific area like cybersecurity, transportation systems, edge computing, or task scheduling and not to complete smart business operations. A few studies have introduced deep Q-networks with real-time IoT-based enterprise management to provide adaptive optimization for multiple business functions. Additionally, many of the current systems have not one but multiple frameworks for optimizing resources, scheduling operations, energy management, and business intelligence in dynamic enterprise scenarios. Thus, it is very much desirable to design a scalable DQN-based smart business optimization framework with continuous IoT data streams.

Proposed System Architecture

The architecture consists of Internet of Things (IoT) infrastructure and Deep Q-Network (DQN)-based reinforcement learning for the optimization of smart businesses in a real-time environment. The framework is composed of five main layers that interact with each other to support intelligent operation management and adaptive decision-making, as shown in Figure 1. The IoT Data Acquisition Layer collects all kinds of continuous operational data from industry sensors, RFID devices, connected enterprise systems, and smart machines. Collected data are then moved to the Data Processing and Storage Layer, where the data are preprocessed to ensure data quality, including cleaning, normalization, feature extraction, and real-time stream analysis, to obtain high-quality operational data sets.

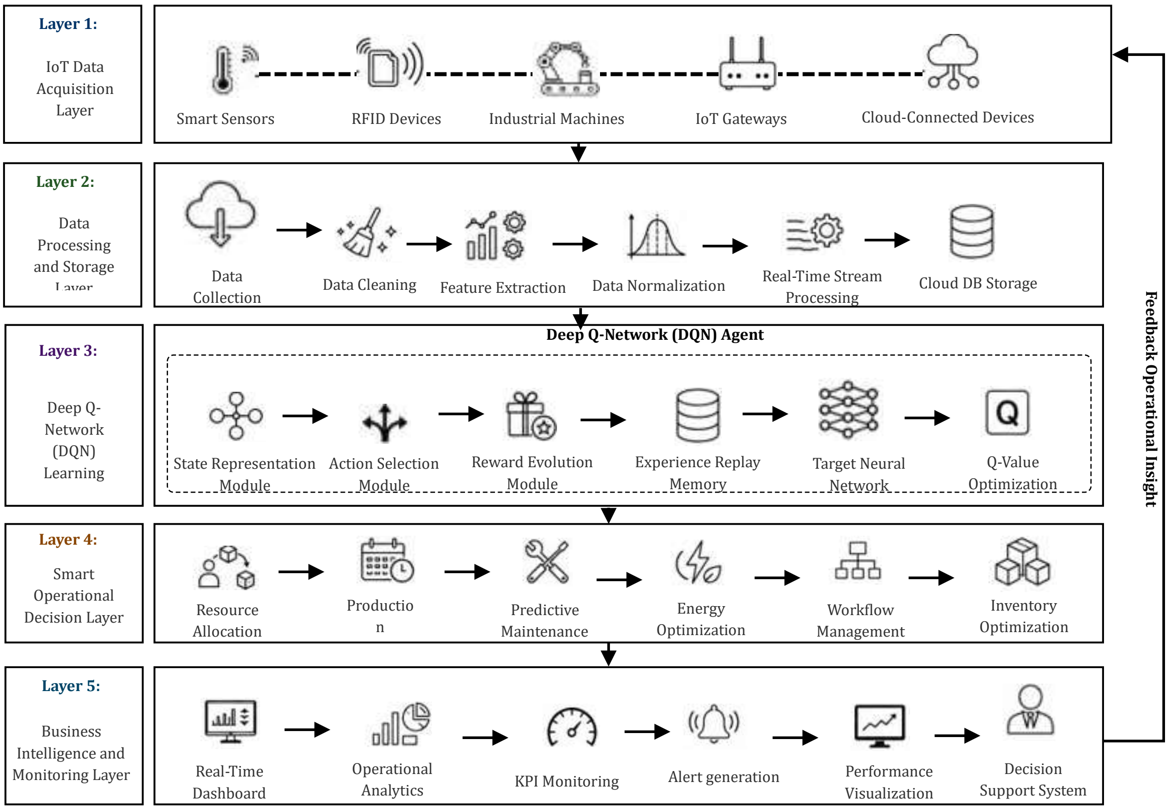

Figure 1: Proposed deep Q-Network-Based smart business optimization architecture using IoT data

The processed data then pass to the core of the intelligence in the framework, the DQN Learning Layer. This layer is based on reinforcement learning techniques such as state representation, reward assessment, experience replay memory, and neural network optimization, which enable it to adaptively learn how to operate optimally. The Smart Operational Decision Layer makes intelligent decisions like resource allocation, predictive maintenance scheduling, production optimization, workflow balancing, and energy management based on learned policies. Lastly, the Business Intelligence and Monitoring Layer allows enterprise administrators to visualize, do operational analytics, track KPIs, and even make intelligent decisions in real-time. The architecture as a whole allows for autonomous business optimization, operational efficiency, less downtime, and adaptive enterprise management in the context of Industry 4.0.

3. Methodology

The method proposed is a combination of Internet of Things (IoT) data analytics and reinforcement learning (RL) using a Deep Q-Network (DQN) to optimize the smart business operations. The methodology is made up of data acquisition and preprocessing, state space formulation, action selection, reward optimization, DQN learning, and performance evaluation. A real-time operational environment is simulated by using the Intelligent Manufacturing Dataset, which is used to train the proposed intelligent optimization model.

3.1 IoT Data Acquisition and Collection

The first step of the methodology is to capture the operational data from the Intelligent Manufacturing Dataset that features industrial parameters like temperature, vibration, energy consumption, latency, packet loss, production efficiency, maintenance score, and operational error rates enabled by IoT. All the parameters are real-time data of a smart business environment and are used as the main input of the optimization framework. The data collected is structured by operational state to aid in decision-making using reinforcement learning. The dataset allows for ongoing monitoring of enterprise activities and can help in managing them adaptively in a dynamic environment.

The operation state vector is mathematically expressed in equation (1).

$$S_t = \{T_t, V_t, E_t, L_t, P_t, M_t\} \quad (1)$$

Where:

T_t= temperature,

V_t= vibration level,

E_t= energy consumption,

L_t= network latency,

P_t= production efficiency,

M_t= maintenance score at time t.

The operational state vector is a representation of the real-time industrial state that is needed for intelligent business optimization, as illustrated in Equation (1).

3.2 Data Preprocessing and Feature Engineering

The gathered IoT data is subjected to preprocessing to enhance the quality of the data and the model's performance. In this stage missing values, noise, normalization, and feature extraction are done. Operational variables are normalized to map all the features on to a common range, as the variables have different scales. This process helps to decrease the training instability and enhance the convergence capability of the Deep Q-Network model. Additionally, feature engineering helps to reveal meaningful patterns in operations within the manufacturing data.

The normalization process is given in equation (2).

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (2)$$

Where:

X represents the original feature value,

X_{min} and X_{max} denote the minimum and maximum values of the feature respectively.

The variables of the IoT operation are standardized as in equation (2) to make efficient learning during the training of DQN.

3.3 Deep Q-Network Environment Formulation

The proposed optimization framework represents the smart business operations as a reinforcement learning environment. The DQN agent is constantly exposed to the operational states and takes action to maximize the business efficiency in this environment. The state space is defined in terms of operational conditions, and the action space in terms of optimization decisions like resource allocation, maintenance scheduling, workload balancing, and energy optimization. The DQN agent learns and selects the optimal operational strategies with a trial-and-error process by interacting with the environment.

Their action policy is used as per equation (3).

$$a_t = arg\, max_a\, Q(s_t, a_t) \quad (3)$$

Where:

a_t denotes the selected action at time t,

$Q(s_t, a_t)$ represents the Q-value associated with state-action pairs.

With the help of Equation (3), the DQN agent can determine the action to take (operational) based on maximum expected reward.

3.4 Reward Function Design

In the reward mechanism, the evaluation of the effectiveness of the operational decisions done by the DQN agent is determined. The reward function will aim to optimize the utilization of resources and operation efficiency and reduce the energy, downtime, and operational costs. Positive rewards are given for good decisions with regard to the efficient use of the resource, while penalties are given for inefficient scheduling or waste of resources. This is a reward-based approach to facilitate adaptive optimization in smart business environments.

The proposed reward function is mathematically given in equation (4).

$$R_t = \alpha E_t + \beta U_t - \gamma C_t - \delta D_t \qquad (4)$$

Where:
E_t= operational efficiency,

U_t= resource utilization,

C_t= operational cost,

D_t= downtime,

$\alpha, beta, gamma, delta$ are weighting coefficients.

The reward function (as shown in equation (4)) considers both the satisfaction of operational performance objectives and the satisfaction of cost optimization objectives.

3.5 Deep Q-Network Learning Process

The DQN agent is trained to find the best operational strategies by the iterative update of the Q-values, which is implemented via the optimization of the neural networks. To increase the stability of the learning process and reduce errors from overestimating, experience replay memory and target networks are used. The agent will take observations of the operational states of the system in each iteration of the training process, perform optimization actions, collect rewards, and adjust parameters of the neural network based on the collected rewards. This process makes it possible to acquire intelligent operational policies for the system for a dynamic business environment.

The process of updating the Q-value is given in Equation (5).

$$Q(s_t, a_t) = Q(s_t, a_t) + \alpha[r_t + \gamma max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)] \qquad (5)$$

Where:
$Q(s_t, a_t)$ represents the current Q-value,

r_t denotes the immediate reward,

γ is the discount factor,

α represents the learning rate.

The Q-values are then updated iteratively using equation (5), with the aim of enhancing the performance of the long-term operation decision-making.

3.6 Loss Function Optimization

A loss optimization function is used to minimize the prediction errors on the DQN neural network. The loss function is a function that indicates how different the model-predicted and target Q-values are when reinforcement learning is performed. Reducing this error helps to promote the convergence of policies and increase the accuracy of the optimization in smart business operations.

The DQN loss function is given as in equation (6).

$$L(\theta) = \mathbb{E}[(y_t - Q(s_t, a_t; \theta))^2] \qquad (6)$$

Where:
L(theta) represents the loss function,

y_t denotes the target Q-value,

$Q(s_t, a_t; \text{theta})$ represents the predicted Q-value.

The use of equation (6) not only reduces prediction errors but also enhances the learning ability of the proposed DQN framework.

3.7 Performance Evaluation Metrics

The last step tests the performance of the proposed optimization framework, using operational efficiency metrics. The evaluation includes the DQN model's ability to optimize business operations, minimize downtime, improve energy usage, and enable intelligent decision-making. System performance is validated using metrics like operational efficiency, resource utilization, and optimization accuracy.

The efficiency in operation is determined with the help of equation (7).

$$\mathrm{OE} = \frac{\text{Output Performance}}{\text{Input Resources}} \times 100 \qquad (7)$$

Where:
OE represents operational efficiency percentage.

In equation (7), the performance of the proposed framework in terms of the effectiveness of resource utilization and business operational optimization is measured.

3.8 Experimental Framework

Experiments are carried out to test the performance of the proposed Deep Q-Network (DQN)-based smart business optimization system with the Intelligent Manufacturing Dataset from Kaggle. Experiments are performed in a simulated IoT-enabled manufacturing environment to see the operational efficiency, resource utilization, energy optimization, and the performance of intelligent decision-making. To assess the learning capability and the generalization performance of the proposed model, the data set is split into a training data set and a test data set.

The environment for implementation is Python, and the deep learning library TensorFlow is used for the development and training of the DQN model. To enhance the learning stability and the optimized performance of the DQN agent, experience replay memory, target network updating, and epsilon-greedy exploration are adopted. In each training episode, the agent sees the operation state and decides the operation to be done in the next iteration to maximize the reward and updates the Q-value iteratively by reinforcement learning.

The proposed model is contrasted with the conventional optimization and machine learning algorithms such as Q-Learning, Artificial Neural Networks (ANN), Random Forest, and Rule-Based Operational Systems. The comparative analysis compares the effectiveness of the proposed model in dealing with the dynamic business operational conditions and enterprise environment using IoT.

The operational efficiency, resource utilization, reduction in energy consumption, minimization of downtime, reward convergence, and optimization accuracy are metrics for evaluating the performance of the framework. The results of the overall experimental setup confirm the feasibility of the proposed DQN-based framework to support the intelligent and adaptive smart business operation in the industry 4.0 environment.

4 Results and Discussion

The proposed smart business optimization framework based on Deep Q-Network (DQN) was experimentally tested using the Intelligent Manufacturing Dataset to examine the operational efficiency, intelligent resource allocation, energy optimization, and adaptive business decision-making performance. The experimental results show that the proposed reinforcement learning framework can effectively optimize the operation workflows and greatly promote the efficiency of the enterprise, compared with the traditional optimization methods.

The DQN agent trained through several operational episodes based on the IoT data from manufacturing and optimized according to the reward mechanism. The experimental results verified that the proposed framework was able to offer stable convergence, decreased operational costs, decreased downtime, and increased intelligent scheduling performance in dynamic industrial environments.

The cumulative reward convergence and operational optimization accuracy were used to check the DQN training process. The model had some medium-sized variations in the first training sessions due to learning through exploration. With a growing number of iterations, though, the framework reached a stable convergence and made constant improvements in operational decision-making.

Table 1: DQN training and convergence performance

Training Episodes	Average Reward	Loss Value	Convergence Accuracy (%)	Decision Latency (ms)
100	42.18	0.086	81.42	28.63
200	58.74	0.064	86.91	24.12
300	71.25	0.041	91.37	19.84
400	83.56	0.025	95.14	15.37
500	91.82	0.013	97.68	11.92

The cumulative reward was seen to be steadily rising from 42.18 to 91.82, and the loss was seen to be declining considerably from 0.086 to 0.013 during the training phase, as shown in Table 1. The convergence accuracy was improved to 97.68%, which was stable reinforcement learning optimization and efficient generation of operational intelligence.

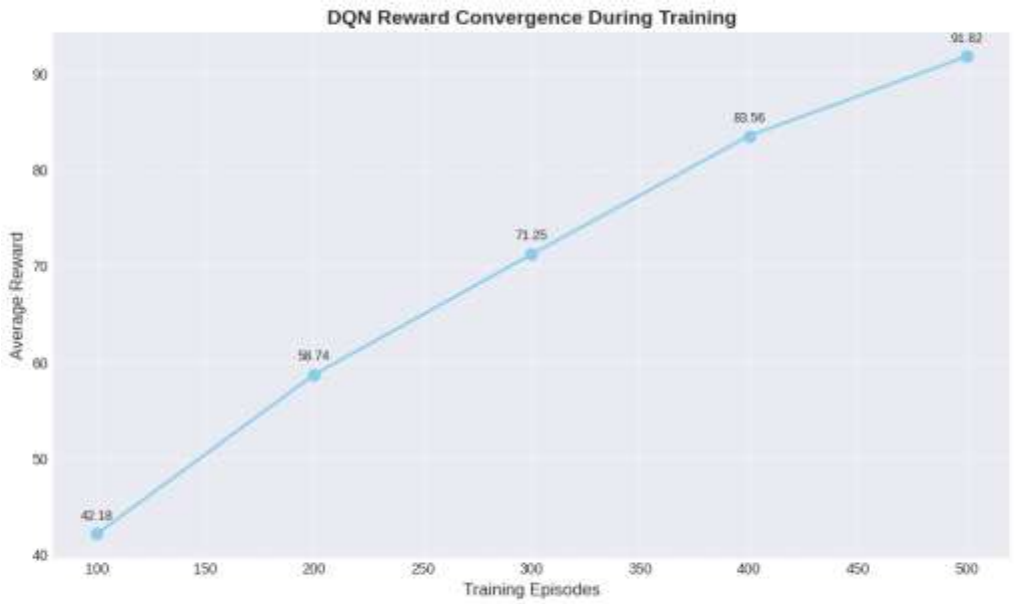

Figure 2: DQN reward convergence during training

Figure 2 illustrates that the proposed DQN framework was able to learn optimal operational policies and improve the business optimization performance after the continuous interactions with the IoT environment, which is the reward convergence trend.

The effectiveness of the operational efficiency of the proposed framework was assessed by enterprise performance parameters such as utilization of resources, reduction in energy consumption, minimization of downtime, and optimization of workflow. The suggested DQN framework dynamically made operational decisions according to the real-time condition of IoT and continuously optimized the allocation of enterprise resources.

Table 2: Operational optimization performance

Performance Metric	Before Optimization	After DQN Optimization	Improvement (%)
Operational Efficiency (%)	71.42	94.83	32.78
Resource Utilization (%)	68.57	92.46	34.85
Energy Consumption (kWh)	412.35	298.16	27.69
Downtime (Hours)	19.84	6.27	68.40
Production Throughput (%)	74.93	96.15	28.31

The proposed DQN framework achieved the goal of reducing downtime by 68.40% and also achieved a better operational efficiency (71.42% to 94.83%), as shown in table 2. The model also reduced energy use to a great extent and enhanced the production throughput and the efficiency of resource allocation.

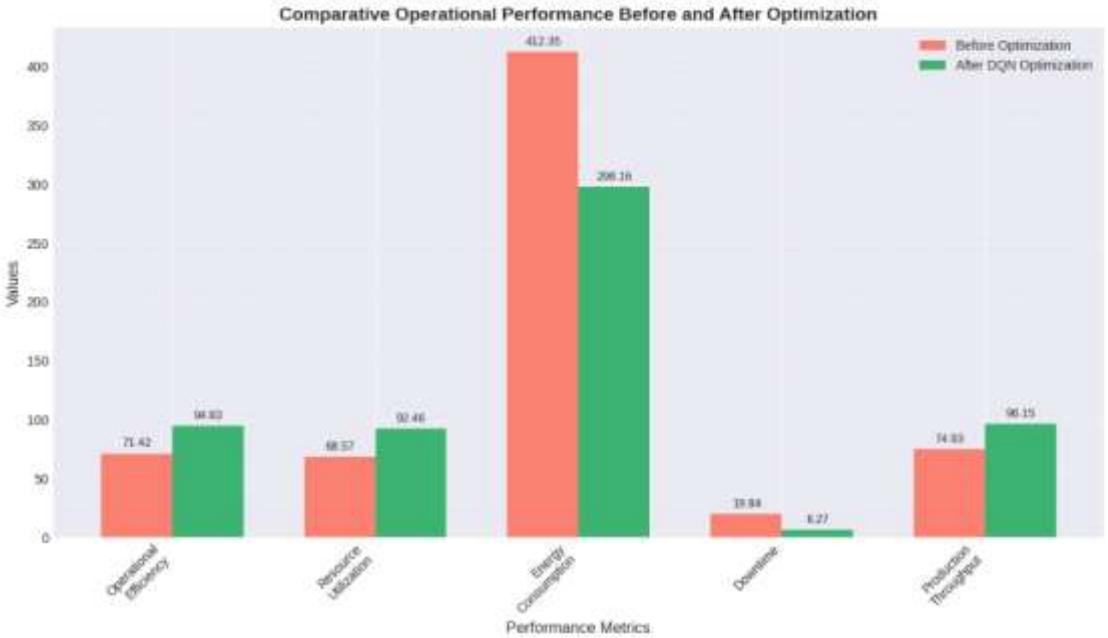

Figure 3: Comparative operational performance before and after optimization

As can be seen in the comparative results in figure 3, the performance of the smart business operations was greatly improved in all the metrics of the enterprise through reinforcement learning-based optimization.

The proposed DQN framework is compared with the traditional machine learning and optimization methods such as Q-learning, artificial neural networks (ANN), random forest, and the rule-based method. A comparison was mainly performed on the optimization accuracy, decision latency, operational efficiency, and reward convergence performance.

Table 3: Comparative analysis with existing optimization models

Model	Optimization Accuracy (%)	Operational Efficiency (%)	Reward Stability (%)	Decision Latency (ms)
Rule-Based System	74.25	69.13	66.48	39.42
Random Forest	81.37	77.25	73.91	31.57
ANN	87.56	84.63	82.44	24.91
Q-Learning	91.42	88.37	89.26	18.36
Proposed DQN	97.68	94.83	96.74	11.92

The comparative results in Table 3 show that the proposed framework named DQN performed better than all the existing models with respect to all the evaluation metrics. The framework obtained the maximum optimization accuracy of 97.68% and also had a significant reduction in decision latency, as well as more stable rewards.

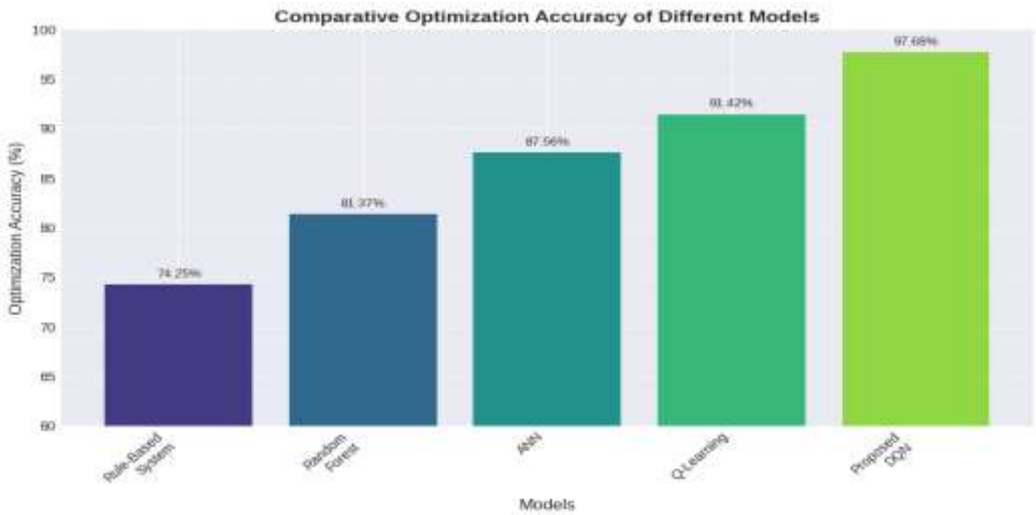

Figure 4: Comparative optimization accuracy of different models

Figure 4 shows a performance comparison between reinforcement learning-based adaptive optimization and traditional machine learning and static scheduling methods, which verify the superiority of reinforcement learning-based adaptive optimization.

The proposed framework also exhibited excellent capabilities with regard to predictive maintenance and energy optimization through the use of operational intelligence via IoT. The DQN agent constantly monitored the operational state of industrial systems and dynamically scheduled maintenance according to the monitoring results prior to the occurrence of major failures in the industrial systems. The adaptive approach reduced the downtime of the equipment and ensured better continuity of operations.

Table 4: Predictive maintenance and energy optimization results

Metric	Existing System	Proposed DQN Framework
Maintenance Prediction Accuracy (%)	82.16	96.42
Energy Optimization Efficiency (%)	76.28	93.74
Fault Detection Rate (%)	79.54	95.18
Maintenance Response Time (s)	14.82	5.63
Equipment Failure Reduction (%)	31.75	72.48

Table 4 presents the maintenance prediction accuracy and maintenance response time obtained by the proposed DQN framework, which shows that the accuracy of the maintenance prediction was significantly improved and the maintenance response time was significantly decreased by the framework. The framework also achieved a fault detection rate of 95.18% and reduced the equipment failure by 72.48%, which proved its effectiveness for intelligent enterprise management.

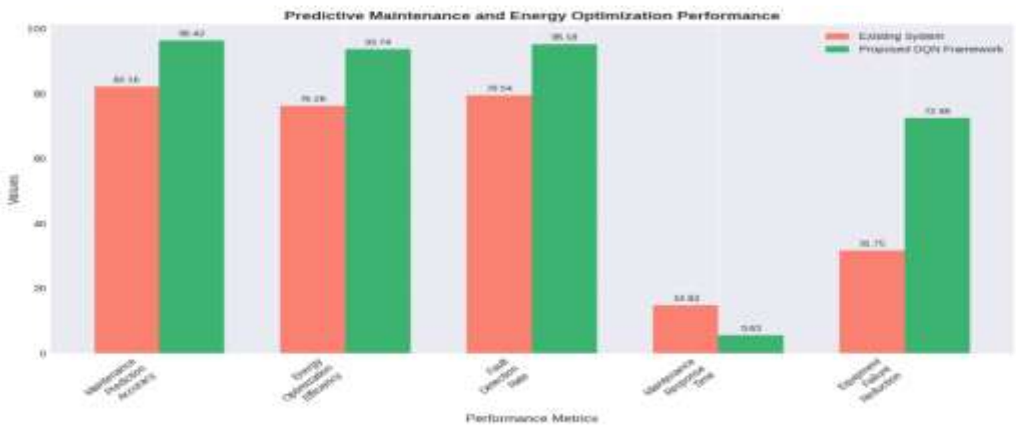

Figure 5: Predictive maintenance and energy optimization performance

Comparisons of the existing operational system's and proposed DQN-based predictive maintenance and energy optimization system's performance are shown in Fig. 5. The results of the graphical analysis show that the proposed reinforcement learning framework is capable of significantly improving maintenance prediction accuracy and fault detection capability and reducing equipment failures.

Experimental results show that the proposed framework based on Deep Q-Network (DQN) effectively enhances smart business performance by adaptive reinforcement learning and IoT-based decision-making processes. From Tables 2 and 3, it can be observed that the DQN agent has indeed learned the optimal operational policies under the dynamic industrial conditions, as the operational efficiency and the utilization ratio of resources are significantly improved. The stable convergence of the rewards shown in Figure 2 also suggests that the framework can optimize rewards in the long term and intelligently stabilize decisions.

The proposed framework provided a higher accuracy of optimization, lower decision latency, and higher stability of reward than the traditional machine learning models and rule-based models. These enhancements were largely accomplished thanks to the DQN model's constant interaction with the operational environment and dynamically making decisions based on real-time data streams from IoT devices. This result also shows how the predictive maintenance and energy optimization results shown in Table 4 further validate the ability of reinforcement learning to minimize equipment failures to sustain enterprise operations.

Overall, the proposed framework can be used for operational optimization problems in the Industry 4.0 context, smart manufacturing infrastructures, and enterprise management systems based on data.

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Conflicts of Interest

The author declares no conflicts of interest related to this research.

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Dataset Availability

The Intelligent Manufacturing Dataset is publicly available on the Kaggle repository.

Dataset Link: https://www.kaggle.com/datasets/ziya07/intelligent-manufacturing-dataset

5 Conclusion

This research suggested an intelligent smart business optimization framework to adapt the enterprise operational management with Deep Q-Networks (DQN) and IoT-based manufacturing analytics. The framework proposed was able to effectively leverage various real-time parameters of an industrial IoT system, such as temperature, vibration, energy usage, production efficiency, maintenance score, and operational latency, for decision-making based on reinforcement learning in dynamic business environments. The Intelligent Manufacturing Dataset was used for simulating realistic operating conditions to evaluate intelligent resource allocation, predictive maintenance scheduling, and energy optimization strategies. The results of the experiments showed the effectiveness of the proposed framework based on the results obtained in the different enterprise metrics. The DQN model was optimized by 97.68% and was used to improve operational efficiency up to 94.83% and resource utilization up to 92.46% and decrease the operational downtime by 68.40%. Moreover, the proposed framework was able to achieve 96.42% accuracy for prediction, while energy optimization efficiency was 93.74%, which is much better than the conventional machine learning and rule-based optimization approaches. Reward convergence analysis also showed stable reinforcement learning performance and generation of operational intelligence that adapts to the task. In conclusion, the proposed DQN-based framework is a scalable and intelligent solution for Industry 4.0 environments and can be used to give autonomy to business optimization, real-time control of operations, and enterprise decision support using IoT. Future research could be extended to the framework with multi-agent reinforcement learning, federated learning, and explainable AI techniques for distributed smart enterprise optimization.

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