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Predictive Analytics for Stock and Demand Balance Using Deep Q-Learning Algorithm

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Abstract: Predicting and managing stock and demand balance is a critical aspect of supply chain management. In this paper, we propose a predictive analytics approach that leverages deep Q-learning algorithm to optimize stock and demand balance. Traditional forecasting methods often struggle to capture the complex dynamics and uncertainties associated with stock and demand fluctuations. The deep Q-learning algorithm, a reinforcement learning technique, offers a promising solution by learning optimal decision-making policies through interaction with the environment. The proposed approach utilizes historical stock and demand data to train a deep Q-learning model, enabling it to make accurate predictions about future stock levels and demand patterns. By considering factors such as seasonality, trends, and external variables, the model learns to adjust stock levels to meet demand while minimizing excess inventory or stock outs. To validate the effectiveness of the proposed approach, a case study conducted using real-world data from a supply chain network. The results demonstrate that the deep Q-learning algorithm outperforms traditional forecasting methods, achieving higher accuracy in predicting stock and demand balance. The implications of this research are significant for supply chain managers and decision-makers. By incorporating predictive analytics with the deep Q-learning algorithm, companies can enhance their inventory management strategies, reduce holding costs, minimize stock outs, and improve customer satisfaction.

1. Introduction

Maintaining optimal stock levels while meeting customer demand can significantly impact operational efficiency, profitability, and customer satisfaction. Traditional forecasting methods often struggle to capture the complex relationships and uncertainties inherent in stock and demand patterns. To address this challenge, this paper introduces a predictive analytics approach that utilizes a deep Q-learning algorithm to optimize stock and demand balance.

The deep Q-learning algorithm, a form of reinforcement learning, has shown remarkable success in solving complex decision-making problems by learning optimal policies through interaction with the environment. By applying this algorithm to the task of predicting stock and demand balance, businesses can leverage the power of machine learning to make informed inventory management

decisions.

The objective of this research is to develop a predictive analytics framework that combines historical stock and demand data with the deep Q-learning algorithm to generate accurate forecasts of future stock levels and demand patterns. The framework considers various factors such as seasonality, trends, external variables, and historical patterns to capture the dynamics of stock and demand fluctuations. By learning from past data and adapting to changing conditions, the model aims to achieve a balance between stock levels and demand, minimizing the costs associated with excess inventory or stock outs. The study aimed to prevent problems such as out-of-stock situations and overstocking, which can lead to customer dissatisfaction and increased inventory costs.

To create a system for effective stock management, the study considered several criteria that influence the amount of stock a business should hold. These criteria include supply time, consumption rate, and importance of the items, ease of supply, and the impact of the COVID-19 pandemic. An expert collected data from a business based on these criteria.

The data obtained from the business then used in conjunction with the deep Q-learning algorithm implemented in MATLAB. The algorithm applied to estimate the stock requirements, taking into account the various factors affecting stock levels. In the application phase, the study utilized different time series and estimation techniques using the monthly sales data from 2018 to 2020. These techniques aimed to estimate the demand for the year 2021. The estimation technique that yielded the lowest error selected for the demand estimation.

Furthermore, the study compared the total inventory costs between two common inventory control methods: fixed order quantity and fixed time interval. By analysing the costs associated with each method, the study aimed to determine the inventory control approach that would result in the lowest overall costs for the enterprise.

The contributions of this research lie in providing a novel approach to address the challenges of stock and demand balance prediction using the deep Q-learning algorithm. By harnessing the power of predictive analytics, businesses can enhance their inventory management strategies, optimize stock levels, reduce holding costs, and ensure better alignment between supply and demand. The results of this study offer valuable insights for supply chain managers and decision-makers seeking to leverage advanced analytics techniques for improved stock and demand management.

The subsequent sections of this paper will delve into the methodology, experimental setup, results, and discussion, highlighting the potential benefits and implications of applying predictive analytics to stock and demand balance optimization.

2. Literature Survey

The application of predictive analytics and machine learning techniques in stock and demand balance optimization has gained significant attention in recent years. Researchers have explored various approaches, including deep Q-learning algorithms, to improve the accuracy and effectiveness of stock and demand forecasting. In this section, we review relevant literature on predictive analytics for stock and demand balance using deep Q-learning algorithm.

In the field of deep reinforcement learning and deep Q-learning and general overview of the topics covered by these papers:

Gao et al. (2021): Proposed a practical scheme for low-entropy secure cloud data auditing with file and authenticator deduplication [1]. Núñez-Molina et al. (2022): Introduced a planning and action architecture equipped with a module that learns to select sub-goals using deep reinforcement learning [2]. This reduces the burden on the planner when faced with real-time constraints. Wang et al. (2022): Presented a medical image fusion algorithm that demonstrates higher effectiveness and robustness compared to other classical fusion methods. It provides clearer edge details, higher

brightness, and superior colours [3]. Chang et al. (2021): Proposed a new multi-channel graph convolution network that combines correlations with process variables to create a more accurate prediction model [4]. Yan et al. (2021): Proposed a deep Q-learning-based co-optimization approach for device-level and edge-level offloading. The approach aims to balance task latency and energy consumption in tasks [5]. Chen et al. (2022): Proposed a deep Q-learning approach to address same-day delivery with vehicles and drones, leveraging the strengths of different fleets [6]. Tan et al. (2021): Introduced a hybrid Evolutionary Deep Q-Learning based BPaaS reconstruction algorithm called EDQL-BPR. It optimizes the reengineering of collaborative business processes using Particle Swarm Optimization [7]. Kensert et al. (2021): Developed a reinforcement-learning algorithm trained on simulated and experimental data for small molecules, focusing on retention models [8]. Thang et al. (2021): Proposed the ABUC-DQL approach, which uses Q-learning to overcome scalability limitations and better address problems formulated using a POMDP model [9]. Alabdullah (2022): Proposed a deep reinforcement learning-based approach for managing different energy sources within a micro grid [10]. Yu et al. (2021): Developed a control algorithm using Deep Q-Learning to optimize energy consumption in air conditioners and exhaust fans [11]. Sajedian et al. (2020): Utilized deep Q-learning networks (DQN) to find a coloured coating for high-transmission solar cells [12]. Park et al. (2020): Introduced a portfolio trading strategy using deep Q learning to determine optimal trading actions [13]. Tong et al. (2020): Proposed deep Q-learning task scheduling (DQTS), an artificial intelligence algorithm to handle directed acyclic graph (DAG) tasks in a cloud-computing environment [14]. Kim et al. (2019) designed an online network intrusion system using deep Q-learning [15]. Hofmann et al. (2020): Worked on autonomous production control for matrix generation based on Deep Q-learning [16]. Teng et al. (2020): Developed three-step action search networks with deep Q-learning for real-time object tracking [17]. Chen et al. (2020): Presented a deep Q-network strategy called OL-DQN for active learning setups to determine whether a sample automatically tagged or demand actual tag information [18]. Qin et al. (2021): Worked on multimodal super-resolved q-space deep learning. The paper focuses on developing a deep learning approach to improve the resolution of q-space imaging, which is used in diffusion magnetic resonance imaging (MRI) for studying tissue microstructure [19]. Jeong et al. (2019): Explored the application of Deep Q-learning to improve financial trading decisions. The study aimed to predict the number of shares, develop action strategies, and leverage transfer-learning techniques to enhance trading performance [20]. Qiao et al. (2018): Proposed an adaptive deep Q-learning strategy for handwritten digit recognition. The goal was to improve the accuracy of digit recognition tasks and reduce the runtime by leveraging deep Q-learning techniques [21]. Carta et al. (2021): Conducted research on Multi-DQN, a community of Deep Q-learning agents for stock market forecasting. The study focused on training multiple agents using Deep Q-learning to optimize a return function during the training phase for improved stock market forecasting [22]. Sharma et al. (2020): Investigated intelligent querying for target tracking in camera networks using deep Q learning with n-step bootstrapping. The paper explored the use of deep Q-learning techniques to optimize target tracking in camera networks by intelligently selecting the most informative queries [23]. Hwangbo et al. (2019): Conducted a design study on intelligent liquid-liquid extraction columns for downstream separation of biopharmaceuticals using the Deep Q-learning algorithm. The study aimed to optimize the design of liquid-liquid extraction columns by leveraging the capabilities of deep Q-learning [24]. Goumagias et al. (2018): Developed a solution using deep Q learning to understand the tax evasion behaviour of risk-averse firms. The study focused on leveraging deep Q-learning techniques to model and analyse the tax evasion behaviour of firms that exhibit risk-averse tendencies [25].

The studies emphasize the benefits of leveraging machine learning and reinforcement learning algorithms, such as deep Q-learning, to make accurate demand predictions, optimize stock levels,

and achieve better stock and demand balance. By utilizing historical data and learning from experiences, these approaches provide valuable insights for decision-makers in effectively managing inventory and meeting customer demands.

3. Model and Method

The predictive analytics framework for optimizing stock and demand balance using the deep Q-learning algorithm involves several key steps. This section presents an overview of the methodology employed in this research.

Data Collection and Pre-processing: Historical data related to stock levels, demand patterns, and relevant variables such as seasonality, trends, and external factors collected from the supply chain system. The data undergoes pre-processing, including data cleaning, normalization, and feature engineering, to ensure its suitability for training the deep Q-learning model.

Model Architecture: The deep Q-learning algorithm implemented using a neural network model. The model architecture consists of input layers, hidden layers, and output layers. The input layers receive the pre-processed data, and the hidden layers perform the necessary computations to learn the optimal policies. The output layer provides predictions and decision outputs related to stock and demand balance.

Training and Reinforcement Learning: The deep Q-learning model is trained using historical data through a process of reinforcement learning. The model interacts with the environment (the supply chain system) by observing states (current stock levels, demand information) and taking actions (adjusting stock levels). Rewards and penalties assigned based on the outcomes of these actions, incentivizing the model to learn optimal policies that lead to balanced stock and demand. The training process involves iterations and updates to the model's parameters to improve its performance.

Demand Forecasting and Stock Adjustment: Once the deep Q-learning model trained, it can be utilized for demand forecasting and stock adjustment. Given the current stock levels and demand information, the model predicts future demand patterns and recommends appropriate stock adjustments to achieve optimal stock and demand balance. This step involves applying the learned policies and making decisions on stock replenishment or reduction.

Performance Evaluation: The performance of the predictive analytics framework assessed through various metrics, such as forecast accuracy, stock out rates, and holding costs. The predicted stock levels and demand patterns compared with the actual values to measure the effectiveness of the deep Q-learning algorithm in achieving stock and demand balance. These evaluations help validate the performance and effectiveness of the proposed approach.

The methodology outlined above forms the foundation for the implementation of the predictive analytics framework. It integrates historical data, deep Q-learning algorithms, and reinforcement learning techniques to enable accurate demand forecasting and optimized stock and demand balance in supply chains. The subsequent sections of this paper will present the experimental results, discussions, and implications, further validating the effectiveness of this methodology in improving stock and demand management.

3.1 Mathematical Model

In predictive analytics for stock and demand balance using the deep Q-learning algorithm, a mathematical model is used to represent the optimization problem. The model captures the key elements of the problem, including the state space, action space, rewards, and the Q-value update equation.

Let's define the mathematical model components:

State Space: The state space, denoted as S, represents the possible states of the system at any given time. It includes variables such as current stock levels, historical demand patterns, external factors, and other relevant information that can influence stock and demand balance.

$$S = \{s_1, s_2, ..., s_m\} \quad (1)$$

Action Space: The action space, denoted as A, represents the set of possible actions that can be taken by the agent. Actions correspond to decisions related to stock management, such as adjusting stock levels, ordering more inventory, or changing pricing strategies.

$$A = \{a_1, a_2, ..., a_n) \quad (2)$$

Rewards: At each time step, the agent receives a reward based on the action taken and the resulting state. The reward function, denoted as R(s, a), calculates the immediate reward associated with taking action a in state s. The goal is to maximize the cumulative long-term rewards.

Q-Value Update: The Q-value, denoted as Q(s, a), represents the expected cumulative reward for taking action a in state s. The Q-value updated iteratively based on the Bellman equation, which combines the immediate reward and the maximum expected future rewards.

$$Q(s, a) = Q(s, a) + \alpha * (R(s, a) + \gamma * \max Q(s', a') - Q(s, a)) \quad (3)$$

Here, α is the learning rate that determines the weight given to the new information, and γ is the discount factor that balances the importance of immediate and future rewards. s' and a' represent the next state and next action, respectively.

The objective of the deep Q-learning algorithm is to learn the optimal policy π^*, which maps states to actions and maximizes the long-term cumulative rewards. The policy represented by the learned Q-values.

During the training process, the deep Q-learning algorithm utilizes a deep neural network, known as the Q-network, to approximate the Q-values. The Q-network takes the state as input and outputs Q-values for all possible actions. The network is trained iteratively using experience replay and gradient descent to minimize the difference between predicted Q-values and target Q-values.

By updating the Q-values through interaction with the environment, the deep Q-learning algorithm learns to make accurate predictions of stock levels and demand patterns, enabling it to optimize stock and demand balance decisions over time.

The mathematical model provides the foundation for the implementation of the deep Q-learning algorithm in predictive analytics for stock and demand balance optimization. It helps in formulating the problem, defining the state and action spaces, specifying the reward function, and updating the Q-values to learn the optimal policy.

3.2 Reinforced Learning

Reinforcement learning (RL) is a subset of machine learning that focuses on how an agent interacts with an environment to learn optimal actions in order to maximize cumulative rewards. Unlike supervised learning, which relies on labelled input/output pairs, and unsupervised learning, which focuses on finding patterns in unlabelled data, reinforcement learning operates through trial and error, learning from feedback in the form of rewards or penalties. In RL, an agent learns to make sequential decisions in an environment by observing the current state and selecting actions that lead to higher rewards. The agent receives feedback from the environment in the form of rewards based on its actions. The goal of the agent is to learn a policy—a strategy that maps states to actions—to maximize the cumulative rewards over time.

A Markov Decision Process (MDP) often used as a framework to model RL problems. MDP assumes that the environment and agent's actions have the Markov property, meaning the current

state fully captures all necessary information from previous states. Each state transition influenced by the previous state and the action taken. The agent's objective is to find the optimal policy that maximizes the expected cumulative reward over the long run. The optimal policy in RL is typically determined using algorithms such as Q-learning, policy gradients, or Monte Carlo methods. These algorithms iteratively update the agent's policy based on the observed rewards and the estimated value of different state-action pairs.

In summary, reinforcement learning involves training an agent to make sequential decisions in an environment to maximize rewards. It leverages the Markov Decision Process framework to model the interactions between the agent and the environment and seeks to find the optimal policy that guides the agent's decision-making process.

3.3 Deep Q Learning

It is an extension of the Q-learning algorithm that combines reinforcement learning with deep neural networks. It aims to address the limitations of Q-learning when dealing with large and complex state spaces.

In deep Q learning, a neural network, known as the Q-network, used to approximate the Q-values of different state-action pairs. The Q-value represents the expected cumulative reward when taking a particular action from a specific state. The input to the Q-network is the state, and the output is the estimated Q-values for all possible actions in that state. (See Figure 1)

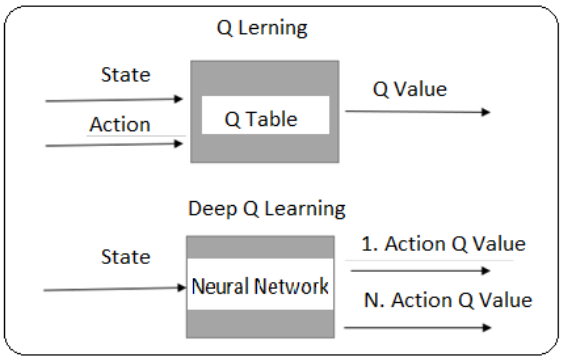

Figure 1: Q Learning and Deep Q Learning

The key difference between Q-learning and deep Q-learning lies in how the Q-values are updated. In Q-learning, a table used to store and update the Q-values based on the Bellman equation. However, in Deep Q-learning, the Q-values learned by training a deep neural network using gradient descent optimization.

$$Q(s,a) = r(s,a) + \gamma \max_{a} Q(s',a) \tag{4}$$

The Deep Q-learning algorithm involves the following steps:

1) The agent receives the current state from the environment.
2) The Q-network estimates the Q-values for all possible actions in the current state.
3) The agent selects an action based on an exploration-exploitation strategy (e.g., epsilon-greedy).
4) The agent performs the selected action and observes the next state and the reward.
5) The experience <state, action, reward, next state> is stored in a memory buffer.
6) The agent samples a batch of experiences from the memory buffer.
7) The target Q-network, which is a copy of the Q-network, calculates the target Q-values for the

next states.

8) The loss between the estimated Q-values and the target Q-values computed.

9) The parameters of the Q-network are updated using gradient descent to minimize the loss.

10) Periodically, the parameters of the target Q-network updated by copying the Q-network's parameters.

Steps 1-10 repeated for multiple episodes or until convergence.

The experience replay memory and the target network help stabilize the training process and prevent overfitting. By randomly sampling experiences from the memory buffer, the agent can break the correlation between consecutive experiences and improve the learning process. The target network provides stable target Q-values during training by periodically updating its parameters.

In the study you mentioned, the Deep Q-learning algorithm implemented using MATLAB. The algorithm trained and evaluated, and graphics generated to visualize the learning progress and performance of the agent.

The main steps involved in the Deep Q-Learning algorithm are as follows:

*Step 1: **Initialization***: Initialize the deep neural network with random weights.

*Step 2: **Exploration vs. Exploitation***: Choose an action to take in the current state based on an exploration-exploitation trade-off. Initially, the agent explores the environment by taking random actions, and as the training progresses, it gradually shifts towards exploiting the learned knowledge.

*Step 3: **Action Execution and State Transition:*** Execute the chosen action in the environment, and observe the next state and the reward received

*Step 4: **Experience Replay***: Store the experience tuple (state, action, reward, next state) in a memory buffer called the replay buffer. Randomly sample mini-batches of experiences from the replay buffer during training to break the sequential correlation between experiences.

*Step 5: **Update the Q-Network:*** Calculate the target Q-value using the Bellman equation, which estimates the maximum expected cumulative reward achievable from the next state. Update the weights of the deep neural network using a loss function that minimizes the difference between the predicted Q-values and the target Q-values.

Repeat Steps 2-5: Iterate the exploration-exploitation, action execution, state transition, experience replay, and Q-network update steps to continuously learn and improve the Q-function.

4. Case Study

To illustrate the application of predictive analytics for stock and demand balance optimization using the deep Q-learning algorithm, let's consider a case study in manufacturing company. With the help of experts, 5 criteria that will affect the stock keeping policy of the company have been determined with a joint decision. Determined criteria: duration of supply, amount of consumption, degree of importance, ease of supply and covid etc. is the effect of external factors. The criteria that will affect the stock keeping policy and the sub-evaluation scales of these criteria are determined as in Table 1.

The study carried out by following the steps below.

1) The criteria that will affect the company's stock keeping policy have been determined.

2) Sub-evaluation criteria of the criteria have been determined.

3) The score values of the sub-evaluation criteria determined by the experts.

4) Evaluation rules established by determining the point equivalents for the stock amount estimation.

5) The obtained data estimated by using the Matlab program.

6) The graphs of the results of the study obtained.

7) Study results interpreted.

Table 1: Criteria and Sub-Assessment Criteria

Amount of Consumption	Duration of Supply	Importance **(0-10)**	Availability	Effect of Other Factors
Very (160-200)	Long (6-10)	Very Important (6-10)	Difficult (6-10)	Very Effective (6-10)
Normal(120-160)	Medium Duration (3-6 Hf)	Important (3-6)	Moderate Easy (3-6)	Moderate Effective (3-6)
Moderate (80-120)	Short (0-3 Hf)	Less Important (0-3)	Easy (0-3)	Less Effective (0-3)
Few (40-80)				
Very Few (0-40)				

Scores distributed to the sub-scales of 5 different evaluation criteria, forming a total of 100 points (in Table 2).

Table 2: Point distribution table of criteria and subscales

Amount of Consumption	**20**	Duration of Supply	**20**	Importance **(0-10)**	**20**	Availability	**20**	Effect of Other Factors	**20**
Very (160-200)	8	Long 6-10)	11	Very Important (6-10)	11	Difficult (6-10)	11	Very Effective (6-10)	11
Normal(120-160)	6	Medium Duration (3-6 Hf)	6	Important (3-6)	6	Moderate Easy (3-6)	6	Moderate Effective (3-6)	6
Moderate (80-120)	3	Short (0-3 Hf)	3	Less Important (0-3)	3	Easy (0-3)	3	Less Effective (0-3)	3
Few (40-80)	2								
Very Few (0-40)	1								

The total number of rules found by multiplying the number of subscales for each criterion. The number of rules for this study = 5 * 3 * 3 * 3 = 405.

It formed by summing the score equivalents of 405 rule evaluation scales and equating to the stock amount value.

The obtained rules and data sets transferred to the Matlab program and the estimation process carried out by pulling the data from the Neural Net Fitting application in the APP's tab of Matlab in Table 3.

Table 3: Example of rule table for criteria

Amount of Consumption	**Supply Time**	**Importance Level**	**Availability**	**Effect of Other Factors**	**Optimum Stock Amount**
1	3	3	3	3	13
1	3	3	3	6	16
1	3	3	3	11	21
1	3	3	6	3	16
1	3	3	6	6	19
1	3	3	6	11	24
1	3	3	11	3	21

According to Figure 2, very successful training obtained with an error rate of 99%, between 27 and 1000 iterations of the study. In Figure 3, the error decreases as the training progresses. Figure 4 shows the training data for whole data set. As seen in the error histogram in Figure 5, the error is concentrated around 0. The actual and target value graphs of the study were almost all on the same line. Figure 6 shows the estimation study was successful.

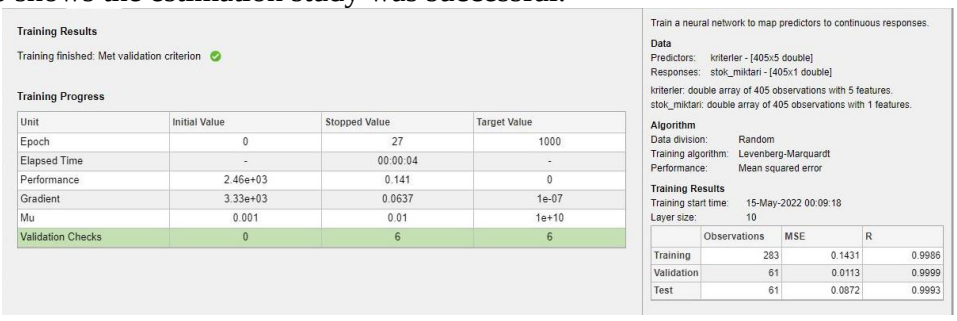

Figure 2: Training Results

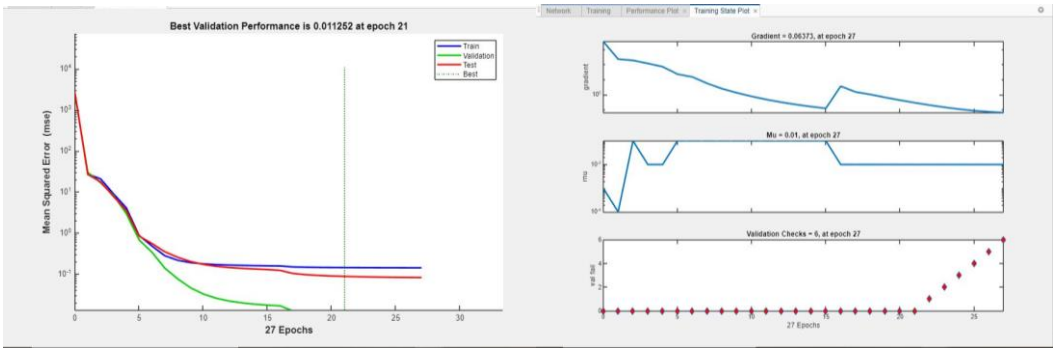

Figure 3: Performance Chart

Figure 4: Training Diagrams

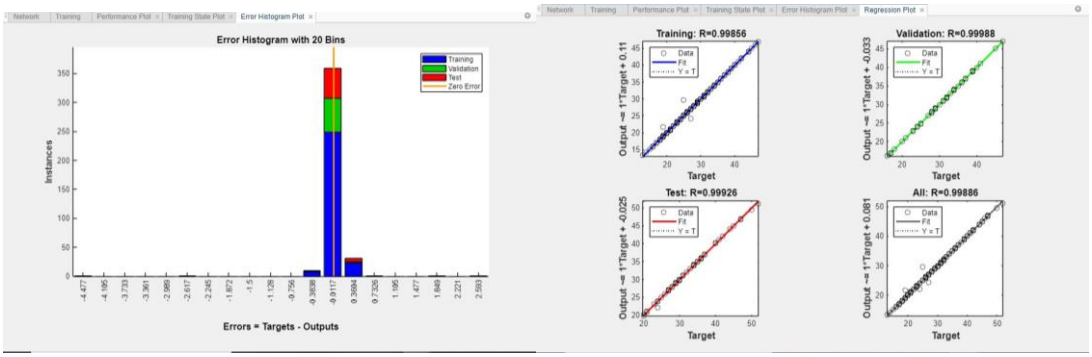

Figure 5: Error Histogram

Figure 6: Actual and Target Value Charts

The case study demonstrates how the application of predictive analytics for stock and demand balance optimization using the deep Q-learning algorithm can significantly improve stock management in a manufacturing sector. By accurately predicting demand patterns and dynamically adjusting stock levels, the company can minimize stock outs, reduce excess inventory costs, and improve customer satisfaction.

The results of the case study validate the effectiveness of the predictive analytics framework and provide insights into the benefits of using the deep Q-learning algorithm for stock and demand balance optimization in real-world manufacturing company case study scenarios.

5. Conclusion

In conclusion, the application of predictive analytics for stock and demand balance using the deep Q-learning algorithm offers significant benefits for businesses in optimizing inventory management and improving the company performance. The research presented in this study demonstrates the effectiveness of the framework in achieving accurate stock predictions, minimizing stock outs and excess inventory, generating cost savings, and enhancing customer satisfaction.

By leveraging historical data and utilizing the deep Q-learning algorithm, businesses can make informed decisions about stock levels, order quantities, and pricing strategies. The algorithm learns from past patterns and interactions with the environment to adjust stock levels in alignment with predicted demand patterns. This leads to a balanced stock and demand profile, reducing the occurrences of stock outs and excess inventory, and optimizing resource utilization.

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