



## **Intelligent Asset Tracking System for Logistics Industry using IoT and Big Data**

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### **Abstract**

The logistics industry is a complex and dynamic ecosystem that requires efficient and reliable asset tracking systems (IATS) to optimize operations and reduce costs. To address these challenges, an IATS is proposed in this paper that leverages the power of IoT and big data technologies to collect real-time data on the location, condition, and status of assets such as trucks, containers, and shipments. The system is designed to provide end-to-end visibility and control of assets throughout the logistics value chain. It uses a combination of RFID, GPS, and other tracking technologies to collect data on asset location, temperature, humidity, vibration, and other relevant parameters. The data is then transmitted to a cloud-based platform for storage, processing, and analysis using big data analytics and machine learning algorithms. The platform enables logistics companies to monitor and manage their assets in real-time, optimize routes and schedules, and improve delivery times. It also provides machine learning tools for predictive modeling of asset price movement, enabling companies to identify potential price changes before they occur and minimize loss. The efficiency and effectiveness of our system were shown through simulation studies using data from real-world assets; as a result, it is an attractive option for the tracking and management of assets in real-world logistic businesses.

**Keywords:** Logistics Industry; Internet of Things (IoT); Asset Tracking System; Logistics Industry.

### **1. Introduction**

The logistics industry is a critical sector responsible for managing the flow of goods and services from their point of origin to their intended destination. It includes transportation, warehousing, inventory management, and distribution services. The industry is vital to businesses of all sizes, as it enables them to move their products efficiently and cost-effectively. The logistics industry has seen significant growth in recent years due to advancements in technology and globalization, making it a complex and competitive field. With the increasing demand for e-commerce and same-day delivery services, the logistics industry continues to evolve to meet the changing needs of consumers and businesses. An Intelligent Asset Tracking System (IATS) for the logistics industry is a sophisticated solution that utilizes cutting-edge technologies such as GPS, RFID, and IoT to track and monitor the movement of assets in real time. The system provides valuable insights into the location, condition, and status of assets, enabling logistics companies to optimize their operations, reduce costs, and improve customer satisfaction. With an IATS, logistics companies can track inventory levels, monitor the condition of goods during transit, and ensure that shipments are delivered on time and in good condition. The system can also provide automated alerts and notifications in case of any delays, damages, or other issues, allowing companies to take corrective action promptly.

Implementing an IATS can provide significant benefits to logistics companies, including increased efficiency, enhanced productivity, and improved customer service. The system can help companies optimize their fleet management and reduce fuel consumption by providing real-time data on vehicle locations and performance. It can also help companies reduce theft and loss of assets by providing continuous monitoring and alert systems. Additionally, an IATS can enable logistics companies to provide more accurate delivery times to their customers, leading to higher customer satisfaction and loyalty.

IoT stands for the Internet of Things, which refers to a network of physical devices, vehicles, and other objects that are embedded with sensors, software, and connectivity that allows them to exchange data with other devices and systems over the internet. In the context of the logistics industry, IoT can be used to create an Intelligent Asset Tracking System that provides real-time visibility and control over the movement of assets. IoT plays a crucial role in an Intelligent Asset Tracking System by providing a platform for connecting different types of assets, including vehicles, containers, and packages, and capturing data about their location, condition, and status. IoT sensors can be embedded in the assets to collect data on factors such as temperature, humidity, and shock, and transmit this data to a central database for analysis and decision-making. This data can then be used to optimize logistics operations, improve asset utilization, and reduce costs. For example, a logistics company can use IoT sensors to track the location of a shipment in real time and monitor the temperature and humidity levels inside a refrigerated container to ensure that the goods are delivered in good condition. The company can also use predictive analytics and machine learning algorithms to analyze the data collected from the IoT sensors and make informed decisions about fleet management, inventory management, and route optimization.

While an IATS can provide significant benefits to the logistics industry, several challenges must be addressed in implementing and using such a system. One challenge is the cost of implementing the technology. IATS s requires the use of sophisticated hardware and software, including sensors, communication devices, and data analytics tools, which can be expensive to install and maintain. Additionally, logistics companies may need to invest in new infrastructure and training programs to ensure that employees can use the system effectively. Another challenge is data security and privacy. An IATS requires the collection and storage of large amounts of data, including sensitive information such as the location of assets and customer details. This data must be protected against cyber threats and unauthorized access, which can be a complex and ongoing challenge for logistics companies. Finally, integrating an IATS with existing logistics systems and processes can be a challenge. The system must be compatible with existing software and infrastructure, and employees must be trained to use the new technology effectively. Additionally, the system must be designed to handle the complex logistics operations of a company, including coordinating multiple shipments, managing inventory levels, and optimizing routes.

In line with the above challenges, this work proposed a novel intelligent system that contributes to the body of knowledge as follows:

- We proposed an intelligent system that makes use of the Internet of Things and big data to track and monitor physical assets in transit, including trucks, containers, and shipments, in real time.
- Our system takes the advantage of machine learning to help companies predict future price movement, and thereby help decision makers to take appropriate action and minimize potential risks.
- Simulation experiments on real-world assets data demonstrated the efficiency and effectiveness of our system, which make it a powerful candidate for tracking and managing assets in real logistic industries.

The structure of this paper is organized as follows. First, a review of related work is given in Section 2. Then, the methodology of the proposed intelligent system is discussed in Section 3. More, the experimentations of the proposed system and the corresponding results are given in section 4. Finally, the conclusion of this work is provided in section 5.

## **2. Related Works**

The work [1] overviewed the use of big data analytics in transportation systems and its potential to transform the logistics industry by examining the challenges facing transportation systems, such as traffic congestion, air pollution, and accidents, and discusses how big data analytics can help address these issues. It also explored the various sources of data that can be used for transportation analytics, including social media, GPS data, and smart city technologies. The work [2] presented an in-depth analysis of the role of IoT, big data, and Industry 4.0 in logistics and supply chain

management. It explored the challenges facing logistics and supply chain management, such as inefficiencies, high costs, and lack of visibility and control, and explains how IoT, big data, and Industry 4.0 can help address these issues. It also explored various case studies and examples of how these technologies are being applied in logistics and supply chain management to improve operational efficiency, reduce costs, and enhance customer satisfaction. The work [3] proposed a cooperative fog computing architecture for dealing with big data in the internet of vehicles (IoV). It discussed the challenges facing IoV, such as the high volume, velocity, and variety of data generated by connected vehicles, and the limitations of traditional cloud computing solutions. It also developed a hierarchical architecture that includes three layers: the edge layer, the fog layer, and the cloud layer. Each layer was responsible for processing and analyzing different types of data, and the architecture allows for cooperative resource management between the layers to ensure optimal performance and efficiency. The paper [4] presented a framework for implementing big data analytics in intelligent manufacturing shop floors, which includes four layers: data collection and pre-processing, data integration and storage, data analysis and mining, and decision-making and control. It discussed the various types of data that can be collected from the manufacturing shop floor, including machine data, sensor data, and production data, and the different types of analytics that can be applied to this data, such as predictive analytics and prescriptive analytics. The work [5] presented a framework for defining smart digital cities using IoT and big data analytics to address the challenges facing cities, such as rapid urbanization, resource constraints, and environmental degradation, and the potential of IoT and big data analytics to address these issues. This framework was composed of three tiers data collection and management, data analysis and visualization, and decision-making and action. The paper [6] proposed a low-cost Real-Time smart traffic Management System to deliver better service by positioning traffic pointers to bring up-to-date traffic particulars promptly. Cheap vehicle detection sensors were embedded in the center of the highway for every 0.5 KM or 1 KM. the system used IoT to attain traffic data rapidly and direct it for dispensation. The work [7] surveyed how big data has been used to facilitate smart cities. It reviewed and contrasts several smart cities and big data definitions and investigates the potential, pitfalls, and upsides of implementing big data applications for smart cities. It also made an effort to pinpoint the prerequisites for deploying big data apps to power smart city services. It was clear from this work that big data has a number of potential applications in smart cities, but there are still numerous obstacles to overcome before its full potential can be realized. The paper [8] provided an overview of the cutting-edge telecommunications and intelligent services deployed in the environment of smart cities. With the example of how big data can radically alter city populations at various scales, the potential of big data analytics to back up smart cities was highlighted. It also proposed a future commercial model for big data in smart cities and identified the economic and technological research problems associated with this area. This research was designed to be used as a standard by academics and businesses as they plan for the evolution of smart cities in the age of big data. The paper [9] proposed a unified IoT solution for smart city development and urban planning. It presented a comprehensive system that incorporates a wide range of sensor deployments, such as those used in smart homes, vehicle networks, weather, and water monitoring systems, intelligent parking lots, and surveillance tools. It proposed a four-tier structure, with the bottom tier-1 handling IoT supplies and reporting systems and gathering, the middle tier-1 handling all communication types between, say, detectors, retransmits, ground stations, and the Internet, the middle tier-2 handling data processing and handling using the Hadoop framework, and the top tier-4 handling

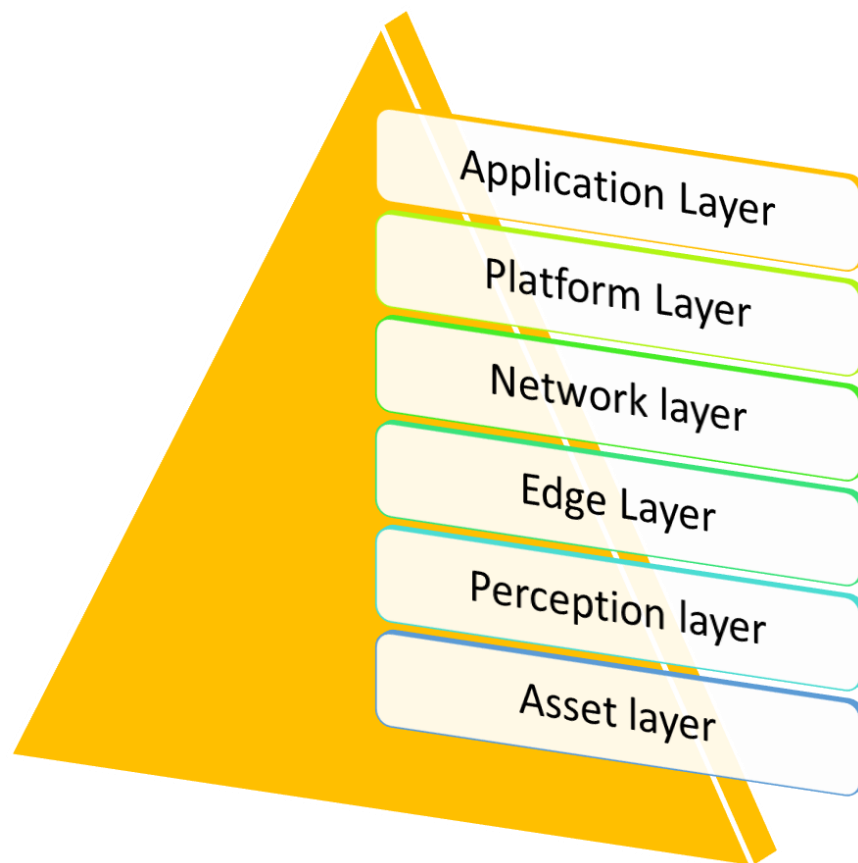


Figure 1: Architecture of our IoT-based system for asset tracking

application and utilization of the data. The generation of data is the first stage of the system implementation, followed by acquisition, gathering, filtering, categorization, preparation, computation, and judgment. For real-time analysis of IoT data to create results to establish the smart city, the suggested system was implemented utilizing Hadoop with Spark, voltDB, Storm, or S4. Hadoop's MapReduce functionality is used to evaluate offsite records for urban planning and city growth to come. Further, the paper [10] examined the role of big data in product lifecycle management (PLM) and its potential to enhance product development and manufacturing processes. It discussed the challenges facing modern product development and manufacturing, such as global competition, rapidly changing consumer preferences, and the need for increased efficiency and productivity. It presented a framework for implementing big data in PLM that includes four layers: data collection and processing, data storage and management, data analysis and visualization, and decision-making and action. It discussed the various types of data that can be collected, such as product usage data, sensor data, and supply chain data, and the different types of analytics that can be applied to this data, such as predictive analytics and machine learning algorithms.

### 3. Methodology of our Intelligent System

The structural design of our system for managing assets is shown in Fig. 1. The levels of the architecture are named for the functions they perform asset, actuation, Edge Layer, Platform Layer, and Application Layer.

**Asset Layer:** All of a company's valuable assets, acquired with the hope of generating profits, are recorded in the asset layer. Principal physical, supportive physical, virtual, and human assets are all distinguished. Production and the goods that result from it rely on a number of primary physical assets. The essential components are various pieces of production and automation equipment that are specific to various industries. Physical assets that aid the primary manufacturing procedure are essential to its success. Integrating IT software enables virtual assets to enable digitalization in the company and manufacturing process. Products have a life cycle that involves people at every

stage, from the first stages of development through the final users. Worker participation in tasks like manual operation, maintenance, and issue-solving that cannot be automated is essential.

**Edge Layer:** This is the lowest layer in the architecture, which includes sensors, actuators, and other edge devices that are used to collect and send data from the assets to the platform. These devices can be installed on the assets themselves or in the surrounding environment. They are responsible for collecting data such as asset location, temperature, humidity, vibration, and other relevant parameters. Edge devices can also be used to control and monitor assets in real time.

**Platform Layer:** This layer provides the core functionality of the IoT system for asset management. It includes cloud-based platforms that receive, store, process, and analyze the data collected from the edge layer. The platform layer typically includes multiple components such as data storage, data processing, data analytics, and data visualization. The data storage component provides a repository for storing large volumes of data collected from edge devices. The data processing component processes and cleans the data to remove noise and outliers. The data analytics component provides tools for extracting insights from the data using machine learning algorithms. The data visualization component provides a user interface for visualizing the data in real time.

**Application Layer:** This is the top layer in the architecture, which provides applications for end-users to access and manage the assets. The application layer can be accessed via web browsers or mobile devices. The applications can be used to monitor the health of the assets, schedule maintenance activities, and generate alerts and notifications in case of any abnormalities or malfunctions. The application layer can also provide dashboards and reports to enable decision-makers to gain insights into asset performance and optimize asset utilization.

### 3.1. Big data analytics for Asset Movement Predictions

Big data analytics is a powerful tool for predicting asset price movements because it allows for the analysis of large and diverse datasets, which can reveal patterns and insights that may not be apparent with smaller datasets. The problem of predicting asset price movements involves developing a model that can accurately forecast the direction and magnitude of changes in the price of an asset over a given time. This problem is important for investors and financial institutions who seek to make informed decisions about buying, selling and holding assets to maximize returns and minimize risk. To formulate this problem for machine learning, historical data on the asset's price movements, as well as any relevant economic, financial, or market indicators, can be collected and preprocessed to create a dataset suitable for training a predictive model. The dataset can be split into training and testing sets, and various machine learning algorithms. In our system, we consider the following algorithms for modeling asset movements.

#### 3.1.1. Logistic regression

Logistic regression is a type of regression analysis used for predicting the outcome of a categorical dependent variable (binary or multi-class) based on one or more predictor variables. It is commonly used in various fields including economics, psychology, marketing, and biomedical research. Unlike linear regression, which predicts a continuous outcome variable, logistic regression models the probability of a categorical outcome variable. The outcome variable is typically binary (0 or 1), where 0 represents the negative class and 1 represents the positive class. The logistic regression is computed as follows:

$$\log \left( \frac{\pi(y_j = 1|x_j)}{1 - \pi(y_j = 1|x_j)} \right) = \beta_0 + \beta x_j, \quad (1)$$

However, logistic regression can also be used for multi-class classification problems. Logistic regression works by transforming the linear regression equation into a logistic function, also known as the sigmoid function, which produces an S-shaped curve. The sigmoid function maps any input value to a range between 0 and 1, representing the probability of the positive class.

#### 3.1.2. Ridge regression

Ridge regression is a type of linear regression that uses L2 regularization to improve the performance of the model by reducing the magnitude of the coefficients. It is particularly useful when dealing with multicollinearity between the predictor variables, where some of the predictors are highly correlated with each other. Ridge regression is particularly useful when dealing with multicollinearity between the predictor variables, where some of the predictors are highly correlated with each other. In such cases, the coefficients of the correlated variables tend to be unstable and sensitive to small changes in the data. Ridge regression can help stabilize the coefficients and improve the model's performance.

$$J(\theta) = \frac{1}{m} \sum_{i=1}^m \text{Cost}(h_{\theta}(x^{(i)}), y^{(i)}) + \frac{\lambda}{2m} \sum_{j=1}^n \theta_j^2 \quad (2)$$

### 3.1.3. Lasso regression

Lasso (Least Absolute Shrinkage and Selection Operator) regression is a type of linear regression that performs both variable selection and regularization to improve the model's performance. It is commonly used in situations where there are many predictor variables, and some of them are likely to be irrelevant or redundant. In lasso regression, the objective is to minimize the sum of squared errors between the predicted values and the actual values, subject to a constraint on the sum of the absolute values of the model coefficients. This constraint helps to shrink the coefficients towards zero, effectively reducing the complexity of the model and avoiding overfitting. The amount of shrinkage is controlled by a hyperparameter called lambda ( $\lambda$ ). As  $\lambda$  increases, the coefficients are shrunk towards zero more aggressively, which can lead to a simpler model with fewer predictors. On the other hand, as  $\lambda$  decreases, the coefficients are allowed to take larger values, which can improve the model's fit but also increase the risk of overfitting. Lasso regression is particularly useful when dealing with high-dimensional data, where the number of predictor variables is much larger than the number of observations. It can also be used for feature selection, as the coefficients of the least important variables can be shrunk to zero, effectively removing them from the model. This can be expressed as follows:

$$\hat{\beta}_{\text{LASSO}} = \underset{\beta}{\text{argmin}} \left[ -l(\beta, y_j) + \lambda \sum_{j=1}^f |\beta_j| \right], \quad (3)$$

whereas  $f$  is the decreased number of features.

### 3.1.4. ElasticNet

ElasticNet is another linear regression method that combines the properties of both Lasso and Ridge regression. Like Lasso regression, it can perform variable selection and eliminate irrelevant features. Like Ridge regression, it can handle multicollinearity between the predictor variables. In ElasticNet, the objective is similar to the above regressors, subject to a constraint on the sum of the squares of the model coefficients and the sum of the absolute values of the coefficients.

$$\hat{\beta}_{\text{ENET}} = \underset{\beta}{\text{argmin}} \left[ -l(\beta, y_j) + \lambda \left( \frac{1-\alpha}{2} \sum_{j=1}^f |\beta_j|^2 + \alpha \sum_{j=1}^f |\beta_j| \right) \right], \quad (4)$$

The regularization parameter alpha,  $\alpha$ , controls the tradeoff between L1 (Lasso) and L2 (Ridge) regularization. When alpha is set to zero, ElasticNet becomes the same as ordinary least squares regression. When alpha is increased, ElasticNet shrinks the coefficients towards zero more aggressively and eliminates irrelevant features. The optimal value of alpha can be determined using cross-validation. ElasticNet is particularly useful in situations where there are many predictor variables, some of which are highly correlated with each other. It can handle multicollinearity better than Lasso regression alone, which tends to randomly select one of the highly correlated variables while ignoring the others. In contrast, ElasticNet tends to select groups of correlated variables together.

### 3.1.5. SGDRegressor

SGDRegressor is a machine learning algorithm used for regression problems that are based on stochastic gradient descent (SGD) optimization. It is a linear regression model that minimizes the mean squared error between the predicted and actual values of the target variable. The SGDRegressor algorithm works by iteratively updating the weights of the linear regression model based on the gradient of the loss function with respect to the weights. The loss function used is the mean squared error (MSE), which is the average of the squared differences between the predicted and actual values. During each iteration, a random subset of the training data (called a batch) is selected to update the weights. This approach reduces the computational requirements of the algorithm, making it more efficient for large datasets.

The SGDRegressor algorithm includes a number of hyperparameters that can be tuned to optimize its performance, including the learning rate, the regularization strength, and the number of iterations (or epochs) to perform.

#### 4. Results and Discussions

The dataset employed in modeling is obtained from Blyth et al. [19]. Returns on global equities, US treasury bills, bond risk premiums, inflation protection, and currency protection are included as parameters for linear modeling. Furthermore, in the dataset, real estate returns serve as the dependent variable  $y$  that we wish to model. The prediction performance of the proposed system is evaluated using the following metrics:

$$\text{Mean Square Error (MSE)} = \frac{1}{n} \sum_{i=1}^n (Y_t - \hat{Y}_t)^2 \quad (5)$$

$$\text{Root MSE (RMSE)} = \sqrt{\frac{1}{n} \sum_{i=1}^n (Y_t - \hat{Y}_t)^2} \quad (6)$$

$$\text{Mean Absolute Error (MAE)} = \frac{1}{n} \sum_{i=1}^n |Y_t - \hat{Y}_t| \quad (7)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (Y_t - \hat{Y}_t)^2}{\sum_{i=1}^n (Y_t - \bar{Y})^2} \quad (8)$$

Exploratory analysis is an important tool for asset management, as it allows for the identification of patterns and insights in data that can inform decision-making. The process involves defining the problem, gathering and cleaning data, examining basic statistics, and visualizing the data. Through exploratory analysis, asset managers can gain a better understanding of the performance of their assets, identify potential risks, and make more informed decisions about investment strategies. By leveraging the power of exploratory analysis, asset managers can make better use of the vast amounts of data at their disposal and gain a competitive edge in an increasingly complex and dynamic market. To this end, we provide a detailed analysis of the asset management data in Table 1.

Skewness is a measure of the asymmetry of a distribution of data. Thus, it is used as an important metric to provide insight into the shape of the distribution and potential outliers. More, Kurtosis is used to measure the peakedness and heaviness of the tails of a distribution of data. In Table 1, a high kurtosis value indicates that the distribution has heavy tails, meaning that there are relatively more data points far from the mean, while a low kurtosis value indicates that the tails are lighter, meaning that there are relatively fewer data points far from the mean. Cornish-Fisher Value at Risk (VaR) is a statistical method used in our exploration to guess the maximum potential loss in a portfolio over a specified time period with a certain level of confidence, typically expressed as a percentage. The reported values of 5% Cornish-Fisher VaR indicate that there is a 5% chance of a portfolio incurring losses greater than the VaR over the specified time period.

Table 1: summary statistics for the assets data used in our system.

	<b>Annualize d Return</b>	<b>Annualize d Vol</b>	<b>Skewnes s</b>	<b>Kurtosi s</b>	<b>Cornish -Fisher VaR (5%)</b>	<b>Historic CVaR (5%)</b>	<b>Sharpe Ratio</b>	<b>Max Drawdow n</b>
<b>World Equities</b>	0.114944	0.204657	-0.36959	4.26587 9	0.09067 4	0.11817 5	0.39242 6	-0.52862
<b>US Treasurie s</b>	0.123571	0.192394	0.304056	5.05093 6	0.09239 1	0.10536 1	0.52552 8	-0.10924
<b>Bond Risk Premium</b>	0.033026	0.223571	-0.51361	9.49557 6	0.10981 1	0.14171 9	-0.22003	-0.59489
<b>Inflation Protectio n</b>	0.031147	0.132202	0.310741	7.18492	0.10381	0.04686 6	-0.30554	-0.23474
<b>Currency Protectio n</b>	0.040037	0.077062	0.423651	4.50702 3	0.03108 7	0.07479 5	-0.20894	-0.19011
<b>Real Estate</b>	0.170329	0.196546	-0.24671	18.9554 6	0.13054 7	0.19853 8	0.33344 3	-0.64857

Currency Protection, Inflation Protection, and Bond Risk Premium assets have negative risk-adjusted returns (Sharpe Ratio) and are hence in the loss. Real Estate has caused the greatest financial loss among investors. The above analysis indicates the dates on which investors suffered the greatest loss of value in relation to each asset. During the worldwide economic downturn of 2007-09, both universal stocks (i.e., worldwide financial marketplaces) and real estate experienced their maximum decline. Bond Risk Premium appears to decline at the outset of the disaster but then stabilizes over time, as shown in Figure 2.

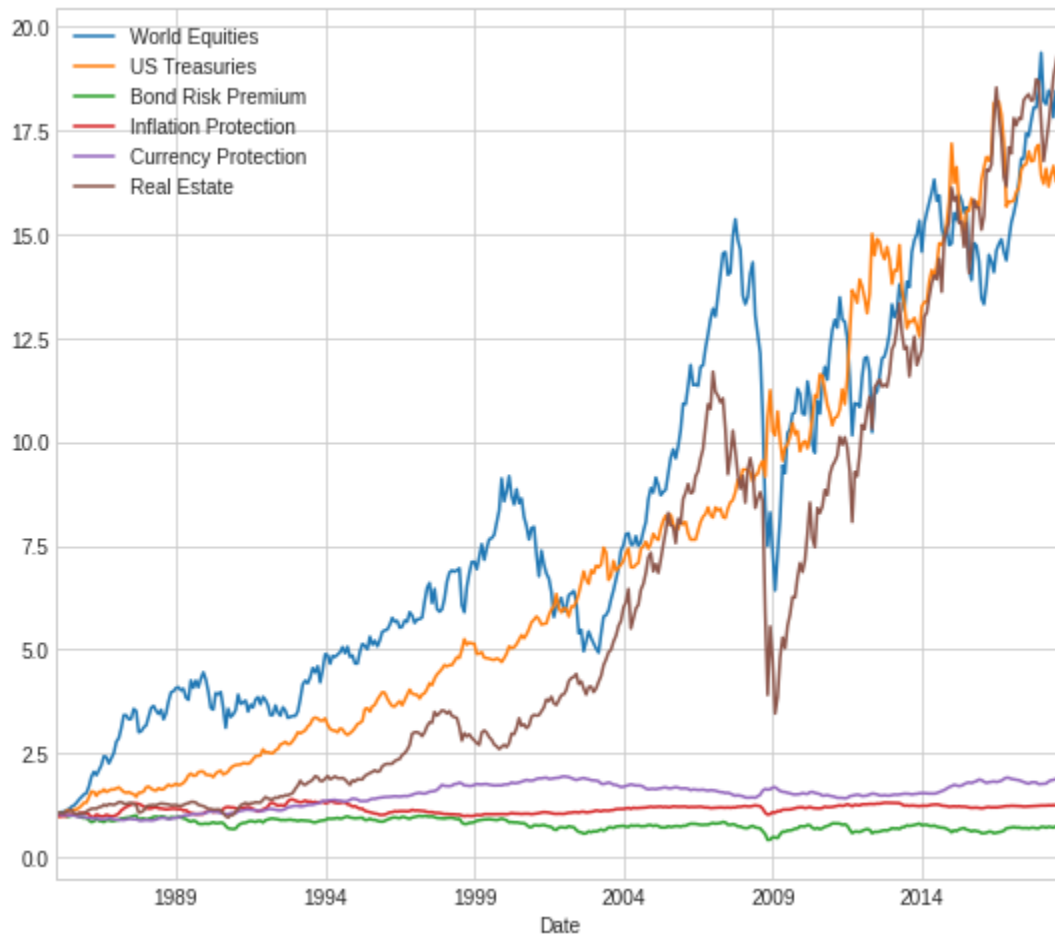


Figure 2: visualization of historical price changes for different assets

Herein, we seek to analyze the predictive power of Machine learning techniques in modeling asset price movements. Thus, we compare the prediction performance of different algorithms, as reported in Table 2. It could be noted that the Elastic Net can achieve the best prediction performance across different metrics. However, the difference between the performance of various algorithms remains marginal. We provide more investigation on the alpha parameters and their influence on performance in Figure 3. It could be noted that the alpha parameter is sensitive and require to be carefully selected.

Table 2: comparison between the prediction performance of different Machine learning techniques.

	MSE	MAE	R2
Lasso regression	0.001281	0.029101	0.038815
LogisticRegression	0.001913	0.014020	0.001175
Ridge regression	0.001335	0.029588	-0.001573
SGDRegressor	0.001299	0.029271	0.025543

Elastic Net	0.000483	0.00944	0.080683
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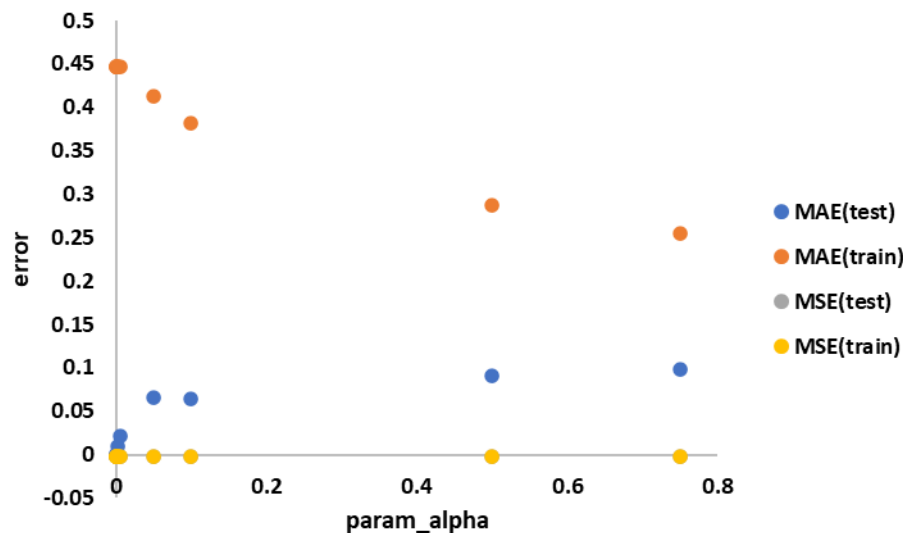


Figure 3: Illustration of the training and testing performance of the elastic net under different value of alpha.

## 5. Conclusion

In conclusion, this research proposes an IATS for the logistics industry using IoT and big data and offers a comprehensive and integrated solution for optimizing asset management and improving operational efficiency. The system leverages the power of connected devices and sensors to collect real-time data on asset location, condition, and status, which is then transmitted to a cloud-based platform for storage, processing, and analysis using big data analytics and machine learning algorithms. The system offers end-to-end visibility and control of assets throughout the logistics value chain, enabling companies to optimize routes and schedules, improve delivery times, and reduce maintenance costs. The system also offers predictive maintenance capabilities, enabling companies to identify potential issues before they occur and minimize downtime. Moreover, the system can generate alerts and notifications in case of any abnormalities or malfunctions, enabling proactive and timely responses. Simulated trials on real-world asset data confirmed the efficiency and efficacy of our system, making it a formidable candidate for asset tracking and management in genuine logistic sectors.

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