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Inventory Demand Forecasting Using Fractal –Chaos Theory with Data Mining and AI Technique

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ABSTRACT

Businesses evolve their priority to insights of predictive analytics as supply chains become more competitive every day in an attempt to minimize expenses and promote productivity and profitability. This study suggests a novel hybrid framework that integrated fractal notion based on the logistic map in chaos theory, combined with data mining and artificial intelligence techniques, to enhance forecasting accuracy. Chaos is generic term used to design numerous nonlinear dynamical systems that depend delicately on launching conditions. Such systems might be quite fundamental and always deterministic nevertheless they always produce behaviors that are completely unpredictable and divergent. By generating forecasts for a range of logistic map parameter (μ) values, enabling dynamic tuning of model behavior. This method shows promise as a potent tool for supply chain planning and inventory management by outperforming traditional models in terms of adapting to data volatility and uncertainty.

Keywords: Supply chain Management, Fractal, Chaos theory, Logistic map, Data mining, Artificial Intelligence.

AMS Classification: 90B06, 28A80, 97P80.

1. INTRODUCTION

Mathematicians interested in nonlinear dynamical systems study chaos theory. A system is just a collection of parts that work together to generate a greater whole. Nonlinear indicated that the whole is more than the sum of its parts because of feedback or multiplicative effects between the components. Basically, dynamical refers to how the system evolves over time in response to its present state. A nonlinear dynamical system is almost any nontrivial real-world system. Nonlinear dynamical systems, or chaotic systems, can have relatively few interacting components and simple rules, but they all have an extremely sensitive dependency on their initial conditions [1]. In the real world, a variety of seemingly unexpected data processing procedures are regularly encountered. Chaos theory argues that although we usually presume that data is generated randomly, some seemingly random sequences are actually the result of predictable laws. By analyzing seemingly unpredictable processes, chaos theory which has origins in both mathematics and physics can be utilized to comprehend the complexity of chaotic systems.

To establish the complexity of chaos theory using a logistic map equation. A logistic map is a degree two polynomial mapping that illustrates how complex chaotic behavior could arise using very simple logistic equations. The mapping gained popularity in the late 1970s as a discrete-time demographic model that was comparable to Pierre Francois Verhulst's logistic equation [2]. The logistic map, also known as a recurrence relation or polynomial mapping of degree 2, is sometimes cited as the classic illustration of how extremely basic nonlinear dynamical equations may give birth to complicated and chaotic behavior. The map was first used by Edward Lorenz in the 1960s to highlight irregular solutions. The biologist Robert May popularized the map in a 1976, partly as a discrete-time demographic model that was comparable to the logistic equation that Pierre Francois Verhulst had recorded [2].

The key features of a nonlinear system are its unpredictable outputs and sensitivity to initial conditions. A nonlinear difference equation represents the logistic map. Chaos often exhibits nonlinearity, which results in intricate and unexpected behavior. By adjusting the rate parameter, the logistic map displays several behavioral patterns by altering the parameters. When the value of rate parameter is low, the system stabilizes at a fixed point. If the value of rate parameter is raised, the system experiences bifurcations, which result in periodic and eventually chaotic behavior. A characteristic of chaotic systems, the bifurcation diagram, shows this process [3].

Companies desire to be able to fill orders quickly, with the fewest amount of inventory, and with an increasing spectrum of demands. They need to have a comprehensive understanding of the chain in order to optimize it as a whole [4]. Demand seasonality and future demand predictions are made easier with the implementation of forecasting techniques. Maintaining a low inventory level can also be beneficially achieved by forecasting [5]. Demand forecasting is an essential resource that the company can use to manage future uncertainty. When demand is seasonal, manufacturing capacity cannot keep up with peak demand. Consequently, production needs to start ahead of schedule based on sales forecasts. The primary goal of the current effort is to apply the logistic map in chaos theory to inventories for demand forecasting [4].

The logistic map is described in this piece as a basic model that can be used to introduce periodic orbits, bifurcations, and deterministic chaos, among other dynamical system traits. Essentially, it covers the logistic map activities after providing a brief mathematical and historical introduction to the recommended model. The extensive range of the growth rate parameter can be intricate, but they are essential for understanding and forecasting system dynamics like demand fluctuations [8].

A logical method for searching through vast amounts of data to located relevant information is named as data mining. Finding previously undisclosed patterns is the aim of this system. An approach to keeping and modifying this treasured data for future decision-making has arose as a result of database and information technology exploration. [6]. The process of gleaning intriguing hidden information form accessible data chunks that might otherwise be impossible to manually extract is commonly referred to as data mining. Despite the fact that this description presents a rather unvamished picture of data mining, the idea has previously been defined in a variety of ways. The term "Knowledge Discovery in Databases" was first used in the first knowledge Discovery in Databases (KDD) work ship (1989), which is why there are different definitions of the term. Because knowledge is the end result of data mining, researchers and authors have since linked KD to data mining, with some arguing that the terms have the same meaning [7].

Recent years have seen a significant increase in production complexity as a result of growing consumer demands for specific products. Simultaneously, extensive, detailed production data has been recorded as a result of on-going digitization. According to research, employing data mining techniques on production data can result in efficient management of production complexity. Manufacturing firms, on the other hand, rarely employ these data mining techniques to aid in the use of data mining by manufacturing companies [9].

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2. METHODOLOGY

2.1 Data Collection

Daily sales and production data for an elected product in a manufacturing company, gathered over a 3-month period (for example October to December). Each variable has approximately 90 records in the dataset represents the actual sales and production amount that were noted at the end of each day. This study main goal is to create a reliable and accurate forecasting model for estimating future production and sales values through a hybrid approach. The model attempts to capture both deterministic nonlinear dynamics and statistical patterns disguised in historical data by fusing data mining methods and artificial intelligence (AI) algorithms with the logistic map from chaos theory.

2.2 Logistic Map

Fractal dimension is typically used to quantify a pattern or shape's self-similarity or complexity. The fractal dimension is a numerical value that represents the self-similarity, scaling and complexity of a pattern. In the context of replenishment policy analysis, the fractal dimension helps explain the complexity and predictability of demand patterns, which helps in decision-making. A greater fractal dimension indicates a more complex and unpredictable demand pattern. The logistic map is discrete time dynamical system and mathematical model that illustrates the evolution of a population over time. And when the value of μ fluctuates this type of straightforward equation reveals a complex character. The equation

$$X_{n+1} = \mu X_n(1 - X_n) \tag{1}$$

represents the well-known logistic equation. Here, μ denotes the control parameter, X_n is the past value, and X_{n+1} is the present value. An indicator of the species' favourable and unfavourable conditions is the coefficient μ. At 0, μ has the least value. The value of X grew beyond unity for μ values greater than *4*.

Applications of the logistic map, a mathematical function derived from chaos theory, to inventory management include supply chain modelling demand forecasting, inventory optimization, inventory control, and fractal inventory management.

2.3 Data Mining Method

Data mining approaches are incorporated into the forecasting model, in this study to progress the precision and dependability of future demand prognostications. This is a detailed explanation of data mining methods. Here, flowchart 2.3.1 provides an outline of the data mining techniques.

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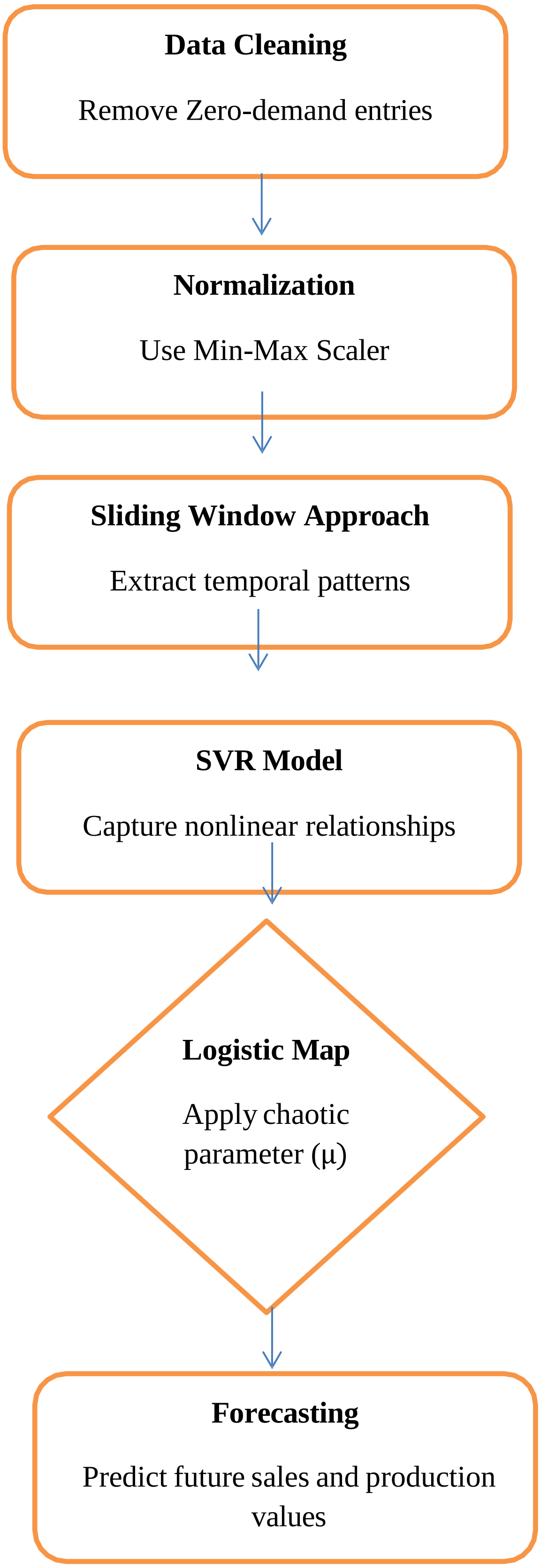

Figure 2.3.1 Flow chart of Data Mining Process

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2.4 Artificial Intelligence

Support Vector Regression (SVR) technique integrates artificial intelligence to predict future production and sales based on historical data trends. The SVR model can learn intricate, nonlinear patterns because it is trained on normalized historical demand using a time-based windowing technique. To replicate demand variability in the real world, this AI model is further coupled with a logistic map. By combining mathematical modeling and data-driven learning, the hybrid approach increases prediction accuracy and facilitates more intelligent and reliable forecasting.

3. NUMERICAL EXAMPLE

The numerical example uses a dataset of daily production and sales data that gathered over a three-month period (October to December 2020). Realistic demand variations that are frequently seen in operational settings are reflected in this data, including erratic peaks and sporadic days with no demand due to holidays or other disruptions. To ensure consistency and prevent noise during training, only the non-zero sales records were kept for modeling purposes. A Support Vector Regression (SVR) model is trained using the normalized dataset. By using logistic map, the model is improved to include nonlinear behavior and possible chaotic trends in the demand. This approach allowed for the analysis of several demand behaviors under different values of the logistic map's control parameter (μ) by forecasting demand for the next ninety days (January to March 2021) based on historic demand patterns.

4. RESULTS AND DISCUSSION

After cleaning and normalizing daily demand data from October to December 2020, a hybrid model that combined the logistic map and Support Vector Regressions (SVR) is used to forecast demand. A 90 days forecast value is generated for five distinct values of the logistic map parameter μ : 0.8, 2.5, 3.7, 3.9, and 4.0, excluding holidays (demand=0). The model iteratively produced forecasts over a 90 day horizon using the last three month daily demand and production based data. Figure X displays the expected demand trends for each μ value, while Y displays the specific daily values.

The result shows that, depending on the μ value, the predicted demand shows different patterns. Less chaotic dynamics were indicated by the forecasts' rapid convergence and relative stability for lower values, such as μ=0.8 and μ= 2.5. Higher μ values, particularly those close to 4.0, on the other hand, produced forecasts that were more erratic and oscillatory, capturing intricate and potentially realistic demand fluctuations. This behavior aligns with the logistic map's known bifurcation and chaotic behavior. Below Figure displays the Actual sales and Forecast sales values. This visual representation illustrates the behavior of demand value to corresponding different μ values, revealing the model's sensitivity and adaptability. Notably, the forecast effectively simulates real-world demand irregularities as μ rises, moving from steady-state predictions to oscillatory and even chaotic dynamics.

This nonlinear response illustrates how the logistic–SVR hybrid not only fits historical trends but also dynamically reshapes its output based on μ, providing a powerful tool for tailoring forecast to different inventory environments, whether stable, seasonal, or highly volatile. Tables 4.1 indicate daily forecasted demand value generated by different value of control parameter (μ).

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Table 4.1 Predicted result of Next Three Months

Day	μ=0.8	μ=2.5	μ=3.7	μ=3.9	μ=4.0
1	144.84	126.57	109.99	106.99	105.47
2	144.84	126.57	109.99	106.99	105.47
3	144.84	126.57	109.99	106.99	105.47
4	144.84	126.57	109.99	106.99	105.47
5	144.84	126.57	109.99	106.99	105.47
6	144.84	126.57	109.99	106.99	105.47
7	144.84	126.57	109.99	106.99	105.47
8	137.67	144.92	165.46	172.7	176.45
9	137.67	144.73	155.86	152	151.43
10	137.67	144.74	159.24	157.39	154.27
11	137.67	144.76	164.49	168.21	168.23
12	137.67	144.76	160.77	164.9	170.23
13	137.67	144.76	157.89	155.01	152.44
14	137.67	144.76	162.16	164.3	162.53
15	137.67	144.76	162.84	167.95	170.35
16	137.67	144.76	159.04	157.74	160.07
17	137.67	144.76	160.26	160.39	158.08
18	137.67	144.76	162.64	167.21	168.39
19	137.67	144.76	160.85	162.81	166.59
20	137.67	144.76	159.64	158.1	155.63
21	137.67	144.76	161.59	164.91	164.93
22	137.67	144.76	161.79	165.95	169.25
23	137.67	144.76	160.12	158.68	158.16
24	137.67	144.76	160.7	162.06	160.91
25	137.67	144.76	161.76	166.42	168.74
26	137.67	144.76	160.89	161.63	163.6
27	137.67	144.76	160.39	159.9	157.73
28	137.67	144.76	161.3	165.17	166.55
29	137.67	144.76	161.33	164.43	167.62
30	137.67	144.76	160.59	159.5	157.44
31	137.67	144.76	160.87	163.11	163.19
32	137.67	144.76	161.35	165.58	168.68
33	137.67	144.76	160.93	161.06	160.99
34	137.67	144.76	160.72	161.19	159.81
35	137.67	144.76	161.14	165.14	167.6
36	137.67	144.76	161.13	163.29	165.45
37	137.67	144.76	160.8	160.31	157.86
38	137.67	144.76	160.94	163.75	165.08
39	137.67	144.76	161.15	164.73	168
40	137.67	144.76	160.95	160.93	159.15
41	137.67	144.76	160.87	162.14	161.86
42	137.67	144.76	161.06	164.89	168.1
43	137.67	144.76	161.05	162.51	163.04
44	137.67	144.76	160.9	161.08	159.1
45	137.67	144.76	160.97	164.08	166.51

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46	137.67	144.76	161.06	163.94	166.6
47	137.67	144.76	160.97	161.08	158.42
48	137.67	144.76	160.93	162.82	163.77
49	137.67	144.76	161.02	164.5	168.02
50	137.67	144.76	161.01	162.06	160.83
51	137.67	144.76	160.95	161.76	160.78
52	137.67	144.76	160.98	164.16	167.43
53	137.67	144.76	161.02	163.29	164.62
54	137.67	144.76	160.98	161.39	158.79
55	137.67	144.76	160.96	163.27	165.42
56	137.67	144.76	161	164.05	167.27
57	137.67	144.76	161	161.87	159.34
58	137.67	144.76	160.97	162.32	162.58
59	137.67	144.76	160.99	164.08	167.8
60	137.67	144.76	161	162.81	162.43
61	137.67	144.76	160.98	161.77	159.95
62	137.67	144.76	160.98	163.52	166.65
63	137.67	144.76	160.99	163.6	165.82
64	137.67	144.76	160.99	161.88	158.88
65	137.67	144.76	160.98	162.75	164.31
66	137.67	144.76	160.99	163.88	167.58
67	137.67	144.76	160.99	162.5	160.52
68	137.67	144.76	160.98	162.15	161.53
69	137.67	144.76	160.98	163.62	167.4
70	137.67	144.76	160.99	163.22	163.88
71	137.67	144.76	160.99	162.01	159.42
72	137.67	144.76	160.98	163.04	165.77
73	137.67	144.76	160.99	163.63	166.66
74	137.67	144.76	160.99	162.35	159.38
75	137.67	144.76	160.98	162.48	163.22
76	137.67	144.76	160.98	163.6	167.6
77	137.67	144.76	160.99	162.92	161.84
78	137.67	144.76	160.99	162.2	160.63
79	137.67	144.76	160.98	163.22	166.83
80	137.67	144.76	160.99	163.37	165.11
81	137.67	144.76	160.99	162.32	159.22
82	137.67	144.76	160.99	162.74	164.81
83	137.67	144.76	160.99	163.5	167.18
84	137.67	144.76	160.99	162.72	160.21
85	137.67	144.76	160.99	162.41	162.19
86	137.67	144.76	160.99	163.3	167.39
87	137.67	144.76	160.99	163.14	163.17
88	137.67	144.76	160.99	162.37	159.95
89	137.67	144.76	160.99	162.94	166.11
90	137.67	144.76	160.99	163.36	166.08

Figure 4.1 represents predicted demand for January-march 2021 generated using by the logistic map-SVR model across different control parameter (μ) values.

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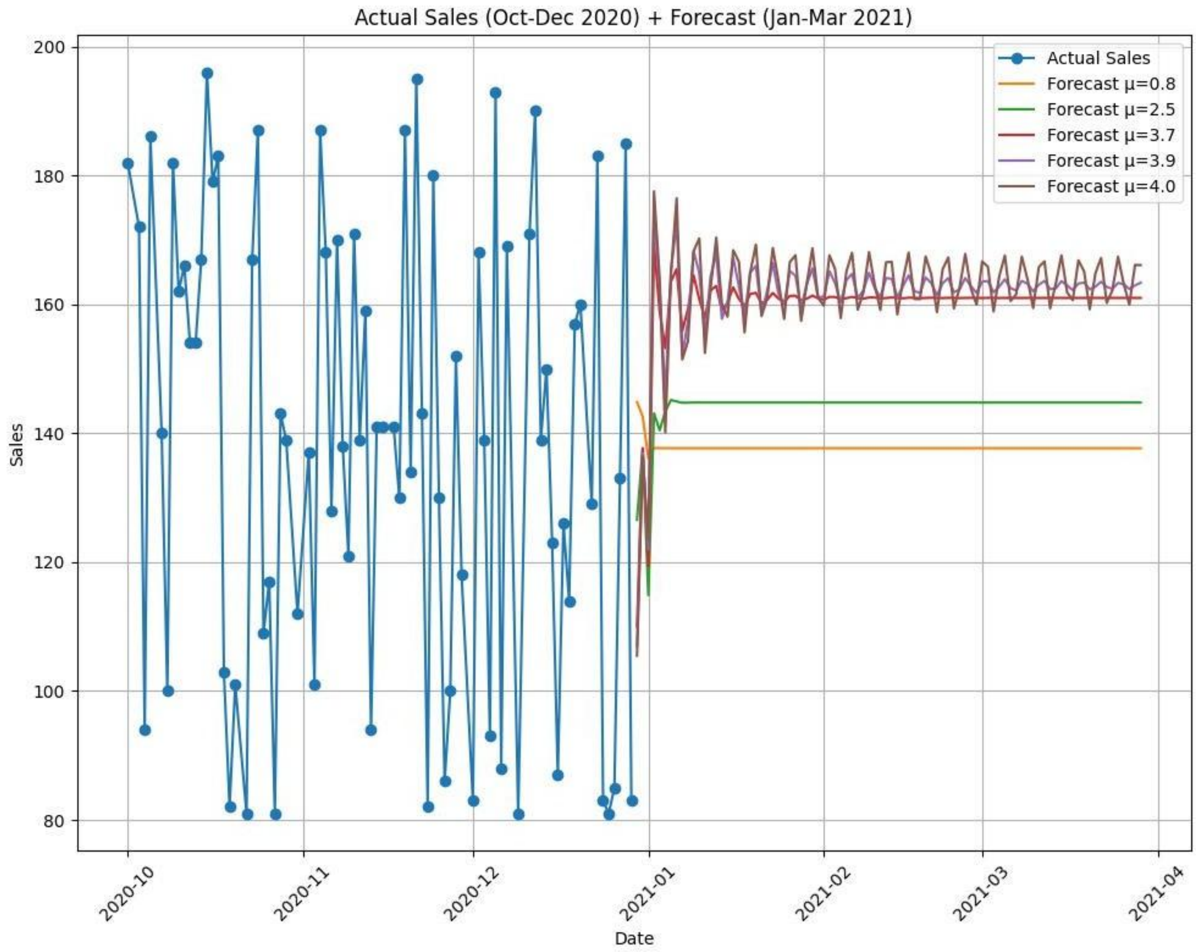

Figure 4.1 –Actual and Predicted Sales

The figure 4.1 present a comparison between the demands forecasted for the next three months using various logistic map parameter (μ) values and the actual sales data from the previous three months. With each line signifying a unique prediction scenario, it graphically illustrates how the predicted trends change based on the selected value.

5. CONCLUSION

In order to predict future demand, the study effectively illustrated a hybrid forecasting model that combines the logistic map and SVR. The model's prediction behavior appeared to be significantly impacted by varying values of the control parameter - μ, which ranged from 0.8 to 4.0 introducing controlled chaos, simulating realistic fluctuations. μ Values of 0.8 and 2.5 produced smoother, more stable forecasts. Depending on the forecasting context, this dual behavior can be advantageous. While higher values can model volatility in uncertain environments, lower values may be ideal for stable markets. The method works well for short-term inventory demand forecasting in nonlinear systems and is adaptable and reliable.

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