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Judgmental Forecasting Uses Agent-Based Modeling and Simulation to Minimize Risks and Losses in Decision-Making

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Abstract. *Forecasting is widely used in many aspects of human life whether it is informal for personal use or formal in organizations or institutions. This study delves into the utilization of judgmental forecasting in determining the ideal number of orders to restock inventory to supply to the restaurant. Through modeling and simulation, this research aims to mitigate uncertainties, reduce risks, and prevent losses. By quantifying the owner's mood, this study comprehensively analyzes the total cost of calculations based on decision-making theories and the mood of the decision-maker. The research employs the NetLogo simulation tool, which is commonly utilized in creating agent-based models and simulations. After conducting five simulations with 1000 data points each, it was discovered that relying on mood for decision-making resulted in a higher total cost ranging from 0.44% to 45% compared to the theoretically calculated cost. Mood-based decision-making is generally riskier and incurs cost losses.*

Keywords: *agent-based modeling; decision making; economic order quantity; judgmental; simulation*

I. INTRODUCTION

There were nearly 4 million small businesses in food and beverage activities based on the 2016 economic census in Indonesia. Some of them were successful and could have grown their business from one restaurant to several restaurants. Even though they can develop their business from one to several, in general, everything is regulated and determined and even a lot is still done by the owner himself.

The theory of forecasting is based on the premise that current and past knowledge can be used to make predictions (Petropoulos et al., 2022). The activities of forecasting are not as simple as we think, they are the process of predicting future values. In general, forecasting is divided into 2 methods (Zellner et al., 2021), human judgment (qualitative methods): probability elicitation, incentive systems, calibration and training, scoring rules, Delphi, focus groups, nominal group technique, and quantitative methods: moving average, exponential smoothing, Autoregressive Integrated Moving Average (ARIMA), naïve approach, time-series decomposition, regression methods, Neural Networks, Bayesian Networks, ensemble methods and simulation.

There is competition M4 (Makridakis et al., 2020) and M5 (Makridakis et al., 2022) i.e. which is aiming to advance the theory and practice of forecasting, exponential smoothing (ETS) and Autoregressive Integrated Moving Average (ARIMA) are used as standards for comparison the performance of the approaches that were submitted by participating teams.

Some scientific papers apply machine learning as a method for forecasting. Machine learning based applied to forecasting include Long Short Term Memory Networks (LSTM) (Schmidt et al., 2022), (Wiranda & Sadikin, 2019), (Ensafi et al., 2022), Random Forest (Dudek, 2022), (Tanizaki et al., 2020), Distributed Random Forest (Islam & Amin, 2020), and tree-based forecasting (Januschowski et al., 2022). In general, many researchers take a hybrid approach with machine learning to do forecasting such as (Vavliakis et al., 2021), (Ensafi et al., 2022) combining ARIMA and LSTM.

In measuring the accuracy of forecasting usually uses models such as Mean Absolute Percentage Error (MAPE), which measures relative

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Table 1. Advantages and disadvantages of measurement models

No	Models	Advantages	Disadvantages
1	MAPE	Independent of the scale of the variable.	Bias since prefer to select too low results.
2	MAE	Simple and measured performance. Less sensitive towards outliers.	Weighted all errors equally when computing the mean.
3	RMSE	Easily differentiable and computationally straightforward.	Sensitive to outliers.

bias; Mean Absolute Error (MAE), which capturing the absolute magnitude of error; and Root Mean Square Error (RMSE), which additionally penalizes large errors (Bijak et al., 2019).

The use of these measurement models has its own advantages and disadvantages (Jadon et al., 2022), which can be summarized as in the Table 1.

Many studies that focus on judgmental forecasting tend to rely on quantitative methods, even though such methods may not always be the most appropriate for the task at hand. The related literature in modeling judgmental forecasting, especially forecasting is related to restaurants (Schmidt et al., 2022), (Posch et al., 2022), (Holmberg & Halldén, 2018), (Nazmuz Sakib, 2021), (Tanizaki et al., 2019), (Athey et al., 2018),(Tsoumakas, 2019) are mostly using machine learning techniques for predicting restaurant sales forecasting, while judgmental forecasting is making forecasts in a system that is carried out by humans which is influenced by various interacting and complex factors. The increasing complexity of a system could result in uncertainty and risk. This increasing complexity phenomenon that is difficult to predict is also known as emergence. One of the ways to overcome this problem is by creating a simulation model using a computer based on real conditions.

System properties that are formed due to interactions between components are emergent properties that can be in the form of patterns, spaces, or numbers. Modeling methods that can be used to model emergence are agent-based modeling and simulation (ABMS). ABMS has several advantages such as being flexible, describing a system naturally in addition to capturing emergent phenomena (Bonabeau, 2002). Another advantage of ABMS is that it does not require expensive costs in addition to reducing or avoiding high risks that can arise or occur.

Restaurants situated within malls typically witness a surge in sales over the weekends and national holidays in contrast to weekdays. Hence, it is imperative for the management to closely monitor the sales cycle at each location to prevent overstocking or understocking of perishable inventory. Nevertheless, business owners tend to rely on their past experiences and intuition while forecasting inventory requirements. However, such human judgmental forecasting poses significant risks and cannot always yield satisfactory or profitable results for their establishments.

Therefore, this study aims to mitigate uncertainties, reduce risks, and prevent losses in judgmental forecasting by using agent-based modeling and simulation.

II. RESEARCH METHOD

This research is centered on small and medium-sized businesses in the food and beverage industry, which have been growing in number steadily over the years. The study makes use of agent-based modeling and simulation (ABMS) and Economic Order Quantity (EOQ) methodology. The steps of the study are illustrated in Figure 1.

The components in ABMS are agent, environment, interaction, and emergence. An agent is an autonomous entity with attributes and behaviors that differ from one agent to another. The environment is the place where the agent is located. Interaction is where agents communicate with each other and can influence each other. Emergent properties or emergent behavior are system properties that arise due to interactions

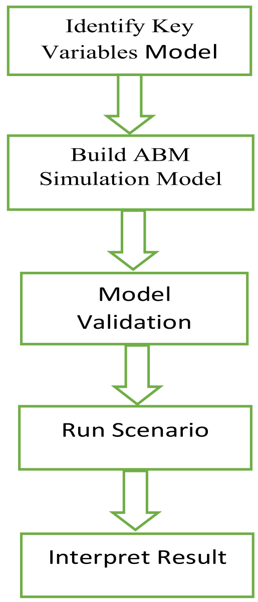

Figure 1. Steps of the study

that occur between elements (Maya Sopha & Sakti, 2020).

There is a platform-independent and open-source application for creating agent-based models and simulations that is quite popular, called NetLogo. It was authored by Uri Wilensky in 1999 and has been in continuous development ever since at Northwestern's Center for Connected Learning and Computer-Based Modeling (Wilensky, 1999).

NetLogo is particularly well suited for modeling complex systems developing over time. Modelers can give instructions to hundreds or thousands of "agents" all operating independently. This makes it possible to explore the connection between the micro-level behavior of individuals and the macro-level patterns that emerge from their interaction.

A business generally has a stock of goods or items which are used in operation. Inventory has an important role in the operations of a company or organization. If a company has inventory, there will be what are known as ordering costs and holding costs and all of them will be the total cost of inventory. Holding costs are not only limited to warehouse operating costs, but can also include costs such as insurance, bank interest, obsolescence and shrinkage costs. This cost is usually in the form of a percentage of the product's unit cost.

The company tries to minimize the total cost so that it purchases with the optimal number of orders or what is known as the Economic Order Quantity (EOQ) theory. The two components that make up the total cost, namely ordering costs and holding costs, are calculated using the following formula (Liu, 2022) :

$$\textit{Total holding costs} = H_c \times Q / 2 \qquad \text{.... (1)}$$

$$\textit{Total ordering costs} = O_c \times D / Q \qquad \text{..... (2)}$$

$$\textit{Total Cost} = \textit{Total holding costs} + \textit{Total ordering costs} \qquad \text{..... (3)}$$

$$EOQ = \sqrt{\frac{2\,Oc\,D}{Hc}} \qquad \text{..... (4)}$$

In (1) Hc is the holding cost (or sometimes called carrying cost) per unit per year, while Q is order quantity. D is annual demand and Oc is ordering cost in (2). By adding total holding costs (1) and total ordering costs (2), we get total cost (3). Use (4) to get Economic Order Quantity.

Then, in the next step which is identifying key variables, we interviewed the owner of the restaurant and some of the supervisors of the restaurants. In this judgmental forecasting study, we focus on decision-making in terms of inventory forecasting decisions. Data and information that we gathered from the owner and the supervisors are selected for the candidate of key variables.

After determining the key variables is build ABM model by using NetLogo as the tool for creating the model and simulation. Before building the model we have to determine the goal of the model and determine the components in ABMS i.e. agent including attribute and the behavior, environment, interaction, and emergence. The purpose of making this judgmental forecasting model is to understand how the owner's mechanism in determining the purchase of restaurant inventory so that no excess or shortage of stock can cause losses, and to understand what variables or parameters affect judgmental forecasting. The agents in this model are restaurant owners. The owner has a great deal of control in running the business even though it has its branches.

Agent attributes include demand, ordering cost, holding cost, economic order quantity, total cost, whether weekdays or weekends, and qualitative variables i.e. the owner's behavior in the form of being happy or unhappy. Agent behavior consists of processing requests, calculating total cost, and determining economic order quantity. Environmental characteristics of agents and visualizing the behavior of the owner whether he is happy or unhappy. Parameters for this model include weekdays, weekends, or holidays. The emergence indicator used to evaluate this phenomenon is the agent reaction and the size of the agent. If the agent is happy, they will appear with a smiling face and vice versa, if they are unhappy, they will appear with a sad face. Red agents mean holidays or weekends, while blue means weekdays. As a first step to introduce modeling for the restaurant owner, we propose a model of Economic Order Quantity with the variables happy or unhappy and variables weekends or weekdays as a measurement in determining judgmental forecasting in decision-making so far. Based on the owner's custom, if it is a holiday and the owner is happy, then the order determination will be judged at around 10 percent higher than the demand and if the owner is unhappy, it will be judged at 80 percent of the request. Meanwhile, if the demand is for weekdays, and the owner is happy, only 60 percent of the demand will be judged, and 40 percent if he is unhappy. The interface of the EOQ simulation model for this study is proposed as described in Figure 2.

In the simulation model, various value conditions for demand, ordering costs and carrying costs (holding costs) can be carried out so that the optimal order quantity with minimum total cost is obtained for the restaurant owner. All demand, ordering cost, carrying cost sliders including weekend and happy switches can be adjusted on the fly.

There are two ways to run this simulation, i.e. by doing it one by one using the Go Step button, or it can be run automatically using the Go button so we just have to change the variable demand, ordering cost, carrying cost, weekend, weekday by choosing a happy state or unhappy.

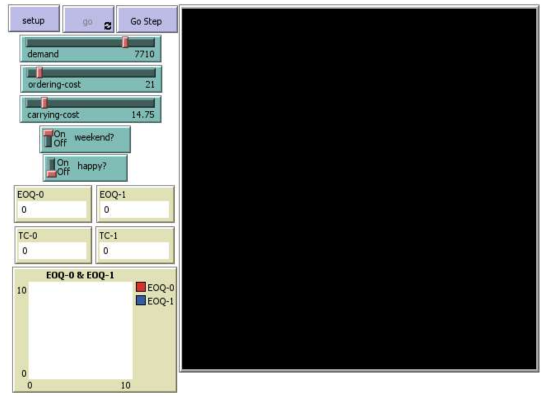

Figure 2. Interface of EOQ Model Simulation

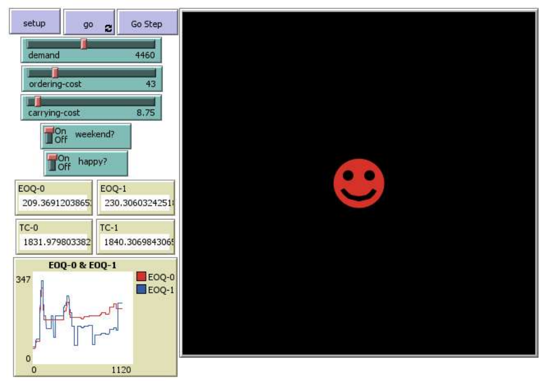

Figure 3. Scenario of simulation 2 result

The results of the simulation can be seen on the monitor and the plot. EOQ-0 and TC-0 for normal EOQ and EOQ-1 and TC-1 are EOQ and total cost (TC) based on variables weekends or weekdays and happy or unhappy. The comparison between normal EOQ and judgmental EOQ is plotted in real mode when the simulation is running on the EOQ-0 & EOQ-1 panel. Reordering inventory for a restaurant is very important. If the order for perishable items is too large and unsold, then it is certain that the owner will bear the loss, and it will become a food waste problem.

There are three validation frameworks (Hunter & Kelleher, 2020) that can be used for this step. The first validation is cross validation which is using the results of another previously validated model as a baseline. The second validation i.e. sensitivity analysis is using various scenarios to see the results with various changes to inputs or parameters. We can proceed the step with different scenario for several times. The third validation framework is to compare to real data. If the model is not valid, we have to go back to the build step for improvement until the model is valid. This study was using the sensitivity analysis by changing the inputs or parameters with various values.

During our research study, we designed and implemented a series of five distinct scenarios to validate the proposed model. Each scenario was constructed with varying parameters, and the simulation run was limited to 1000 steps for each scenario. We aimed to assess the effectiveness and accuracy of the model under different input conditions and to determine its overall robustness and adaptability. The results of our analysis will provide valuable insights into the potential applications and limitations of the model and will help guide future research in this area.

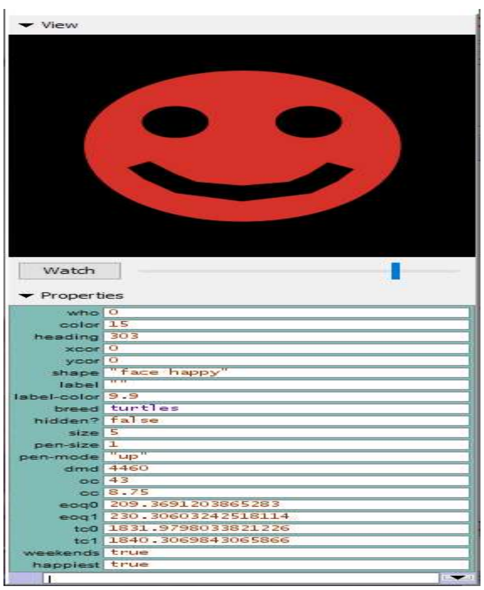

Figure 4. Agent inspection of Simulation 2

III. RESULT AND DISCUSSION

Simulation Result: Below is the result of interface for the model used in Simulation 2. This scenario involves 1000 steps and factors in various elements such as demand, ordering cost, carrying cost, and whether orders are placed on the weekend or weekday. Additionally, the owner's happiness level is also taken into consideration. Figure 3 depicts the agent in red and smiling, indicating that the order quantity is for the weekend and the owner is content. The most recent demand was 4460, with an ordering cost of 43 and a carrying cost of 8.75. The normal EOQ-0 and TC-0 are 210 and 1832, respectively. The judgmental EOQ-1 and TC-1 are 231 and 1840.

To further analyze the results, one can examine the agent to determine demand, ordering cost, carrying cost, and the normal EOQ calculated through formula (4). Additionally, comparisons can be made between EOQ based on variables such as weekends or weekdays and the owner's satisfaction level. Figure 4 presents a sample agent inspection from simulation 2.

Utilizing a simulation model, restaurant owners can identify the ideal order quantity by manipulating demand, ordering costs, and carrying costs to minimize overall expenses.

Model Validation: To confirm the accuracy of our model, we conducted a series of simulations across five distinct scenarios, identified as Simulation 1 through Simulation 5. Each simulation was designed to reflect differing levels of demand (dmd), ordering cost (oc), and carrying cost (cc), while also incorporating unique combinations of weekdays/weekends and satisfied/dissatisfied customers. Across 1000 individual steps, we carefully monitored each simulation, and the resulting data is presented in Table 2.

Simulation 1 with demand value of dmd 2100, ordering cost (oc) 14, carrying cost (cc) 5, on weekend = True and the mood of the owner unhappy (happy = False) will give normal EOQ (eoq0) 108 with normal Total Cost (tc0) 542. Based on the mood of the owner, he will judge 87 for EOQ (eoq1) and the value of the Total Cost (tc1) will be 556. From this simulation it will be clearly seen that in terms of total costs the owner will bear higher costs about 2.58 %. It could be worse if we look at the total cost in simulation 4 where normal total cost is 4578 and the total cost with the judgment of the owner is 6638. The total cost is higher about 45 % of the normal total cost

Table 2. Summary of the simulation results

Properties	Simulation 1	Simumation 2	Simulation 3	Simulation 4	Simulation 5
dmd	2100	4460	7200	7770	5910
oc	14	43	57	58	87
cc	5	8.75	14.75	23.25	23.25
weekends	True	True	False	False	True
happy	False	True	True	False	True
eoq0	108	209	236	197	210
eoq1	87	230	142	79	231
tc0	542	1832	3480	4578	4890
tc1	556	1840	3943	6638	4912

Table 3. Simulation results of variable mood and days (in %)

Variables	Simulation 1	Simumation 2	Simulation 3	Simulation 4	Simulation 5
Cost	2.58	0.44	13.30	45.00	0.45
Weekend-happy	5	40	72	18	100
Weekend-unhappy	79	25	9	10	0
Weekday-happy	3	29	13	67	0
Weekday-unhappy	13	7	6	5	0

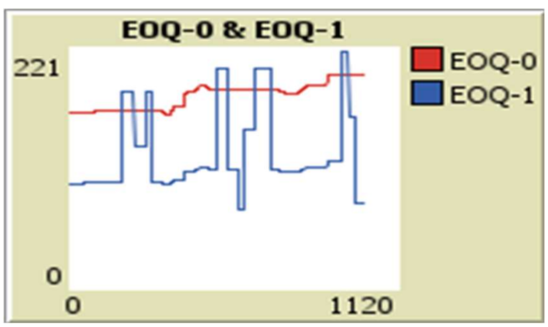

Figure 5. The plotting of Simulation 4

calculation. If we plot the graph of simulation 4 will be depicted as in the Figure 5.

Interpretation of Result: In the simulation, the process begins on the left and progresses towards the right for a maximum of one thousand steps. As shown in Figure 5, the final step on the right exhibits a notable discrepancy between the typical EOQ depicted by the red line and the EOQ determined by the owner's judgment represented by the blue line. Further examination of the data in Figure 5 discloses that it comprises 18% instances on joyful weekends, 10% instances on gloomy weekends, 67% on joyous weekdays, and 5% on unhappy weekdays. Table 3 offers an overview of the outcomes for the various simulation components concerning mood and days.

The variables for cost are displayed in Table 3, determined by the disparity between the complete expenses of regular EOQ and judgmental EOQ. According to simulations 1 through 5, the overall cost of judgmental EOQ (tc1) exceeded that of normal EOQ (tc0).

IV. CONCLUSION

In summary, relying solely on emotions to make business decisions can lead to substantial financial setbacks, varying from a slight 0.44% decrease to a staggering 45% of overall expenditures. To mitigate potential risks and losses, it is recommended to construct agent-based models and conduct simulations before making consequential decisions. This method lessens uncertainties and permits more knowledgeable decisions, resulting in more favorable outcomes.

The purpose of this paper is to propose the implementation of agent-based modeling and simulation techniques in the field of judgmental forecasting. Given that effective forecasting often depends on the intuition and actions of decision-makers, this approach offers a promising avenue for improving accuracy and reliability. However, it is important to note that the study is limited in its scope, as it has yet to establish parameters for gauging additional emotional states that may affect decision-making. Given the complex and multifaceted nature of human decision-making, it is imperative that future research endeavors to measure these factors to enhance the efficacy of critical decision-making processes.

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