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DEVELOPMENT OF FUZZY LOGIC APPROACH TO OPTIMIZE SAFETY STOCK LEVEL IN DETERIORATED PRODUCTS/A SUPPLY CHAIN DAIRY INDUSTRIES CASE STUDY

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Abstract: In today's complex environment, a high responding ability represents a core for each organization to survive in a competitive environment. To grip your position in intense competition market, the organization must design high efficiency inventory system that has the ability to respond to changes in demand and at the same time reduce holding cost of accommodation to the lowest possible value by controlling inventory drivers such as safety stock level (SS). The traditional approaches of safety stock are limited to deal with dynamic behavior of market. Advanced approaches based on soft computing allow the dynamic updating of SS level. In this paper, a highly advanced dynamic fuzzy logic (DFL) has been suggested as an innovation step to identify safety stock level in dairy industries with objective of minimizing total cost and meet with customer requirements. The proposed approach consists of three main steps firstly, identifying demand uncertainty conditions by applying fuzzy logic steps embedded by identifying dynamic (N) factor which represents the increasing level in demand in period time. Secondly, identifying of raw material availability conditions by applying fuzzy logic steps, and finally, identification of inventory on hand conditions by applying fuzzy logic steps. It is necessary to identify the level of SS dynamically in fuzzy logic as an output embedded with identifying of period specification concept which describes states of demand in a specific period in which the demand is high, medium, or low which leads to identify maximum values of universe of discourse of output (safety stock). Here Matlab program was used. The provided solution demonstrates the proposed model validity. There has been a significant reduction in safety stock level ranging from (7-98)% depending on product type and period specification with a reduction also in holding cost, while keeping the requirements fulfillment of customers demand.

Key words: *dynamic fuzzy logic, Inventory optimization, safety stock, dairy industries, supply chain.*

INTRODUCTION:

Deterioration is defined as decay, damage, spoilage, or perishability and its effect cannot be disregarded in inventory models(Yang & Tseng, 2015). The performance of supply chain is greatly affected by the inventory policy followed by organizations (Beheshti, 2010). So, if inventory strategy is poor, this will lead to high burdened enterprises and high holding costs. Therefore, many organizations work to find the most suitable inventory strategy (Yang & Tseng, 2015). The shelf life of perishable products like meat , fruits, and dairy or any cooked vegetable, or grain products depends upon the specification of products and environment conditions in which that products are stored, so an efficient system of inventory is a crucial element to ensure that the products are still fresh and satisfy the customer's demand efficiently(Chiadamrong & Lhamo, 2017). Dairy supply chain takes more attention to the products perishability, so poor network integration may lead to excessive inventory and then enormous losses(Touil, Echchtabii, & Charkaoui, 2016).

For example, M.Kummu et al. (2012) noted that 25% of the global food produced was lost within the food supply chain before consumption and, roughly estimated that global food losses could be 30% to 40%. Lack of effective supply chain management practices could be one of the major reasons for food losses, hence analyzing and improving food supply chains may reduce food losses(Kummu et al., 2012). According to Gruen et al. (2002), the rate of average stock-out is 8.3% (Duan & Liao, 2013), Inventory annual holding costs today can be as high as 40% of inventory value (or, in some situations, even higher), while competition continually puts pressure on companies to achieve higher service levels; therefore, efficient inventory management is essential to all companies except the few that do not deal with any type of inventory(Wanke, Alvarenga, Correa, Hadi-Vencheh, & Azad, 2017).

The Products with finite shelf life which are subject to perishability are considered as an important issue and force the organizations to manage carefully. Expired products consuming time and cost to rework (if it is possible) or destroy. This problem emerges significantly in healthcare or food industry where all products lose their value easily during the manufacturing process, storage process or distribution, and this explains the fact that a one third of food production is damaged(Duong, Wood, & Wang, 2015).

Ghare and Schrader are the first researchers who considered deterioration concept in their research. They indicated that inventories are depleted not only by demand but also by their work. They presented a model that explained how deterioration affects the inventory model(Yang & Tseng, 2015).

The aim of this research is to provide a dynamic approach to identify safety stock and it can be implemented in different industries.

1. FUZZY INVENTORY IN PERISHABLE PRODUCTS

Fuzzy logic is considered an alternative approach to the traditional probabilistic approach which deals with ambiguity and uncertainty in inventory. Fuzzy logic was emerged for the first time by Lotfi A. Zadeh (1965) while traditional probabilistic inventory models were used for many decades. The first use of inventory fuzzy logic was started fairly in the 90’s (Kao & Hsu, 2002) as that reported by (Wanke et al) in 2017 (Wanke et al., 2017).

Fuzzy inventory control for highly perishable products was presented by Hideki Katagiri & Hiroaki Ishii 2002). The objective was to maximize the profit. Fuzzy shortage cost and fuzzy outdates cost were the variables of the proposed model while the fuzzy profit is the output(Katagiri & Ishii, 2002). Multi-objective model of inventory deterioration products was developed by Savita Pathak & Seema Sarkar in 2012. The main objective was to maximize the profit of different items(Pathak & Sarkar, 2012).

2. LITERATURE REVIEW

An improved model to identify reorder point and order quantity in dairy industry was developed by [E. Khanlarpour et al 2013]. The researchers presented a distinctive model where they began using fuzzy logic to calculate the time of re-ordering rather than the amount of re-ordering as in most researches. The researchers designed a fuzzy logic system consisting of six inputs which are (air condition, competitor

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company, customer income, religious and non-religious ceremonies, passenger & vacation, and customer satisfaction and one output (order quantity). Genetic algorithm was also used to identify optimal level of order quantity. Thus, researchers were able to introduce an intelligent warehouse system, which was an important shift in research(Khanlarpour, Fazlollahtabar, & Mahdavi, 2013).

The study of pricing strategy effect on inventory level was studied by Panda et al in (2013) where they thought that a perishable product was a very important element of inventory system management. They also began their study by investigating the impact of price discounts policy and used dynamic pricing rather than using static pricing. Dynamic pricing policy for pre and post deterioration of products was employed in order to increase the rate of inventory depletion which leads to decrease in inventory level, reduction in holding cost, and then maximization in profit. Discount in prices is presented before and after starting of deterioration process. The discount with cumulative way is presented also for reduced units(Panda, Saha, & Basu, 2013).

Ming-Feng Yang andWei-Chung Tseng (2015) presented a study on the effect of product perishability on inventory system. Where the researcher combined traditional deterioration model with quality prediction model in order to quantize the quality and determine the remaining value of each product. (Yang & Tseng, 2015). Rigzin Lhamo & Navee Chiadamrong developed a simulation optimization model to study replenishment policy for each scenario in order to manage the inventory of perishable products taking into account the age of these products. ARENA software simulation is used in order to identify the best inventory policy taking into consideration FIFO and LIFO withdrawal behavior by customer. The computational results concluded that policies based products age will lead to great reduction in cost compared to the case of without inventory age of product taken into consideration(Chiadamrong & Lhamo, 2017).

Integration of location-inventory problem into SCN is presented by (Zhuo Daia et al in 2018). The model develops optimization conditions for perishable products based on fuzzy statues for capacity and carbon emission. The authors used hybrid genetic algorithm (HGA), hybrid harmony search (HHS), and Lindo software to solve optimization problem under different scenarios of different capacity confidence levels and carbon emission confidence levels. Through the numerical experiments, it is easy to conclude that the Lindo programming is faster than HGA & HHS while the last two are considered more efficient than Lindo. (Dai, Aqlan, Zheng, & Gao, 2018).
According to our survey about safety stock, it is clear to notice the scarcity of research that deals with safety stock by using fuzzy logic. Table (1) below shows the approaches used in different researches to calculate safety stock level.

Table (1). Summary of safety stock researches approaches.

No	Researcher	Year	Reference	Tool	Items	
					Single	Multi
1	Ming-Feng Yang & Wei-Chung Tseng	2015	(Yang & Tseng, 2015)	quality prediction model	✓	
2	Linh N. K. Duonga et al.	2015	(Duong et al., 2015)	simulation	perishable and substitutable products	
3	Hui-Ming Wee	1997	(Wee, 1997)	price-dependent demand	✓	
4	Savita Pathak and Seema Sarkar	2012	(Pathak & Sarkar, 2012)	Fuzzy logic		✓
5	S. Panda et al.	2013	[14]	price discounts policy	Applicable for different cases	
6	Qinglin Duan,T.WarrenLiao	2013	(Duan & Liao, 2013)	Optimization based simulation	✓	

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7	1RIGZIN LHAMO& 2NAVEE CHIADAMRONG	2017	(Chiadamrong & Lhamo,	Simulation by ARENA	ے
8	Zhuo Daia et al.	2018	(Dai et al., 2018)	Optimization model with fuzzy logic	ے
9	E. Khanlarpour et al	2013	(Khanlarpour et al., 2013)	fuzzy logic & genetic algorithm	Just dairy firm

3. DESCRIPTION OF PROPOSED APPROACH

The general architecture of the proposed model is shown in Figure (1). The proposed model has three steps: Identifying demand uncertainty level, identifying raw material level, and identifying inventory level.

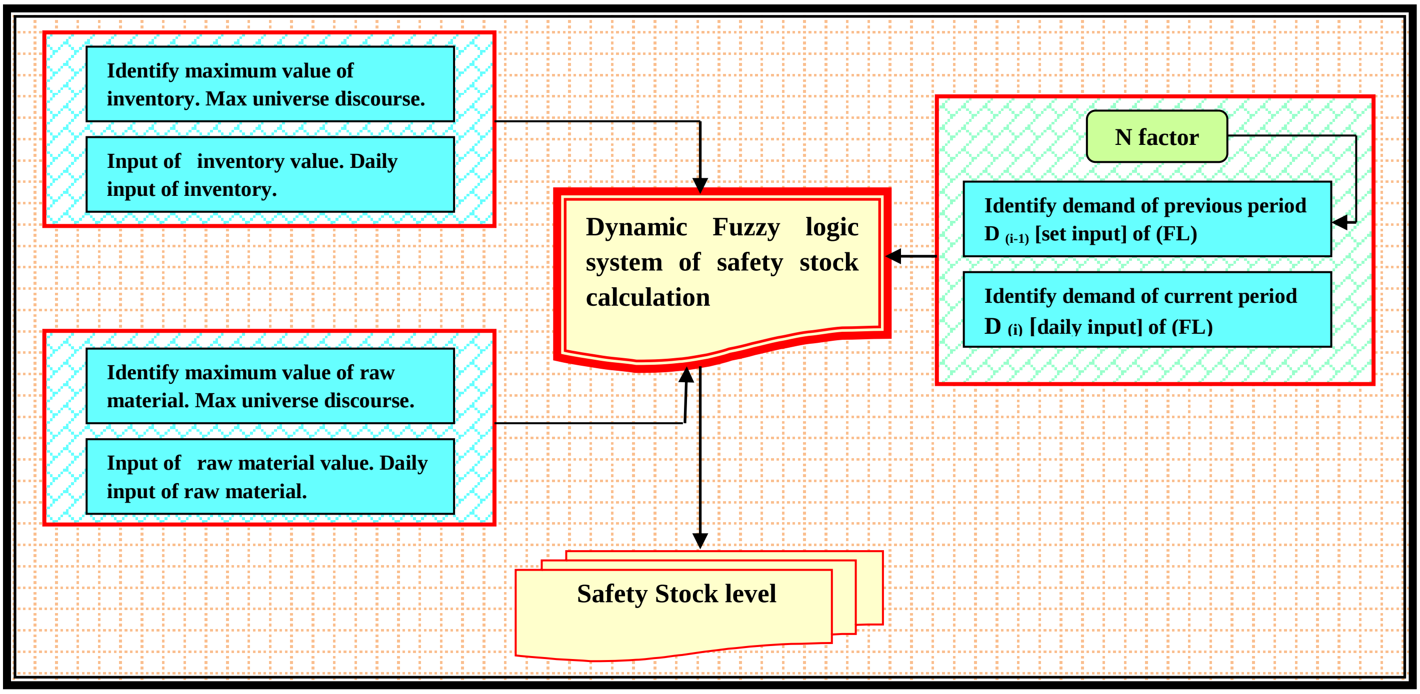

Figure (1). Architecture of the proposed model

3.1 GENERAL DESCRIPTION OF THE PROPOSED APPROACH

The proposed approach takes into consideration three variables and treats them by applying fuzzy logic system to identify appropriate level of safety stock. The sub section below will explain this process.

3.1.1 DEMAND UNCERTAINTY CONDITIONS

The process of employment demand uncertainty was done by following the steps below;

- Identification of dynamic factor (N) factor which represents maximum rate of demand increasing for a specific time period (monthly basis values were identified).
- Building the set of membership functions to describe the status of demand as shown in figure (2).
- Identification maximum value of universe of discourse which obtained by multiplying dynamic (N) factor by demand level of previous day ($D_{(i-1)}$) and this value is changed daily.

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- Input the current day demand ($D_{(i)}$) and this value is also changed daily.

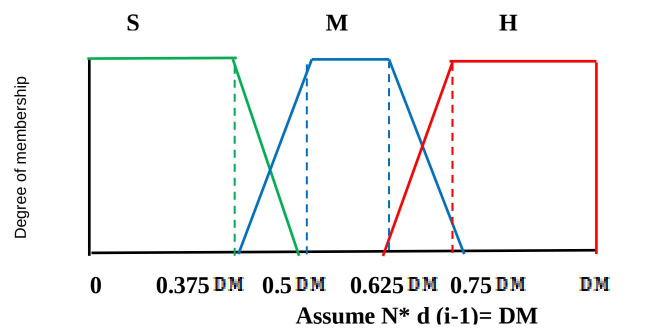

Figure (2) Fuzzy set of demand stability level.

3.1.2 RAW MATERIAL AVAILABILITY

Raw material availability is considered as an important part in identifying safety stock level because unavailability of raw material will lead to unmet customer requirements. The steps below show how raw material availability was employed in this model;

- Building set of membership functions to describe the statues of raw material availability as shown in figure (3).
- Identifying maximum value and minimum values of raw material availability which represent universe of discourse of this variable.
- Input daily value of raw material availability current day ($D_{(i)}$) and this value is also changed daily.

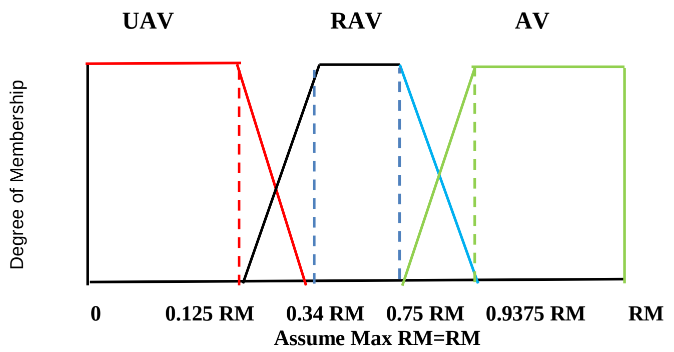

Figure (3) Fuzzy set of availability of raw material.

3.1.3 INVENTORY LEVEL ON HAND

The level of on hand inventory is an crucial part and must be taken in account in order to identify safety stock level. Suitable management of inventory leads to reduction the level of safety stock. Next steps explain how inventory on hand was employed in the proposed model approach:

- Building a set of membership functions to describe the status of on hand inventory as shown in figure (4).

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- Identifying the max value and min values of on hand inventory to represent universe of discourse of the variable.

- Input of daily value of on hand current day inventory ($D_{(i)}$) and this value is also changed daily.

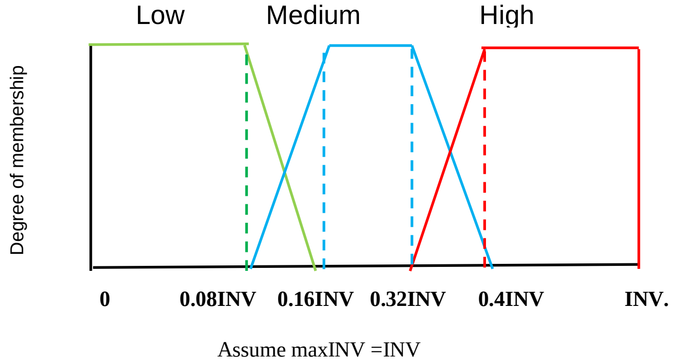

Figure (4). Fuzzy sets of inventory level.

3.1.4 SAFETY STOCK LEVEL

Safety stock level (SSL) is the unique output of the model. Where the rules of reasoning, are applied to the system after entering of all the variables. Maximum values of universe of discourse are changed daily allow high flexibility for the system and dynamic status based on period specification and this change of maximum value will be done by executing the following steps:

- Identifying the (**dynamic value which represents period specification**) ranging from (10-30)% of current period demand **$D_{(i)}$**, and the value chosen based on season conditions of product, the value is (10%) for weak period, (20)% for normal period, and (30)% for peak period.

- Building a set of membership functions to describe the status of demand as shown in figure (5).

- Identifying the maximum value of universe of discourse by multiplying **(dynamic value**) by demand of current the day **($D_{(i)}$)** and this value is changed daily.

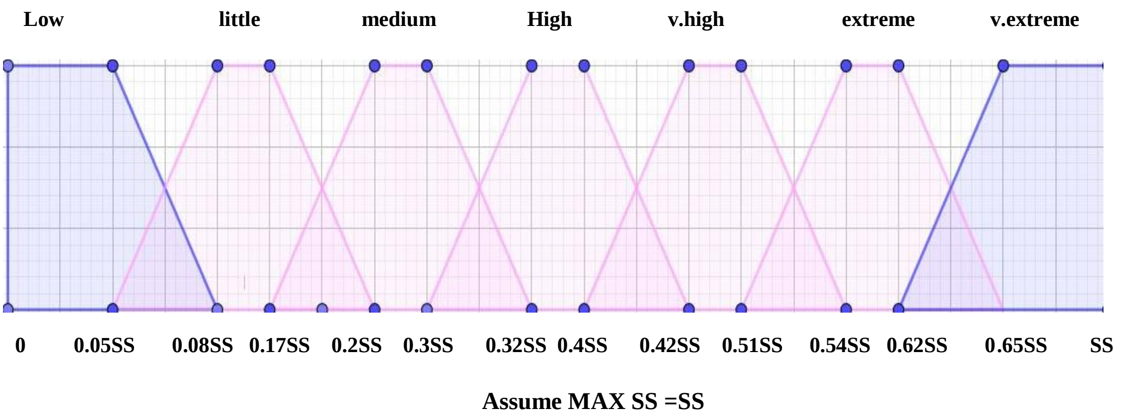

Figure (5). Fuzzy sets of safety stock (output variable).

procedures described in section (4.1.1), whereas for maximum universe of discourse of safety stock, the

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procedures are presented in section (4.1.4). By calling the procedures of sections (4.1.2) & (4.1.3) the maximum values of universe of discourse of raw material and inventory on hand are identified respectively.
The algorithm called Dynamic Fuzzy Safety Stock (DFSS) is used to identify safety stock level based on dynamic fuzzy logic; the steps below will explain this algorithm.
Step (1): Identification of dynamic (N) factor for each product at each period.
Step (2): Identification of universe of discourse of current period for the first variable (demand stability level) by multiplying of demand of previse period $D_{(i-1)}$ by dynamic (N) factor.
Step (3): Identification of universe of discourse of the second variable (raw material availability).
Step (4): Identification of universe of discourse of the third variable (inventory on hand level).
Step (5): Identification of period specification for all products (PS).
This specification includes the description of the period in which the demand is high, medium, or low in order to integrate with demand stability level which is identified later to know the maximum safety stock.
Step (6): Identification of universe discourse of the unique output (safety stock level) based on period specification which was identified in step (5).

3.3 CASE STUDY

The examination of the proposed model validation is presented in this case study. The dairy products are considered good example of perished products, so the process of inventory optimization is crucial. High demand variability and short shelf life forced toward adapting suitable inventory approach which can deal with this complexity. Demand stability level, raw material availability, and inventory on hand as inputs and safety stock as output form the fuzzy logic system to solve the problem of dairy industries company. Three products are selected which are (butter 100g, yoghurt 1 kg, and cheddar cheese 100gm). It must be called the algorithm of Dynamic Fuzzy Safety Stock (DFSS) which is used to optimize inventory level by identifying safety stock based on dynamic fuzzy logic as shown in steps below. In order to simplify the process we will use sample of data related to third product (cheddar 100gm) as shown in Table (2).

Table (2). Snap of required data of third product (cheddar cheese 100gm).

Product	Month	Day	(N) factor	d(i)[demand]	Max raw material	daily raw material	max inventory	On hand inventory [first
P3	T1	1	3	1080	30	17.09	750	128
P3	T1	2	3	45	30	9.22	750	
P3	T1	3	3	1305	30	6.33	750	
P3	T1	4	3	1575	30	17.5	750	
P3	T1	5	3	1329	30	19.3	750	

Step (1): Identification of dynamic (N) factor for each product at each period.

The identification of dynamic factor represents a heart of the model; it is the identification of the dynamic state of the system through which the universe of discourse of demand stability level (first variable) is identified. It is determined based on daily basis. (if- function) Excel program was employed in order to identify these values, where the change rate in demand is determined between each two adjacent periods (previous and next day). For example if the demand changed from 50 to 100, it means that the change from the first order and (N) dynamic factor is equal to (2). After applying the function for demand columns of all products for all periods, we can obtain (N) dynamic factor as shown in Table (3).

Table (3), the values of (N) for all selected products at (12 months).

(N) dynamic factor												
	T1	T2	T3	T4	T5	T6	T7	T8	T9	10	T11	T12
P1	0	0	5	3	5	5	4	2	3	0	4	4
P2	0	3	3	2	5	2	5	2	4	2	0	3
P3	3	3	3	2	6	2	4	3	3	3	3	3

Step (2): Identification of universe of discourse of the current period for the first variable (demand stability level)

The universe of discourse for demand stability level is obtained by multiplying the demand of previous period $D_{(i-1)}$ by dynamic (N) factor. Equation (1) shows the application of this process. Table (4) represents universe of discourse of first variable (demand stability level) while Table (5) shows the implementation of fuzzy set boundary conditions for cheddar cheese (P4) for first day. The demand of previous day is (100).

Max. Universe of discourse for second day $_{(}$DM) $_{=}$ $D_{(i-1)}$ *N (1)

Table (4), universe of discourse of demand uncertainty conditions.

System variables	Linguistic variable	Linguistic values	Numerical ranges
Demand uncertainty condition	Low	L	(0-0.5 DM)
	Medium	M	(0.375-0.75 DM)
	High	H	(0.625-1DM)

From Tables (2 &3), the universe of discourse for second day according to Eq. (1) equals to (3*100=300) where (3) represents (N factor) for cheddar cheese in January and (100) represents the demand of previous day. Table (5) shows the results of demand uncertainty universe of discourse.

Table (5), universe of discourse of demand uncertainty conditions for the third day.

System variables	Linguistic variable	Linguistic values	Numerical ranges
Demand uncertainty condition	Low	L	(0-0.5) *300
	Medium	M	(0.375-0.75) *300
	High	H	(0.625-1) *300

Step (3): Identification of universe of discourse of the second variable (raw material availability).

Universe of discourse of second variable (raw material) is identified on monthly basis, while daily level of raw material is entered to the model to identify the impact of this variable on safety stock (SS) level. Table (6) shows the universe of discourse of this variable while Table (7) presents the value of universe of discourse of the variable in January where max level of raw material is (30ton).

Table (6), universe of discourse of raw material availability conditions.

Raw material availability	Unavailable	UAV	(0-0.34 RM)
	Rare available	RAV	(0.125-0.9375 RM)
	Available	AV	(0.75-1RM)

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Table (7), universe of discourse of raw material availability conditions for January.

Raw material availability	Unavailable	UAV	(0-0.34) *30
	Rare available	RAV	(0.125-0.9375) *30
	Available	AV	(0.75-1) *30

Step (4): Identification universe of discourse of the third variable (inventory on hand level).

Inventory on hand universe of discourse and fuzzy sets are identified in this step, Table (8) shows the universe of discourse of this variable and Table (9) presents the value of universe of discourse of the variable in January where maximum level of on hand inventory is (75 packages).

Table (8). Universe of discourse of inventory on hand conditions.

On hand inventory	Low	L	(0-0.16 INV)
	Medium	M	(0.08-0.4 INV)
	High	H	(0.32-1 INV)

Table (9). Universe of discourse of inventory on hand for January.

On hand inventory	Low	L	(0-0.16)*750
	Medium	M	(0.08-0.4) *750
	High	H	(0.32-1) *750

Step (5); Safety Stock Level (Output)

Only one output i.e. safety stock level is determined by this model. Seven sets are used to identify the SS level. It is crucial to identify period specification. In January for the cheddar cheese the period is peak, so the percentage is (30%) of $D_{(i)}$, while for yogurt 400gm the period specification is (20)% of $D_{(i)}$. For example, the max universe of discourse of the first day of January of cheddar cheese is (0.3*1080) where (0.3) represents the period specification value and (1080) represents the demand of first day. Table (10) shows the universe of discourse of SS level while table (11) presents the value of universe of discourse of the first day for the cheddar cheese in January where max level of SS is changed daily.

Table (10). Universe of discourse of SS level.

Safety stock level	Low	L	(0.-0.08 SS)
	Little	LI	(0.05-0.2 SS)
	Medium	M	(0.17-0.32 SS)
	High	H	(0.3-0.42 SS)
	Very high	VH	(0.4-0.54 SS)
	Extreme	E	(0.51-0.65 SS)
	Very extreme	VE	(0.62-1 SS)

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Table (11). Universe of discourse of SS level for soft cheese in third day of January.

Safety stock level	Low	L	(0.-0.08)*324
	Little	LI	(0.05-0.2)*324
	Medium	M	(0.17-0.32)*324
	High	H	(0.3-0.42)*324
	Very high	VH	(0.4-0.54)*324
	Extreme	E	(0.51-0.65)*324
	Very extreme	VE	(0.62-1)*324

Referring to Table (2) and in order to simplify the process, third product (***cheddar 100gm cheese (P3)***) parameter was selected for (January), when calculate SS for first day. The demand of the previous period equals to (100) package with inventory on hand equals to (128) package and raw material available of (30) tone of raw milk, and demand of current day is (1080) package, then the safety stock is (116) package. Depending upon the specific percentage which mentioned in proposed model i.e. (MAX.SS= 30% of D(i)), SS= 30%*1080=324 and then distribute all percentage values as shown in figure (5). Figure (6) shows the results of SS level for (P3) in the first day of January

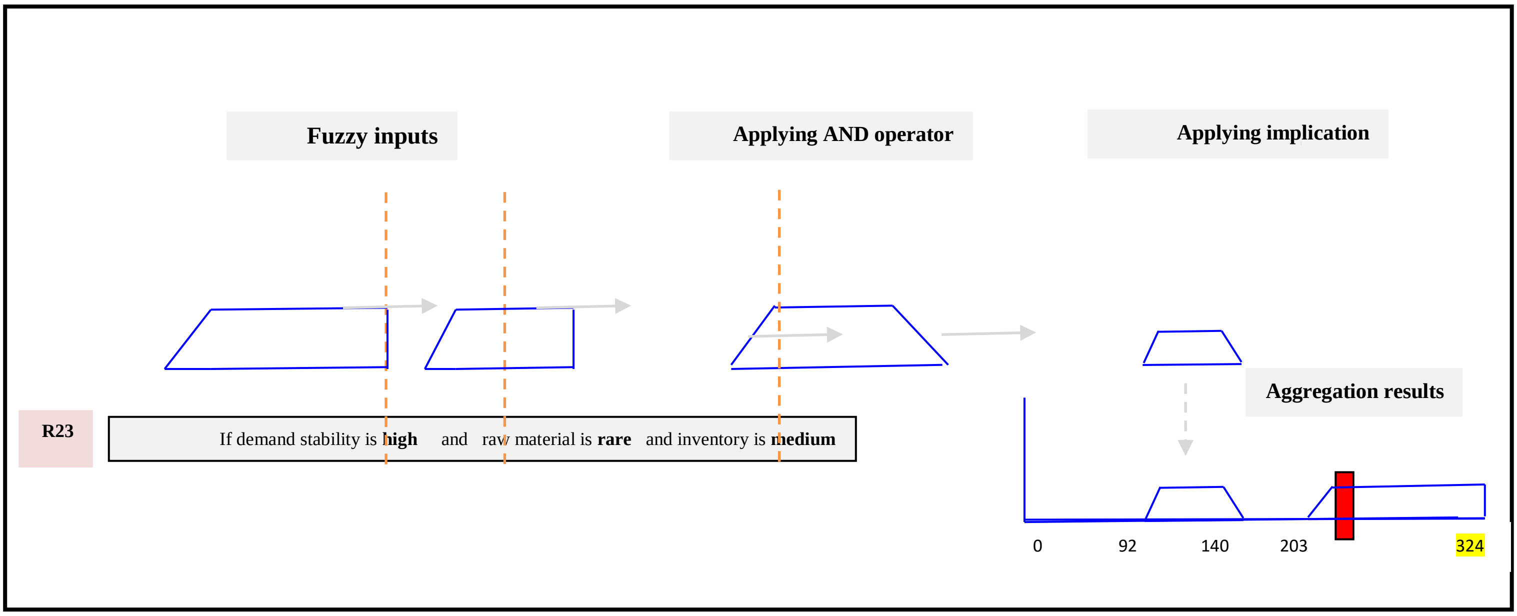

Figure (6); implication process for identifying SS level for third day of January for soft cheese

The mechanism of dynamic fuzzy logic represents continuous change (depending on the specific time period) of fuzzy system which depends on the change occurred in universe of discourse of one or more of included variables, which results in a flexible system that deals with these changes that occurred periodically and thus lead to obtain high accuracy results. Figure (7) illustrates the dynamic behavior of fuzzy logic.

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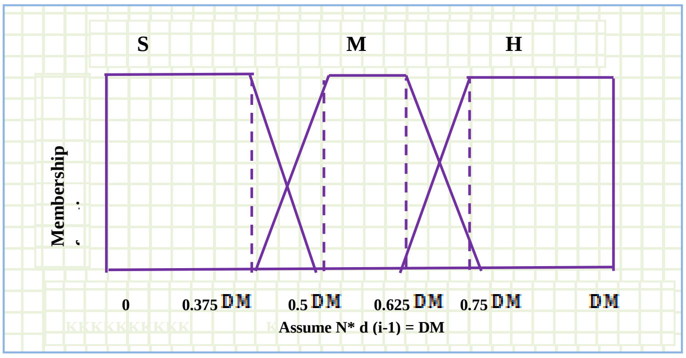
N factor	Demand
3	1080
3	45
3	1305
3	1575
3	1320
3	1435
3	577
3	1166
3	1665
3	1150
3	1295
3	1365
3	770
3	1380
3	1570
3	1345

$DM = D_{(i-1)} * N$



specification	Demand
0.3	1080
0.3	45
0.3	1305
0.3	1575
0.3	1320
0.3	1435
0.3	577
0.3	1166
0.3	1665
0.3	1150
0.3	1295
0.3	1365
0.3	770
0.3	1380
0.3	1570
0.3	1345

$SS = D_{(i)} * specification$

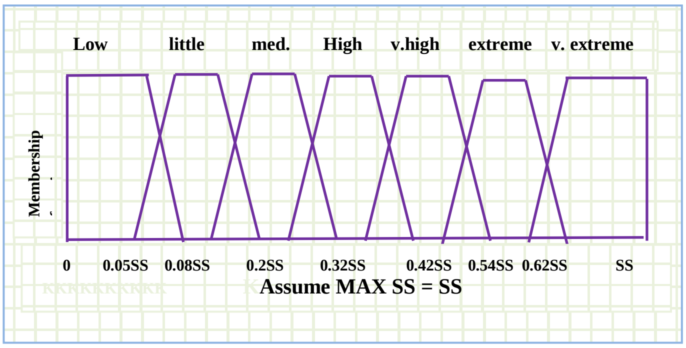


Figure (7) dynamic mechanism of proposed fuzzy logic

By applying the proposed model on the case study parameters, great results were obtained. Clear reduction in SS level for all products is gained while keeping customer satisfactions, the reduction of SS level is varying between (7-98)% as shown in table (12);

Table (12). Percentage reduction in SS level for three products in 12 months.

	Percentage impact of the proposed approach on Safety Stock											
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
P1	0	0	93%	93%	93%	96%	96%	93%	92%	0	87%	88%
P2	97%	96%	97%	96%	96%	96%	96%	91%	92%	97%	97%	98%
P3	35%	7%	86%	68%	72%	82%	87%	86%	81%	95%	74%	72%

In order to provide detailed description about the obtained results, Table (13) shows the values of the original demand, current SS level (identified by company), and safety stock of proposed model for butter 100gm product in January. The (current SS) for butter 100gm in March is (1219) and the (developed SS) is (74), so the reduction is about 93% as mentioned in table (13):-

Table (13). Demand, current SS and developed SS for P1 (butter 100gm) in (T3).

Butter 100gm (March)	Butter 100gm (March)

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Day	Demand	Current SS	Developed SS	Day	Demand	Current SS	Developed SS
1	14	61	2	12	18	32	2
2	92	19	23	13	22	60	2
3	66	3	3	14	15	45	2
4	41	112	2	15	16	79	2
5	18	94	2	16	24	55	2
6	48	46	6	17	6	49	1
7	40	6	3	18	20	79	5
8	23	83	2	19	13	66	1
9	21	62	2	20	20	46	2
10	46	66	5	21	8	38	1
11	16	50	1	22	20	68	3
						Sum=1219	Sum=74
						Reduction= 93%	

CONCLUSIONS

In today's dynamic and global market environment, it is very important to use advanced approaches rather than traditional ones to identifying safety stock (SS) level. This seems more important when applied in the dairy industry due to the short shelf life of products and high competitive situations, which made the application of soft computing techniques absolutely indispensable. As the experience of the model on more than one product which has different specifications in terms of the dynamic factor and the amount of demand stability level proved the importance and success of the proposed model. Moreover the implementation of dynamic fuzzy logic in identifying SS level leads to more control on demand variation by employing an expert knowledge which enables the owners to overcome the problem of excessive inventory level due to reliance only on common statistical equations. The dynamic fuzzy logic has an excellent ability to deal with the advanced global market which is characterized by dynamic and competitive nature.

It is crucial to notice that the dynamic fuzzy logic is considered as flexible tool because the dynamic input variable i.e. (demand level) and dynamic output variable (safety stock) can be readjusted and modified easily. Despite the success of the proposed model, there are some future areas of research, such as the use of advanced techniques in identifying inference rules, which gives the models high robustness in the identification of outputs.

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