Hindawi
Journal of Sensors
Volume 2020, Article ID 3503895, 15 pages
https://doi.org/10.1155/2020/3503895

Research Article

The Simulation of Implications of Sensor Technology on the New Product Development to Solve Lot-Sizing Problems with Fuzzy Approach

Ford Lumban Gaol[1] **and Tokuro Matsuo**[2,3]

[1]*Computer Science Department, BINUS Graduate Program-Doctor of Computer Science, Bina Nusantara University, Jakarta 11480, Indonesia*
[2]*Advanced Institute of Industrial Technology, Tokyo, Japan*
[3]*Department of M-Commerce and Multimedia Applications, Asia University, Taiwan*

Correspondence should be addressed to Ford Lumban Gaol; fordlg@gmail.com

Received 3 January 2020; Revised 21 May 2020; Accepted 4 July 2020; Published 13 August 2020

Academic Editor: Ghufran Ahmed

Implications of sensor technology on new product introduction requires critical decisions on divergent marketing and operational aspects. In this paper, we employed the Bass model for a new product that used the sensor technology diffusion from the perspective of the Wagner-Whitin lot-sizing model which discusses this matter related to suitability of sensor technology on the market and operational dimensions. The objective of this study is to propose an uncertain fuzzy approach to specify the new product that applied the sensor technology introduction's optimum time, price, production scheduling, and rate simultaneously. This model will be applied to analyze the impact of sensor technology diffusion on the market acceptance and some operational parameters, for instance, total customer population, price elasticities, startup and maintenance costs, the unit's variable cost and research and development costs on optimized benefit, and the product's optimized lifespan. In this experiment, we have inspiration from the version of the Sale et al. (2017) model which considers uncertainty by using fuzzy triangular numbers and performing the alpha cut method. Moreover, in this research, variable cost is considered as a Cobb-Douglas function. Initially, in Research Methodology, mathematical modeling is applied, wherein utilizing simulation and the experimental design method, data were generated. Eventually, using LINGO optimization software, the problem was solved, and for further examinations considering the existence of various parameters, design of experiment (DoE) by Design-Expert 8 software and response surface methodology was adopted to analyze and optimize the problem's parameters. The results indicated that the objective function's climax occurs when the higher limit of alpha being 0.7 is assumed; hence, the optimum state of demand belongs to this amount of alpha.

1. Introduction

Sensor technology diffusion on new product decisions is considered a significant element to enhance the competitive advantages. The ordering and timing diversity influences organizational performances. Base on Klastorin and Tsai, risk-taking and innovativeness are considered as first movers' qualifications. Acting primarily in new sensor technology diffusion, products' moves illustrate several advantages; for instance, brand image, scale effects, experience, product quality's asymmetric information, and advertising influences (Klastorin and Tsai, 2004; [1]).

Sensor technology diffusion has a lot influence on the lot sizing. The sensor technology will influence the multistage inventory systems, incentives, or productivity issues that become a critical point on the lot-sizing problems. The issue on sensor technology also has advantages compared to other products due to production environment that is composed of several production centers for the automation as well as the data gathering.

The unique and specific aspect of the sensors are compared to other products such as consumer products.

Fast product production is assumed to have more financial independence as a result of gaining earlier cash flow, attaining legitimacy and external visibility, achieving greater market share, and boosting the possibility of survival (Schoonhoven et al., 1990; [2]). However, on the other hand, other researches depict disadvantages of moving first in new products; more extreme market risk and uncertainty and missing the opportunity of imitating first movers' decisions are deliberated as some negative points (Klastorin and Tsai, 2004; [3]). More researches depict that being a first mover is not always a correct decision. This strategy's achievement relies on the company's knowledge of market requirements, size and rivals, and weakness and strength points. An accurate analysis of the firm's internal and external situation is needed for optimal intentions (Bayus et al., 1997; [4]).

There are many studies that show that two main categories have a great impression on the timing of the organizations to ship their products: organizational conditions and environmental circumstances. Below, we provide a survey for significant influencing elements: technological innovation, entrepreneurial team, organizational structure, financial resources, external power and influence, and environmental conditions.

Generally, considering the results of the cost and benefit comparison in quickening the product introduction time indicates whether to be a market pioneer or a late market entrant (Bayus et al., 1997). "The process by which an innovation is communicated through certain channels over time among the members of a social system." Regarding the diffusion's definition, four key elements are employed:

(1) *The innovation*: "an innovation is an idea, practice, or object that is perceived as new by an individual or other unit of adoption."

(2) *Communication channels*: communication is defined as mutual understanding attainment by means of creating and sharing information. Diffusion is known as a specific type of communication in which the information deals with innovation. A communication channel is the means of relation by which the messages are transmitted from the sender(s) to the receiver(s).

(3) *Time*: time as an essential element in studies is often ignored in nondiffusional researches, though it is designated in diffusion-related concepts.

(4) *A social system*: individuals or a group of units sharing a common problem seeking to so attain a mutual goal is defined as a social system. It is worth noting that diffusion requires a social system due to its structure [5].

Moreover, Rogers has stated nine cardinal research traditions related to diffusion: anthropology, early sociology, rural sociology, education, medical sociology, communication, marketing, geography, and general sociology. Although numerous descriptions are given through divergent paradigms, the mentioned definition is the most practical and comprehensive. The history of diffusion in innovation goes back to the late 1940s. Rogers and Bass had a great influence on the matter's progress in the 1960s and introduced effective parameters on this subject. Diffusion of innovation is categorized into two main segments: communication and administration. Based on Rogers and Yildirmaz et al., the sociology, social psychology, and technology are the three key discerned aspects from the administrative perspective of diffusion in innovation which are scrutinized in the following [5, 6].

1.1. Diffusion of Innovations in Sociology. The social sight of the topic includes innovation diffusion theory and perceived characteristics of innovating scopes. The innovation diffusion theory (henceforth, IDT) contains Bass, Moore, and Roger's paradigms; Bass had a mathematical perspective illustrating a model characterizing the diffusion of the innovation procedure. Moore extended the researches on the basis of Bass's probes into the necessity of technological innovation in firms. Furthermore, Rogers had an extreme influence on the matter. Progress on Roger's studies with emphasis on reordering the variables led to the Perceived Characteristics of Innovating (PCI) by Moore and Benbasat.

1.2. Diffusion of Innovations in Social Psychology. Theory of the Reasoned Action and Theory of Planned Behavior are the two theories scrutinizing human behaviors' comprehension in the social aspect of diffusion of innovation. To Ajzen and Fishbein, men are intellectual creatures making decisions according to an event's data. In addition, they are able to handle the decision making progress. Hence, their behaviors are affected by a behavior's attempt. This is known as the Theory of the Reasoned Action (henceforward, TRA). On the other hand, Bianchi and Figueiredo accentuate the condition in which an individual does not have a thorough control on his conduct, instead of the state in which human behaviors are predicted when decisions are made under full control in TRA. The novel theory is named the Theory of Planned Behavior (hereafter, TPB).

1.3. Diffusion of Innovations in Information Technology. From the information technology aspect of diffusion of innovation, two main theories are propounded considering the technology acceptance procedure: the Technology Acceptance Model (henceforward, TAM) presented by Davis and the Unified Theory of Acceptance and Use of Technology introduced by Venkatesh, Morris, and Davis. The TAM forecasts the influence of technology derivation in a corporation, particularly productivity alterations. Through the years, this model was upgraded, and precise external factors were appended, and the Extension of the Technology Acceptance Model (TAM2) was represented by Venkatesh and Davis. Furthermore, the Technology Acceptance Model 3 (TAM3) was illustrated emphasizing on enhancing efficiency through employing new technologies by supervisors.

The Unified Theory of Acceptance and Use of Technology (UTAUT) is illustrated by Venkatesh and utilizes the institutional environment as a means to perceive elements, for instance, facilitating conditions, function expectation, endeavor expectation and social influence. Afterwards, the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) was demonstrated by Venkatesh, Thong, and Xu, containing the elements from UTAUT and auxiliary

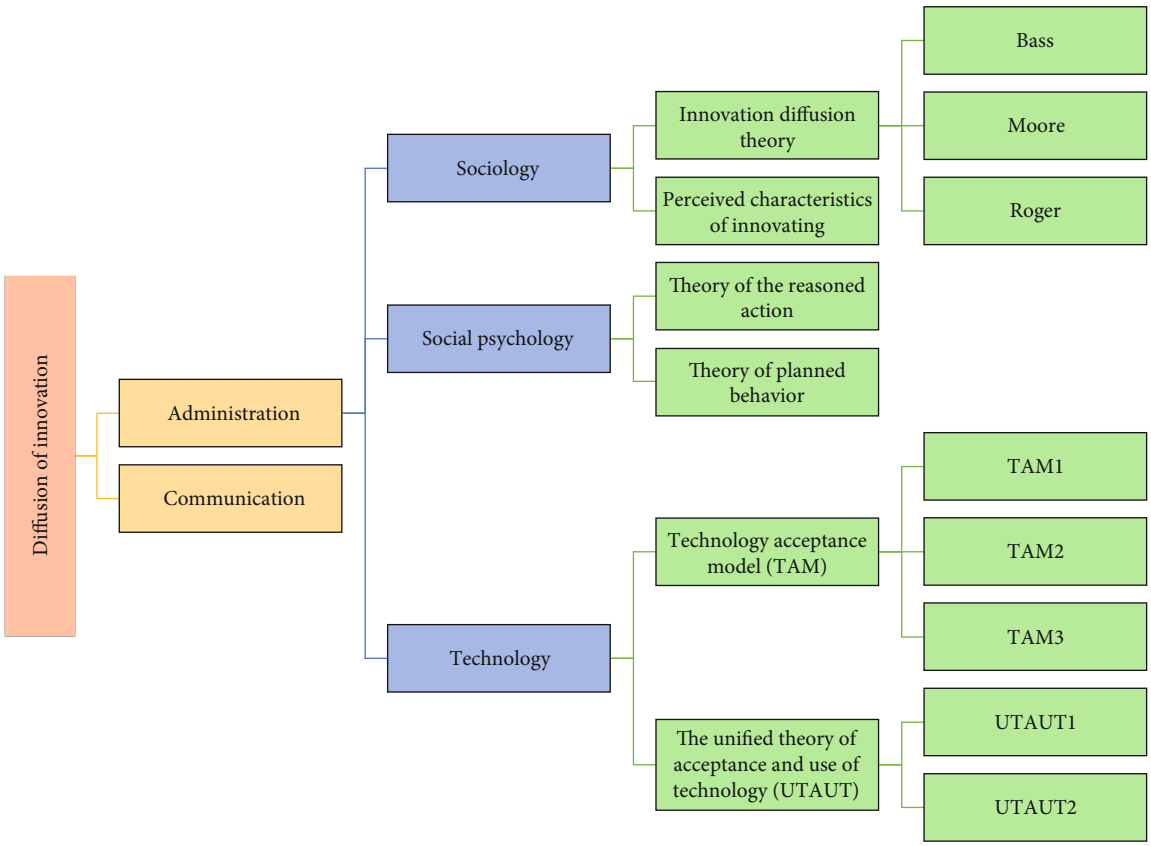

Figure 1: Categorizing diffusion of innovation [7].

parameters to fill the gap of orientation of the customer's point of view. The hierarchy in Figure 1 illustrates the embodiment of the discussed matter.

This paper is intended to employ the Bass model for the sensor technology diffusion, and the Wagner-Whitin lot-sizing model discusses this matter related to acceptance of the product and operational dimensions. The objective of this study is to propose an uncertain fuzzy approach to specify the new product introduction's optimum time, price, production scheduling, and rate simultaneously. This model will be applied to analyze the impact of marketing and operational parameters, for instance, total customer population, price elasticities, startup and maintenance costs, the unit's variable cost and research and development costs on optimized benefit, and the product's optimized lifespan. The proposed approach is the evolved version of the Sale et al. [8] model with regard to their research limitations considering a deterministic demand function and constant variable costs. To solve these limitations, some changes have been taken in the previous research preliminaries.

The remainder of this research is organized as follows. First, lot sizing, sensor technology implementation, and related literature have been presented. Afterwards, considering previous researches, the novelty and contribution of this research are presented. Subsequently, the Sale et al. [8] model has been scheduled, and the changes to solve their research limitations have been illustrated (Sale, 2017). Next, by applying the design of experiment and response surface methodology, the uncertain model has been analyzed and optimal values of decision variables and objective function were emanated. Eventually, the results were designed and future researches proposed.

2. Lot Sizing

Facing difficulties in replenishing sensor technology product stocks at the proper time and price and in the appropriate quality and quantity by manufacturing corporations' managers led to endeavors to solve the lot-sizing problems (henceforth, LSP) in the 1990s [9]. The LSP specifies the minimum cost of a production of sensor technology product schedule regarding the bilateral relation between the inventory holding expenditures and the established expenses meeting the requirements (Melega et al., 2018). The aforementioned method was presented for an individual element primarily by Wagner and Whitin in 1958 and developed to multiplex components considering capacity constraints in the same year. The subject under discussion can be categorized by various specifications, for instance, demand (steady or fluctuating), time series (discrete or continuous), deadline (own or disown), and quantity of production levels (single or multilevel) (Melega et al., 2018).

The concerns to the mentioned matter deliberate from divergent of sensor technology products industries' issues. For instance, with regard to sensor technology in the paper industry, for producing gross reels, managers face the lot-sizing problem in order to determine the scale of the lots. Afterwards, the cutting stock problem is formed along with cutting the reels into tinier pieces which might satisfy the

Table 1: Research background.

Author	Year	Tool/method
Emblemsvag [12]	2001	Simulation-based modeling, activity-based life cycle assessment (LCA)
Klastorin & Tsai (2004)	2004	Mathematical modeling, Nash equilibrium, game theory
Pflieger et al. [13]	2005	Simulation based modeling, life cycle assessment (LCA) modeling
Srivastava & Lee [14]	2005	Conceptual modeling, multiple linear regression models
Xie & Simon [15]	2006	Simulation-based modeling, computer simulation with ARENA software
Settanni & Emblemsvåg [16]	2010	Mathematical modeling, simulation-based modeling, input-output analysis (IOA), Monte Carlo methods
Bauer & Auer-Srnka [17]	2012	Conceptual modeling
Von Westarp & Schinas [18]	2016	Mathematical modeling, fuzzy linear programming (FLP) approach
Ma & Fildes [19]	2017	Mathematical modeling, simulation-based modeling, nonlinear integer programming model
Bianchi & Figueiredo [7]	2017	Review article
O'Neill & Sanni [20]	2018	Mathematical modeling, conceptual modeling, numerical analysis, generalized economic-order-quantity (EOQ) model
Zhang [21]	2018	Conceptual modeling, diffusion of innovation model
Melega et al. (2018)	2018	Review article, mathematical modeling
Sombultawee & Boon Itt (2018)	2018	Review article
Hirunyawipada & Xiong [22]	2018	Conceptual modeling
Ou & Feng [23]	2019	Mathematical modeling
Feng & Chan [24]	2019	Mathematical modeling
Carreiro & Oliveira [25]	2019	Review article
Amati et al. (2019)	2019	Review article, conceptual modeling
Current research	2019	Design of experiment, alpha cut, response surface methodology

client's requirements. Based on the results of LSP, using the sensor technology on the smaller reels might turn into paper sheets by being cut once more (Melega et al., 2018).

A manifest dilemma for administrators related to the ongoing matter is the conflict between the decrement of unit prices in high quantity demands by discounts and the increase in the inventory holding expenditures. Hence, the manufacturers of sensor technology products ought to set suitable discounts, not only to encourage customers for purchasing greater orders but also to maximize the benefit. Furthermore, the clients should make the convenient decision concerning the benefits and costs deriving from large amount orders. Despite numerous modern and classic methods to achieve competitive advantages in markets, sensor technology products on the expenditure mitigation are recognized as a chief factor in boosting a firm's market share; subsequently, shrinkage of ordering costs is considered as a priority for managers. Employing lot-sizing models besides quantity discounts succor to make the foremost purchasing decisions [9].

Through time, more complex and specialized models are introduced; for instance, [10] formulated a make-to-stock (hereafter, MTS) lot-sizing problem in which one class of each product is produced; therefore, one set-up is allowed, and this case is known as lot sizing with 1 set-up (LS1S). In this model, m illustrates the number of considered items and n denotes the number of time periods which is divided into two subperiods in which N_1 is allocated to production planning and contains extra production capacity and N_2 for inventory management aspects. Hence, the demand for item $i \in M$ is partitioned into two parts: d_{it}^{e} for time period N_1 and considered to be known and d_{it}^{p} for time period N_2 which is forecasted.

Table 2: Parameter levels.

Parameter	Parameter surfaces
a	2, 8, 14, 20
b	0.01, 0.04, 0.07, 0.1
I	4M, 14M, 22M, 30M
S	3K, 12K, 21K, 30K
m	6M, 14M, 22M, 30M
η	2, 4, 6, 8
H	0.1, 0.4, 0.7, 1

Furthermore, since previous articles mostly shed light on Dynamic Lot-Sizing (hereafter, DLS) models for sensor technology products, Wu et al. [11] studied DLS models for new products via pricing. In this situation, a firm's new product is considered to be introduced to consumers by word of mouth and mass media. It is assumed that customers buy the maximum quantity of one product in the whole planning time; hence, the demand at time period t equals to the new gained buyers in the mentioned time horizon, $d(t) = n(t)$. Additionally, this model has the potential to include multi-item and repeated purchases, calculated, respectively, as $d(t) = wn(t)$ and $d(t) = N(t) = \sum_{i=1}^{t} n(t)$ in which w indicates the quantity of each customer's purchase [11].

```
DATA:
a = 14;
b = 0.04;
m =30000000;! The total size of the potential market;
Elas = 2;! Elasticity;
H = 0.7;! Holding costs;
S = 21000;! Setup cost;
I = 18000000;! New product introduction costs;
Alpha = 0.7;
Lambda =100;! Coef in cap-doglass function for variable cost;
Gamma = 1; ! Elasticity parameter in cap-doglass function for variable cost;
pp = 5;
ENDDATA.
SETS:
Time/1...pp/: D, P, Inv, X, F, Delta, V;
ENDSETS.
CALC:
@for (Time (t): F(t) = (1 - @exp (-b * t))/(1 + (a * @exp (-b * t))));
ENDCALC.
Max = (@sum (Time (t): ((P(t)- V(t))* D(t)) - (S * Delta(t)) - (H * Inv (t))) - I)/period;
@for (Time (t)| t #GT#1: Inv(t) = Inv(t-1) + X(t)- D(t));
@for (Time (t) | t #EQ#1: Inv(t) = 0);
@for (Time (j: @)sum(Time (t) | t #LE# j: X(t) - D(t)) > = 0);
@for (Time (t): m * Delta(t) - X(t) > = 0);
!@for (Time (t) | t #GT#1: D(t) = (0.9 + (0.1 * alpha)) * m * (F(t) - F(t-1)) * @pow((P(t)/P(1, -))elas));
@for (Time (t) | t #GT#1: D(t) = (1.1 - (0.1 * alpha)) * m * (F(t) - F(t-1)) * @pow((P(t)/P(1, -))elas));
@for (Time (t) | t #EQ#1: P(t) = (V(t) * elas)/(elas -1));
@for (Time (t) | t #GT#1: P(t) = (((V(t) + (H * t)) * elas)/(elas -1)));
@for (Time (t): V(t) = lambda * @pow (X(t),-gamma));
@for (Time (t: @)bin(Delta(t)));
@for (Time (t: @)Gin(X(t)));
Period < = pp;
Period > = 1;
@Gin (period);
```

Algorithm 1

Summary (detailed tables shown below)

Source	Sequential p value	Lack of fit p value	Adjusted R-squared	Predicted R-squared	
Linear	0.0072	<0.0001	0.2664	0.1286	Suggested
2FI	0.9735	<0.0001	−0.0907	−3.0872	
Quadratic	0.3729	<0.0001	0.0013	−57.8495	
Cubic	<0.0001		1.0000		Aliased

Figure 2: Surface modeling with lower demand limit and $\alpha = 0.5$.

We already conducted rigorously with the used tools, and the objective and the application field are revealed in Table 1.

It is demonstrated that the fields of application in the vast majority of the cases are related to managerial purposes. Moreover, preponderance studies employed mathematical modeling and other utilized tools were conceptual modeling, simulation-based modeling and review article with the rates of 54.54%, 31.82%, 22.73%, and 9.09%, respectively. It is worth mentioning that recent researches have studied sensor technology products that optimize the life cycle and compute the optimal profit separately, yet this article scrutinizes the combination of the two aforementioned topics. The augmented features of this study are as below. Note that this research is an evolved version of the Sale et al. [8] research with regard to their research limitations considering deterministic demand function and constant variable costs. To solve these limitations, some changes have been taken in the previous research preliminaries, including

Lack of fit tests

Source	Sum of squares	df	Mean square	F value	p value Prob > F	
Linear	4.368E+016	33	1.324E+015	2.030E+005	<0.0001	Suggested
2FI	2.905E+016	12	2.421E+015	3.713E+005	<0.0001	
Quadratic	1.565E+016	5	3.130E+015	4.799E+005	<0.0001	
Cubic	0.000	0				Aliased
Pure error	3.261E+010	5	6.521E+009			

"*Lack of fit tests*": want the selected model to have insignificant lack of fit

Figure 3: Scrutinizing models and suggesting a linear model.

ANOVA for response surface linear model

Analysis of variance table [partial sum of squares: type III]

Source	Sum of squares	df	Mean square	F value	p value Prob > F	
Model	2.683E+016	7	3.833E+015	3.33	0.0072	Significant
A-a	1.881E+015	1	1.881E+015	1.64	0.2086	
B-b	1.124E+014	1	1.124E+014	0.098	0.7562	
C-m	1.439E+016	1	1.439E+016	12.52	0.0011	
D-elas	2.136E+015	1	2.136E+015	1.86	0.1809	
E-H	7.016E+015	1	7.016E+015	6.10	0.0181	
F-S	9.398E+014	1	9.398E+014	0.82	0.3716	
G-I	2.962E+014	1	2.962E+014	0.26	0.6146	
Residul	4.368E+016	38	1.150E+015			
Lack of fit	4.368E+016	33	1.324E+015	2.030E+055	<0.0001	Significant
Pure error	3.261E+010	5	6.521E+009			
Cor total	7.051E+016	45				

Figure 4: ANOVA analysis with lower demand limit and $\alpha = 0.5$.

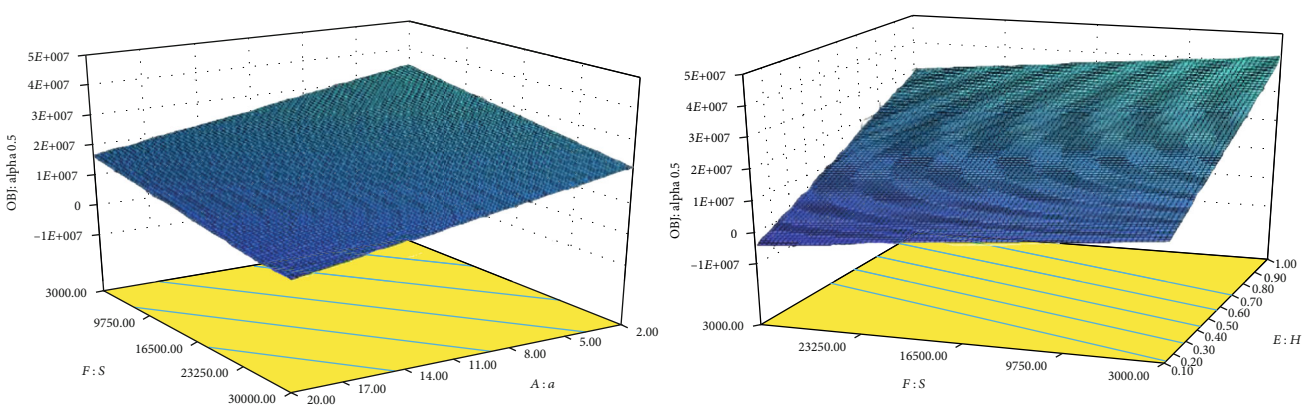

Figure 5: Objective function diagram as a function of A and S and H and S parameters with lower demand limit and $\alpha = 0.5$.

(1) considering divergent periods' demand as triangular fuzzy number (TFN)

(2) applying the alpha cut method in order to calculate demand's upper and lower limits

(3) analyzing various values of alpha, demand's upper and lower limits, and objective function

(4) employing Cobb-Douglas for the model's variable costs

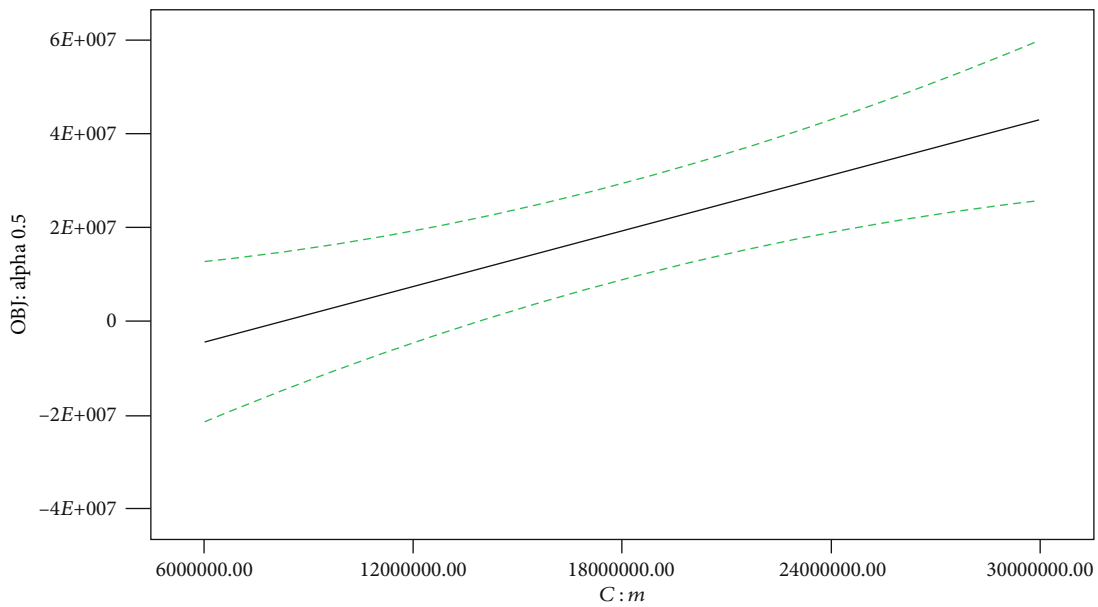

Figure 6: Objective function diagram as a function of parameter m with lower demand limit and $\alpha = 0.5$.

(5) exclusive analysis on the utilized Cobb-Douglas model for variable costs

3. Research Methodology

3.1. Assumptions

(1) The succeeding generations of sensor technology products are introduced in the same product family in a low innovated industry whilst product success is based on mode

(2) The planning horizon of sensor technology products is adequately extended, and the product life cycle is short in order to be able to plan for several product generations

(3) The manufacturer of sensor technology products employs the solo-product roll; previous product inventory is depleted by the time the new product is introduced

(4) The modified Bass model considering the price of sensor technology products is applied for each product's demand

(5) Variable costs and demand of sensor technology products are considered dependent and uncertain, respectively

(6) Demand backlogs of sensor technology products are not allowed, and unsatisfied demand is considered as lost sales

(7) The manufacturer of sensor technology products operates in a monopolistic market, and the diminutive competitors are not capable of affecting the market

Table 3: The coefficients of the parameters in the surface estimation function with a lower demand level and $\alpha = 0.5$.

Parameter	Parameter coefficient in surface estimation function
a	-9.52
b	-466.62
I	-0.32
S	-454.55
m	+1.97
η	-30.8
H	+3.70

Table 4: Optimized value of parameters with a lower demand level and $\alpha = 0.5$.

Parameter	Optimized parameter value
a	2.0
b	0.04
I	4M
S	3K
m	30M
η	2.0
H	0.1

3.2. Modeling. The basic model of sensor technology products is presented by Sale et al. [8] with changes in demand and cost function (Sale, 2017). The demand curve in the proposed model of sensor technology products is based on the Bass model. Bass model consists of two behavioral forces: innovation and imitation. Part of the demand occurring

Table 5: Variable level estimation and their effect on objective function with a lower demand level and $\alpha = 0.5$.

Objective function	Number of periods	X1	X2	X3	X4	X5	Inv_1	Inv_2	Inv_3	Inv_4	Inv_5	P1	P2	P3	P4	P5
-775,726	2	3028	589				0	151				21.7	20.1			
2,628,204	4	840	3190	2288	1864		0	360	275	384		15.5	8.7	0.8	7.8	
4,520,129	4	1323	5581	1835	4539		0	32	195	281		2	12.9	17.6	1.6	
105,343,900	5	3237	894	3511	2163	2336	0	196	231	232	410	17	13.8	12.9	13.6	1.6
39,017,830	3	4314	2567	616			0	165	49			1.8	16.6	10.2		
139,707,800	5	270	4416	5159	3622	1723	0	34	33	399	293	6.2	1.4	15.9	9.3	15
-529,911	2	436	742				0	143				30.6	9.6			
-2,223,997	2	4670	729				0	265				22.2	2.1			
-798,267	3	5175	6007	2222			0	10	79			8.1	5.6	8.5		
-2,985,145	3	2941	1159	5906			0	129	13			16.7	13.1	4.5		
64,563,470	3	1755	1535	5600			0	29	312			6.8	12.1	2.6		
-672,829	3	1289	4656	6055			0	219	329			27.2	20.7	8.9		
-672,829	3	4144	5889	3277			0	130	7			30.4	19.3	9.3		
-592,877	3	5635	350	1073			0	43	200			0.8	12.3	3.1		
33,379,380	3	2339	1688	1394			0	381	210			17.4	4.9	0		
-5,022,771	2	3782	4667				0	383				24.5	13.9			
25,935,700	3	4147	5435	2820			0	84	294			10.5	1.7	8.5		
-550,993	3	5402	6078	5080			0	36	313			26.1	30.2	18.5		
39,074,650	3	3966	3773	423			0	286	106			17	2.7	1.1		
33,379,380	4	5742	3194	5563	1039		0	132	112	266		8.7	16.6	4.7	6.6	
8,211,317	5	630	5876	1556	1894	6172	0	378	200	189	382	5.8	15.3	9.2	14.2	14.1
12,599,110	4	93	3853	5451	5720		0	297	148	190		0.8	2.5	17.5	16.1	
-1,430,400	2	4509	4996				0	154				14	30.7			
-5,004,801	2	3501	2300				0	5				15.8	18			
-1,540,536	3	4011	2426	3840			0	163	200			14.6	22.1	18.9		
27,210,220	3	5809	5530	565			0	274	401			7.1	16.5	0.1		
-2,422,504	2	5928	3712				0	347				10.6	12.4			
6,464,523	4	2365	1303	1389	4030		0	68	376	262		18	7.7	14.8	8.1	
92,752,950	5	5887	5286	3132	1458	2948	0	180	415	403	412	4.3	3.6	10.9	2.3	15.4
-805,997	3	4296	3260	2784			0	29	416			1.2	22.5	0		
12,195,740	5	1424	2074	1394	3674	5399	0	276	387	291	337	14.3	17	1.8	8.3	10.5
88,075,850	3	1142	1898	1414			0	36	376			2.4	12.2	17.1		
13,544,910	5	2850	4002	1605	779	358	0	7	44	378	275	17.3	3.4	15.3	15.1	7.9
-620,046	2	4765	5894				0	243				16.7	14.8			
-804,199	2	3927	1585				0	195				18.8	28			
171,139,600	3	4800	2116	5227			0	333	253			8.2	1.8	9		
15,305,520	5	4144	2860	809	3533	6186	0	272	69	147	131	0.9	5	13.3	4.3	1.4
2,628,204	4	4636	1846	5307	1354		0	120	227	368		7	12.4	4.7	0.4	
-3,598,438	3	2587	826	2459			0	121	70			23.2	16.1	28.1		
7,264,818	4	1742	4859	337	882		0	15	196	199		10.9	12.5	14.4	1.8	
-4,467,215	3	6054	6140	250			0	126	266			5.2	6.7	3.5		
-5,005,997	2	5496	1995				0	196				29.6	9			
71,200	3	5996	1630	2560			0	210	334			9.4	4.1	8		
-5,017,997	3	1742	1105	5289			0	92	203			4.1	11	8.5		
8,232,533	4	1149	5508	1566	5051		0	336	407	144		8.8	1.9	0.3	4.5	
-3,498,032	2	3851	279				0	393				11.2	24.9			

Figure 7: Relation between objective function and number of periods with a lower demand level and $\alpha = 0.5$.

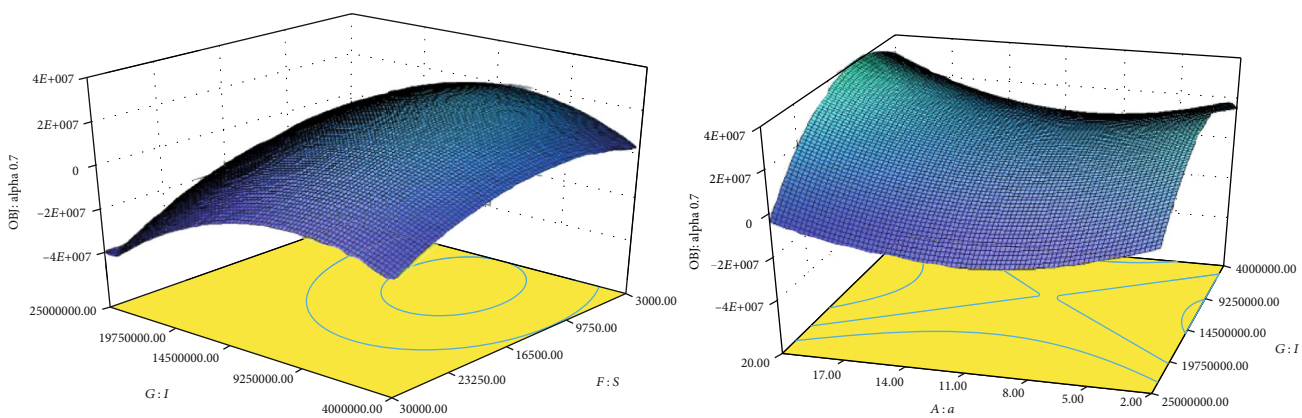

Figure 8: Objective function diagram as a function of S and I and a and I parameters with lower demand limit and $\alpha = 0.7$.

independently from cumulative demand is related to the innovation coefficient (p) and the other part altering with the cumulative demand is linked with the imitation coefficient (q). Assuming m to be the market size, a to be the ratio of q to p, and b to be the summation of q and p, the cumulative demand for time period t is evaluate with equation (1); hence, the demand for the period t is illustrated by equation (2).

$$F(t) = \frac{1 - e^{-bt}}{1 + ae^{-bt}}, \tag{1}$$

$$\widetilde{D_\beta}(t) = m * [F(t) - F(t-1)]. \tag{2}$$

The index β determines that the aforementioned equation does not consider the price effects. On the one hand, manufacturer takes advantage of the earned revenue of selling its goods; on the other hand, it confronts variable unit cost, fixed set-up cost, fixed production cost, inventory cost, and new sensor technology product introduction cost. The corporation aims to maximize the acquired profit resulting from deducting the expenses from the earnings; thus, the objective function is obtained as

Table 6: Optimized value of parameters with a lower demand level and $\alpha = 0.7$.

Parameters	Optimized parameter value
A	20.0
B	0.04
I	11M
S	12K
m	30M
η	8.0
H	0.4

$$\max \frac{\sum_{t=1}^{T}\left((p_t - v_t) * \tilde{D}_t - S * \sigma_t - H * Inv_t\right) - I}{T}. \tag{3}$$

Inventory at the end of period t is computed as follows:

$$\mathrm{Inv}_t = \mathrm{Inv}_{t-1} + X_t - \tilde{D}_t \quad \text{for } t = 1 \text{ to } T. \tag{4}$$

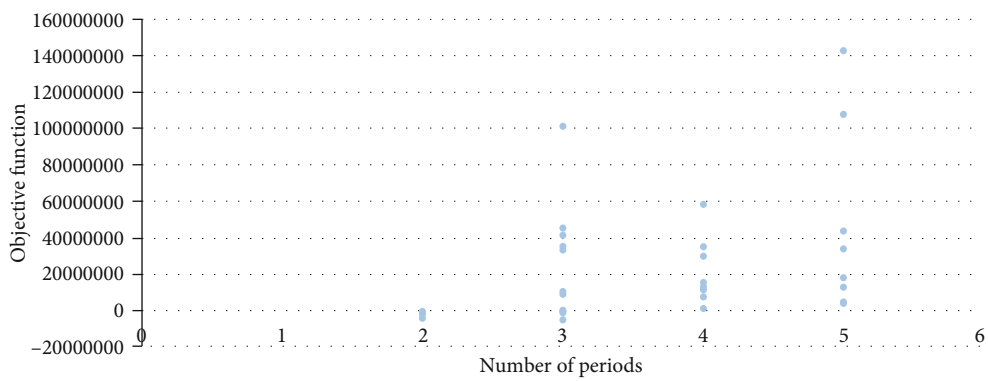

Figure 9: Relation between objective function and number of periods with a lower demand level and $\alpha = 0.7$.

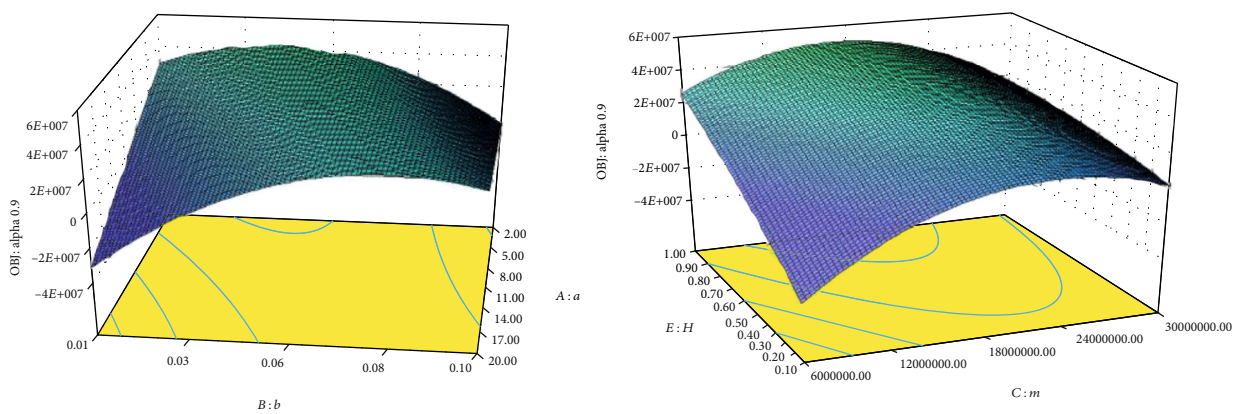

Figure 10: Objective function diagram as a function of a and b and m and H parameters with lower demand limit and $\alpha = 0.9$.

Table 7: Optimized value of parameters with a lower demand level and $\alpha = 0.9$.

Parameter	Optimized parameter value
A	2.0
B	0.04
I	4M
S	30K
m	22M
η	2.0
H	1.0

Remark that the decision variable X_t illustrates the production level in period t and Inv_0 is assumed to be zero. In order to make production of sensor technology products responsible for the demand, the following production constraint is written as

$$\sum_{t=1}^{i} X_t \geq \sum_{t=1}^{i} \tilde{D}_t. \tag{5}$$

The abovementioned equation indicates that the cumulative production until the desired period covers its cumulative demand. Set-ups ought to take place in periods in which production level is positive. This constraint is demonstrated as

$$m * \sigma_t - X_t \geq 0 \quad \text{for } t = 1 \text{ to } T. \tag{6}$$

The net profit function is modelled as equation (7) on condition that the stock level at the first period is equal to zero.

$$(P_1 - V) * \tilde{D}_t. \tag{7}$$

The optimized value of P_1 is equal to the root of derivation of equation (7) with respect to price; hence, the value for p_1 is as

$$p_1 = \frac{v_t + \eta}{\eta - 1}. \tag{8}$$

Note that η is assumed to be considerably bigger than 1. Equation (8) is only valid when the period of sensor technology product stock is empty. Inventory holding of sensor technology product costs result in a divergent equation for indicating the optimized price value as

$$p_t = \frac{(v_t + HN_t) + \eta}{\eta - 1}. \tag{9}$$

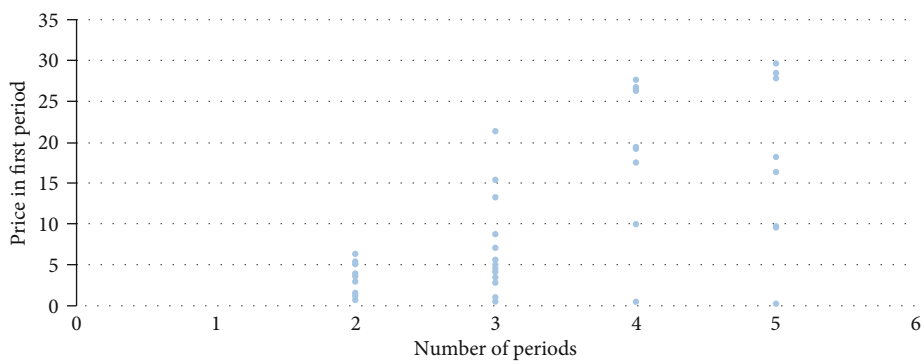

Figure 11: Relation between the first period's price and the number of periods with a lower demand level and $\alpha = 0.9$.

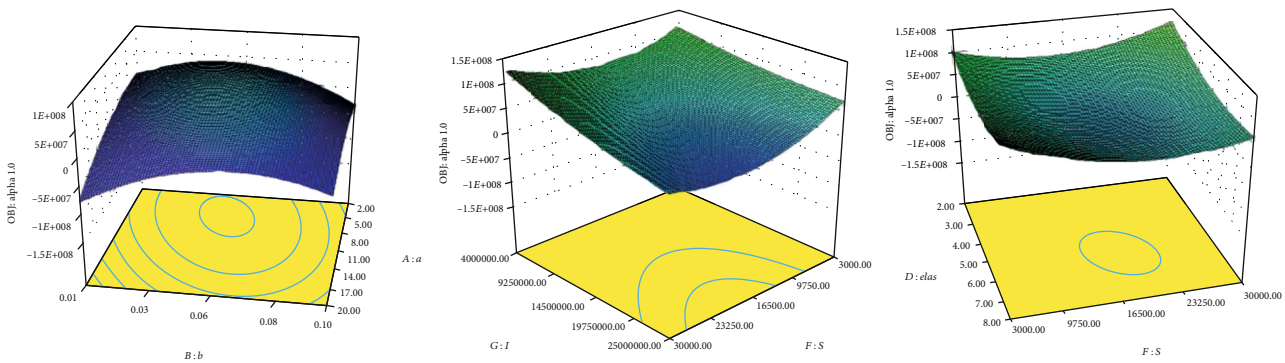

Figure 12: Objective function diagram as a function of S and price elasticity coefficient, S and I, and a and b with lower demand limit and $\alpha = 1$.

N determines the periods which the sensor technology products are held in the inventory before sale.

4. Numerical Example and Sensitivity Analysis

First of all, the utilized parameters of sensor technology products for experimental design and their surfaces are described; subsequently, the statistical results of modeling with the upper and lower limits and the alpha cut method are determined; finally, each parameter's influence on the objective function is illustrated by sensitivity analysis. Table 2 indicates the utilized parameters of sensor technology products for experiments and their numerical surfaces considering the Sale (2017) research.

Employing Design-Expert software and response surface methodology has shed light on the parameters' impact on the proposed model. Regarding the demand to be fuzzy, considering a 10% tolerance, the upper and lower limits are as follows [26–28]:

$$A_\alpha = [(0.9 + 0.1\alpha)D_{t'}(1.1 - 0.1\alpha)D_t]. \quad (10)$$

The following reveals divergent parameters' effects on the model considering the mentioned limits using the experimental design approach (Algorithm 1). The coded basic model in LINGO is as follows.

Statistical results are presented in four sections, each indicating the value of alpha used for fuzzy demand function.

Table 8: Optimized value of parameters with a lower demand level and $\alpha = 1$.

Parameter	Optimized parameter value
A	2.0
B	0.04
I	11M
S	30K
m	22M
η	8.0
H	1.0

For alpha 0.5, 0.7, 0.9, and 1, results were demonstrated separately and finally compared.

4.1. Section (A): Statistical Results of Surface Modeling with Lower Demand Limit and $\alpha = 0.5$. The results are issued in Figures 2 and 3. As depicted, a linear model is suggested by the software and contains fewer errors than other models.

Additionally, ANOVA analysis determines that the linear model is valid, and each parameter's influence on the model is pictured in Figure 4.

Figure 5 presents objective function as a function of parameters$S$and$S$.

Furthermore, Figure 6 pictures the objective function based on parameter m.

Table 9: Comparison of the upper and lower limits of demand according to the values of alpha.

	$\alpha = 0.5$		$\alpha = 0.7$		$\alpha = 0.9$		$\alpha = 1$
	Lower limit	Higher limit	Lower limit	Higher limit	Lower limit	Higher limit	
Recommended level for surface	Linear	Linear	Quadratic	Linear	Quadratic	Quadratic	Quadratic
p value of the model	0.0072	0.0087	0.0493	0.0219	0.0016	0.0299	0.0008
Highest amount of the objective function	1.71E+08	2.15E+08	1.43E+08	2.33E+08	1.32E+08	1.98E+08	2.04E+08
Objective function's average	1.96E+07	2.09E+07	1.79E+07	2.05E+07	1.32E+07	1.95E+07	2.33E+07

As depicted, escalation in market size of sensor technology products has a positive correlation with the objective function. Moreover, in each problem parameter's coefficient in regression function, response surface prediction of the mentioned issue is explicit which is indicated in Table 3.

Design-Expert software is employed in order to measure each parameter's optimized value which calculates the optimized parameter values based on the targeted object by experimental design and response surface methodology. Aiming to hit the zenith of the objective function model, the obtained optimized parameter values are as noted in Table 4.

Table 5 indicates number of periods, production amount, inventory level, price of each period, and objective function's value.

In Figure 7, the relation between objective function and number of periods is revealed.

Considering Table 5 and Figure 7, it is perceived that a negative objective function value leads to less period numbers.

4.2. Section (B): Statistical Results of Surface Modeling with Lower Demand Limit and $\alpha = 0.7$. To avoid repeated results, three other alpha sections were presented briefly. It is indicated that for this amount of alpha, linear and quadratic models are suggested. Figure 8 depicts the objective function as a function of divergent parameters.

According to the analyses, the quadratic model proposed a more accurate prediction of the objective function surface. At this level of alpha, optimal values of parameters are also obtained using the Design-Expert software to maximize the objective function as presented in Table 6.

The relation between objective function and the number of periods is demonstrated in Figure 9.

4.3. Section (C): Statistical Results of Surface Modeling with Lower Demand Limit and $\alpha = 0.9$. Not unlike the previous amounts of alpha, linear and quadratic models of sensor technology products are recommended for the response surface by the software. Variance analysis results validate the quadric model of sensor technology products. The objective function's graph as a function of the below mentioned parameters is pictured in Figure 10.

Intending to reach an apogee in the objective function, Table 7 demonstrates the optimized value of the parameters.

The relation between the number of periods and the first period's price is indicated in Figure 11. As it is apprehended, in a lower number of periods, the price in the first timespan does not exceed more than the limit, owing to the fact that the relation between the number of periods and the objective function indicates that the model's condition leads to a lower price, resulting in a higher ratio of costs to the income; thus, a negative objective function ensues.

Table 10: Parameter surfaces in the Cobb-Douglas function.

Parameter	Parameter surfaces
λ	150, 130, 110, 90
γ	2, 1.5, 1.25, 1

4.4. Section (D): Statistical Results of Surface Modeling with Lower Demand Limit and $\alpha = 1$. Given that alpha equals one, similar to the two former amounts for alpha, the linear and quadratic models for the surface are advised as in Figure 12.

Furthermore, for the stated value of alpha, the optimized amounts of parameters are also calculated as shown in Table 8.

Table 9 briefly describes the result of comparing the upper and lower limits of demand with different amounts for alpha.

As observed in Table 9, the objective function's climax occurs when a higher limit of alpha being 0.7 is assumed; hence, the optimum state of demand belongs to this amount of alpha. The objective function reaches the culmination while the number of periods are four with a higher demand level and $\alpha = 0.7$.

In order to discuss the impact of the Cobb-Douglas variable cost function's parameters on the model of sensor technology products, regarding the obtained values of the parameters from the results of the experimental design for the model in the previous section, the analysis of two parameters of the function will be performed. Table 10 indicates the divergent surfaces of the two parameters for a variable cost from the Sale et al. [8] research.

Experimental design results for Cobb-Douglas function's parameters illustrated that the quadratic model of sensor technology products best fits the response surface. Moreover, ANOVA analysis proves the validity of the model. For the Cobb-Douglas function as a function ofλandγ, onlyλandγ are demonstrated in Figure 13.

The software for the two aforementioned parameters predicts that as the amount of λ diminishes, this leads to reduction in variable costs resulting in the objective function's upsurge. Table 11 issues parameter coefficients in function surface fitting.

Moreover, considering the purpose of maximizing the objective function (profit) of sensor technology products,

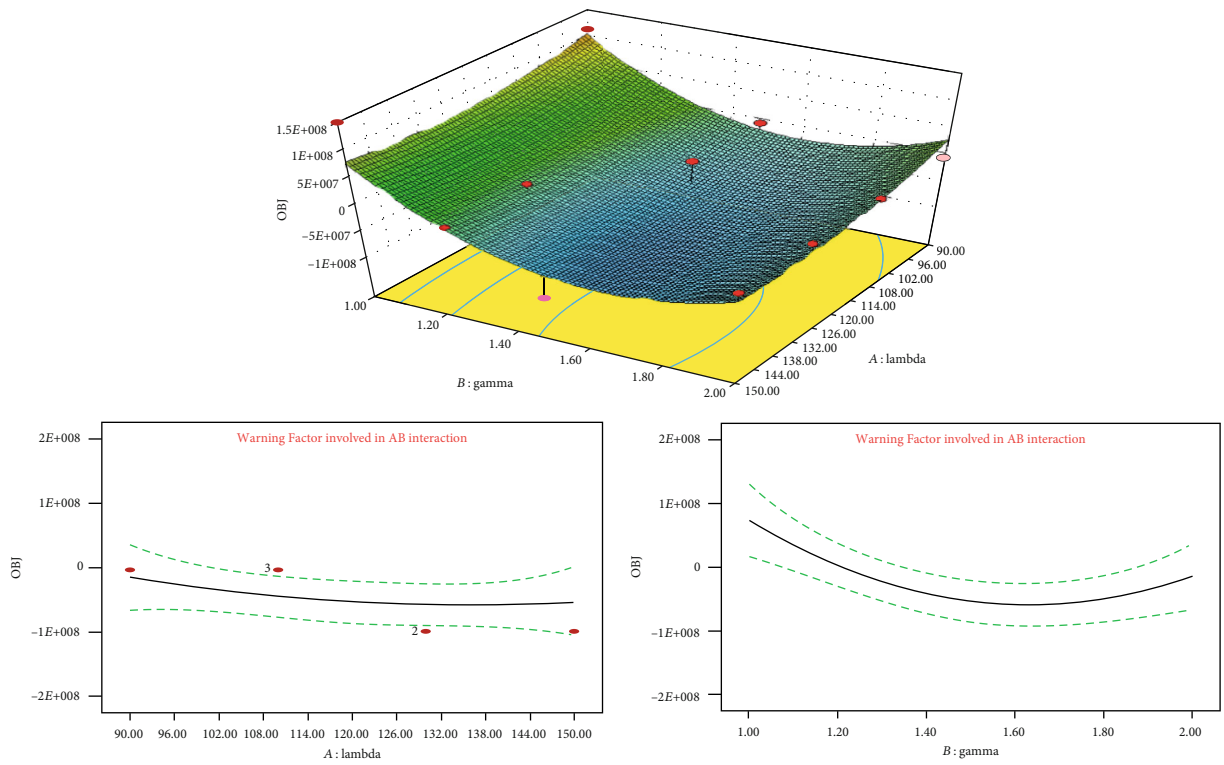

Figure 13: Cobb-Douglas function's diagram as a function of λ and γ, as a function of λ, and as a function of γ.

Table 11: Optimal values of Cobb-Douglas function parameters.

Parameter	Parameter coefficient in surface estimation function
λ	-51.02
γ	-1033.62
$\lambda \times \gamma$	-4.15
λ^2	+0.21
γ^2	+331.95

the software attained optimized values of Cobb-Douglas parameters as 90 and 1 for λ and γ, respectively.

5. Conclusion

Acceptance of sensor technology products and operational decision making is an integral part of introducing new sensor technology products to the market. In order to succeed in presenting a new product, the basic step is to be acquainted with concepts related to diffusion of innovation, lot sizing, optimal product lifetime, etc. This paper evolved and analyzed a basic related model to determine the new sensor technology product introduction's optimum time, price, production scheduling, and rate simultaneously.

In this study, the abovementioned tenors are foremost elucidated. Hence, after determining the model's sensor technology product assumptions, the effecting parameters, variables, objective function(s), and constraints on the model are explained. Afterwards, thereinafter mentioned mathematical models for the optimized level of the lifespan and profit of a product are presented. Thereafter, experimental design and simulation methods were used to generate data. To solve the problem, Lingo software optimized the model with Design-Expert 8 software to present experimental designs of the parameters. Subsequently, the issued model's validity is measured employing the alpha cut method (for uncertain demand) giving 0.5, 0.7, 0.9, and 1 values to alpha and solving the method with lower and higher demand limits. Optimized levels of the parameters are calculated, and eventually, the validity of the model is proved by the ANOVA analysis.

It is eventuated that the optimal amount of the profit occurs when $\alpha = 0.7$ with a higher demand limit. Additionally, for considering the cost as a function, the two Cobb-Douglas function's parameters, λ and γ, were calculated to be 90 and 1, respectively. To sum up, it is deduced that more profit and higher pace in new product introduction have a positive correlation with faster diffusion of innovation, lower price elasticity, higher market potential, and lower product introduction cost, verifying previous results.

Assumptions of preceding studies have created limitations leading to discrepancy between the paper results and reality, for instance, certain demand, constant variable cost, and fixed model parameters. With a view to cover a portion of the weaknesses caused by the assumptions, this paper has considered demand to be fuzzy and employed the Cobb-Douglas function for variable cost to use the model in real cases. Considering cost experience, demand shortage constraint, and the competitors' impact on demand will lead the researchers to a more realistic model in the future. In addition, providing a dynamic model varying its parameters as time

goes by develops the model. Moreover, considering new numbers and approaches such as hesitant fuzzy and intuitionistic fuzzy would increase the uncertainty of the model.

Notations

Note	Description	Type
Inv_t	Inventory at the end of period t	Parameter
X_t	Production amount in period t	Decision variable
T	Time period sets	Decision variable
D_t	Demand in period t	Function
σ_t	Binary variable taking value 1 if production takes place in time period t	Binary variable
P_t	Product price in time period t	Parameter
λ	Variable cost's coefficient in Cobb-Douglas function	Parameter
γ	Variable cost's elasticity in Cobb-Douglas function	Parameter
a	The ratio of coefficient of imitation (q) to coefficient of innovation (p)	Variable
b	The summation of p and q	Variable
m	Market size	Variable
n	Price elasticity of demand	Variable
S	Fixed set-up cost	Variable
I	New product introduction cost	Variable
H	Holding cost	Variable
V_t	Variable unit production cost in time period t	Function

Data Availability

The data of SENSOR DATA used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there is no conflict of interest.

Acknowledgments

The authors declare that the research was funded by the Doctor of Computer Science, Bina Nusantara University, and Advanced Institute of Industry Technology, Tokyo, Japan.

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