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A DSS-Based Dynamic Programming for Finding Optimal Markets Using Neural Networks and Pricing

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Abstract
One of the substantial challenges in marketing efforts is determining optimal markets, specifically in market segmentation. The problem is more controversial in electronic commerce and electronic marketing. Consumer behaviour is influenced by different factors and thus varies in different time periods. These dynamic impacts lead to the uncertain behaviour of consumers and therefore harden the target market determination. Real time decision making is a crucial task for obtaining competitive advantage. Decision Support Systems (DSSs) can be an appropriate process for taking real time decisions. DSSs are classified as information system based computational systems helping in decision making supporting business decision making and facilitate data collection and processing within market analysis. In this paper, different markets exist that are supplied by a producer. The producers need to find out which markets provide more profits for more marketing focuses. All consumers' transactions are recorded in databases as unstructured data. Then, neural network is employed for large amount of data processing. Outputs are inserted to an economic producer behaviour mathematical model and integrated with a proposed dynamic program to find the optimal chain of markets. The sensitivity analysis is performed using pricing concept. The applicability of the model is illustrated in a numerical example.

Keywords
Information Technology (IT); Decision Support Systems (DSS); Perceptron Neural Network; Dynamic Programming (DP).

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Introduction and Literature Review

Information and communication technologies transformed the process of acquisition, processing, and deposition of data for multiple purposes (Hassanlou et al., 2009; Arvanitis & Loukis, 2009). The process influenced decision making of complex systems in industry, trade, investment, etc. At the same time, the value of information evolved in operations management of maintenance, supply, logistics, demand analysis, and raw material consumptions (Johnson, 2020; Murgia et al., 2019; Özer, 2019). Various disciplines of statistics, operations research, and financial analysis are developed for better decision making and determining optimal choices leading to a more complicated data flow and decision making (Zhai et al., 2020). Environments that are able to process complex decision matrix or data structure are called decision support systems (DSSs) (Guo, 2020). This concept is broad and encompasses both structured and unstructured data by integrating different sources of information based on intelligent data processing through artificial intelligence methods (Bhargava et al., 2007; Boshkoska et al., 2019). Dynamic programming is used to decompose large sized problems into smaller ones, and by solving the smaller sub-problems and integrating them the whole problem is solved efficiently. Nowadays, complexity and unpredictability are two challenging factors influencing business environment (Garrigós et al., 2008). The simple access of customers to information and drastic competition among competitors increases the dynamism and impacts the marketing activities by information technology (Jallat & Ancarani, 2008). Marketing strategies focus on different elements of market such as customer, competitor, product, promotion, price, etc. in order to manage business environment (Narangajavana et al., 2014).

Implementing businesses in a challenging and dynamic environment of market requires appropriate and effective decisions in different dimensions (Yaziji, 2004; Banerjee, 2002). Considering just profit is not any more effective in decision makings, in contrast with traditional business management (Aragon-Correa et al., 2004; Clemens & Douglas, 2006). Multi-dimension analysis and decision making provides various aspects of performance criteria being substantial in dynamic decisions (Plambeck & Denend, 2008;

Braunsberger & Buckler, 2011). Applying information technology in business decisions led to fast actions with respect to rapid changes of market and customer behaviors (Lakshmanaprabu et al., 2019; Mete et al., 2019). Combining business decisions through information technology and artificial intelligence resulted in the inclusion of higher impact of dynamism in decisions (Erozan, 2019; Ramirez, 2013). A summary of the related works in the literature are presented in Table 1.

Table 1. Summary of Literature Review

Researchers	Year	Problem	Method
Bhargava et al.	2007	Web-based decision support	Statistical analysis
Garrigós et al.	2008	Tourism management	Statistical analysis
Jallat, & Ancarani	2008	Customer relationship management	Dynamic pricing
Boshkoska et al.	2019	DSS in knowledge sharing	Mathematical model
Murgia et al.	2019	Electronic market	Statistical analysis
Özer	2019	Internet auction	Heuristics
Lakshmanaprabu et al.	2019	Clinical DSS	Deep neural network
Mete et al.	2019	Risk DSS	Pythagorean fuzzy VIKOR
Erozan	2019	Maintenance DSS	Fuzzy method
Johnson	2020	Electronic market	Mathematical model
Zhai et al.	2020	Agriculture DSS	Review
Guo et al.	2020	IoT based DSS	Data mining
This research	2020	Electronic market DSS	Neural network dynamic programming integrated with producer behaviour theory and pricing

Nonetheless, past researches mostly focused on single stage decision making via DSSs in different areas and businesses. Also, computational intelligence within a dynamic circumstance was neglected. Therefore, to fill the gap, a bi-stage DSS is proposed in this work to handle two strategic and tactical decisions at the same time. The essence of market selection and the profit of the firm are the strategic and tactical decisions, respectively. Meanwhile, to counteract the dynamism of the data flow, a dynamic programming approach is employed. Also, computational intelligence is considered using artificial neural networks.

Here, we propose a DSS to find out optimal markets for a producer by integrating neural network and dynamic programming models. The aim of the producer is to determine optimal markets providing more profit. The market data are collected by market research department and deposited in databases. Due to the large amount of data, neural network is applied to pre-processing and an economic behaviour mathematical formulation is developed for obtaining profits of different markets. Then, a dynamic program is proposed to find the optimal markets.

Problem Description

One of the challenging marketing decisions for companies that produce multiple products is determining target markets. Target markets are the ones marketing team believes have more attraction and thus provide more profit. Different approaches can be used for target market determination. However, it should be noted that dynamism, uncertainty, and large amount of market data should be considered and integrated for decision-making. Therefore, here a decision support system is proposed to analyze consumer behavior based on the shopping trends. We consider homogenous markets in one stage. Parameters such as geography, demographic properties, consumer budget, etc. are effective in categorizing homogenous markets. Then, several stages are formed to configure a network of markets. Here, the producer needs to decide to enter the market that provides maximum profit. The basis of decision-making is the demand collected from each market. The schematic presentation of the proposed problem is shown in Figure 1.

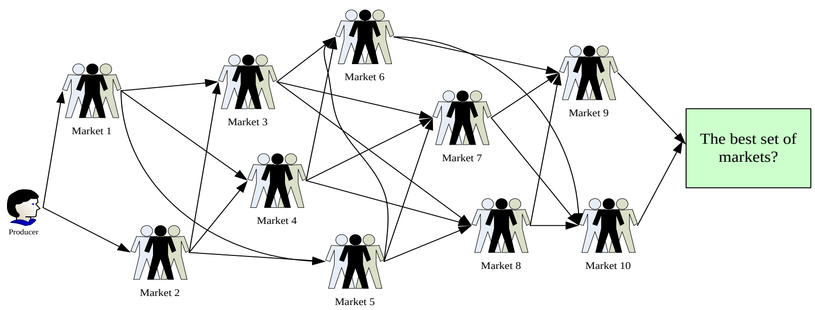

Fig. 1. An Overview of the Proposed Problem

To simplify, a network of markets in stages is configured. The aim is to find markets in each stage providing maximum profit. This decision-making is performed in all stages and finally a set of markets that maximize the total integrated profit of the network is obtained. To facilitate computations with respect to the large amount of data and dynamic changes that occur in consumer behavior, a DSS is developed. The computation core of the DSS is based on producer behavior theory. The data flow among different markets within the network is collected and analyzed for processing. The DSS calculates the profit for each market separately in each stage and then automatically chooses the maximum profit market. The market network and the function of DSS are depicted in Figure 2.

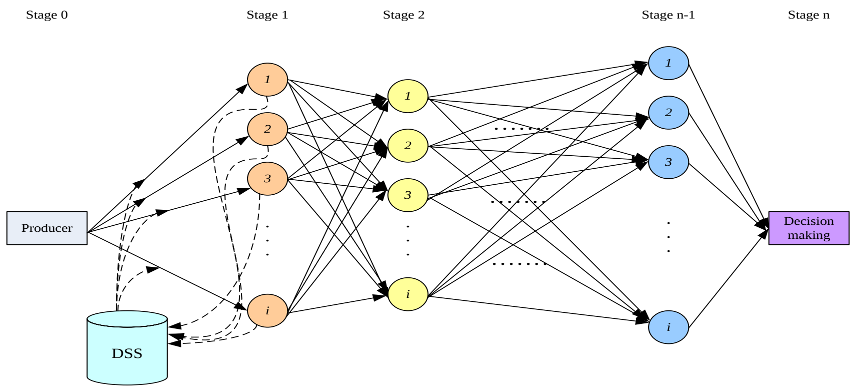

Fig. 2. A Structure of DSS Function in a Network

The Proposed DSS

The proposed DSS here works as a decision aid for market analysis and provides optimal markets having maximum profits. In the proposed DSS, three layers of input, analysis, and output are categorized. Inputs are products, their prices, and operational costs. Analysis is performed based on producer behavior theory optimization model. Output is the expected profit of the markets. Using the data acquired from markets, the DSS is triggered. Due to the dynamics of data and changes in market condition, a real time decision making process is worked out. The structure of the DSS is indicated in Figure 3.

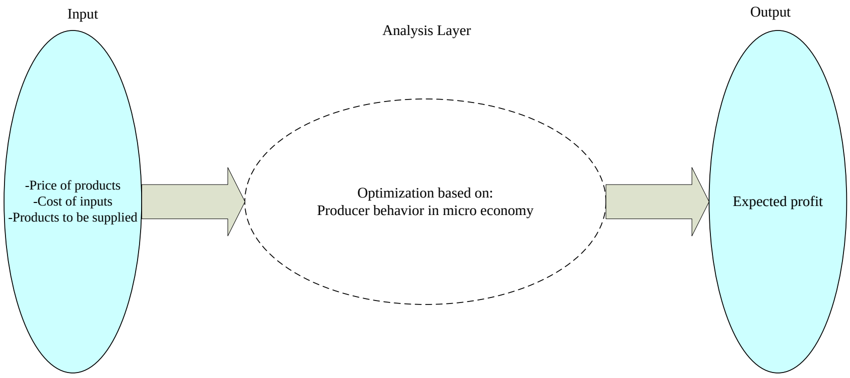

Fig. 3. The Structure of DSS

As indicated in Figure 3, the expected profit of each market is obtained in an optimization model of producer behavior theory. Profit is the differences of revenue and costs, mathematically. The required mathematical notations follow here.

Index

j Index of products; j=1,2,…,m

Parameters

p_j	Price of product j^{th}
q_j	Number of product j^{th}
r_j	Operational cost for input j^{th}
x_j	Number of input j^{th}
F	Function

The profit mathematical model

$$Max \quad \pi = \sum_{j=1}^{m} p_j q_j - \sum_{i=1}^{m} r_j x_j \Rightarrow \pi = \sum_{i=1}^{m} p_j q_j - \sum_{j=1}^{m} r_j F(q_1,...,q_j) \tag{1}$$

where x_j s are the output quantity function $F(q_1,...,q_j)$. The aim here is to maximize the profit of the consumer. Thus, to solve the problem, the partial derivatives are set and equal to zero (first order conditions):

$$\frac{\partial \pi}{\partial q_1} = p_1 - r_1 f_1 = 0 \tag{2}$$

$$\frac{\partial \pi}{\partial q_2} = p_2 - r_2 f_2 = 0 \tag{3}$$

$$\frac{\partial \pi}{\partial q_j} = p_j - r_j f_j = 0 \tag{4}$$

where f_j is the Marginal Productivity (MP):

$$f_j = \frac{\partial x_j}{\partial q_j} \tag{5}$$

Moving the price terms to the right and dividing by marginal productivity, $r_j = \frac{p_j}{f_j}$, or substituting the MP formulae:

$$r_j = p_j \frac{\partial q_j}{\partial x_j} \tag{6}$$

In practice, the price of x_j is equal to the value of MP. As for the sufficient condition of optimization, the hessian matrix of the model above is formed as follows:

$$\begin{vmatrix} -r_1 f_{11} & -r_1 f_{12} & \dots & -r_1 f_{1j} \\ -r_2 f_{21} & -r_2 f_{22} & \dots & -r_2 f_{2j} \\ & \dots\dots & & \\ -r_j f_{j1} & -r_j f_{j2} & \dots & -r_j f_{jj} \end{vmatrix} > 0 \tag{7}$$

When we have positive r_j, the second order condition implies that MP is increasing. Thus, the output is optimal. Due to fluctuations of demand and other inputs we make use of artificial neural network (Syriopoulos & Roumpis, 2009).

Artificial Neural Network

An artificial neural network (ANN) is a mathematical presentation of natural neurons of human body in biology (Liu et al., 2020). Generally, neural networks are implemented in computer software (Castellani & Rowlands, 2009).

A multilayer perceptron (MLP) is a feedforward ANN model that relates a set of inputs to a set of peer outputs being a modified version of linear perceptron having three or more layers and a nonlinear activation function. The two main activation functions used here are Sigmoids, as given below:

$$\phi(v_i) = \tanh(v_i) \text{ and } \phi(v_i) = (1 + e^{-v_i})^{-1} \tag{8}$$

in which both functions are hyperbolic tangent with different ranges, where the former ranges from -1 to 1, and the latter ranges from 0 to 1. Also,

y_i = output of the *ith* node (neuron)

v_i = weighted sum of the input synapses

Then, the error in output node j in the nth data point is,

$e_j(n) = d_j(n) - y_j(n)$,

and

d = target value

y = value produced by the perceptron

Then, the corrected weights are updated using minimized energy error of output,

$$\varepsilon(n) = \frac{1}{2}\sum_j e_j^2(n) \tag{9}$$

Variations in weights are computed using the theory of differentials,

$$\Delta w_{ji}(n) = -\tau \frac{\partial \varepsilon(n)}{\partial v_j(n)} y_i(n) \tag{10}$$

where

y_i = output of the previous neuron

τ = learning rate (ranges from 0.2 to 0.8).

Then, the derivation to obtain the rate is,

$$-\frac{\partial \varepsilon(n)}{\partial v_j(n)} = e_j(n)\phi'(v_j(n)) \tag{11}$$

ϕ' = derivative of the activation function

As stated in DSS, the inputs are fed into the MLP in each layer and based on different time periods. The training period is performed using the required input data leading to counteract the fluctuations of demands and prices.

Dynamic Programming for Optimization

Dynamic programming (DP) was initially proposed by Bellman (1957) and then developed by Toth (1980) in numerical efforts. Combining DP with other methods was tested by Plateau and Elkihel (1985). Here, we make use of a DP to model and optimize our proposed network for determining the markets providing more integrated profits for producers. This model helps the producer to determine the more profitable markets. The proposed dynamic program follows here:

Indices

s	Number of stages;	s= 0,1,2,…, n
i	Start node number;	i=1,2, …, I
i'	End node number;	i'=2,3, …, I

Notations

$\varphi_s(i')$	The maximum value of moving from stage s-1 to the end node i' in stage s
$P_{ii'}$	Numerical value of an arc between node i to node i'

Objective function

$$\varphi_s(i') = \underset{i \text{ in layer s}-1}{Max}\left\{\varphi_{s-1}\left(i\right) + P_{ii'}\right\}, \qquad \text{s} = 1, 2, ..., n.$$

$$\varphi_1\left(i\right) = 0, \quad i = 1, ..., I, \tag{12}$$

$$\varphi^* = \ \varphi_s(i).$$

$i = 0$ (for the start node)

where $P_{ii'}$ is the profit of moving from market *i* to *i'* and *S** identifies the optimal path.

The process of finding the optimal sets of markets in all stages follows here. The proposed dynamic program is an enumerative model begins with the zero state and zero stage (i.e., the beginning value is considered to be zero). Then for the next stage, the value function computes the values of all the nodes (markets) that exist in that stage. Note that, the value of moving between any two nodes is determined by the proposed mathematical profit maximization model based on the presented neural network. Repeating the procedure for all stages provides the optimal markets throughout the proposed network. After checking all the stages, a set of markets that provide the integrated more profit is gained. Next section gives an illustrative example for the proposed DDS-based Dynamic Programming approach.

Illustrative Example

Here, an illustrative example is worked out to show the effectiveness and efficiency of the proposed DSS. There are 3 products, 3 markets in stage one, and 3 markets in stages two and three, respectively. A configuration of the example is shown in Figure 4.

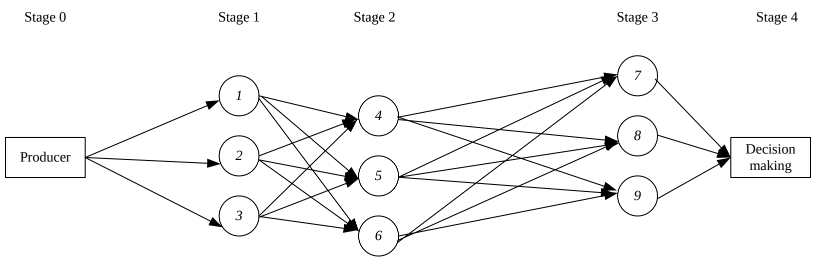

Fig. 4. The Configuration of the Proposed Example

The production functions for products (1, 2, 3) are as follows:

$$x_1 = q_1 q_2 + q_3 \tag{13}$$

$$x_2 = 2q_1 - q_2 + q_3 \tag{14}$$

$$x_3 = q_1{}^2 + q_2 q_3 \tag{15}$$

The production functions given above are composed of the materials used to produce a product. To handle computations, NN ToolBox in MATLAB 7.0 environment is applied. The price and costs as inputs and outputs for three markets given in the first stage are as below, i.e., the first three rows are for prices and the second three rows are for costs.

```
Input=[35 44 53 35 22 53 35 38;...
       44 41 32 29 32 38 35 47;...
       53 50 38 41 44 56 35 41;...
       08 10 14 11 06 14 10 08;...
       10 11 08 06 08 10 09 12;...
       12 14 10 11 11 15 08 10];

output=[38.0 52.4 51.8 35.9 31.0 52.0 44.0 41.5;...
        41.0 41.9 33.5 28.1 32.6 41.0 38.0 51.4;...
        54.5 48.5 41.5 42.5 42.8 51.5 36.5 44.0;...
        9.70 11.5 15.0 11.9 7.00 14.5 11.0 8.00;...
        11.0 11.0 11.0 9.00 8.80 12.8 12.0 12.2;...
        14.8 15.3 11.0 13.8 13.0 14.5 8.90 12.5];
```

A user interface in MATLAB 7.0 environment is worked out for computations that receives inputs and then provides outputs. The user interface is depicted in Figure 5.

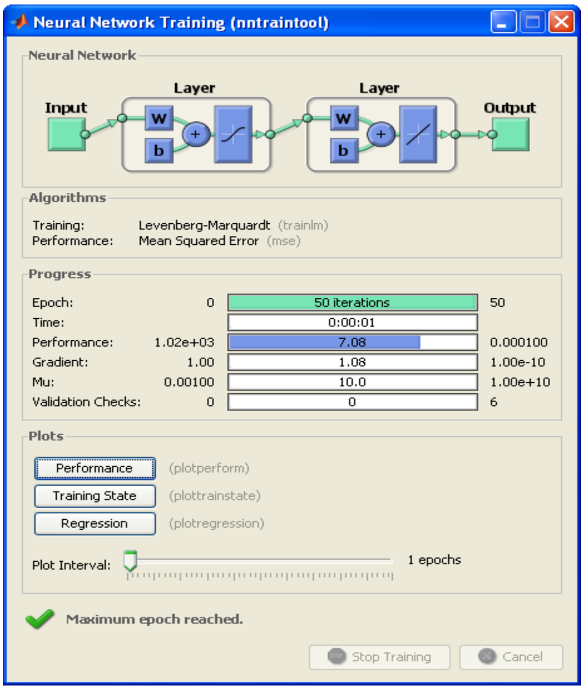

Fig. 5. MATLAB User Interface

The optimization is performed based on the first order condition. The results of numbers of products in the first stage of the proposed network are given in Table 2.

$$\pi = p_1q_1 + p_2q_2 + p_3q_3 - r_1(q_1q_2 + q_3) + r_2(2q_1 - q_2 + q_3) + r_3(q_1^2 + q_2q_3)) \qquad (16)$$

Table 2. The Quantity of Products in Stage One

Markets Product quantity	Market one	Market two	Market three
q_1	0.3	0.2	0.6
q_2	0.6	1.7	1.4
q_3	5.9	3.4	2.8
π	67.902	95.226	72.6

The same computations are performed for markets in stages two and three as shown in Tables 3 and 4, respectively. The results are associated with the profit of each market, too.

Table 3. The Quantity of Products in Stage Two

Markets Product quantity	From market one to four	From market one to five	From market one to six
q1	0.2	0.1	0.2
q2	0.4	2.1	0.5
q3	6.3	5.3	6.4
π	48.352	131.059	49.654
Markets Product quantity	**From market two to four**	**From market two to five**	**From market two to six**
q1	0.2	0.3	0.5
q2	0.4	0.8	0.2
q3	6.3	5.8	9.3
π	47.742	61.866	29.882
Markets Product quantity	**From market three to four**	**From market three to five**	**From market three to six**
q1	0.2	0.1	0.1
q2	0.5	1.1	1.1
q3	6.1	6.4	6.4
π	45.059	78.177	78.177

Table 4. The Quantity of Products in Stage Three

Markets Product quantity	From market four to seven	From market four to eight	From market four to nine
q_1	0.4	0	0.2
q_2	0.2	2.1	1.5
q_3	3.7	3.4	3.4
π	61.618	115.302	76.852
Markets Product quantity	**From market five to seven**	**From market five to eight**	**From market five to nine**
q_1	0.2	0	0
q_2	1.7	1.9	1.6
q_3	3.9	3.4	4.4
π	94.872	92.072	71.192
Markets Product quantity	**From market six to seven**	**From market six to eight**	**From market six to nine**
q_1	0	0.1	0.1
q_2	2.2	1	1.7
q_3	3.9	3.3	3.5
π	138.974	38.876	92.793

After finding the expected profit of each market, the producer is looking for a set of markets in the proposed network to obtain the maximum total profit. To achieve that, dynamic programming is applied. To facilitate the computations LINGO 9 is used. The values of all markets considering the movement from previous market are given in Table 5.

Table 5. The Values of All Markets

Variable	Value
$\varphi(0)$	293.8330
$\varphi(1)$	225.9310
$\varphi(2)$	168.8560
$\varphi(3)$	217.1510
$\varphi(4)$	115.3020
$\varphi(5)$	94.87200
$\varphi(6)$	138.9740
$\varphi(7)$	0
$\varphi(8)$	0
$\varphi(9)$	0

As Table 5 shows, the maximum integrated value is 293.833 and the corresponding optimal set of markets is 1-5-7, as presented in Figure 6.

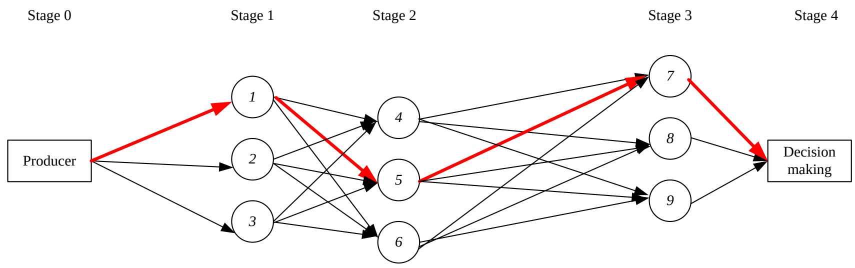

Fig. 6. The Optimal Set of Markets

This way, the identified path provides the maximum integrated profit throughout the market network. The obtained optimal path implies sets of markets in each stage maximizing the profit of the firm. As shown in Figure 6, in stage one and with respect to the products supplied by the firm, market one is chosen which provides more profit based on mathematical optimization developed in Section 4. Also, in stage two, market 5 and in stage three and market 7 are chosen having more profits. The obtained path is called firm economic expansion path. Maintaining and keeping this expansion path leads to the stronger presence of firms in competitive markets and helps the customer relationship units of firm to add values by long time covering of customers with regard to economic profit.

Discussions and Implications

Here, the essence of employing the proposed MLP is discussed on the computational results. As we stated, the use of the MLP is due to the fluctuations in supply and demand and therefore the prices and costs in the markets. The aim is to counteract the fluctuations in decision making about the profit. To point out the significance of the application of the MLP, we work out another computational effort. In this case, we ignore the fluctuations and the proposed DSS performs the model using the pricing concept with respect to the specified demands of markets. Here we consider

q_{ji} demand for product j from market i
p_{ji} price of product j to be sold in market i

Then we have,

$$p_{ji} = \alpha_{ji} - \beta_{ji}.q_{ji}, \qquad \forall i, j \tag{17}$$

where,

$$\beta_{ji} = \frac{-\sum_i \sum_j \left(q_{ji} - \bar{q}\right)\left(p_{ji} - \bar{p}\right)}{\sum_i \sum_j \left(p_{ji} - \bar{p}\right)^2}, \qquad \forall i, j \tag{18}$$

$$\alpha_{ji} = \bar{q} + \beta_{ji}.\bar{p}, \qquad \forall i, j \tag{19}$$

$$\bar{p} = \frac{\sum_i \sum_j p_{ji}}{R}, \qquad \forall i, j, \tag{20}$$

$$\bar{q} = \frac{\sum_i \sum_j q_{ji}}{R}, \qquad \forall i, j \tag{21}$$

$$R = I \times J, \qquad \forall i, j \tag{22}$$

This way, by using the demand received and the past prices data, we can set the pricing mathematical model and obtain the prices to be used in the profit maximization model. Also, the profit results are used to find the optimal sets of markets via the proposed dynamic program. We do so and obtain 2-5-9 as optimal path having the maximum integrated value of 221.014 as shown in Figure 7 below.

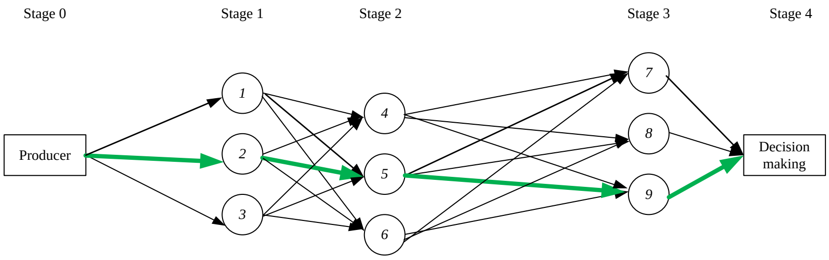

Fig. 7. The Optimal Set of Markets Using Pricing Model

The difference is due to the accuracy of data used in the pricing model since the integrated profit decreased. Thus, it is proved that the DSS-based MLP is necessary in effective decision making for a fluctuated supply and demand market data.

Some of the main implications of the research are listed below:

- The dynamic data are inserted into the neural network model and real-time outputs are obtained. Due to multi period planning and different consumer behavior, input data are changed dynamically. Therefore, neural network is employed to handle dynamic data and provide outputs at any time.
- Multi-dimension analysis on the results of both stages of the proposed DSS is performed using a pricing model that is a trivial operational decision. Several factors are effective on consumer behavior, leading to influences on the optimal market determination. Thus, pricing decision is a valuation process performed on different markets to obtain the optimal ones.
- Due to the aims of decision maker, the proposed bi-stage DSS flexibly provides the required results for better policy making: it is necessary to enable the decision makers for more resiliency, i.e., the possibility of various conditions in consumer behavior are analyzed and the decision is made accordingly in a real time manner.

Conclusions

A DSS is proposed to handle producers' concerns on finding target markets as a significant marketing decision. The policy was to find the integrated profit of a set of target markets for producers that make multiple products. The cost, demand, and prices were estimated using the data collected from the existing markets. For handling dynamic price and costs values, an MLP in ANN was modeled and developed. To find the optimal set of markets, we used a dynamic program. An example was worked out to imply the benefits of the proposed DSS in practice. A discussion was investigated using the concept of pricing to validate the results of the DSS. The achievements developed an MLP through ANN in DSS for costs and benefits data, employing producer behavior theory for analyzing the supply and demand of markets, and analytical pricing concept for sensitivity analysis. Managers and policy makers can make use of the proposed DSS for entering into profitable markets as a significant stage in target market determination and market segmentation; meanwhile an insightful image of market analysis is provided enabling decision makers to investigate data-driven optimization analytically. Also, production managers can employ the model for designing market-friendly products leading to higher profits. Business managers, at the same time, apply the model for pricing products based on demand fluctuation to have a stable portfolio. The results of numerical study show that the accuracy of the neural network based dynamic programming is high since the multi period data are updated and the outputs are obtained accordingly. Also, the pricing model shows that the profit is impacted by demands and prices rather than other environmental factors effective on consumer buying behavior. As for future research direction, developing other nature-inspired methods such as genetic algorithm for the optimization of general market environment with big data is suggested.

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