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Simulation of Supply Chain Performance in the Period of Implicit Uncertainty using Cellular Automata

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Abstract
Managing a distribution planning problem in an integrated supply chain environment is daunting. These challenges are aggravated when there are multiple stakeholders involved. The proposed simulation model provides an environment to gauge the existing adversities in the distribution plan of a two-stage supply chain (SC) network. In addition to the underlined issues, the model captures the influence of decisions from neighboring firms in a periodical decision-making plan. A cellular automaton (CA) based approach is implemented to present the complete analysis and impact of endogenous and exogenous situations affecting the decision-making. The decision environment involves two states of selecting an efficient supply chain strategy (ESC) and responsive supply chain strategy (RSC) based on the implicit uncertainty and performance of Moore-based neighboring cells. The study contributes to the scant literature on the application of CA-based evolutionary decisions in the SC context. The simulation model characterizes the neighboring firm's influences in strategic decision-making and the implicit uncertainty in supply and demand. The modeling framework is tested with a significantly larger set, and the results are graphically presented to provide further clarity.

Keywords- Cellular automata, Cellular space, Strategic decision-making, Implicit uncertainty.

1. Introduction

A supply chain (SC) is a series of an inter-connected network of business entities primarily interested in satisfying customer requirements via different procurement, manufacturing, and distribution activities. A typical SC structure involving multiple stakeholders with the direction of the flow of products going from suppliers to end customers while information flows otherwise. In addition to meeting customer demand, SC must ensure the best performance by optimizing its resources and deploying strategies for different activities (Swaminathan et al., 1998). Therefore, the SC strategies facilitate growth on the longer planning horizon. The SC strategies involve making decisions related to raw material purchase, product trans-shipment, production, and distribution planning (Beamon, 1999). Moreover, simply optimizing the operations does not make SCs more effective. Staying ahead of the competition shall also be the primary objective of the SC businesses. Therefore, most of the SC are categorized as efficient SC and responsive SC (Randall et al., 2003).

1.1 Efficient Supply Chains (ESC)

Formerly defined, ESC focuses on making all SC operations efficient. The main objective of the decision maker is to optimally use all the resources to maximize profit or customer satisfaction (Beamon, 1999). To build an ESC, the managers often bring the third-party service providers on board or cut the unnecessary cost in the operations. The improvement is mainly seen in reduced working hours, hard work, resources in hand, and expenditure on unnecessary objects (Storey et al., 2006). An ESC provides a higher satisfaction rate to the clients and a better business for the company. The efficiency benefits are propagated across the stakeholder, making overall progress in the business implementations (Randall et al., 2003). In conclusion, the ESC has to strive in trying times to overcome the hurdles of uncertainty and disruption.

1.2 Responsive Supply Chain (RSC)

A responsive SC is the second type of SC strategy observed in the SC network structures. The alternate name of such kinds of SC is an effective SC. Almost all the SCs focus on being efficient considering various dimensions. However, that is not the only focus of the decision-makers. Instead, it is highly important to be more flexible, i.e., responsive to the customer's and externalities (Das, 2019). According to the authors, the RSC performs operations considering the changing environment and exogenous variables. The external events include unplanned events and natural disasters. Similar to ESC, the final goal of the RSC is to meet the customer requirements and their demands. Such objectives require changing the production processes and occasionally making strategic calls to revise the complete network structure (Wang et al., 2014). Nevertheless, both type of SCs contributes to the competitive strategies of business growth.

Analysing previous studies on the given topic, we realized that Kumar et al. (2019) is among a few that identified the attributes to analyse lean and agile ways of SC implementation. The study has not covered the aspect of responsive or efficient SC. Das et al. (2021) designed an SC network design model considering the pandemic impact of COVID-19. Authors promoted flexibility at multiple layers to create a resilient distribution network. Similarly, the application of CA has been realized quite effectively in recent times. However, it is limited to a few research domains. For example, Chen and Chang (2021) developed a CA model to provide efficient decision-making under cyber-attacks on cloud SC. Some recent advancements in CA as an optimization problem can be seen in Cui and Xu (2022) for implementing effective urban logistics and distribution channels. Similar to previous studies, Nair and Vidal (2011) and Chen et al. (2015) proposed a CA model to all the echelon of the SC rather than independent firm's involved in the decision-making. Additionally, the primary motive of these studies is to provide decision plan under disruption situation arising from man-made and natural disasters. To the best of our knowledge, hardly any studies provide better decision plans in times of volatile environments and situations where the decisions of external firms affect the decision-maker's choice.

Thus, the ultimate goal of such strategies is to meet the marketplace demands and satisfy customer requirements. These strategies shall be implemented efficiently to create value propositions for the customers and generate revenues for the firms. However, the past studies have given least importance on a mechanism to gauge the impact of these strategies on SC performance metrics. The motivation for the research is to provide a simulation tool that can help to measure the quantitative aspect of the SC strategies on the actual decision-making of different firms. Notably, the study aims to build an optimization model that can help to decide the strategic move across the planning horizons given the effect of negative externalities and global competition. The authors proposed a cellular automata (CA) based simulation model to achieve the underlined objective. The model is then subject to sensitivity analysis to provide the robustness of the solution. Mainly, the contribution of the existing study is threefold: (i) to highlight the importance of CA modeling to a traditional SC setting consisting of multiple firms and an uncertain decision-making environment, and (ii) to gauge the quantitative aspect of ESC and RSC on the actual decisions of a different firm in the proposed simulation model, (iii) to suggest research avenues contributing to less explored space of CA modeling and SC decision optimization.

1.3 CA based Strategic Decision-Making Model

SC involves different operations of procuring raw materials from the suppliers, distribution, production, and transportation of materials and products across different SC stages. Many times, services are exchanged among various stakeholders. All the actions performed by the SC's firm should be in line with the central strategies of the focal firm for efficient implementation (Wang et al., 2014). The initial step for any SC firm is to understand the customer requirements. Demand is influenced by different aspects of customers, such as product pricing, service level, product innovation, product variety, etc. Therefore, uncertain demand can be mapped on the probabilistic space by referring to it as an implied demand uncertainty (Yan and Feng, 2011). There is a fine difference between uncertainty in demand, and implied uncertainty of demand. The former denotes the uncertainty in the product's demand, whereas the latter also includes the SC dimensions making the demand uncertain. Similarly, the SC is equally affected by the uncertainty in the supply. Thus, it becomes crucial for firms to decide between staying efficient and being responsive in a highly competitive and uncertain environment. The study attempts to incorporate such uncertainty due to the supply and demand on a spectrum of uncertainty. The complete model is presented mathematically by the CA approach. The model also includes the competition due to upside and downside firms.

For more clarity in understating the study, the paper is divided into five major sections. The first section introduces to readers the problem description and background of the study. Section 2 highlights the importance of cellular automata in decision-making, particularly under uncertain environments. It also provides a fundamental understanding of CA and some basic formulas for the implementation of the CA model. Section 3 incorporates the simulation model in the actual problem description with the SC setup. Results with sensitivity analysis are devised in Section 4. Finally, Section 5 concludes the paper with some practical implications and future avenues of research in the CA and SC analytics domain.

2. Cellular Automata in Optimization

Early literature on CA was to inspect the behavior of complex computational systems. On the other hand, the present study explores CA to solve problems related to optimization. CA appears to be an effective optimization tool because of the ability to include the local information and simultaneously consider the neighborhood effect (Wolfram, 1983). Formally, CA is defined with the help of regular grids and a finite number of dimensions (Kari, 2005). Each cell in the grid has limited states such as “On" and "Off", "True" and "False" etc. The CA is governed by partial differential equations and presents the macroscopic behavior of the system. In modern times, such methods are applied as a simple mathematical tool to various phenomena of gas diffusion systems, crystal growth of solids, and hydrodynamic flow (Wąs and Sirakoulis, 2015). Further, CA is often used to approach complex optimization problems in the Artificial Intelligence area, where automation of repeating actions of different robots is observed (Gong, 2017).

As per Kari (2005), a CA model is designed primarily with the help of five elements: 1) Cellular space, 2) Cells, 3) State-space, 4) Neighbors and 5) Evolution rules. Cells are considered the basic units in the CA model. They can distribute in 1D, 2D, or multi-dimensional space. Therefore, it collectively comprises a cellular space. This space is further divided into grids, precisely as special discrete grids. This grid formation is developed with the help of evolutionary functions depending on the context of the application. For example, a one-dimensional CA is presented in Figure 1. Since the two neighbors of the middle cells are alive, cells are automatically alive in the next step. Another vital definition in CA is Euclidean space grids. The grids are often defined as sets of finitely discrete components at the time of evolution. When a particular cell is searched, it will be searched in the nearby vicinity, termed neighborhood (Ceccherini and Coornaert, 2010). Since the evolution rules are defined locally, the active cell recognizes only the neighboring states. For a 2D CA model, Von Neumann, Moore, and Extended Moore models are the primary neighbors. In the dynamic model, the cellular evolution rule is derived as the functions which can determine the cellular state next time step. The simulations are affected by employing local transition rules. A detailed description of the transition rule is presented in Figure 2 and Figure 3, it can be seen that a cell will remain active if all its neighbors are alive in period t-1. To demonstrate the state of the cells in time stamp of $t = 2$, the status of the cell in time stamp t=1 is shown in Figure 2. Based on the activity of the neighboring cells, the status of the next time stamp cell is decided in Figure 2. Similarly, illustration is demonstrated by combining both the time stamps in Figure 3.

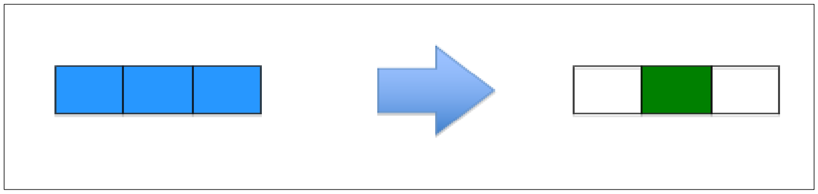

Figure 1. ON/OFF rule for one dimensional CA.

Each cell in the above diagram is called a state. There are various possibilities for neighbors under such circumstances. These combinations are presented in Figure 2 below. The various possibilities of neighbors having odd color are numerous while the transition rules are decided based on the entries in Table 1. The table shows the transition in the future state is decided on the basis of the present state of the cell and the status of the neighboring cell state. The graphical presentation of this transition rule is presented in Figure 3.

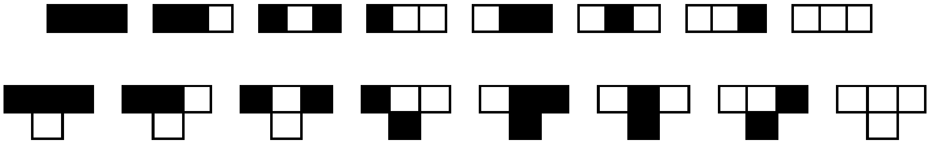

Figure 2. Neighboring state possible combination of 1- dimensional cellular automata with $t = 1$ and $t = 2$.

t = 1

t = 2

Figure 3. State transition of the neighboring state of 1- dimensional cellular automata at $t = 2$.

Table 1. Transition rule for the cell.

Current cell state	Neighbor state	Transformed cell state in next time
black	Left-right, both black neighbor	white
black	Left-black and right-white	white
White	Left-right both white	white
white	Left-black and right-white	Black
black	Left-white and right-black	Black
black	Left-right both white	Black
white	Left-white and right-black	Black
white	Left-right both white	white

2.1 Definition of Cellular Automata

CA is a collection, also referred to as a tuple, (d, S, N, f). Where S represents a set of finite states, $N \subseteq \mathbb{Z}^d$ Where N is a finite neighborhood. And, $f : S^N \longrightarrow S$ is the function for the local rule of the CA model. Further, A layout of $c \in S^{\mathbb{Z}^d}$ is a coloring $\mathbb{Z}^d$ of space S and the global map $h : S^{\mathbb{Z}^d} \longrightarrow S^{\mathbb{Z}^d}$ is considered uniformly as well as locally.

$$\forall\, c \in S^{\mathbb{Z}^d}, h(c)\, z = f\left(c_{|z+N}\right).$$

A space-time mapping $\Delta \in S^{\mathbb{Z}^d \times N}$ fulfills a state equation; $\Delta(t+1) = h(\Delta(t))\ \forall\ t \in N$. N represents the Von Neumann neighborhood. The Moore neighborhood can be described as Equation (1) and Equation (2), respectively. Additionally, $S^{\mathbb{Z}^d}$ presents a set of uncountable configurations. Moreover, the set of configurations is innumerable. However, we assumed a countable subset of recursive configurations. Some of the other assumptions as adopted from Gong (2017) are; 1) Finite configurations have a quiescent state, 2) Periodic configurations are assumed periodic, and finally, 3) Ultimately, periodic configurations compromise. It is important to note that the local rule considers a partial space-time mapping to understand all the configurations.

$$N_{vN} = \{0\} \times \{-1,0,1\} \cup \{-1,0,1\} \times \{0\} \tag{1}$$

$$N_{Moore} = \{-1,0,1\} \times \{-1,0,1\} \tag{2}$$

3. CA in the SC Environment

As stated in past studies, a typical cellular automata (CA) model consists of four components ($S_d, D, \mathbb{N}, f$). The model is extended to build the strategic decision-making for the proposed SC configuration. The 2D square grids represent the cellular space S_d, dimensions *d*, each cell in the cellular space denotes the firm. In general, retailers, distributors, manufacturers, and the like. (x, y) $where\ x, y = 1,2,3, \ldots\ldots n$ are the coordinates for the supply chain.

The underlined binary decision of which strategy to select is included in the set $D = \{0,1\}$. The variable with a value of '0' selects the efficient strategy under the threats of uncertainty and competition due to other firms. This is primarily to achieve customer satisfaction at minimum cost. The variable with value *D*=1 denotes a responsive strategy to manage the rapid demand situations. On a *p* decision horizon, the proposed decision function of strategic policy for the SC is defined by Equation (3).

$$D_f(p) = I_f(p) + N_f(p) \tag{3}$$

where, $I_f(p)$ is implied uncertainty due to supply-side issues and demand-side fluctuations. This time-dependent uncertain function follows a uniform distribution at $[-0.5,0.5]$. The low implied uncertainties are characterized by $I < 0$; whereas higher implied uncertainty due to the input factors is denoted by $I > 0$. $N_f(p)$ is another function included in the model to capture the effect of decisions of the neighboring firms on firm f at p^{th} period. The transition plan for the selection of competitive strategy is presented in Table 2. The state of condition row defines the local transition rule, which navigates the firm to decide the underlined strategies to select. Note that all the neighbor firms influence the decision of f firm at δ_p probability.

$$N_f(p) = \delta_p \sum_{i \in \mathbb{N}} D_f^{p-1} \tag{4}$$

The CA model proposed in Equation (3) and Equation (4) primarily address the following research questions in particular:

- Which strategy to follow by a firm considering the implied input uncertainty and global competition?
- What is the decision scope of a firm under the influence of neighboring firms?

Table 2. Decision-making policy for selecting ESC and RSC.

	$D = 0$		$D = 1$	
State of condition	$D_f \leq rule$	$D_f > rule$	$D_f \leq rule$	$D_f > rule$
Transition plans	$D_f^{p+1} = 0$	$D_f^{p+1} = 1$	$D_f^{p+1} = 0$	$D_f^{p+1} = 1$

4. Results and Sensitivity Analysis

The CA model, also called the simulation model, is coded in the python programming platform. The primary aim of the model involves two objectives, as stated earlier. One is to provide strategic decision-making for selecting two effective competitive strategies. Second, gauge the influence of global firms on strategic decision-making. These two cases are mentioned in the independent analysis and indented in the subsequent subsections. We highlight the steps carried out to perform the simulation and depict the overall flowchart of the analysis in Figure 4. Initially, the analysis starts with setting uncertain parameters. The next step is to set the states of the neighboring firms and the local transition rule. Table 2 explains the former procedure, including the transition plan and state position of different firms in the analysis. The independent steps performed to carry the algorithm are underlined below in Figure 4.

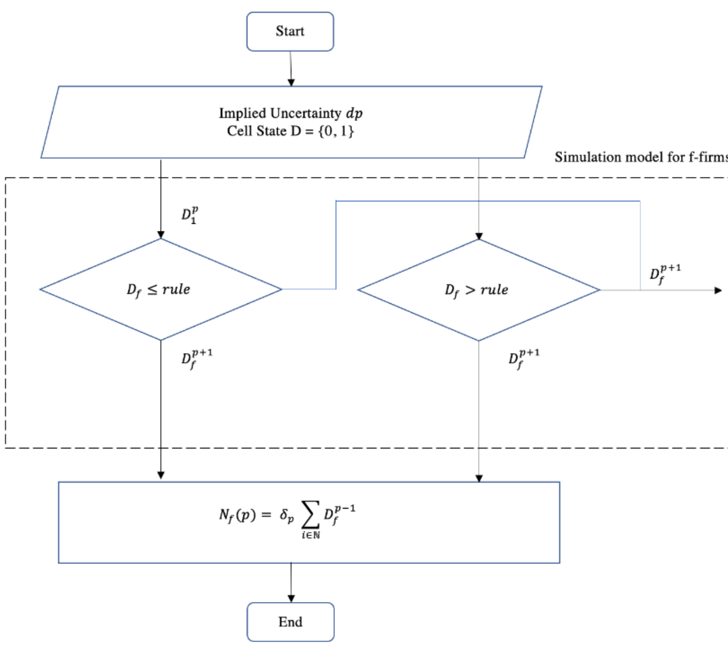

Figure 4. Flowchart for CA-based simulation approach for strategic decision making for *f* firms.

(i) The uncertainty space is generated on a 50 X 50 square grid matrix.
(ii) Each square represents the cell, and the step size for the evolution is taken as 50
(iii) Flowchart: For *p*=1, the *D* is a binary decision on the selection of competitive strategy of the firm initially,

a. Supply and demand are subject to uncertainty and assumed to be uniformly distributed between [-0.5,0.5].
b. Different levels of uncertainty are characterized on an uncertainty spectrum of [-0.5, -0.25], [-0.25,0], [0,0.25], and [0.25, 0.5] is assigned throughout the analysis.
c. The probability of δ_p is set constant for the initial iteration.

(iv) Implementation: For every iteration, the firm i.e., cell f generates implied uncertainty $I_f(p)$. Then $D_f(p)$, a strategic decision is to decide based on the competition posed by the neighboring firms $N_f(p)$. The rule is designed for the four values -1.5, -0.5, 0.5, and 1.5. The steps are repeated till the end of evolution to make final decisions.

4.1 CA in Deciding Strategic Decisions under Implied Uncertainty

To gauge the influence of the supply and demand uncertainty on strategic decision making, the rate of decision function is kept constant at 0.25. Later, the simulation model is run to understand the pattern of decision-making under uncertainty. The implicit uncertainty of supply and demand is varied at four levels. The resultant selection of the type of SC is presented in Table 3.

Table 3. Decisions under implicit uncertainty.

State of implicit uncertainty (0.25 of rate of decision function)		Preferred decision-making outcome
Supply	Demand	
-0.5	-0.25	ESC
-0.25	0	ESC
0	0.25	RSC
0.25	0.5	RSC

The analysis also incorporates the overarching idea of how strategic decisions are taken across time in Figure 5. For example, as the uncertainty in the demand increase, the firms switch between efficient and responsive strategies. In Figure 5, quadrant I and II represents the decision environment of responsive events, whereas quadrant III and IV specify situations of the efficient domain.

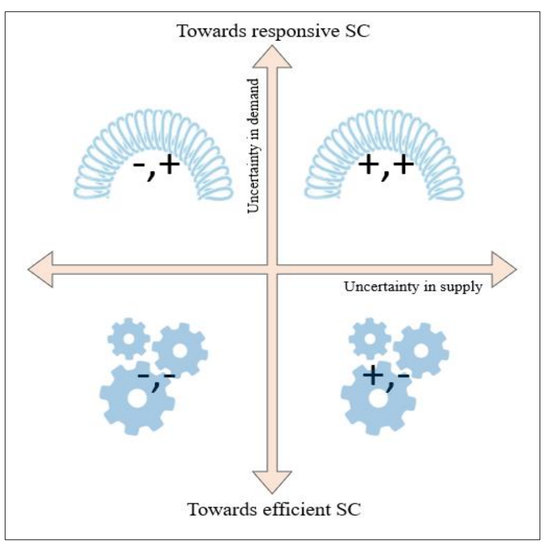

Figure 5. Effect of implied uncertainty on strategic decision making of firm.

The analysis also captures the evolution of decision phases in Figure 6(a)-(f). The implicit uncertainty varies in [-0.5, 0.5] to cover the complete uncertainty domain. It is highlighted in each of these figures a δ_p is varying, resulting in new combinations of a set of solutions for a firm size of ten. Further, the thematic map reveals the inclination towards a specific strategy of ESC or RSC for each of the different δ_p conditions. The decision rate is set to change as understanding the impact due to implied uncertainty affects the decision-making. It was observed from the figures that an ESC implementation is adopted across the firms over the RSC approach. The primary reason for such an adoption is that the demand uncertainty is insignificant. Additionally, the rate of decision function is kept low to understand the evolution of the selection ratio between ESC and RSC situations.

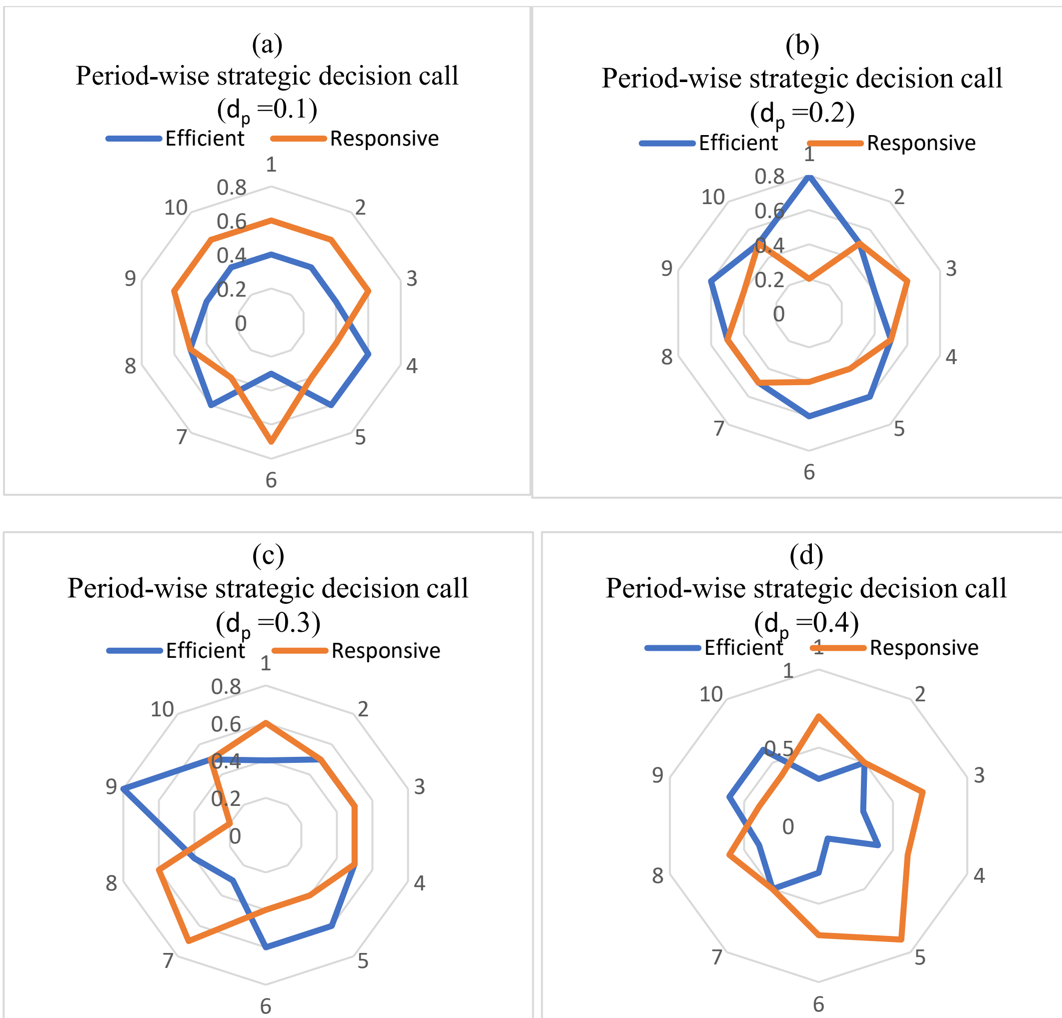

Figure 6 continued…

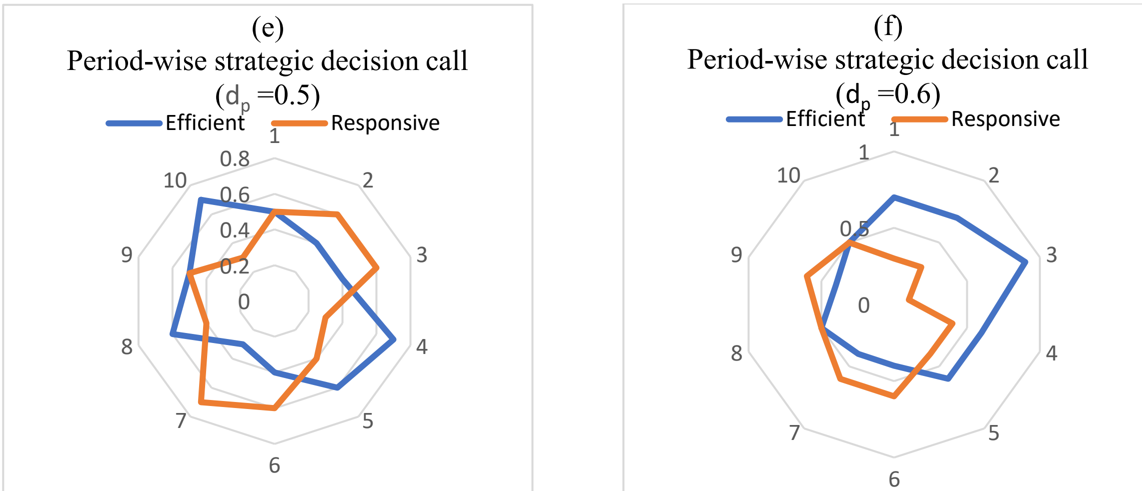

Figure 6. Period-wise strategic decision-making with varying rates of decision function.

Table 4 is particularly used to derive multiple inferences from the simulation analysis. Some implications are pictorially presented in different figures, for example, Figures 6, 7, and 8. The simulation started in 0^{th} period with no strategies for individual firms. The initial step also incorporates the uncertainty in the demand-supply parameters to provide analysis at the next iteration. This step also defines the rate of the decision function (δ_p). For every other iteration, the strategies are determined based on the implied uncertain parameters and the influence of the neighboring firm. The algorithm presented above justifies the values of different parameters. For every iteration, the strategic decisions are made for each firm for a given time period.

Table 4. Single scenario representation of the input parameters and strategic decision-making output.

1	0	-	0.3636	0.25	0.4227	-	1	6	0.0326	-0.4311	0.25	-0.3985	ESC
2	0	-	0.4897	0.25	0.7230	-	2	6	-0.0763	0.0772	0.25	0.0009	RSC
3	0	-	-0.1310	0.25	-0.7513	-	3	6	-0.1104	0.4378	0.25	0.3274	RSC
4	0	-	0.1110	0.25	-1.1241	-	4	6	-0.0454	-0.1842	0.25	-0.2295	ESC
5	0	-	-0.1754	0.25	0.2843	-	5	6	-0.0923	0.2024	0.25	0.1101	RSC
6	0	-	-0.0053	0.25	-0.1283	-	6	6	-0.0665	-0.2372	0.25	-0.3037	ESC
7	0	-	-0.1996	0.25	-1.2636	-	7	6	-0.0111	-0.4496	0.25	-0.4607	ESC
8	0	-	0.1079	0.25	1.4817	-	8	6	-0.0234	0.1814	0.25	0.1580	RSC
9	0	-	0.2359	0.25	-1.4981	-	9	6	0.1015	0.2172	0.25	0.3187	RSC
10	0	-	-0.2831	0.25	1.0539	-	10	6	-0.0033	-0.0283	0.25	-0.0317	ESC
1	1	0.1057	0.2948	0.25	0.4005	RSC	1	7	-0.0996	-0.4543	0.25	-0.5540	ESC
2	1	0.1807	0.0960	0.25	0.2767	ESC	2	7	0.0002	0.4591	0.25	0.4594	RSC
3	1	-0.1878	-0.1415	0.25	-0.3294	ESC	3	7	0.0819	-0.2335	0.25	-0.1517	ESC
4	1	-0.2810	-0.4927	0.25	-0.7737	ESC	4	7	-0.0574	0.2341	0.25	0.1767	RSC
5	1	0.0711	-0.0059	0.25	0.0652	RSC	5	7	0.0275	0.3301	0.25	0.3576	RSC
6	1	-0.0321	0.4255	0.25	0.3934	RSC	6	7	-0.0759	-0.2886	0.25	-0.3645	ESC
7	1	-0.3159	0.1526	0.25	-0.1633	ESC	7	7	-0.1152	-0.4946	0.25	-0.6098	ESC
8	1	0.3704	0.4846	0.25	0.8551	RSC	8	7	0.0395	-0.1493	0.25	-0.1098	ESC
9	1	-0.3745	0.2047	0.25	-0.1698	ESC	9	7	0.0797	0.0083	0.25	0.0879	RSC
10	1	0.2635	-0.3161	0.25	-0.0527	ESC	10	7	-0.0079	0.0498	0.25	0.0419	RSC
1	2	0.1001	-0.3083	0.25	-0.2082	ESC	1	8	-0.1385	0.0324	0.25	-0.1061	ESC
2	2	0.0692	-0.2796	0.25	-0.2104	ESC	2	8	0.1148	-0.0800	0.25	0.0348	RSC
3	2	-0.0823	-0.0743	0.25	-0.1566	ESC	3	8	-0.0379	-0.4362	0.25	-0.4742	ESC
4	2	-0.1934	-0.2046	0.25	-0.3981	ESC	4	8	0.0442	-0.4303	0.25	-0.3861	ESC
5	2	0.0163	0.4391	0.25	0.4554	RSC	5	8	0.0894	0.4379	0.25	0.5273	RSC
6	2	0.0984	0.4050	0.25	0.5034	RSC	6	8	-0.0911	0.0420	0.25	-0.0491	ESC

Table 4 continued…

7	2	-0.0408	0.3469	0.25	0.3060	RSC	7	8	-0.1525	-0.1023	0.25	-0.2548	ESC
8	2	0.2138	-0.1159	0.25	0.0979	RSC	8	8	-0.0275	-0.3404	0.25	-0.3678	ESC
9	2	-0.0424	-0.0596	0.25	-0.1020	ESC	9	8	0.0220	-0.1481	0.25	-0.1261	ESC
10	2	-0.0132	0.2947	0.25	0.2815	RSC	10	8	0.0105	-0.3067	0.25	-0.2962	ESC
1	3	-0.0521	-0.0708	0.25	-0.1228	ESC	1	9	-0.0265	-0.3681	0.25	-0.3946	ESC
2	3	-0.0526	-0.0420	0.25	-0.0946	ESC	2	9	0.0087	0.2928	0.25	0.3015	RSC
3	3	-0.0392	0.1859	0.25	0.1467	RSC	3	9	-0.1185	0.2842	0.25	0.1656	RSC
4	3	-0.0995	0.0389	0.25	-0.0606	ESC	4	9	-0.0965	-0.0122	0.25	-0.1087	ESC
5	3	0.1139	-0.3840	0.25	-0.2701	ESC	5	9	0.1318	0.3021	0.25	0.4340	RSC
6	3	0.1258	-0.3706	0.25	-0.2447	ESC	6	9	-0.0123	-0.3004	0.25	-0.3127	ESC
7	3	0.0765	0.2829	0.25	0.3594	RSC	7	9	-0.0637	-0.1844	0.25	-0.2481	ESC
8	3	0.0245	0.2529	0.25	0.2774	RSC	8	9	-0.0920	0.4898	0.25	0.3978	RSC
9	3	-0.0255	0.1577	0.25	0.1322	RSC	9	9	-0.0315	-0.0171	0.25	-0.0486	ESC
10	3	0.0704	0.0274	0.25	0.0978	RSC	10	9	-0.0740	-0.4278	0.25	-0.5018	ESC
1	4	-0.0307	0.0392	0.25	0.0085	RSC	1	10	-0.0986	0.3027	0.25	0.2040	RSC
2	4	-0.0237	-0.3692	0.25	-0.3928	ESC	2	10	0.0754	-0.0648	0.25	0.0106	RSC
3	4	0.0367	0.1202	0.25	0.1569	RSC	3	10	0.0414	-0.2501	0.25	-0.2087	ESC
4	4	-0.0151	-0.2475	0.25	-0.2626	ESC	4	10	-0.0272	-0.1546	0.25	-0.1818	ESC
5	4	-0.0675	-0.2481	0.25	-0.3157	ESC	5	10	0.1085	-0.3522	0.25	-0.2437	ESC
6	4	-0.0612	-0.3774	0.25	-0.4386	ESC	6	10	-0.0782	-0.4348	0.25	-0.5129	ESC
7	4	0.0898	-0.2941	0.25	-0.2042	ESC	7	10	-0.0620	-0.1132	0.25	-0.1752	ESC
8	4	0.0693	0.1680	0.25	0.2373	RSC	8	10	0.0995	0.1940	0.25	0.2935	RSC
9	4	0.0330	-0.2377	0.25	-0.2047	ESC	9	10	-0.0121	0.4602	0.25	0.4481	RSC
10	4	0.0244	0.1246	0.25	0.1491	RSC	10	10	-0.1255	-0.1821	0.25	-0.3076	ESC
1	**5**	0.0021	0.1283	0.25	0.1304	RSC	6	**5**	-0.1096	-0.1562	0.25	-0.2659	ESC
2	**5**	-0.0982	-0.2068	0.25	-0.3050	ESC	7	**5**	-0.0511	0.0065	0.25	-0.0446	ESC
3	**5**	0.0392	-0.4808	0.25	-0.4416	ESC	8	**5**	0.0593	-0.1528	0.25	-0.0935	ESC
4	**5**	-0.0657	-0.1159	0.25	-0.1815	ESC	9	**5**	-0.0512	0.4573	0.25	0.4062	RSC
5	**5**	-0.0789	-0.2903	0.25	-0.3692	ESC	10	**5**	0.0373	-0.0506	0.25	-0.0134	ESC

4.2 CA in Understanding the Influence of Neighborhood Firms in Decision-Making

It is irrational to consider only the uncertainties in the demand and supply. In many real-life situations, the decisions of competing firms matter significantly. The proposed CA-based modeling approach can be helpful in such cases. The idea is to vary the rate of decision function probability to capture the neighborhood influence, as stated in Equation (2). The effect of this rate is then accounted for in the decision-making process in Figure 7a. For example, different series are considered for the various values of δ_p. The influence of the rate of decision function provides a causal relation to the selection of different SC strategies. The variation in the selection of these strategies for the given firms is highlighted in Figure 7a. It is evident that even though the probability increases, the firms take an efficient method more often than a responsive one as the implicit uncertainty is low for the underlined scenario. Note that the implicit uncertainty in demand and supply is set at [-0.5, -0.25].

It is observed from Figure 7b) that the decision-making switches between efficient to responsive selection when the implied uncertainty in supply and demand changes. For the constant δ_p and at a higher impact due to implied uncertainty, the inclination towards RSC is more likely than ESC. Such findings are helpful for decision-making in an uncertain environment. The simulation model creates data-driven decision-making considering such uncertainties. Therefore, the proposed optimization is applicable for implementation in real-world situations. Further, the period-wise decision call is exhibited in Figure 8. The decision-making in the current situation is more dynamic and depends on the implied uncertainty due to input parameters. For example, Figure 8a) prefers more of an efficient approach of manging the uncertainty. Whereas, Figure 8b) suggests responsive decision-making considering the volatility of uncertain situations and impact of neighbouring firms.

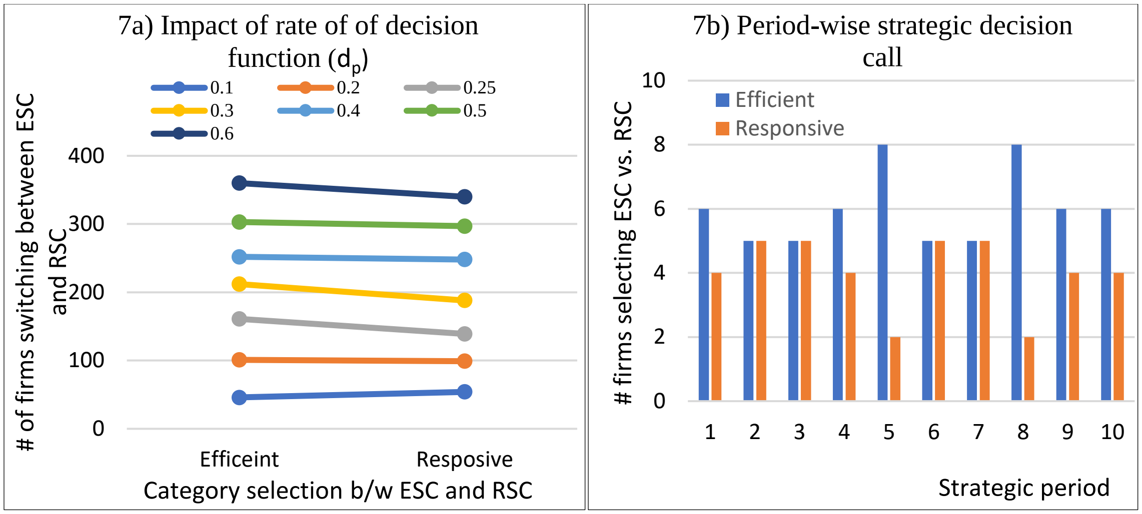

Figure 7. Influence of neighboring firms and decision-making at every time-step analysis.

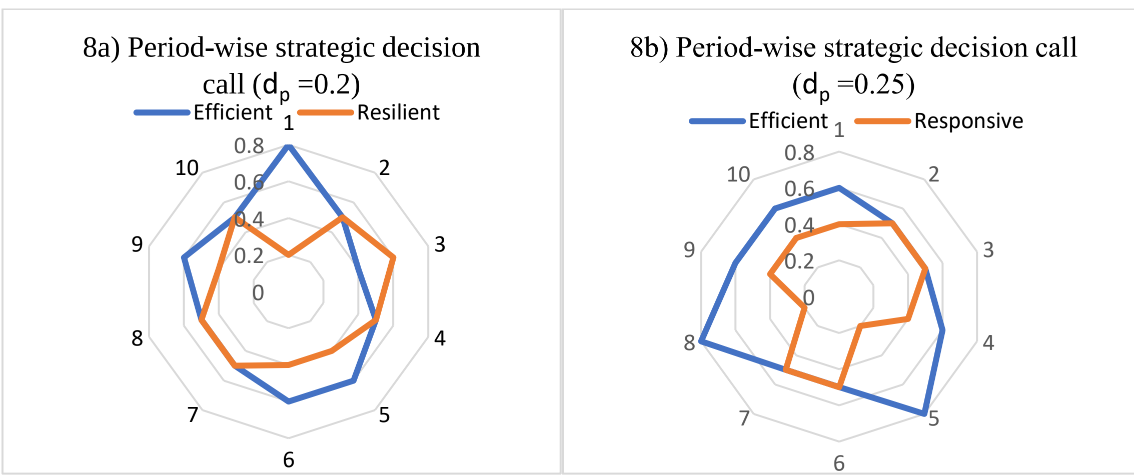

Figure 8. Firm-specific strategic decision for varied uncertainty at a constant rate of decision function.

5. Conclusion

The current study aims to provide a decision plan for strategic leaders to decide in times of uncertainty and promote effective planning. The results illustrate the finding considering different situations of uncertainties by varying some underlined SC parameters. The automata model then proposes the strategic decision plan to select between two of the best strategies. The sensitivity analysis in the paper further provides essential findings and elaborates on various possibilities of implied uncertainties and the influence of decisions due to neighboring firms. In the event of global competition, it is vital to incorporate the effect of competing firms in the decision analysis. The simulation is presented considering numerous firms and large data sets consisting of uncertainty due to supply and demand variables. Theoretically, the simulation model incorporates some real-world business issues arising from exogenous supply and demand variables with conceptual parameters and constraint decision-making. The CA model provides an optimal decision plan by maximizing the SC performance offering a binary decision of selecting ESC or RSC strategies. Such a mathematical framework has practical implications and actionable insights for decision-making under uncertainty. Especially the proposed model is applicable when there is influence due to the decisions of neighboring firms. The model also covers practical scenarios of volatility due to supply and demand, and their impact on the decision-making of the select firms. Some of the immediate extensions of the current model are to consider multiple options for the strategic call, unlike only the two options taken in the study. Further, the local optimization rule is relatively more straightforward and can be improved by considering different risks, such as societal or disruption related. Finally, a case study with real industrial data can provide valuable insights in decision-making.

Conflict of Interest
The authors confirm that there is no conflict of interest to declare for this publication.

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