Developing a simulation model: The impact of seasonal demand fluctuations on dynamics of service business in Bergen, Norway

Master thesis in System Dynamics

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Content Overview

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List of abbreviations

SD- System dynamics
BOTG- Behavior over time graph
CLD- Causal loop diagram
SFD- Stock and Flow diagram
NC- Non-Customers
WC- Was Customers
OC- Occasional Attainable Customers
R&D- Research and Development

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Abstract

Purpose–*This research aims to understand, investigate, and explore the causes of customer loss in a restaurant located in Bergen, Norway. The case study is an example of applied research. The study's topic was initiated by both the author, who is employed by the case company, and by the restaurant manager. The study has a 5-year time horizon (2014-2019).*

Method/approach–*A simulation model presenting the company structure has been developed to discover the root causes of customer loss and to understand the dynamics of the actual internal processes. The model explores the impact of seasonal fluctuations on demand and effect of word of mouth, service failure, hiring, and advertising policies on customer acquisition and retention. Through the application of the System Dynamics (SD) method, the system as a whole may be simulated, and various cause-and-effect relationships in the company may be explained.*

Findings– *The results show that a minimal modification of the base variables (productivity or employee base) through increasing employees' staff may be critical for change in employees' burnout. Furthermore, advertising has a substantial impact on customer base through a change in customers' acquisition rates. Policies in terms of hiring and advertising resolve problematic behavior of internal workplace dynamics and lead to growth in the number of attainable customers and the number of actual customers. Moreover, the implementation of a mix of policies brings about the most effective outcome.*

Practical implications–*The model provides an analytical framework for investigating internal processes, customer base, and various effects driving company performance. Through simulation and conceptual analysis of behavior, the model offers added insight into the company's structure.*

Originality/value–*The model outlines the vital structural characteristics and real internal processes in the company. It helps explain the power of an individual's mental model on the decision-making process and how these decisions impact the behavior of the entire system.*

***Keywords**: System dynamics (SD), Causal Loop Diagram (CLD), Stock and Flow Diagram (SFD), performance, schedule pressure, productivity, burnout, service failure, growth of company, word-of-mouth, advertising, market potential, market demand, customers, strategic planning for seasonal service-based business.*

Introduction

Background

The restaurant business is one of the most challenging industries in the market. Its growth and development are remarkably affected by continuous changes in various types of environments, such as social, economic, technological, and political environments. In this thesis, the investigated case-study business is significantly affected by shifts in the seasons. As studies show, adverse weather conditions reduce the operating and financial performance of 70% of companies globally (Larsen, 2006). If a business is losing customers for some reason, it may suffer devastating financial losses. As research shows, the prime reason for difficulties in managing organizational change is a miserable human performance in complex systems (Sterman, 1989, 2000). Thus, managers who do not use prognostic methods and prediction models to help them to estimate expected demand might struggle to handle the complexity of dynamics in managing systems.

Statistics show that during the period 2016-2018, the number of bankruptcies of restaurants and cafés in Norway fluctuated, but, at the end of 2018, it reached a peak of 100 bankruptcies (Ridder, 2019)**.** This result was the outcome of various factors, which can be split into two main categories:

- Internal system factors (e.g., insufficient organizational resources, inadequate strategy, lack of objectives, conflicting priorities, resistance to change policy and plans, inflexibility, and many more.)

- External factors out of a manager's control (e.g., demographics, lower minimum living standards, market demand, competitors, seasonality, and weather conditions.)

Both internal and external system factors impact customers' acquisition and retention. The loss of customers profoundly influences service-based business growth and has a tremendous impact on a business's future and development. As a result of customer churn, companies may experience a drop in actual sales and revenue. The questions investigated in this thesis include: Why in the 21st century with new technologies for managing organizations, so many managers find it arduous to develop an effective strategy for their business? Why are top leaders unfamiliar with their customers' desires, needs, and expectations?

As found in the literature, a wise course of action towards developing the limitless capacity of humans' brains and using available knowledge as a higher category level source of information about the system, might lead to better solving complex management problems through rational decisions and effective strategy planning:

"Knowledge is a higher-level resource than simple data, and can make a powerful contribution to an organization's products and services, performance in delivering those products and services, its acquisition and retention of customers, and productivity and performance on staff."

(Warren, 2008 p.619)

In this thesis, a case study of a restaurant in the city center of Bergen was conducted. This study aimed to build a simulation model for the case company to analyze the behavior of the company's structure and identify the real workplace dynamics. Through the model-building process, the authentic mechanisms governing a company's performance might be revealed and understood. Through this, the roots of the problematic behavior leading to customer loss might be determined, and a compelling mix of policies to solve the problem can be created.

The secondary purpose is to encourage the restaurant manager to change the existing strategy and implement a useful and feasible mix of policies designed during the research. To build the manager's trust in results and forecasted behavior, the manager will simulate all possible scenarios and decide which strategy is most beneficial.

The research highlights customers as a crucial resource for the company. As the acquisition or loss of customers is mainly dependent on the company's performance, the three most significant organizations' resources are presented: financial, staff skills, and production resources. Moreover, the study emphasizes the contrast between unrealistic mental internal processes (which are only the illusion of a manager's mental model), and real internal processes (perceived by staff). This conflict between the manager's mental model about the company's internal processes and the actual internal processes is the focal point of this research and the bottom line for the problematic behavior.

It is assumed that the seasonality constitutes the principal reason for fluctuations in the number of customers and hinders the proper management. Generally, in summer, tourists abound, and the number of customers increases until it reaches a peak and then remains at a steady level or subsequently falls. The overload of customers during each season might induce employee burnout, whereas too few customers force managers to close restaurants for wintertime, leaving employees jobless.

A framework with a wider variety of measures could allow the manager to include and control both financial and non-financial factors, which are drivers for improvement of the internal processes, production capacity, company's performance, and revenue. Building a strategy based on different perspectives could give a broad view of the company's performance. A complete framework for a perfect vision of the company's future might be simulated based on the suitable modeling approach. In the research, the System Dynamics (SD) method was applied to build a dynamic model to provide a comprehensive overview of the current company's performance. The model reflecting the investigated system's reality might help change the inefficient current organizational strategy into a practical plan by designing a feasible and operative mix of policies:

"Industrial Dynamics is the investigation of the information-feedback character of industrial systems and the use of models for the design of improved organizational form and guiding policy"

(Forrester, 1961, p.13).

The usefulness of the System Dynamics approach is convenient as it facilitates the building of a simulation model of the company's strategy. Through this method, complex feedback systems can be built to cope with tough business challenges. The head manager and employees were active in the model-building process, injecting their thoughts and ideas based on years of experience. This process resulted in the creation of a useful simulation model for managing the company's performance.

The case-study

The case company is a restaurant in Bergen, Norway, which provides dine-in service within the food and beverage industry. Additionally, the restaurant offers take-away service, especially in busy times and on special days when the restaurant is overcrowded.

The restaurant has a fantastic location in the city center, and this is the most substantial source of competitive advantage over its competitors. The significant advantage is the restaurant's localization in the center. It increases the probability of a restaurant's visibility for casual customers and for many regular and occasional customers who visit the restaurant more frequently.

On the other hand, the restaurant's major disadvantage is that it highly depends on the season and pleasant weather. Two rainy weeks might dramatically decrease monthly income. An early fall with cold evenings will also cut profits significantly. Seasonal business is a risk for the owner, manager, and employees. Difficulties lie in the massive influx of tourists during favorable weather and the problem of how to attract them if the weather is not promising.

The overarching issue that the company has been facing is the decreasing number of actual customers over the last five years (2014-2019). In each of these years, the company experienced similar problems, including fluctuations in the number of customers and employee burnout. The manager observed that these challenges result from variability in seasonality and the occasional unexpected tsunami of customers. Each year employees were working overtime and feeling overwhelmed, which caused them to feel burnt out.

This company was explicitly selected since its strategy was not adequately developed in such a way to meet its goals. There are up to 6 workers employed each year, but not each employee works full-time. The employees come from various countries and have different work experiences covering multiple professions, which affects their productivity and, therefore, the entire company's performance. Overall, as the customers' peak was declining each year, the company's reported revenue decreased over the years (2014-2019).

Principally, the financial results are the critical indicators for the manager in measuring the case business performance and its failure or success. However, measuring the profitability of a company based only on operating profit is a historical approach.
The company's strategic plan, carried out from 2014-2019, focused on customer service, original product quality, and employee productivity improvement. Although the manager indicated the importance of employee training and skills development, there were no measures to expand them. Overall, this has led to poor company development and a lack of customer service improvement.

Throughout these five years, the restaurant manager practiced this same strategy, to employ a minimum number of employees, but put no effort into providing them with proper training and skills. On specific days during the year, the company would become overcrowded, and employees experienced burnout. It can be stemmed from the fact that the company was mostly focused on the business's financial aspect while forgetting the non-financial measures in its strategic map.

This study shows that the restaurant's internal processes are the roots of the emerging system's behavior. Moreover, the research focuses on unmeasurable soft variables, which have a substantial impact on internal processes' behavior. Thus, the standard and healthy conditions in the internal processes are affected by invisible forces such as schedule pressure and burnout, leading to breaking the internal processes' normal conditions into the internal processes' actual conditions.

The Strategy Map in the company

The table (Figure 1) shows the company's existing **strategy map**. The manager was of the impression that the strategy map illustrates to all employees how their attitude and engagement in work relate to the company's objectives. According to the manager, the strategy covers the most crucial aspects which the case company deals with and it is well-designed to push the company's growth.

	Strategy Map
Internal Business Process	Exceed employee satisfaction, Maximize employee productivity, Increase production capacity, Increase service quality,
Customer	Exceed Customer satisfaction Maximize customers' acquisition,
Financial	Increase operating profit, Increase Revenue, Average unit price, Increase sales growth, Decrease overhead expenses

Table 1: Original company's Strategy Map.

This oversimplified strategy map comprises only three perspectives: internal processes perspective, the customer's perspective, and financial perspective. The main strategic objectives assigned to these perspectives reveal the company's priorities. The strategy map gives a feeling that the restaurant has full control over its procedures; however, the current restaurant's strategy does not reflect its effectivity in the real-world.

Stakeholders

This study follows one of the most widely used definitions of the stakeholders' concept, which defines stakeholders as: *"any group or individual who can affect or is affected by the achievement of the firm's objectives"* (Freeman, 1984.) Thus, the primary stakeholder of this research is the restaurant manager and employees are secondary types of stakeholders of the present study.

The manager's principal task is to enforce the restaurant's management process, which includes:

- Decision-making planning (deliveries, employment, marketing activities)
- Organization (work of the premises, logistics, events)
- Effective human resource management (motivating and controlling employees)
- Increasing the quality of offered services and products

An interview with the manager (personal communication, May 9, 2019) was performed to present the case-study more quantitatively. The manager answered three questions:

Question 1: *What are the pros and cons of seasonal venues?*

"A primary advantage is that people immediately adapt to this seasonal variety, and in sunny weather, they always come to us. Our cafe is open to them for nine months a year (April-December), but only four months (June- September) the cafe makes the highest profits. The major downside is that rainy weather reduces customers' flow, as only a few will drink coffee outside when it rains. Apart from the primary disadvantages related to the weather and the late start or untimely end of the season, there is a lack of time to train employees. "

(Restaurant manager,2019)

Question 2: *Do you have requirements for seasonal staff? Are there any recruitment problems?*

"I have no special requirements for the staff. There is no shortage of applicants, but a small rotation always happens. These are not directors who have been working in one place for ten years; rather, these are young people who are constantly looking for development."

(Restaurant manager, 2019)

Questions 3: *How do you advertise your place?*

"There is no particular advertisement, but I plan to develop it only online. I believe that the Internet is the best way of marketing. I think online advertising can bring us many customers."

(Restaurant manager,2019)

The manager's statement shows that the restaurant’s activity is mainly dependent on seasonal alterations and whether conditions. That is the primary reason for the problematic strategic planning and management process of the restaurant.

Hiring employees only during the season remains a separate problem. The manager has a proven core team that shows up regularly when the new season starts. However, in the high season, when there is a massive influx of customers, the manager must hire additional employees who need to be trained from scratch.

Unfortunately, the manager does not care about hiring the right people in advance. There is a shortage of extra employees before the start of the season, and only the regular employees come to work. The manager assumes that he might find additional waiters a little later.

Overall, the restaurant has potential as its significant competitive advantage is the place: as mentioned above, the restaurant has a perfect location in the center of Bergen, and this is the most influential decisive factor affecting the success of the restaurant when the weather conditions are favorable. For that reason, the café was chosen as a case study for this thesis.

Research question

Summarizing all the identified queries of the presented system, the resulting research question is following:

"How can a service-based business in a highly weather-dependent location raise revenue, increase their customer base, and eradicate the employees' burnout?"

The above question encouraged the modeler to develop a simulation model needed to, first of all, reveal the roots of problematic behavior, which are necessary to know in order to design an appropriate policy. Thus, by using the System Dynamics modeling method, the author could establish the most plausible policy. The questions guided in making major model assumptions and defining the critical organizational resources.

Furthermore, the inquiries spur the author about the qualitative and quantitative research approaches. Using a mix of research, the simulation model can reflect real-world dynamics, and it helps to understand the restaurant's real internal processes. Moreover, it helps improve the current strategy by developing the most effective policy, which can impact and shape the future dynamics of the real-world system.

Thus, the dynamic model revealing the system's reality can be used by the restaurant manager in a complex decision-making process and effective strategic planning also in the future.

Method

Method of the study

Most people simplify their investigation of systems' complexity by ending their search toward finding the roots of problematic behavior when they saw a single likely reason leading to the problematic behavior they study (Moxnes, 2004). The biggest challenge for prominent leaders towards efficient management is to realize that they are following their secret mental model. Throughout our lives, we create and use our unique mental models of reality to interact with the dynamic systems and difficulties that continuously emerge from the real world's complexity. According to Forrester, management is the process of converting information into action:

"If management is the process of converting information into action, then management success depends primarily on what information is chosen and how the conversion is executed. Moreover, the difference between a good manager and a poor manager lies right at this point between information and action".

(Forrester, 1961, p.93)

This inspiring quote may evoke question such as: What if the information chosen is based only on the manager's mental model? As in the real world, complete information is not always available; probably, many top managers could be called "poor managers." The human ability to experience, feel, perceive, and interpret the real world is intriguing and infinite, but naturally, it is not planned to master real systems' complexity. Also, routine, external pressures such as customer complaints, the amount of available time and information, and various other factors can diminish brainpower, leading to poor judgment and chaotic decision making. In terms of management, this can be harmful to the company's performance when it leads to ineffective policies and decisions.

Thus, the manager should be provided with the right set of information that may act as a guide in the decision-making process. By that, the problematic misperception of reality could be resolved. Therefore, the System Dynamic (SD) method was accepted as the most useful approach to coping with the system's case study's intricacy. The principal feature of System dynamics (SD) methodology is long-term forecasting, strategic modeling, and complex system simulation. Moreover, this abstract method enables a qualitative and quantitative investigation of complex dynamic systems actively operating within multiple feedback loops over time. The SD approach is widely used in organizing, investigating, and planning different businesses and marketing.

With the focus on facilitating effective decision making and problem-solving, this research follows four principal patterns of thought provided by the field of system thinking and method of system dynamics modeling *(*Richardson, Andersen, 2019):

- Thinking dynamically
- Thinking in feedback loops
- Thinking in stocks and flows
- Thinking endogenously

The dynamic thinking pattern of thought suggests that a state of a system can be interpreted as an active behavioral pattern, which displayed on a graph, continuously changes over time. That suggests, the current problematic behavior emerged in the past, and it will progressively act from now on.

The causal thinking brings to light feedback loops, which help create a hypothetical explanation of the problem. Feedback loops interpreted by causal loop diagrams (CLD) help route causal relationships of the elements impacting the system's behavior. This magnitude mechanism of creating feedback loops facilitates and simplifies the model-building process and stock-and flow-thinking. Found in literature:

"…a system must consist of three kinds of things: elements, interconnections, and a function or purpose."

(Meadows 2008, p.29)

Here, the stock-and-flow thinking is crucial to develop a structure which, by visible language, can uncover invisible patterns of system's behavior. Thus, the final model's structure comprises stocks and flows and other relevant variables.

However, the most influential is the systems thinking, which refers to observing and perceiving the 'system in one perspective' and thinking out of our conventional boundaries. In literature, Laszlo argues for the system as a whole approach:

"A System in one perspective is a subsystem in another. But the systems view always treats systems as integrated wholes of their subsidiary components and never as the mechanistic aggregate of parts in isolable causal relations."

(Laszlo, 1972, p.14)

This approach considers the real world as a whole system consisting of an infinite number of subsystems, directly or by other parts of that system affecting each other. Moreover, the causal relationships of the parts of systems are continuously developing and changing.

Based on our mental models, we drive conclusions to make decisions and change those systems' state.

The modelling processes.

According to Sterman (2000, p.88), the dynamic modeling process to be productive requires: *"...constant iteration between experiments and learning in the virtual world and experiments and learning in the real world."* Following that, a modeler should interact with the real-world dynamics during the entire period of virtual modeling and conduct the modeling process repeatedly until the model's outputs adequately reflect the actual condition of the simulated system. Figure 1 displays the approach used in this study.

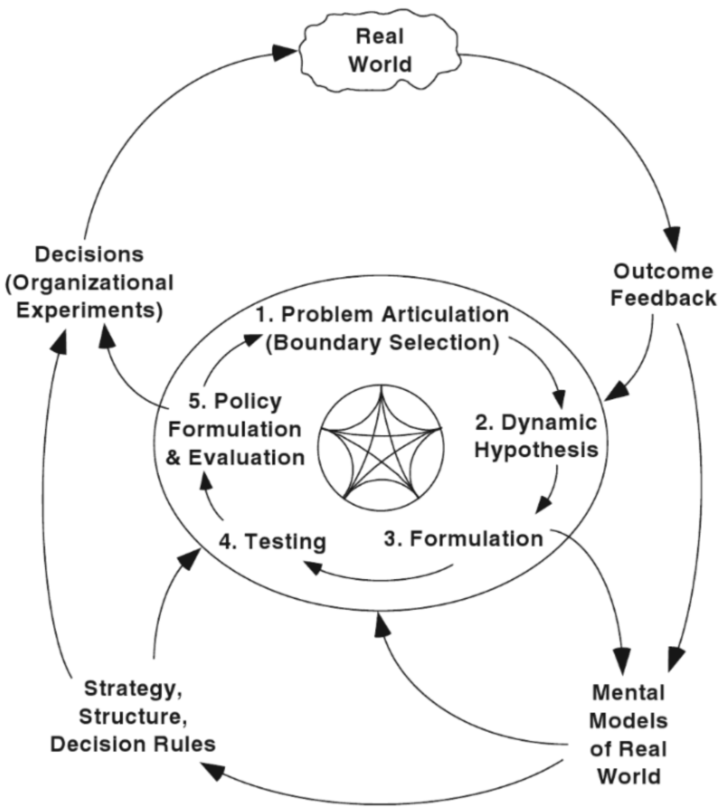


Figure 1: The Modelling Process (Sterman, 2000, p. 88).

Building and formulating the model's structure was performed iteratively and followed the steps suggested by Sterman (2000, p. 86). These include defining a dynamic problem, formulation of a dynamic hypothesis, developing a simulation model, testing the simulation model, and policy design.

The reference mode in Figure 3 in the form of behavior over time graph (BOTG) was first sketched. The key 11 stocks were identified and split into distinct modules based on their relevance:

- four stocks of customers, disaggregated by their meaning, and embedded in the *Customers* module,
- three stocks of employees, disaggregated by their skill level, and embedded in the *R&G Policy Hiring* module,
- stock of the desired workforce, embedded in the *R&G Policy Hiring* module,
- stock of workload, embedded in the *Internal Processes real* module,
- stock of burnout, embedded in the *Internal Processes real* module,
- stock of operating profit embedded in the *Finance* module.

In the second step, the dynamic hypothesis was formulated and demonstrated by a high-level aggregate causal loop diagram (CLD). Based on that, the stock-and-flow model was constructed in the form of a stock-and flow-diagram (SFD). In the fourth step, the model was tested in the order of three stages of formal model validation (Barlas, 1996), which include: direct structure tests, structure-oriented behavior tests, and behavior pattern tests. In the last step policy experiments were performed, and the most effective mix of policies giving the desired outcomes was established.

Data collection

As Forrester (1992) suggested, in general, there are three types of data available for modelers to investigate all kinds of dynamic systems. These three types of data build up knowledge and increase awareness about the system. They might be found in many sources; numerical (e.g., time-series data), written (documentary data found in articles, other documentary papers, and web pages), and the most potent mental data hidden in people’s minds. Figure 2 presents this concept:

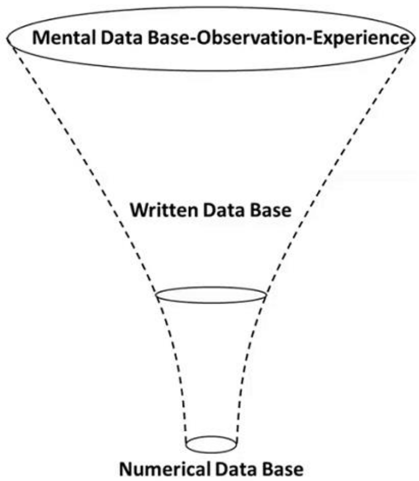


Figure 2: Mental database and other knowledge sources (Forrester, 1994, p.72).

All three types of mentioned data are relevant for modelers to proceed with the dynamic model building process and were used in this study. As people's mental models are the most valuable sources of actual data, this study is a mix of research that comprises both qualitative and quantitative research approaches. The qualitative part of the case study relates to human experiences, observations, personal perspectives, and intangibles. The study gives a holistic view of a dynamic work environment, and it reveals the reality of its internal processes. On the other hand, it quantifies how big the total population of market demand is, how many attainable customers are in the market, and the number of actual customers.

Overall, to construct the model's structure, which could be an acceptable representation of the real-world system, the human mind, which is the most powerful tool on the earth that possesses an infinite amount of data and unlimited mental capacity, was the primary source of knowledge.

Qualitative data collection

The approach was applied to collect the information from the mental database and written database. Most of the qualitative data were collected from the author's observations and experience that could not be counted or expressed in numbers. For the five years of working in the case restaurant (2014-19), the author could observe the system as a whole, both endogenously (while being at work) and from the external perspective (regular conversations with customers). Moreover, the author had daily contact with employees and regular weekly meetings with the manager. The study included the following types of qualitative research:

- Interview with customers: asking customers if they like the place, a menu and what they believe to be not appetizing.
- Individual interview with the restaurant manager.
- Focus groups: group interviews with the manager and employees to discuss the current restaurant's situation, customers' behavior and reveal individual opinion and feelings about existing strategy.

- Daily conversations with the restaurant manager and employees over five years (2014-19).
- Observation: observing the customers' behavior who visit the restaurant to see vital elements of their satisfaction or dissatisfaction.

Quantitative data collection

A quantitative approach was also a significant part of the research to collect and analyze the data needed to construct the model. Even though numerical data is a tiny percentage of all the actual knowledge (Forrester, 2009), the System dynamics method relies strongly on quantitative data to develop dynamic simulation models. The numerical data were collected from the company's database and averaged to the degree, which provides satisfactory results. The written data were gathered from online customer surveys and other web pages. whereas the leading qualitative data of this study were assembled from experience and observations. The most vital quantitative research in this study included the following data searching:

- Counting the market size and total population of market demand.
- Counting the employees' productivity.
- Calculating the number of people vising the restaurant.
- Calculating the number of attainable customers versus the actual customer.
- Ascertain busy/quiet periods of restaurant caused by customers' flow.

Modeling software

The Stella Architect was used as a simulation tool for modeling a dynamic model of the complex system investigated in this study. During the model building process, learning about the system was the most enjoyable and fascinating. The constructed model's structure and emerging behavior from that structure reveal how the system changes over time. This visual language in the form of the Stock and Flows diagram facilitates strategy planning, decision making, process, and policy design.

Dynamic Problem

With the purpose of the study, the reference mode, i.e., a dynamic historical explanation of a problem is essential. Presented in Figure 3 chart displays the historical number of customers over the five years (2015-2020) using the behavior over time graph (BOTG). As mentioned earlier, customers' historical data were collected from the company's database and simplified to achieve an average number over the model's simulation time.

The manager primarily wants to understand why the number of customers was steadily dropping each year despite his investments. Second, the manager wants to know the expected demand for the company. Third, the manager needs a new strategy that could lead to a better company's performance and increase employee productivity.

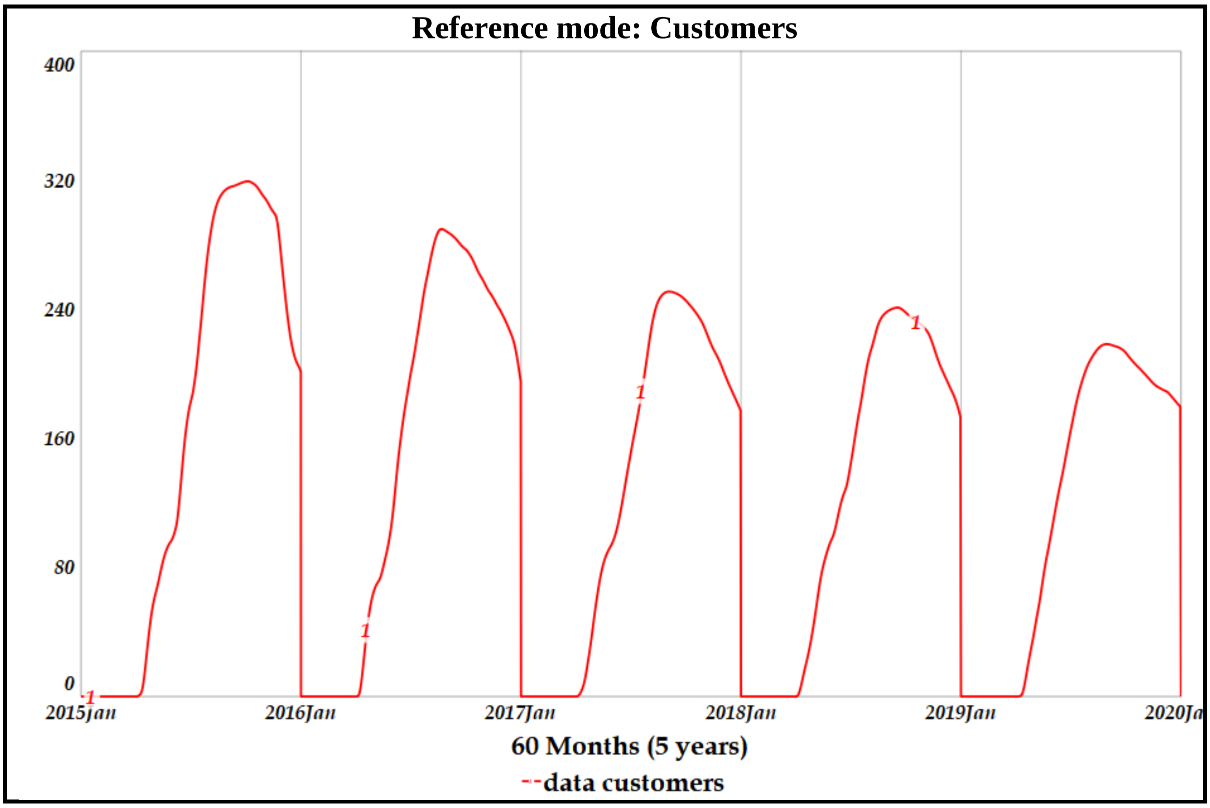


Figure 3: Reference Mode of Customers.

The manager explained that when the restaurant was reopened on 1st April each year (2015-2020), customers' historical behavior presented rapid growth, reaching its maximum value in summer. Following that, after the summer each year, there was a sharp decline until the end of December. The rationale behind fewer customers inflow at the end of December compelled the manager to close the restaurant for wintertime (January-March) each year. This pattern of customers' behavior was repeated over the five years period (2015-2020), with fewer customers in summer. Intriguingly, the peak of customers was lower each subsequent year. This ironic fact appears to be a solid foundation for this case study. As the historical graph presented in Figure 3 shows the peak of customers each year reached the value of:

- In 2015 the customers peaked at 319
- In 2016 the customers peaked at 290
- In 2017 the customers peaked at 251
- In 2018 the customers peaked at 241
- In 2019 the customers peaked at 219

Overall, the number of customers decreased over the five years, even though the local population and the number of tourists, visitors, and business travelers did not remarkably alter. Thus, to bring light to this problem, the hypothesis is presented in the next part of the thesis.

For service-based businesses, customers are one of the crucial resources; thus, appropriate supervision of customers' stock is essential for managers to estimate future successful strategies and increase organizations' revenue.

Figure 4 presents the historical behavior of customers (red line) from the company's database compared to the manager's expectations (blue line) over a five-year time horizon (2015-2020).

Figure 4: Reference mode of customers compared to expected customers.

The presented behavior pattern reveals that the manager's earlier assumptions and mental hopes for a customer's stability differ from reality. The graph displayed in Figure 4 shows that the expected customers' stock does not decline (blue line); instead, it reaches a slightly higher value each year. Thus, the number of likely customers is marginally higher each year. In general, the manager's mental model presents no outstanding loss or growth of customers over the entire five-year period. It confirms that the manager expected sustainable company development. In reality, there was a decrease in the number of customers, which contributed to a notable drop in revenue.

It is a problem for the company as a drop off in the revenue led to a decrease in the desired workforce, which led to reductions in production capacity and a further decline in the number of actual customers i.e., occasional customers and more valuable for the company: regular customers. It led to even lower revenue year after year. Moreover, with no changes in the existing strategy, future company growth seems unlikely and beyond the manager's beliefs. In the most severe period for the company, the number of employees dropped to 2, which is critical for the company to continue its business operations. It leaves the manager and employees in a vulnerable position.

Dynamic Hypothesis

The author's experience as one of the employees in the case company was essential for making meaningful assumptions and for the founding hypothesis of the existing problem of customers' loss. Through observation, the author discovered that inefficient production capacity was the leading cause of difficulties surrounding the execution of desired sales. Additionally, the author noticed a contradiction between the manager's mental model of internal processes and the real world. In System Dynamics, the concept of the mental model has its definition:

"A mental model of a dynamic system is a relatively enduring and accessible, but limited, internal conceptual representation of an external system (historical, existing, or projected) whose structure is analogous to the perceived structure of that system."

(Doyle and Ford, 1999, p. 414)

This understanding, enriched with archival data collected from the company database, provides a base for judging the hypothesis. The Dynamics Hypothesis chapter comprises six sections in the following order: the boundary of the model, time horizon, causal loop diagrams, model overview, major model assumptions, and stock and flow diagrams.

The boundary of the model

The entire model comprises 292 variables, 11 stocks, and 24 graphical functions. Thus, to provide a clear overview of the model's boundary, table 2 presents only the most essential variables. Table 2 expresses six modules, and in these distinct modules, it represents only the most crucial variables. The chart shows 86 variables, where 44 are endogenous, 33 are exogenous, and nine are excluded.

Module	***Endogenous***	***Exogenous***	***Excluded***
Customers	Non-customers, Was-customers, Occasional customers, Regular customers, occasional creation rate, occasional customer promotion rate, was-customers retry rate, occasional leaving rate, regular customer demotion rate, forgetting experience rate, regular customer leaving rate attainable customers, actual customers,	average order rate per occasional customers per month, average order rate per regular customers per month, contact rate, market size, time to forget experience,	customer satisfaction, customer expectations,

	desired sales rate, actual sales rate,		
Internal Processes base	normal rookies' production, normal skilled production, normal practiced production, normal production capacity, rookies, practiced, skilled, rookies' production, skilled production, practiced production, production capacity,	normal rookies, normal practiced, normal skilled, normal rookies' productivity, normal skilled productivity, normal practiced productivity,	employees' satisfaction,
Internal Processes real	Burnout, Workload, actual working rate, actual productivity, actual production capacity	normal burnout, normal time to dissipate burnout, workload's time, time for workload to affect capacity, time to execute orders,	
R&G Policy Hiring	Desired extra staff, Extra rookies, Extra practiced, Extra skilled, hiring rookies, hiring practiced, rookie's leaving rate, practiced leaving rate, skilled leaving rate, skilled churn rate,	normal rookie's attrition rate, normal practiced attrition rate, normal skilled attrition rate, normal workforce adj. time, time to perceive extra staff need, time of contract's employment, time go gain experience, time to gain skills,	employees' experience, employees' skills, training, coaching,
R&G Policy Advertising	NC adoption from advertising, OC adoption from advertising, WC adoption from advertising,	NC advertising effectiveness, OC advertising effectiveness, WC advertising effectiveness	
Finance	Operating profit, sales revenue, expenses, net cash flow, labour costs, production costs, rental costs,	average unit price, allocation of revenue for production, allocation of revenue to rent, allocation of revenue to salary,	other operating costs, tax,

	advertising costs	NC advertising costs, OC advertising costs, WC advertising costs,	
Top-level model	service failure rate,	normal service failure rate,	

After contrasting the company's strategy map presented in table 1 to the model's boundary shown in table 2, it is clear that the model is much more broadly developed, and its structure is more advanced *Table 2: Boundary of the model.* than the sketch of the original strategy map.

Time horizon

The time horizon of the model is five years, from 1st January 2015 to 1st January 2020. It was narrowed to this period to concentrate on the time from the problem originated until the company's data was available to collect. The time units in the model are months, as the company's data were gathered every month. However, to expose a coherent overview of the model's behavior, both months and years are used as the time unit on the presented graphs' vertical axes.

Causal Loop Diagrams

In this section, the dynamic hypothesis of the problematic behavior in the form of causal loop diagrams (CLDs) is presented. There are 88 loops in the model, but only the most important are shown and described. The feedback analysis begins with an overview of the decisive feedback loops considered to be the principal drivers for the uncontrolled and ineffective real internal processes in the company, leading to problematic behavior of customers' loss.

For a more detailed view, the loop of the entire model can be found in Appendix 1.

The decisive loops

As already pointed out, the hypothesis of the problematic behavior is based on the author's experience as one of the company's employees. More interviews with the employees and the restaurant manager were taken in the past (1st January 2015- 1st January 2020).

The current company's strategy to increase the schedule pressure was the only workable solution in the busy days. The manager explained that the employees were asked to work overtime and be more productive when there was an increase in customers' flow in the restaurant. The manager did not want to hire extra staff, as he was afraid the customers would not visit the restaurant if the weather conditions are adverse. Lack of additional staff and high pressure on employees to work overtime for an extended period led to employees' burnout at the end of each season. Eventually, the manager realized that his strategy was insufficient after noting the decline in the number of customers and revenue each year over the five years (2015-2020).

In the interest to understand the complexity of the entire restaurant's system and its real internal processes, the qualitative research approach was critical during the conceptualization step of the modeling process.

Applying System Dynamics approach, this step was performed by mapping circular causality of elements thought to affect or cause each other. The feedback loops presented in the Figure 5 are the hypothetical decisive loops creating the problematic behavior of customers' loss:

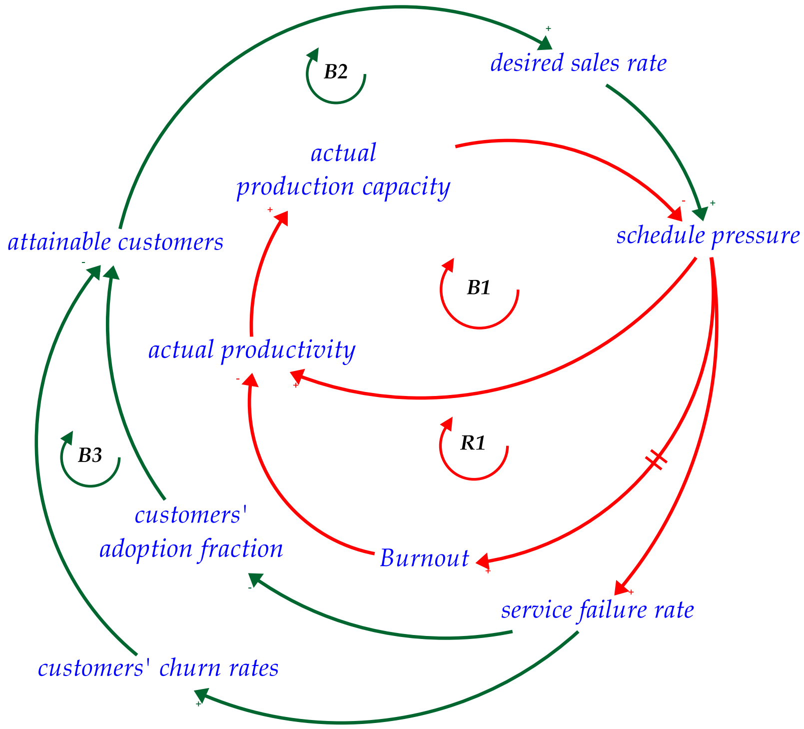


Figure 5: The CLD: decisive loops.

The graph presented in Figure 5 shows that the higher the number of *attainable customers* (among the total population of market demand), the higher the *desired sales rate*. An increase in the *desired sales rate* leads to higher *schedule pressure.* An increase in the *schedule pressure leads* to*:*

- higher *actual productivity,*
- building up *burnout (*which takes more time, as marked on the graph with a delayed sign in the link between the *schedule pressure* and *burnout),* and
- increase of *service failure rate.*

Thus, the *schedule pressure* is the primer influencer in all presented loops. These loops are described below in the following order: the **B1** balancing loop, the **R1** reinforcing loop, the **B2** balancing loop, and the **B3** balancing loop.

<u>The B1 balancing loop</u>

As *schedule pressure* goes up, the *actual productivity* goes up, as *schedule pressure* goes down, the *actual productivity* goes down. And that is marked by a positive sign in the link between *schedule pressure* and *actual productivity*. The higher *actual productivity*, the higher the *actual production capacity*, and oppositely, lower *actual productivity* leads to lower *actual production capacity*. An increase in the *actual production capacity* leads to a decrease in the *schedule pressure*, and lower *actual production capacity* leads to higher *schedule pressure*. That closes the **B1** loop, which in its nature is counteracting (balancing), leading to asymptotic growth to limit or exponential decay pattern of behavior.

The R1 reinforcing loop

As *schedule pressure* increases, it affects building up *burnout*; as *schedule pressure* goes up, the *burnout* goes up after some delay. *Burnout* affects *actual productivity;* as *burnout* goes up, the *actual productivity* falls off. That is marked by a negative sign in the link between *burnout* and *actual productivity*. The lower the *actual productivity*, the lower is the *actual production capacity*. A decrease in the actual production capacity leads to higher *schedule pressure*. That is marked by the second negative sign on the link between *actual production capacity* and *schedule pressure*. That closes the **R1** feedback loop, which is reinforcing, producing exponential growth or exponential collapse.

The B2 balancing loop

An increase in the *schedule pressure* leads to a higher *service failure rate*. If the *service failure rate* goes up, this leads to lower *customers' adoption fraction*. A decrease in the *customers' adoption fraction* leads to less *attainable customers:* the lower the number of *attainable customers*, the lower the *desired sales rate*. A decline in the *desired sales rate* leads to lower *schedule pressure.* That closes the **B2** balancing loop.

The balancing B3 loop

As mentioned above, an increase in the *schedule pressure* leads to a higher *service failure rate.* If the *service failure rate* goes up, it leads to a rise in the *customers' churn rates*. The higher the *customers' churn rates*, the less *attainable customers*, and the less the *attainable customers*, the lower the *desired sales rate.* A decrease in the *desired sales rate* leads to a decline in the *schedule pressure*, closing the **B3** balancing loop.

Customers' structure loops

The reinforcing pull loops

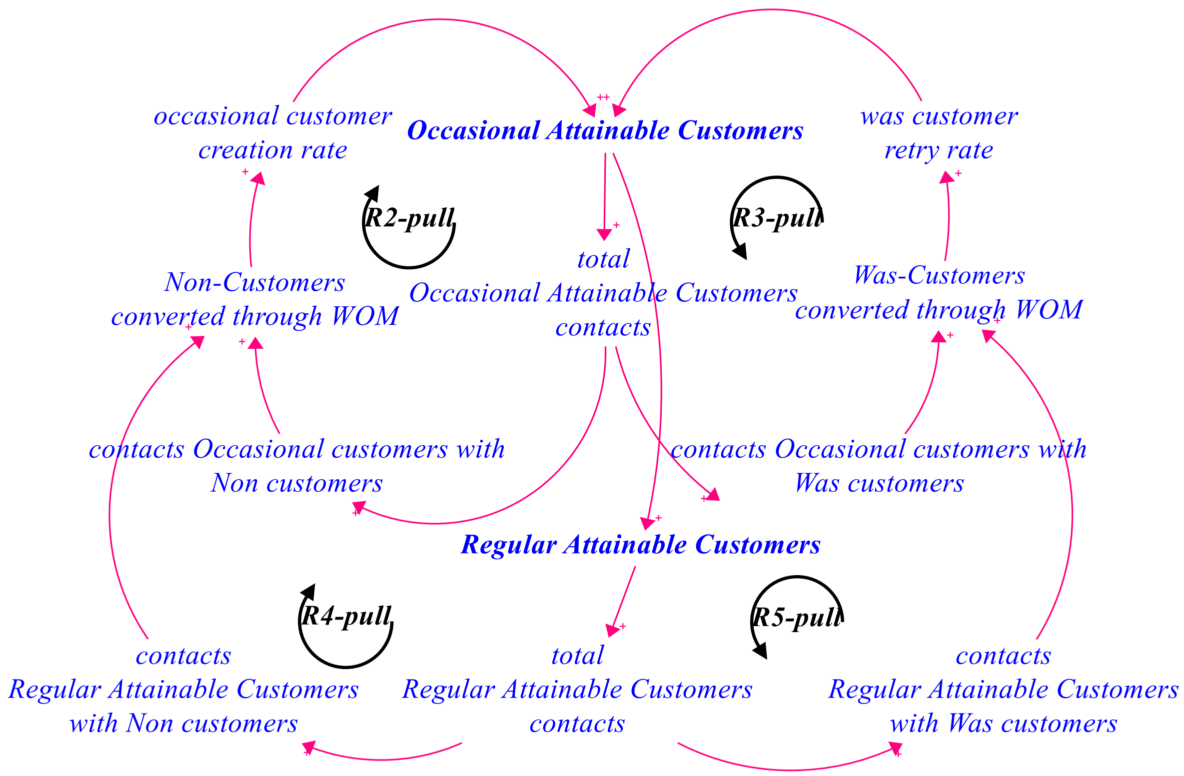


Figure 6:The R2-pull, R3-pull, R4-pull, and R5-pull reinforcing loops.

The **R2-pull** and **R3-pull** loops presented in Figure 6 reveal how the changes in the *occasional customer creation rate* and *was-customer retry rate* lead to a change in the number of *Occasional Attainable Customers*. The reinforcing pull loops are the effects of word-of-mouth and naturally generate an exponential behavior, either positive or negative, depending on the change in the *occasional customer creation rate* and *was-customer retry rate*. The same mechanisms are driving the **R4-pull** and **R5-pull** loops. All reinforcing pull loops are described:

- The variable *Non-Customers converted through WOM* in the **R2-pull loop** represents additional **Occasional Attainable Customers,** who are encouraged to purchase at the case restaurant as a result of contact with **Occasional Attainable Customers,** who have had a positive experience and recommend it.
- The variable *Was-Customers converted through WOM* in the **R3-pull loop** represent additional **Occasional Attainable Customers,** who are encouraged to visit the case restaurant again because of contact with **Occasional Attainable Customers,** who have had a positive experience and recommend it.
- The variable *Non-Customers converted through WOM* in the **R4-pull loop** represent additional **Occasional Attainable Customers,** who are encouraged to purchase at the

case restaurant due to contact with **Regular Attainable Customers,** who regularly visit the restaurant and recommend it.

- The variable *Was-Customers converted through WOM* in the **R5-pull loop** represent additional **Occasional Attainable Customers,** who are encouraged to visit the case restaurant due to contact with **Regular Attainable Customers,** who regularly visit the restaurant and recommend it.

The balancing limit loops

The graph depicted in Figure 7 presents four reinforcing pull loops and four balancing limit loops (marked with bold red links). These loops are part of the map for customers' structure, which is presented later in the thesis. As the reinforcing limit loops were already described, this subheading focuses on describing the counteracting **B2-limit, B3-limit, B8-limit**, and **B-9 limit** balancing loops.

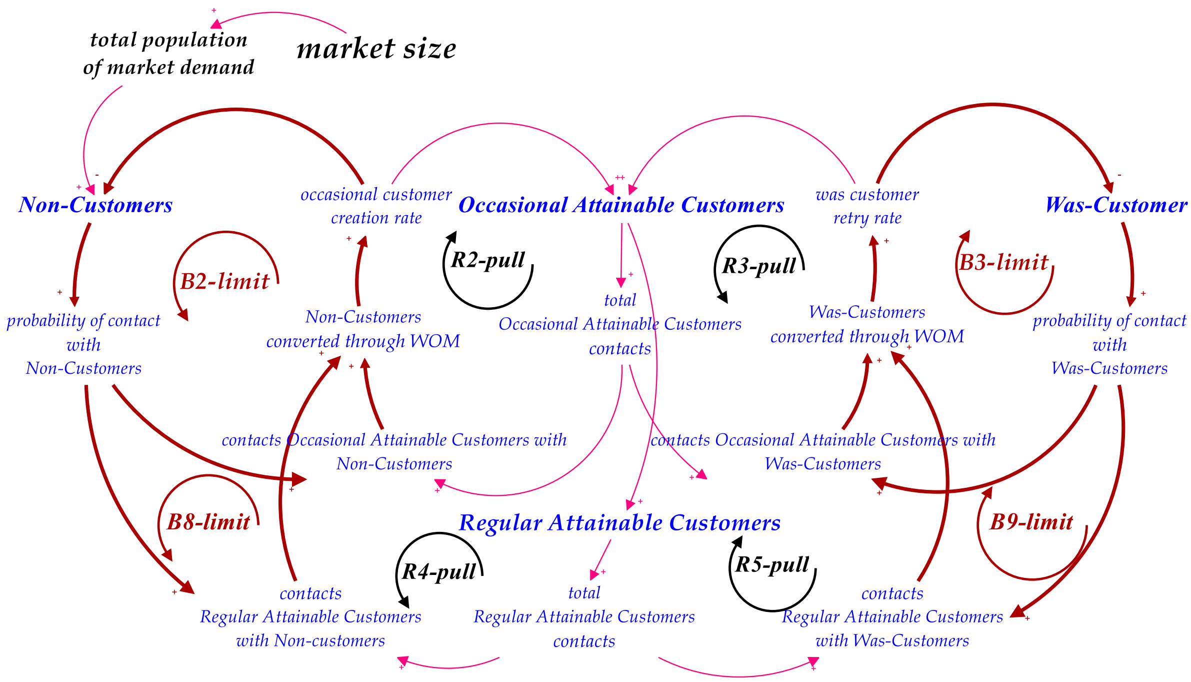


Figure 7:The pull-reinforcing and limit-balancing loops.

The *total population of market demand* limits the *Non-Customers* and thus limits the **B2-limit**, **B3-limit**, **B8-limit**, and **B9-limit** balancing loops. However, *the total population of market demand* is an unstable limitation. An efficacious mix of policies (e.g., advertising, hiring) might increase the *total population of market demand,* whereas ineffective strategy planning might decrease. Thus, the *market size* is the ultimate and unchangeable limit in the presented customers' structure. The exhibited causality of customers' diffusion is a natural process, and it closely matches what is observed in the real world. The structure of the developed model in this study reveals that in its behavior, which resembles reality. The graphs in Figures 8,9 display more precisely the **B2-limit**, **B3-limit**, **B8-limit**, and **B9 limit** balancing loops.

- The **B2-limit** and **B8-limit** balancing loops.

As mentioned above, the *market size* is the ultimate limit in the presented causal loop diagram of customers' diffusion. The higher is the *market size*, the higher is the *total population of market demand*, leading to a higher number of *Non-Customers*. The **B2-limit** and **B8-limit** counteracting loops presented in Figure 8 show how the change in the number of *Non-Customers* affects the *occasional customer creation rate*, which in feedback leads to a change in the balance of the *Non-Customers*.

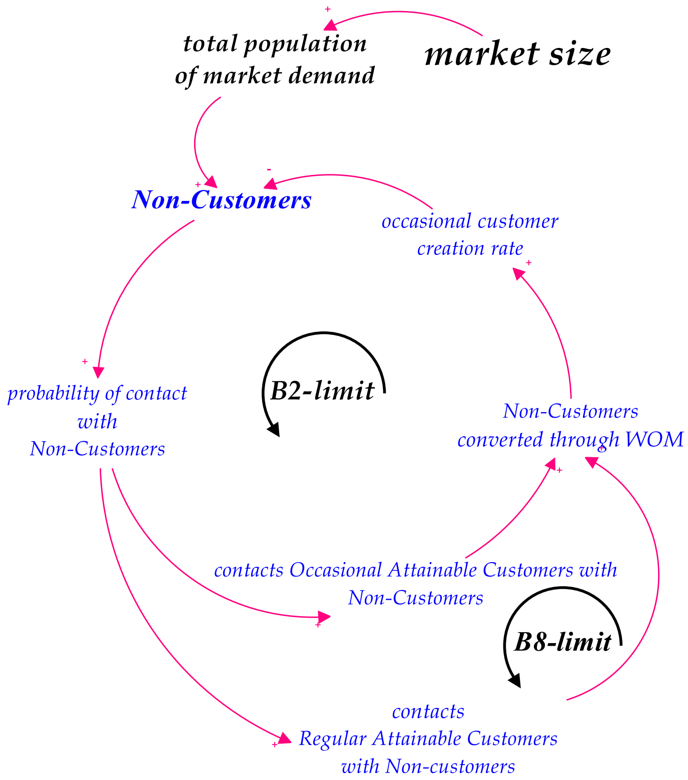


Figure 8: The B2-limit and B8-limit balancing loops.

An increase of *Non-Customers* increases the *probability of contact with Non-Customers*, leading to a rise in the *contacts Occasional Attainable Customers with Non-customers*. If the *contacts Occasional Attainable Customers with Non-customers* increases, thus the *Non-Customers converted through WOM* increases. The more *Non-Customers converted through WOM*; the higher is the *occasional customer creation rate*. If the *occasional customer creation rate* increases, thus the number of *Non-Customers* decreases, and finally, the **B2-limit** loop is closed. As the **B2-limit** loop comprises an odd number of negative links, this is a balancing loop.

The **B8-limit** counteracting loop follows the same pathway; however, the number of *Non-Customers converted through WOM* increases not through *contacts Occasional Attainable Customers with Non-customers,* but through *contacts Regular Attainable Customers with Non-customers.*

- The **B3-limit** and **B9-limit** balancing loops.

The **B3-limit** and **B9-limit** counteracting loops displayed in Figure 9 represent how the change in the number of *Was-Customers* affects the *was-customer retry rate*, which in feedback leads to a change in the balance of the *Was-Customers*.

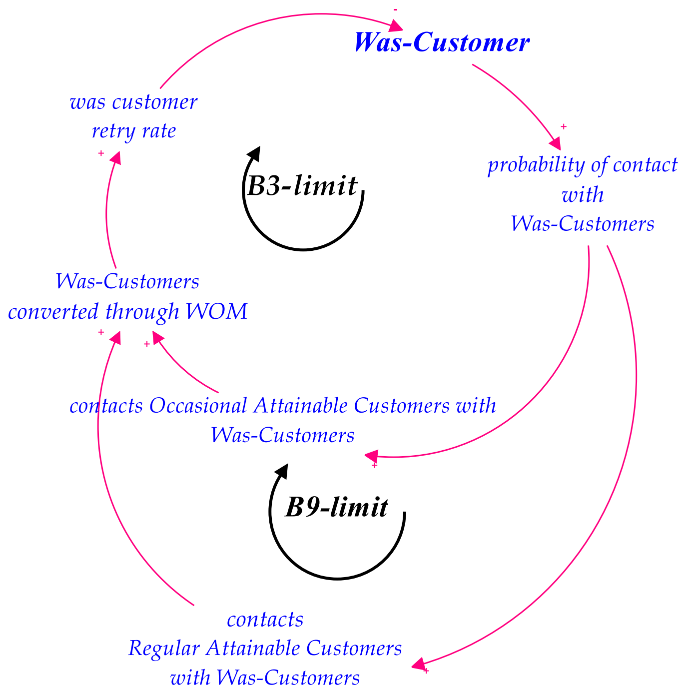


Figure 9: The B3-limit and B9-limit balancing loops.

If the number of *Was-Customers* rises, thus the *probability of contact with Was-Customers* increases. Further, an increase in the *probability of contact with Was-Customers* leads to a rise in the *contacts Occasional Attainable Customers with Was-customers*. If the *contacts Occasional Attainable Customers with Was-customers* increases, thus the number of *Was-Customers converted through WOM* increases. If the *Was-Customers converted through WOM increases,* thus the *was customer retry rate* increases. If the *was customer retry rate* increases, thus the number of *Was-Customer* drops, and finally, the **B3-limit** loop is closed. As the **B3 limit** loop contains an odd number of negative links, this is a balancing loop.

The **B9-limit** balancing loop reflects the same pathway; however, the number of *Was Customers converted through WOM* increases not through *contacts Occasional Attainable Customers with Was-customers,* but through *contacts Regular Attainable Customers with Was-customers.*

The balancing push loops

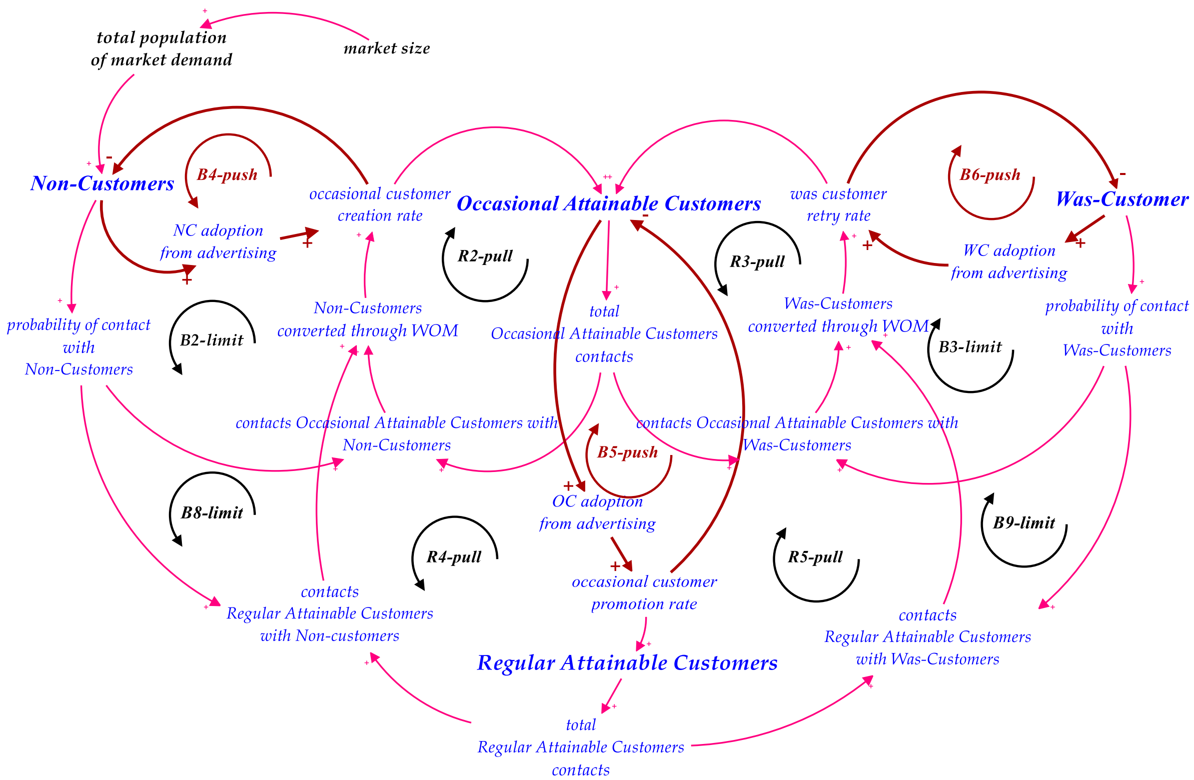


Figure 10:The pull-reinforcing, limit-balancing, and push-balancing loops.

In the causal loop diagram presented in Figure 10, the loops **B4-push**, **B5-push,** and **B6-push (**marked with bold red links**)** regulate the number of people encouraged to become *Occasional Attainable Customers* (from being *Non-Customers* or *Was- Customers*) or *Regular Attainable Customers* (from being *Occasional Attainable Customers*) as a result of the advertising policy. The push loops in the model have different advertising effectiveness. It is more challenging to encourage *Was-Customers* (which are lost customers) to become customers again than to encourage *Non-Customers* to become first-time clients.

- The loop **B4-push** represents how the change in the number of *Non-Customers* affects the *occasional creation rate*, which in turn leads to a change in the balance of the *Non-Customers.*
- The loop **B5-push** represents how the change in the number of *Occasional Attainable Customers* affects the *occasional customer promotion rate*, which in turn leads to a change in the balance of the *Occasional Attainable Customers*.
- The loop **B6-push** represents how the change in the number of *Was-Customers* affects the *was-customer retry rate*, which in turn leads to a change in the balance of the *Was-Customers.*

Model overview

The model comprises seven modules: *Customers*, *Internal Processes base*, *Internal processes real* module, *Finance*, *R&G Policy Hiring*, *R&G Policy Advertising*, and *Data &*

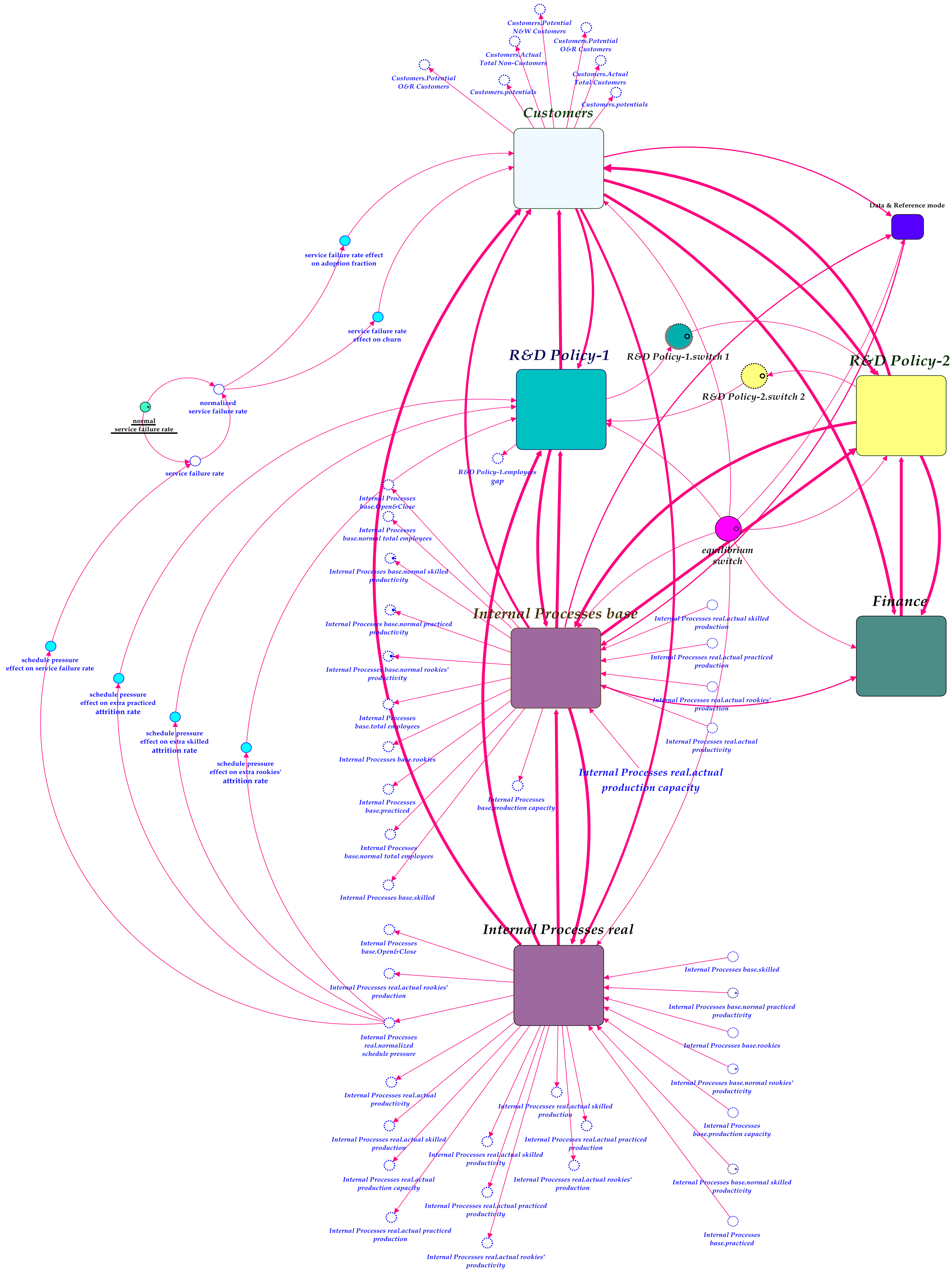


Figure 11: Modules diagram.

Reference Mode module. The module diagram in Figure 11 presents all modules and their relationships in the model:

As already mentioned, in the model there are over 200 variables and 23 graphical functions. Thus, an overview of the entire model's structure and all model variables with equations are available in an appendix. The Customers module and Internal processes modules are presented in the *Stock and flow diagrams* sub-chapter of this chapter.

Major model assumptions

The major model's assumptions are presented in this section. Other still meaningful assumptions behind each module are represented according to the order of the displayed stock-and-flow diagrams in the third *Stock and flow diagrams* section of this chapter.

Market size and market demand

- The market size is 65 000 (local population & tourist, visitor, and business travelers).
- The *total population of market demand* is assumed to be 5% of the *market size*. It determines the number of potential customers at the district of Bergenhus. The assumption is based on surveys and case studies accessible through webpages (written data) and the author's conclusions (qualitative information).There are competitors in the market, but the service is in high demand, and the restaurant has the potential to grow on the market.

Seasonality

- The restaurant is open from 1st April to the end of December, and it is closed for wintertime from 1st January to the end of March each year.
- For the model to reflect reality, the *Enclose* variable was embedded in the model to automatically reset the model's variables when the restaurant is closed (1st January - 31st March) each year.

Resources

- Key resources are customers (in the model disaggregated into four stocks based on their meaning).
- Other meaningful resources are employees (in the model disaggregated into three stocks based on their productivity).

Factors that trigger customers' diffusion

- In business as usual (BAU) scenario, customers' growth arises only from word-of-mouth (WOM).
- This assumption complies with the Bass Model (Bass,1969), which presumes that diffusion of a new product or service is first and foremost boosted by the word-of-mouth coming from active customers' referrals founded on their positive experience.

The word-of-mouth part of the customers' structure assumes that both *Occasional Attainable Customers* and *Regular Attainable Customers* interact with *Was-Customers* and *Non-Customers* and convert them to become customers.

- Advertising is a policy, and in business as usual (**BAU**) scenario does not influence customers' behavior. The advertising policy is presented further in this thesis

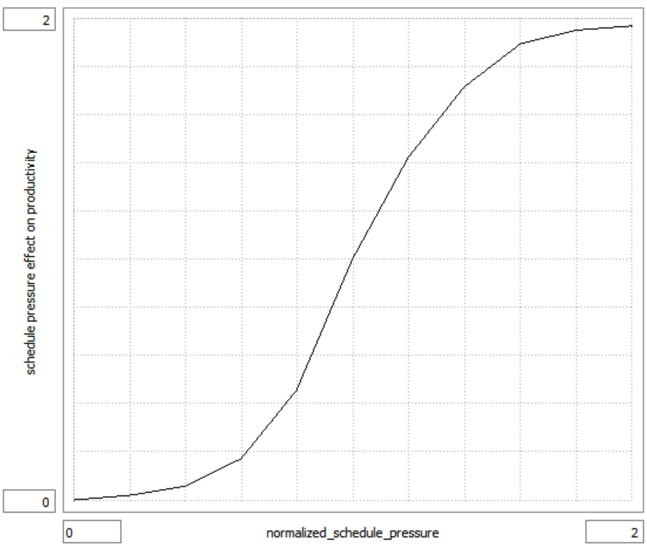
Intangibles

There are three intangible parameters in the model: *schedule pressure*, *burnout*, and *service failure rate*. These are naturally not measurable parameters that actively shape the real processes in the company. In the model, the *schedule pressure* affects:

- employees' productivity (*normal practiced productivity*, *normal skilled productivity*, and *normal rookies' productivity*),
- *service failure rate*,
- employees' attrition rates (*normal rookies' attrition rate*, *normal practiced attrition rate*, and *normal skilled attrition rate*),
- building up *burnout*.

Moreover, in the model, the *burnout* affects employees' productivity, and *time to recover*, while the *service failure rate* affects customers' adoption fraction (through *service failure rate effect on adoption fraction*), and customers' churn (through *service failure rate effect on churn*). In the model, the effects of intangibles are revealed by the graphical functions. As in total, there are 23 graphical functions in the model, only three, the most critical graphical functions are presented and described in the following order: *schedule pressure effect on productivity*, *schedule pressure effect on burnout*, and *burnout effect on productivity*.

1. ***Schedule pressure effect on productivity***

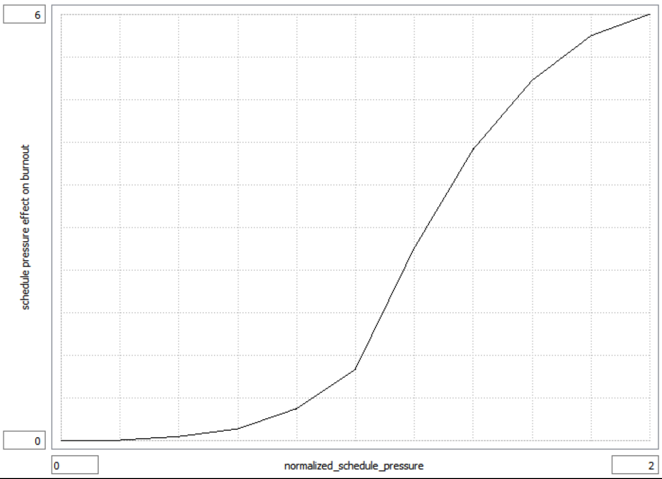


	normalized_schedule_pressure	schedule pressure effect on productivity
1	0,000	0,000
2	0,200	0,0190476190476
3	0,400	0,0571428571429
4	0,600	0,171428571429
5	0,800	0,457142857143
6	1,000	1,000
7	1,200	1,42222222222
8	1,400	1,71428571429
9	1,600	1,89206349206
10	1,800	1,94920634921
11	2,000	1,967

Figure 12:Schedule pressure effect on productivity

The graph in Figure 12 shows the standard S-shaped graphical function, which illustrates the *effect of schedule pressure on productivity*. If the schedule pressure goes up, the productivity increases, and the range of schedule pressure is from 0 to 2.

2. *Schedule pressure effect on burnout*



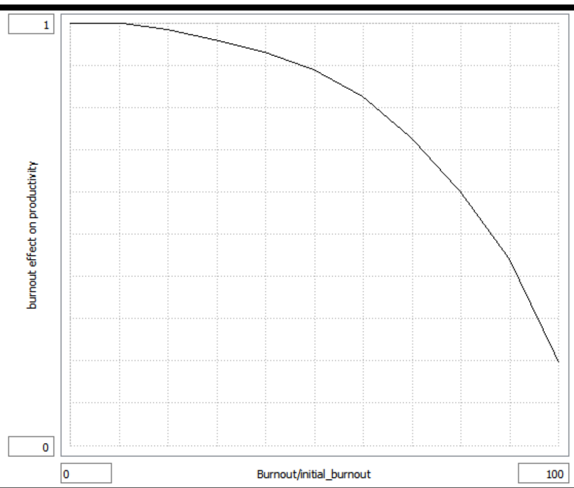
	normalized_schedule_pressure	schedule pressure effect on burnout
1	0,000	0,000
2	0,200	0,000
3	0,400	0,0507936507937
4	0,600	0,15873015873
5	0,800	0,444444444444
6	1,000	1,000
7	1,200	2,70476190476
8	1,400	4,09523809524
9	1,600	5,06666666667
10	1,800	5,69523809524
11	2,000	6,000

Figure 13:Schedule pressure effect on burnout

The graph displayed in Figure 13 shows the standard S-shaped graphical function, which illustrates the *effect of schedule pressure on burnout*. The chart shows that if the *schedule pressure* goes up (above 1), burnout increases. The range of *schedule pressure* is from 0 to 2. That means that if there is two times growth in the amount of *schedule pressure*, there is six times growth in *burnout*.

It is vital to mention that in the model, it is assumed that if the *desired sales rate* is equal to the *actual production capacity*, there is no *schedule pressure* on employees (*schedule pressure effect on burnout* is equal to 1). However, if the *desired sales rate* is above the *actual production capacity*, there is an increase *in employees' schedule pressure* to work overtime. Opposite to that, when the *schedule pressure* is decreasing, the *burnout* is faltering.

3. *Burnout effect on productivity*



	Burnout*Intern...s_base.Enclose	burnout effect on productivity
1	0,0	1,000
2	10,0	1,000
3	20,0	0,984126984127
4	30,0	0,95873015873
5	40,0	0,930158730159
6	50,0	0,888888888889
7	60,0	0,825396825397
8	70,0	0,726984126984
9	80,0	0,600
10	90,0	0,44126984127
11	100,0	0,200

Figure 14: Burnout effect on productivity.

The graphical function displayed in Figure 15 shows the *burnout effect on productivity*. As the *burnout* goes up, thus the productivity goes down. The burnout range is from 0 to 100, which indicated that the *burnout* might be measured as a percent. It is assumed that the amount of *burnout* up to 10 is acceptable; thus, *burnout* does not affect employees' productivity if the stock level of burnout is in the range: 0-10. Moreover, it is assumed that *burnout* cannot lead the productivity to fall to zero. As the graphical function shows, *burnout* might decrease employees' productivity by up to 20% of their normal productivity. Because the employees are disaggregated into three types based on their productivity, the minimum value of normal productivity when the burnout is 100% will be equal:

- Minimum normal rookies' productivity:

$$895 * 0.2 = 179 \text{ [orders per employee per month]}$$

- Minimum normal practiced productivity:

$$480 * 0.2 = 96 \text{ [orders per employee per month]}$$

- Minimum normal skilled productivity:

$$100 * 0.2 = 20 \text{ [orders per employee per month]}$$

Stock and flow diagrams

As the root model comprises seven modules with seven sectors, and over 200 variables, only the most essential parts of the model are presented in Stock and Flow Diagrams (SFD) in the following order:

- Customers' Module
    - Background
    - Customers' structure
    - Assumptions behind the Customers' module

- Internal Processes Base Module
    - Internal Processes base structure
    - Assumptions behind Internal processes base module
- Internal Processes Real Module
    - Internal Processes real structure
    - Assumptions behind Internal processes real module

Customers' Module

In this sub-section, first, a background for the customers' investigation and origin of ideas for the development of customers' module is presented. After that, a more profound overview of the customers' structure is presented, and the essential assumptions are listed.

Background

The structure of customers was inspired by the Bass diffusion model published in 1969 by Professor Frank M. Bass to describe the innovation diffusion process of new product or service (Bass, 1969), (Sterman, 2000, p. 332). The 1969 Bass Model paper provided empirical evidence supporting the model; however, the model's mathematical derivation was published six years earlier (Bass, 1963) in the scholarly paper "*A dynamic Model of Market Share and Sales Behavior."*

The Bass diffusion model is among the most applicable models in forecasting. It is broadly used in marketing and strategic planning (e.g., in customers' diffusion), technology adoption, and epidemics and infectious disease investigations (e.g., viruses or bacteria spreading through a population.) The Bass model is efficient and advantageous. Its remarkable simple structure produces meaningful dynamic behavior, which is still not understood and easy to predict by some of the top leaders.

The generic structure of the Bass model consists of two stocks: *potential adopters* and *adopters.* In principle, the *potential adopters* become adopters through the *word-of-mouth* (WOM) concept. Once a new product or service has been developed, it begins to be purchased by first buyers who interact with other people, and through that process, they convert them to adopt the same product or service. Thus, primarily people from *potential adopters'* stock diffuse into *adopters'* stock through referrals.

As the primary purpose of this research is to understand the reasons for customers' loss, the author went a step further in the model building process and expanded the generic diffusion model's structure to investigate customers' diffusion more profoundly. The customer's map displayed in Figure 15 gives a comprehensive overview of different types of customers in that structure. The author of the study designed the map, based on experience and observations regularly collected for five years (2014-19) while working in the case company.

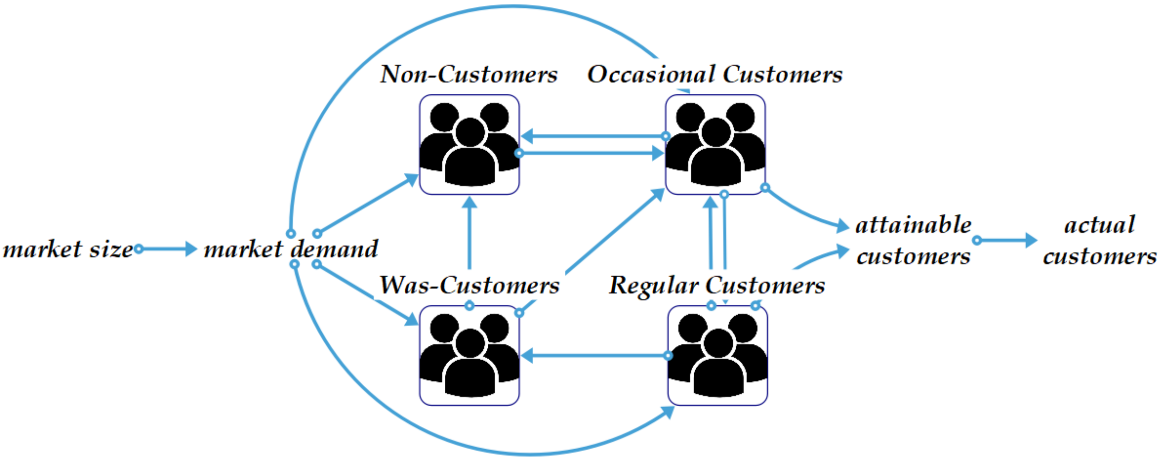


Figure 15: Diffusion of different types of customers.

The map represents the parametric assumption about the shape of a normal distribution in the total population of market demand.

<u>Parametric assumptions about customers' population</u>

It is assumed that all four stocks representing different customers' populations are normal, and the only way that they differ is by their meaning:

- The population of *Non-Customers* stock is the set of all potential *Non-customers* of a *total population of market demand.*
- The population of *Occasional Attainable Customers* stock is the set of all potential *Occasional Attainable Customers* of a *total population of market demand*.
- The population of *Regular Attainable Customers* stock is the set of all attainable *Regular Attainable Customers* of a *total population of market demand*.
- The population of *Was- Customers* stock is the set of all potential *Was-customers* of a *total population of market demand*.

SFD Customers module

Figure 16 presents the customer's structure, which comprises four key stocks: Non-customers, Occasional Attainable Customers, Regular Attainable Customers, and Was-customers:

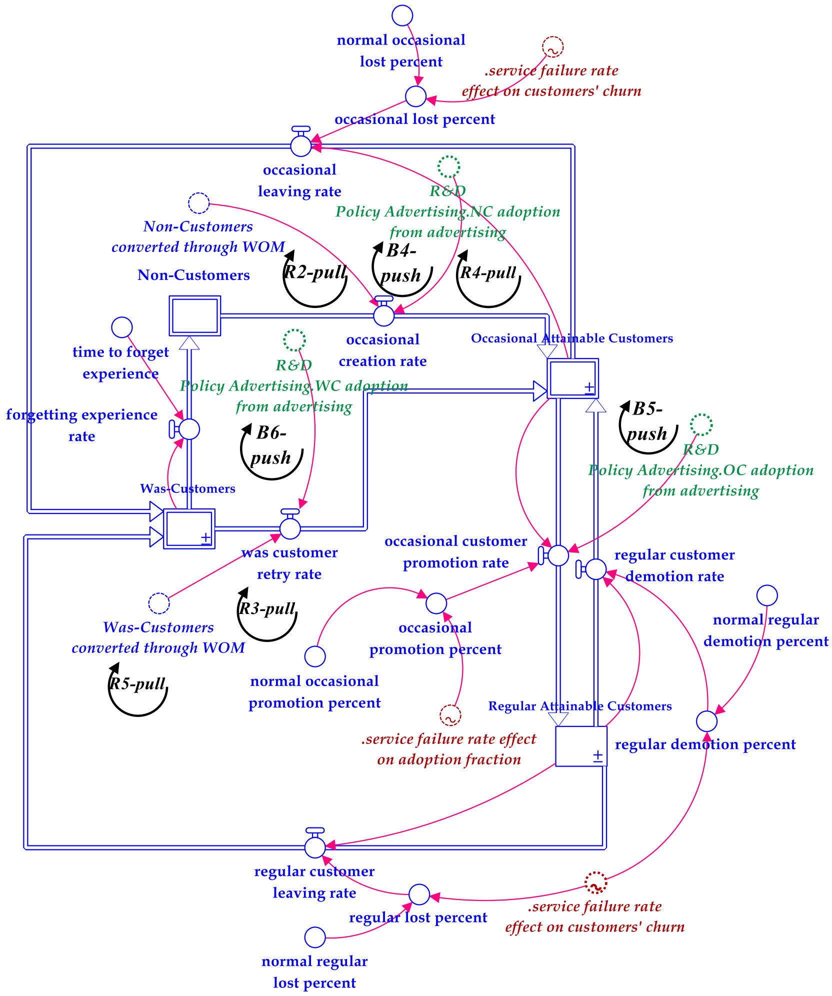


Figure 16: SFD: Customers' structure.

The disaggregation of customers in four distinct stocks facilitates the investigation of *the word-of-mouth* impact on customers' acquisition and retention. Moreover, it gives more reliable information to the manager, how the advertising policy should be formed to gain all attainable customers and to maximize the number of *Regular Attainable Customers*. As previously stated, it is assumed that word-of-mouth is primarily driving customers' diffusion, and advertising is a policy.

There are seven flows in the customers’ structure. These meaning of the flows in the base run is described below in the following order:

1) *occasional creation rate,*
2) *occasional leaving rate,*
3) *was-customer retry rate,*
4) *regular customer leaving rate,*
5) *occasional customer promotion rate,*
6) *regular customer promotion rate,*
7) *forgetting experience rate.*

1) ***<u>The " occasional creation rate"</u>***

The flow called *occasional creation rate* converts the *Non-Customer*s to *Occasional Attainable Customers* only when the restaurant is open: from 1st April to the end of December each year. When the restaurant is closed for wintertime from 1st January to the end of March each year the *occasional creation rate* becomes zero. This is reasonable as in reality when the restaurant is closed there will be not referrals. By that model is in line with one of the model's major assumption: seasonality (presented in the *Major model assumptions* section of the Dynamic Hypothesis chapter in this thesis.) This flow is affected by two sources:

- *Non-Customers converted through WOM* (determined by the word-of-mouth)
- *NC adoption from advertising* (determined by the advertising), which is embedded in the *R&D Policy Advertising* module, and it is a ghost in the *Customers* module

As advertising is a policy; thus, in the business as usual (BAU) scenario, the *NC adoption from advertising* is equal to zero and does not affect the *occasional creation rate.* Only the word-of-mouth affects the *occasional creation rate* through the variable called *Non-Customers converted through WOM*

The variable ***Non-Customers converted through WOM*** is determined by:

- *contacts Occasional Attainable Customers with Non-Customers*

  These contacts are defined by the *probability of contact with Non-Customers* and the *total Occasional Attainable Customers contacts.*

  The *total Occasional Attainable Customers contacts* are affected by the number of *Occasional Attainable Customers* and *contact rate*.

- *contacts Regular Attainable Customers with Non-Customers*

  These contacts are defined by the *probability of contact with Non-Customers* and the *total Regular Attainable Customers contacts.*

  The *total Regular Attainable Customers contacts* are affected by the *Regular Attainable Customers* and *contact rate*.

- *adoption fraction Non-Customers*

  The *adoption fraction Non-Customers* is the *normal adoption fraction Non-Customers* affected by the *service failure rate effect on adoption fraction.*

Thus, in total, the variable ***Non-Customers converted through WOM*** in principle is affected by three variables:

- *probability of contact with Non-Customers,*
- *adoption fraction Non-Customers,*

- *contact rate*.

The *probability of contact with Non-Customers* is the ratio of *Non-Customers* to the *total population of market demand*. Therefore, the more *Non-Customers* there are in the *total population of market demand*, the higher the probability of *Occasional Attainable Customers* and Regular *Attainable Customers* meeting *Non-Customers*.

When an "occasional attainable customer" or "regular attainable customer" meets a "non-customer," there is a certain probability that the "non-customer" will become "occasional attainable customer." This probability is called the *adoption fraction Non-Customers*, and it reveals the persuasiveness of "occasional attainable customer" or "regular attainable customer" when meeting the "non-customer".

The *contact rate* parameter determines the total number of interactions or contacts that *Occasional Attainable Customers* or *Regular Attainable Customers* have with their friends who are *Non-Customers* or *Was-Customers* during a month.

2) ***The " occasional leaving rate"***

The *occasional leaving rate* converts *Occasional Attainable Customers* back to *Non-Customers*, at a certain percentage called *occasional lost percent* only when the restaurant is open each year.

The *occasional lost percent* is the *normal occasional lost percent* affected by the *service failure rate effect on customers' churn*.

3) ***The " was customer retry rate"***

In the base run, the flow called *was customer retry rate* converts the *Was-Customer*s to *Occasional Attainable Customers* each year, and only when the restaurant is open. This flow is affected by two sources:

- *Was-Customers converted through WOM* (determined by the word-of-mouth)
- *WC adoption from advertising* (determined by the advertising), which is embedded in the *R&D Policy Advertising* module, and it is a ghost in the *Customers* module

As already mentioned, advertising is a policy; thus, in the business as usual (BAU) scenario, the *NC adoption from advertising* does not affect the *occasional creation rate.* Only the word-of-mouth affects the *was customer retry rate* through the variable called *Was-Customers converted through WOM.*

The variable ***Was-Customers converted through WOM*** is determined by:

- *contacts Occasional Attainable Customers with Was-Customers*

  These contacts are defined by the *probability of contact with Was-Customers* and the *total Occasional Attainable Customers contacts.*

- *contacts Regular Attainable Customers with Was-Customers*

These contacts are defined by the *probability of contact with Was-Customers* and the *total Regular Attainable Customers contacts.*

- *adoption fraction Was-Customers*

  The *adoption fraction Was-Customers* is the *normal adoption fraction Was-Customers* affected by the *service failure rate effect on adoption fraction.*

Thus, in total, the variable ***Was-Customers converted through WOM*** in principle is affected by three variables:

- *probability of contact with Was-Customers*,
- *adoption fraction Was-Customers*,
- *contact rate*.

The *probability of contact with Was-Customers* is the ratio of *Was-Customers* to the *total population of market demand*. Therefore, the more *Was-Customers* there are in the *total population of market demand*, the higher the probability of *Occasional Attainable Customers* and Regular *Attainable Customers* meeting the *Was-Customers*.

When an "occasional attainable customer" or "regular attainable customer" meets a "was-customer," there is a certain probability that the "was-customer" will become "occasional attainable customer" again. This probability is called the *adoption fraction Was-Customers,* and it reveals the persuasiveness of "occasional attainable customer" or "regular attainable customer" when meeting the "was-customer."

The *contact rate* parameter was already described above when the occasional creation rate was presented as first.

4) ***<u>The "regular customer leaving rate rate"</u>***

The *regular customer leaving rate* converts *Regular Attainable Customers* back to *Was-Customers* at a certain percentage called *regular lost percent* each year, only when the restaurant is open.

The *regular lost percent* is the *normal regular lost percent* affected by the *service failure rate effect on customers' churn*.

5) ***<u>The " occasional customer promotion rate"</u>***

In the model, regular customers do not become "regular" from the first time visiting the restaurant. These regular customers are first "occasional," and they might become "regular" through *occasional customer promotion rate*.

Thus, the *occasional customer promotion rate* diffuses the *Occasional Attainable Customers* to the *Regular Attainable Customers* at a certain percentage called *occasional promotion percent* each year, only when the restaurant is open.

The *occasional promotion percent* is the *normal occasional promotion percent* affected by the *service failure rate effect on adoption fraction*.

An additional source affecting this rate is advertising through *OC adoption from advertising*, which is embedded in the *R&D Policy Advertising* module, and it is a ghost in the *Customers* module. However, as already mentioned, in the base run scenario, advertising does not affect customers' diffusion.

6) ***The " regular customer demotion rate"***

The *regular customer promotion rate* converts *Regular Attainable Customers* back to *Occasional Attainable Customer* at a certain percentage called *regular demotion percent* each year, only when the restaurant is open.

The *regular demotion percent* is the *normal regular demotion percent* affected by the *service failure rate effect on customers' churn*.

7) ***The " forgetting experience rate"***

The *forgetting experience rate* converts *Was-Customers* back to *Non-Customers* with a time delay called *time to forget experience* over the entire simulation time. This is reasonable, as people may be forgetting their negative experience from visiting the restaurant also during the time when the restaurant is closed.

Based on experience and observations, the *time to forget experience* is assumed to be 12 months (1 year).

Figure 17 represents the with word-of-mouth (WOM) part of the customers' structure:

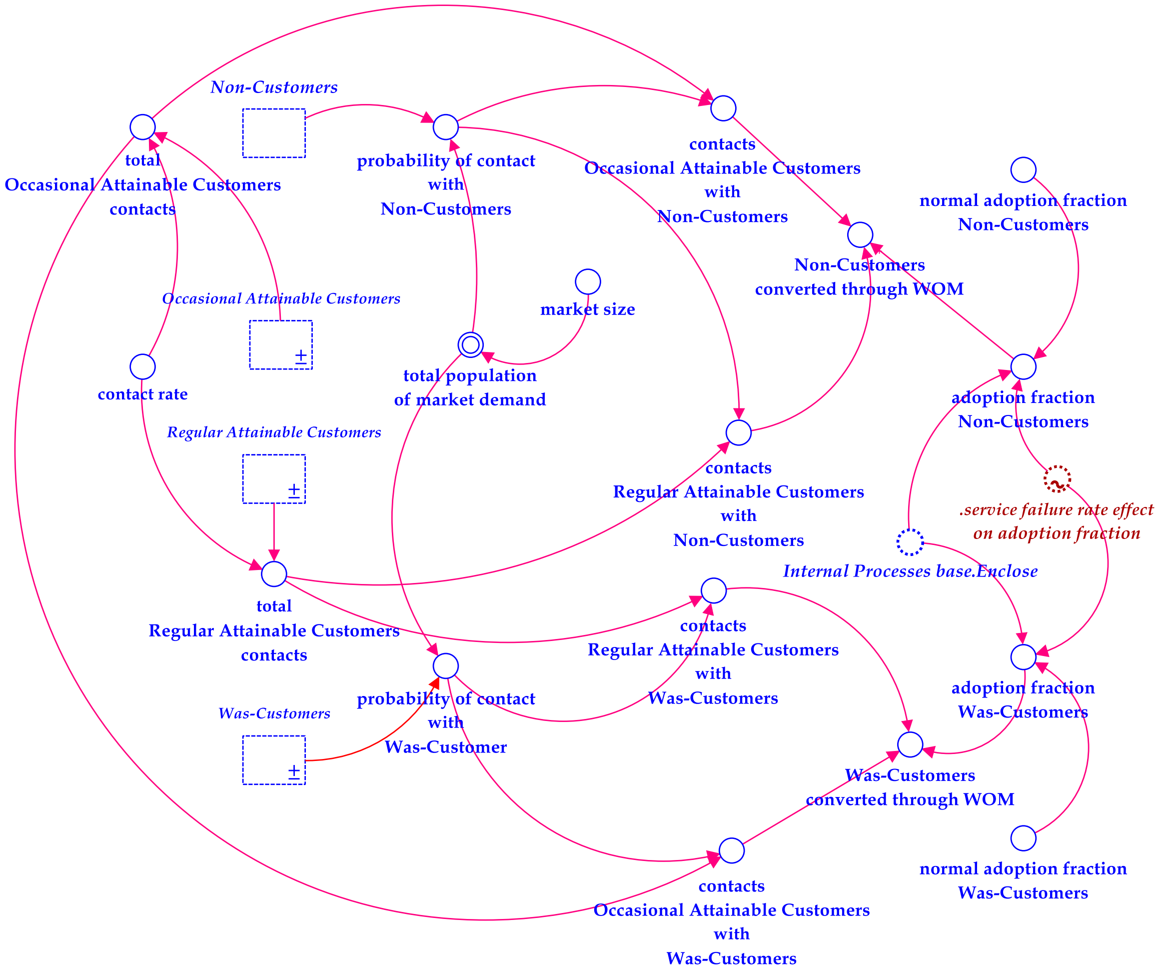


Figure 17: SFD: Customers' structure with WOM algebra.

In order to line the model with reality, which will produce lifelike results, it is assumed that the *normal adoption fraction Non-Customers* and *normal adoption fraction Was-Customers* are affected by the service failure rate. The assumption seems reasonable, as, in the real world, an increase in service failure decreases customers' adoption fraction.

Figure 18 on the next page shows part of the ***Customer's module*** containing a ghost of the *actual production capacity* variable from the ***Internal Processes Real module.*** Here, the *actual production capacity* limits the *actual sales rate*:

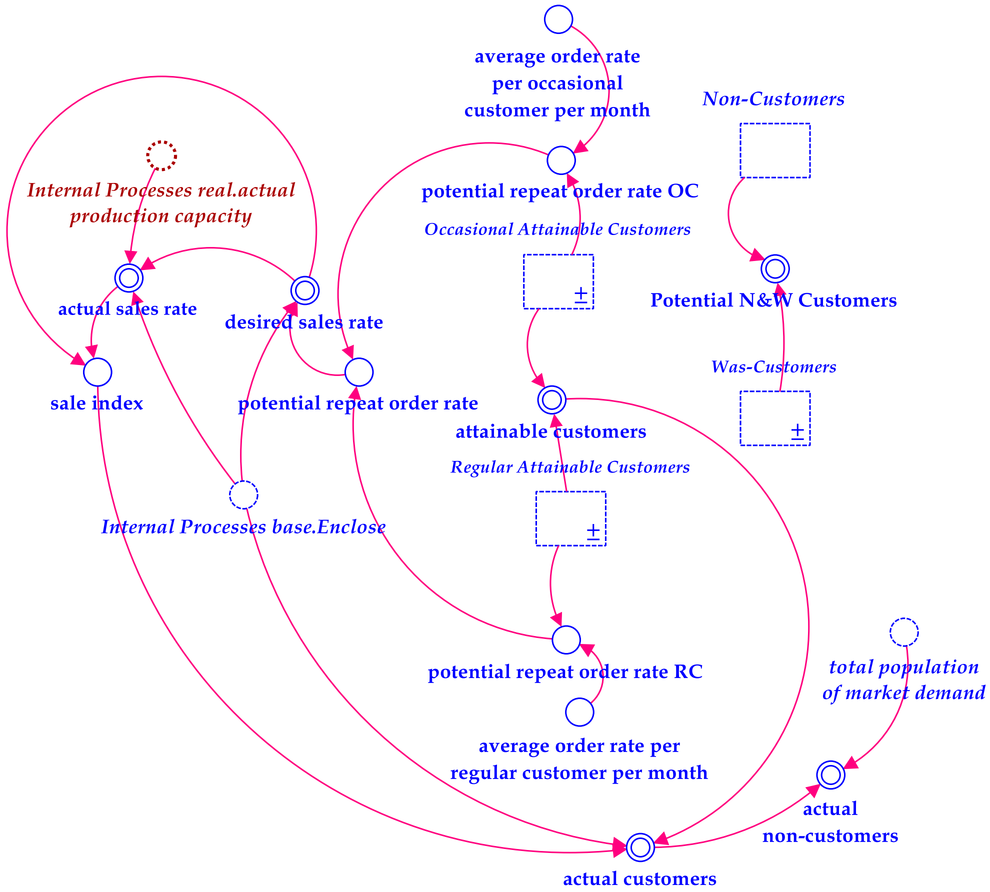


Figure 18: SFD: Customers' module and "actual production capacity" variable.

As Figure 18 shows, the actual sales rate is determined by the desired sales rate and the actual production capacity. The attainable customers are people who purchased in the restaurant.

Assumptions in the Customers' module

- Different types of potential customers are disaggregated in four distinct stocks: *Non-Customers*, *Occasional Attainable Customers*, *Regular Attainable Customers*, and *Was- Customers*.
- Initially, the stock of *Occasional Attainable Customers* is assumed to be 10% of *the total population of market demand*.
- Initially, the stock of *Regular Attainable Customers* is assumed to be 5% of the *total population of market demand*.
- The *contact rate* expresses how often *Occasional Attainable Customers* and *Regular Attainable Customers* interact with *Was- Customers* or *Non-Customers*.

  ***contact rate**= 2 [people/person/month]*

- The *adoption fraction Non-Customers* and the *adoption fraction Was-Customers* reflect persuasiveness of *Occasional Attainable Customers* and *Regular Attainable Customers* on *Non-Customers* and *Was-Customers* to visit the restaurant.

By that, N*on-Customers* and *Was-Customers* might become first *attainable customers*, and then *actual customers*.

normal adoption fraction Non-Customers *= 0.02942 [dmnl]*
normal adoption fraction Was-Customers *= 0.02942 [dmnl]*

- Sum of *Occasional Attainable Customers* and *Regular Attainable Customers* gives the number of *attainable customers*.

- It is assumed (based on experience, observations, and numerical data from the company's database) that the *Occasional Attainable Customers* visit the restaurant eight times monthly:

  ***average order rate per occasional customer per month*=** 8 [orders/person/month]

- It is assumed (based on experience, observations, and numerical data from the company's database) that the *Regular Attainable Customers* visit the restaurant 15 times monthly:

  average order rate per regular customer per month= *15 [orders/person/month]*

- The *potential repeat order rate OC* reveals the potential repeat order rate of *Occasional Attainable Customers* at any point in time.

- The *potential repeat order rate RC* reveals the potential repeat order rate of *Regular Attainable Customers* at any point in time.

- The *potential repeat order rate* is determined by the sum of the *potential repeat order rate OC* from *Occasional Attainable Customers* and the *potential repeat order rate RC* from *Regular Attainable Customers*.

- The *potential repeat order rate* determines the *desired sales rate,* and it reveals potential sales at any point in time.

- The *attainable customers* who purchased in the restaurant became *actual customers*.

- *The sale index* indicates the degree of *actual sales rate* to *the desired sales rate*.

  - The *sale index* equals to 1.0 means that the *actual sales rate* is equal to *the desired sales rate*, and there are no lost sales (*actual sales* are top-notch).
  - In case the value of the *sale index* dropped below 1.0, it indicates the company's poor performance and that the *actual sales rate* could be higher because not all *attainable customers* become *actual customers*.

Internal Processes Base Module

The *Internal Processes base module* expresses normal conditions of the parameters which govern the company's internal processes. The module's structure is intended to show the contrast between the manager's mental model and the reality. These standard conditions of the system are unrealistic in the real- world. In the model, the authentic conditions are affected by two intangibles: schedule pressure and burnout, are revealed in the structure of the *Internal Processes real* module.

SFD Internal Processes base module

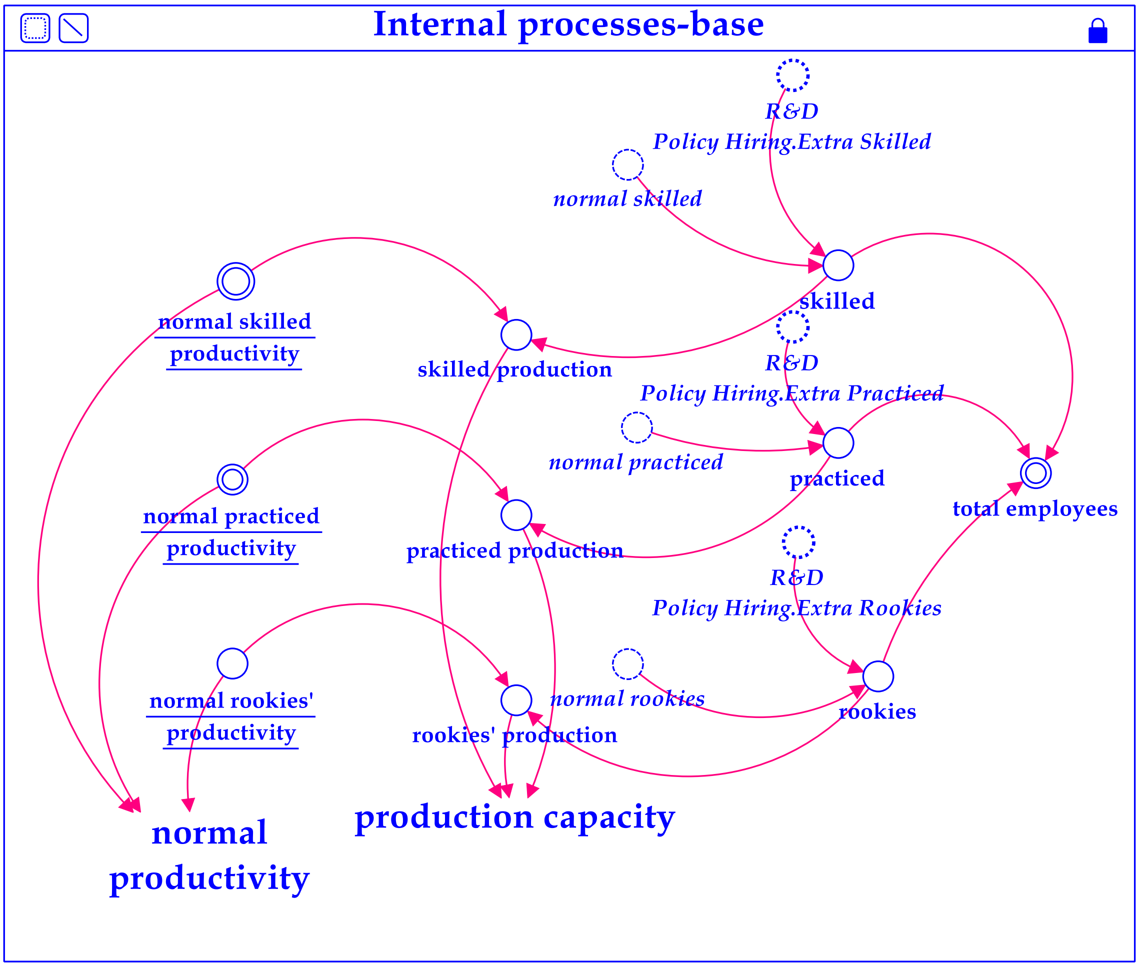


Figure 19: SFD: Internal Processes Base Module.

The *normal productivity* is the sum of *normal skilled productivity*, *normal practiced productivity*, and *normal rookies' productivity*. The *production capacity* is determined by the sum of *skilled production*, *practiced production*, and *rookies' production*. Production of different types of employees (skilled production, practiced production, and rookies' production) differs regarding their normal productivity level (*normal skilled productivity*, *normal practiced productivity*, and *normal rookie's productivity*) and the total number of each type of employees.

As mentioned earlier in the *Data Collection* section, the numerical data for the number *of employees was collected from the company's database.*

Assumptions about the Internal Processes Base Module:

- ***normal production capacity***

  It expresses an illusion of production capacity, which exists only in the manager's mental model. It is determined by the number of employees and their normal productivity. It is not affected by any intangibles or other parameters.

- ***normal employees' productivity***

  As employees are disaggregated based on their skill level into three distinct stocks, their normal productivity differs:

  1. Normal rookies' productivity: 716 [orders per employee per month]
  2. Normal practiced productivity= 480 [orders per employee per month]
  3. Normal skilled productivity= 100 [orders per employee per month]

Internal Processes Real Module

The Internal Processes real module represents real conditions of the internal processes in the company, in which *the effect of schedule pressure on productivity, effect of burnout on productivity*, *effect of schedule pressure on burnout* and *effect of burnout on time to recover* alter the state of the system and by that have an impact on the entire company's performance. All the graphical functions are consistent and displayed below in the *Assumptions about Internal Processes real* section.

SFD Internal Processes real module

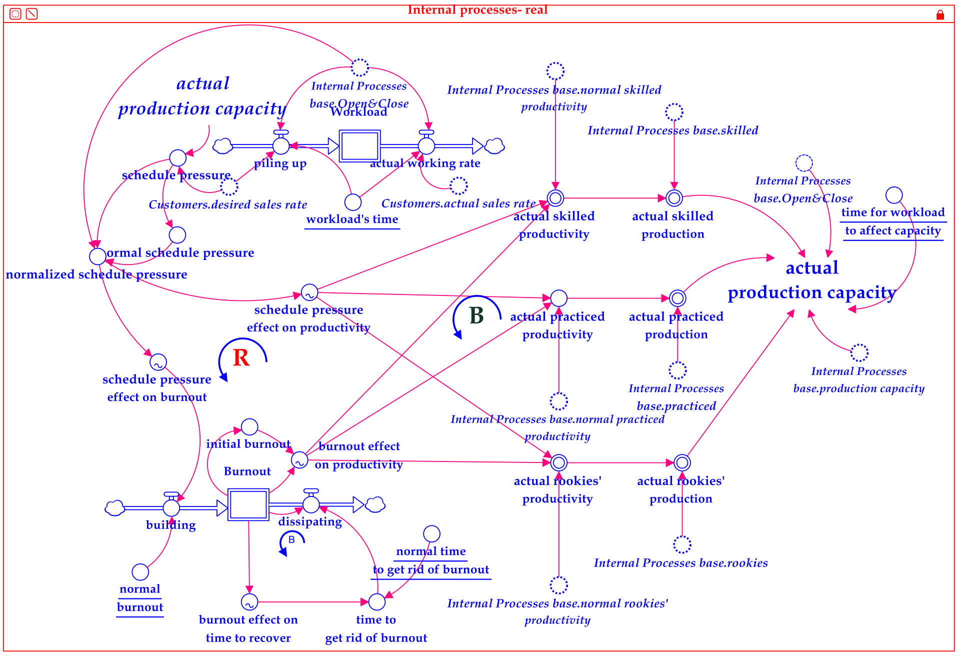


Figure 20: SFD: Internal Processes Real Module.

Assumptions about the Internal Processes real module

- ***actual production capacity***

It reveals the authentic conditions of production capacity. It is determined in the same way as the *normal production capacity*; however, it is affected by intangibles: schedule pressure and burnout.

- ***schedule pressure***

A soft variable, which is determined by a desired sales rate and the actual production capacity. It is important to notice that the long-term effect of schedule pressure on burnout does not exists only in the manager’s mental model. Schedule pressure builds up burnout and it increases employees’ productivity. Normal schedule pressure is: 1, and its range is: 0-2

- ***Burnout***

A soft variable, which in the study means employees’ exhaustion which comes from working overtime (working too many hours every day, on average). Burnout above its normal value decreases employees’ productivity.

Model validation and testing

The primary purpose of this chapter is to prove the validity of the model and to confirm that its behavior reflects the genuine nature of the system. By that, the author builds up the manager's confidence in the model's structure and trust in the resulting outcomes.

The process of model validation in System Dynamics is a relative concept, and it depends on the intended purpose and expected use. It comprises three stages: direct structural tests, structure-oriented tests, and behavior pattern prediction (Barlas 1996). It is an iterative and repeated process that tests the structure which help to redefine it if inaccuracies are found. (Sterman, 2000.)

Structure validity

A surprising and intriguing phenomenon is that naturally, "all models are wrong" since they are all simplified representations of reality (Sterman 2000 p.846). So, it does not matter how many iterations the modeler performs; it might never be considered entirely validated.

Direst structure tests

Direct structure tests do not require the model's simulations. They are executed by inspecting and each equation, each logical function, and their relationship in the model and comparing them against the real-world knowledge about the system (Barlas, 1994). Thus, to verify the model's structure, a structure confirmation test, a parameter confirmation test, and a dimensional consistency test was conducted.

The model's structure verification process was performed by going through the logic behind it and analyzing mathematical equations and relationships of all variables included in the model. Any discrepancies in the structure were revealed and confirmed to the desire model's fit. The model passed the ***structure confirmation test.***

During the presentation, all manager's disputes were pointed out and resolved. Based on the collective discussion, it was possible to conduct the ***parameter confirmation test***. The ***dimensional consistency*** *test* was run by Stella software, in which the model was developed. Finally, the software proved that „All units within the model appear to be consistent. The model was approved as it passed all direct structure tests.

Structure-oriented behavior tests

The process of structure-oriented behavior validation is conducted by running various behavior tests to the behavior patterns developed by the model (Barlas, 1996; Forrester and Senge, 1980). Under the model's purpose, the extreme condition test and the behavior-sensitivity test were elected and ran.

Steady-state initialization

With the aim to facilitate and simplify the behavior analysis, the model was initialized in an equilibrium by making the sum of inflows to stocks equal to the sum of outflows from the stocks (see the appendix 4). In steady-state, the parameter *Enclose* embedded in the Internal Processes base module is set to 1 to not affect the system's behavior in steady-state. By that, the seasonality does not affect the model's behavior when it is tested. Thus, the model runs over five years smoothly as the store was never closed. The initialization of the model in equilibrium clarifies observing the model's behavior under different parameter conditions (Richmond, 2013).

Behavior sensitivity tests

The sensitivity tests were conducted to see whether the model behavior is sensitive to changes of the most vital exogenous parameters, with the low level of accuracy included in the model's structure. Only the most vigorous parameters were chosen and tested in the following order: contact rate, normal adoption fraction Was-Customers, normal adoption fraction Non-Customers.

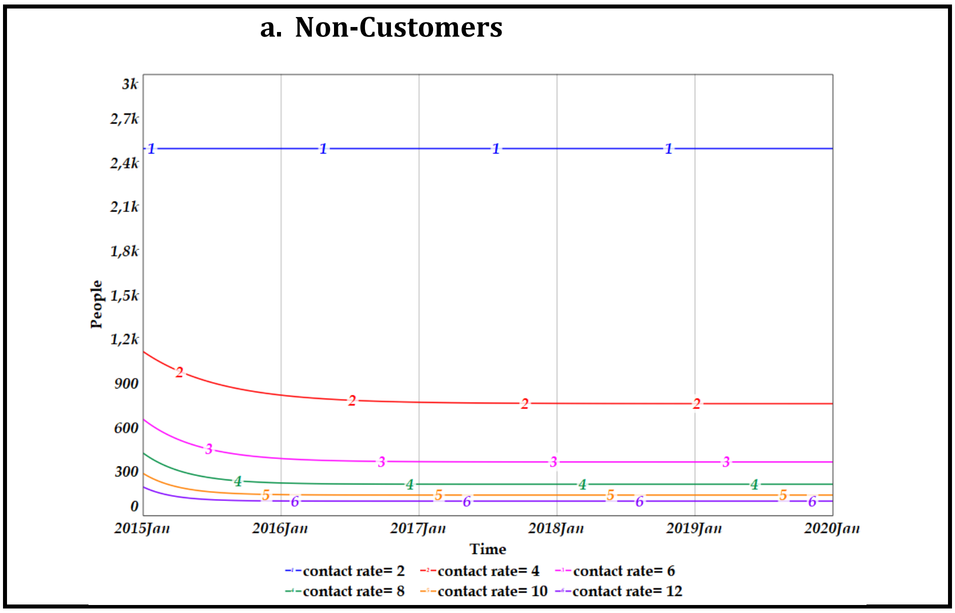
The tests of chosen parameters give an overview on the behavior of entire model. Moreover, they navigate towards the logic of the entire model and its robustness.

<u>Sensitivity test of “contact rate” parameter.</u>

The parameter *contact rate* defines how often attainable customers, defined as a sum of *Occasional Attainable Customers* and *Regular Attainable Customers* contact their friends, which are *Non-Customers* or *Was-Customers* each month. As the estimation of the *contact rate* is disputable, the sensitivity test of that parameter, among other sensitivity parameters' tests, is of utmost importance. Naturally, the *contact rate* might vary depending on the person's personality and person’s usual contact frequency. In this test, a person can contact 2, 4, 6, 8, 10, or 12 people each month, and table shows that values. Figures 12 and 13 show the behavior over time graphs (BOTG) of Non-Customers, Occasional Attainable customers, and Regular Attainable Customers stocks.

Contact rate
2 (BAU)
4
6
8
10
12

Table 3: Contact rate test values.



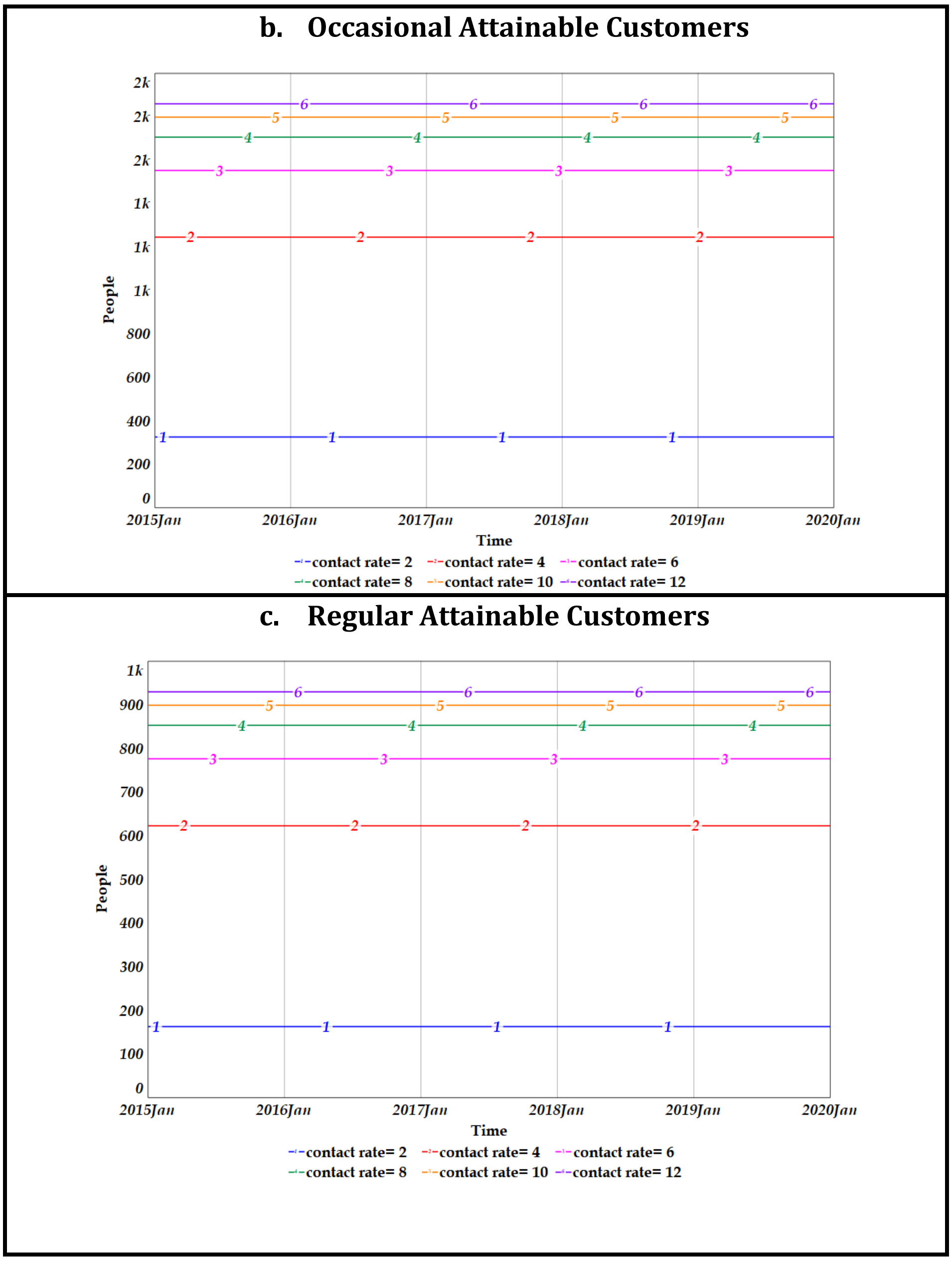


Figure 21: Behavior-sensitivity test of "contact rate" parameter: the effects on the "Non-Customers", "Occasional Attainable Customers", and "Regular Attainable Customers" stocks.

Comparing curves 1, 2, 3, 4, 5, and 6 displayed on the graph in Figure 21 shows that increasing the *contact rate* increases the equilibrium values of Occasional Attainable Customers and Regular Attainable Customers stocks, while the equilibrium value of Non-Customers decreases. Table 4 reveals the reported values of the *contact rate* after its sensitivity test:

Contact rate [people/person/month]	**2(BAU)**	**4**	**6**	**8**	**10**	**12**
Non-Customers	2 500	762	366	214	141	99
Occasional Attainable Customers	326	1000	2000	2000	2000	2000
Regular Attainable Customers	163	623	776	853	899	930

Table 4:"Contact rate" sensitivity testing results.

<u>Sensitivity test of the "normal adoption fraction Was-Customers" parameter</u>

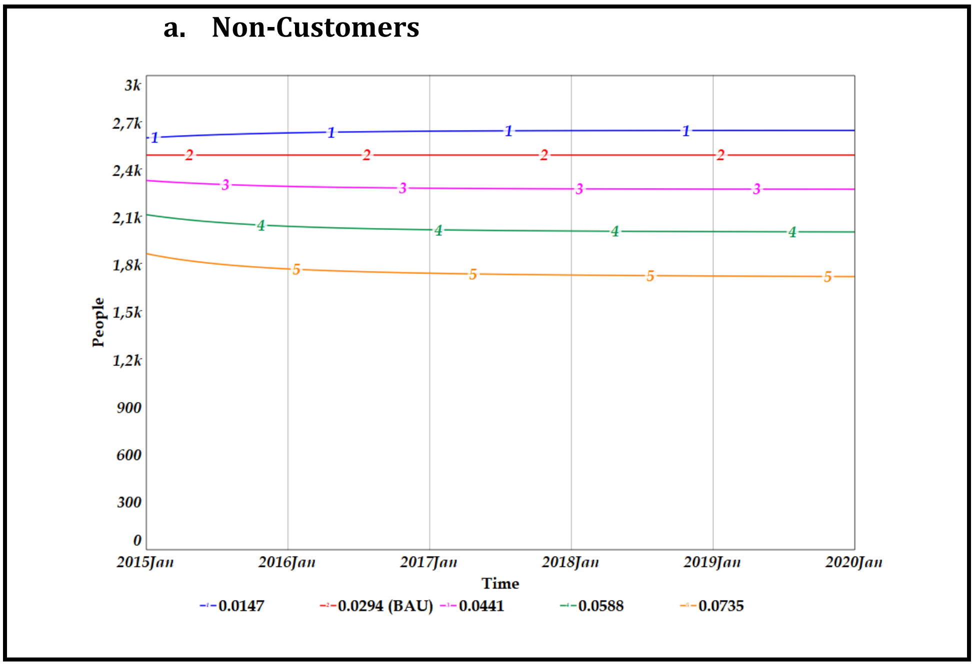
The table 5 shows the testing values of normal adoption fraction Was-customers:

Normal adoption fraction Was-Customers
0.0147
0.0294 (BAU)
0.0441
0.0588
0.0735

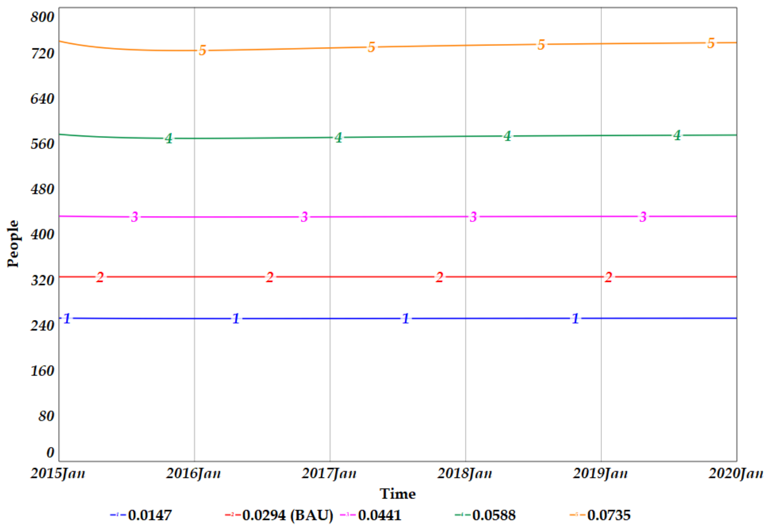
Table 5: "Normal adoption fraction Was-Customers" test values.

In the *business as usual* (BAU) scenario, the initial value for *normal adoption fraction Was-Customers* parameter is equal to 0.0294

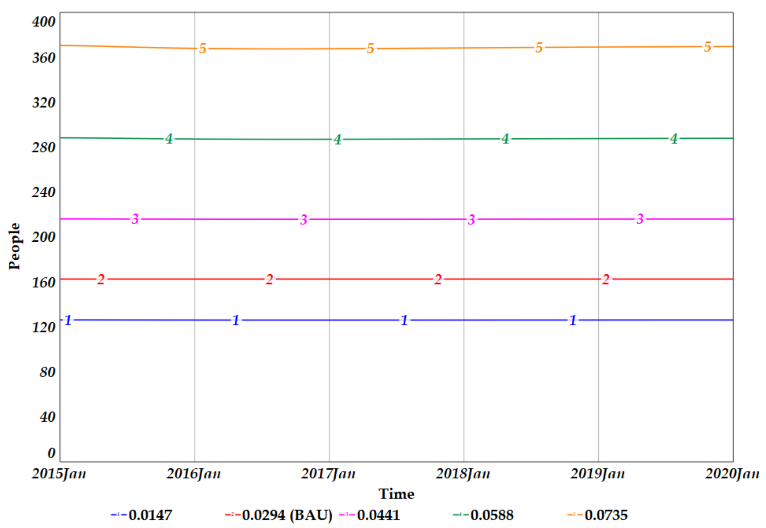
Figure 22 show the behavior over time graphs (BOTG) of four stocks (Non-Customers, Occasional Attainable customers, Regular Attainable Customers, and Was-Customers.)



b. Occasional Attainable Customers



c. Regular Attainable Customers



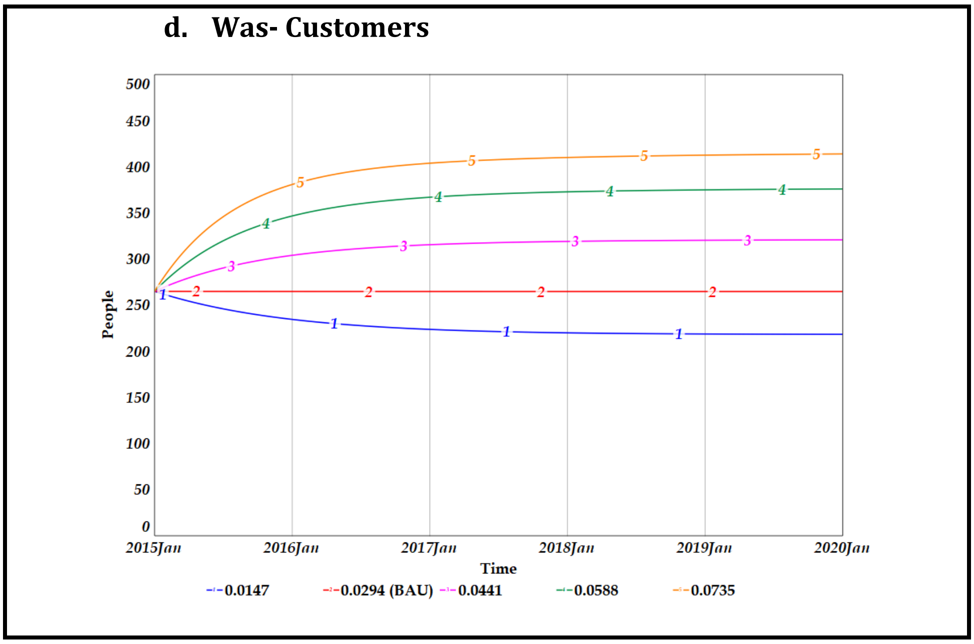


Figure 22:Behavior-sensitivity test of "normal adoption fraction Was-Customers" parameter: the effects on the a. "Non-Customers", b. "Occasional Attainable Customers", c. "Regular Attainable Customers" and "Was-Customers" stocks.

By comparing curves 1, 2, 3, 4, and 5 tells that raising the normal adoption fraction Was- Customers increases the equilibrium values of Occasional Attainable Customers, Regular Attainable Customers, and Was-Customers stocks, while the equilibrium value of Non-Customers decreases. Table 4 reveals the results of the *normal adoption fraction Was-Customers* after its sensitivity test:

Normal adoption fraction Was-Customers Stock *[Dimensionless]* *[People]*	0.0147	0.0294 (BAU)	0.0441	0.0588	0.0735
Non-Customers	2 650	2 500	2 280	2 002	1 730
Occasional Attainable Customers	252	326	432	575	738
Regular Attainable Customers	126	163	216	288	370
Was- Customers	218	265	321	376	414

Table 6: "normal adoption fraction Was-Customers" sensitivity testing results.

<u>Sensitivity test of "normal adoption fraction Non-Customers" parameter.</u>

The table 7 shows the testing values of normal adoption fraction Non-customers:

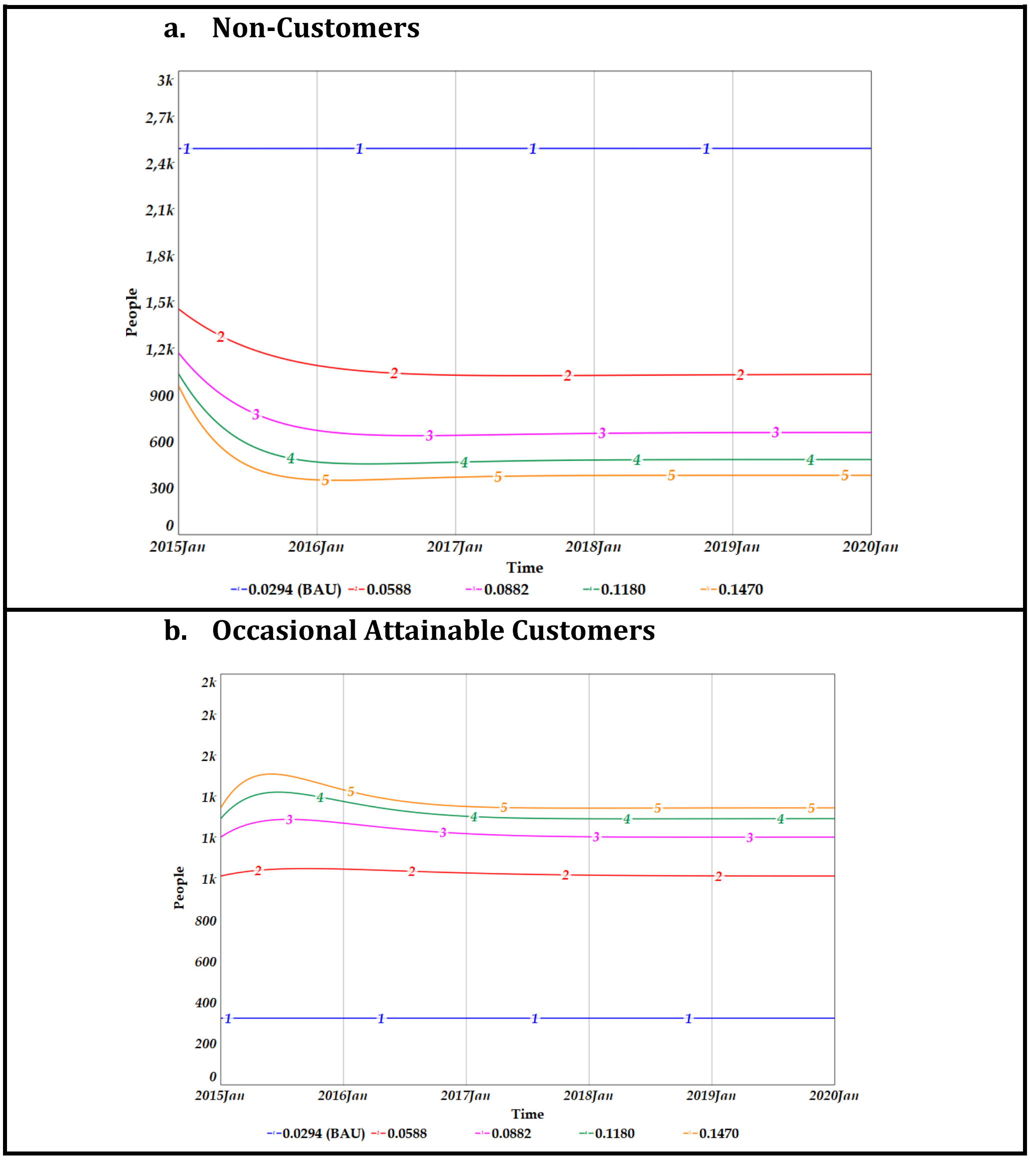
Normal adoption fraction Non-Customers
0.0294 (BAU)
0.0588

0.0882
0.1180
0.1470

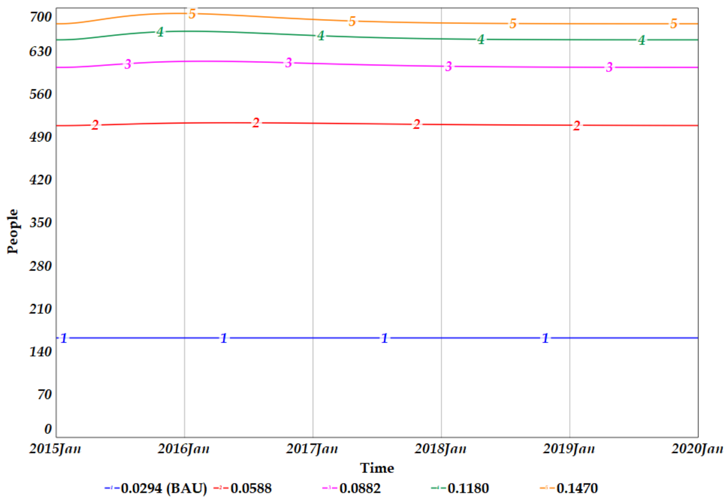
Table 7: Tested values of "normal adoption fraction Non-Customers" parameter.

In the *business as usual* (BAU) scenario, the initial value for *normal adoption fraction Was-Customers* parameter is equal to 0.0294

Figures 23 shows the behavior over time graphs (BOTG) of four stocks (Non-Customers, Occasional Attainable customers, Regular Attainable Customers, and Was-Customers) under different conditions of *normal adoption fraction Non-Customers variable*.



c. Regular Attainable Customers



d. Was- Customers

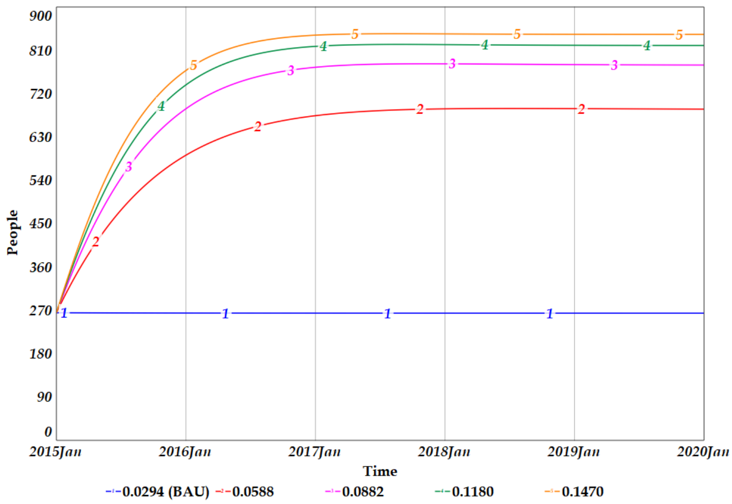


Figure 23: Behavior-sensitivity test of "normal adoption fraction Non-Customers" parameter: the effects on the a. "Non-Customers", b. "Occasional Attainable Customers", c. "Regular Attainable Customers" and "Was-Customers" stocks.

After comparing curves 1, 2, 3, 4, and 5 tells that raising the *normal adoption fraction Non-Customers* increases the equilibrium values of *Occasional Attainable Customers, Regular Attainable Customers*, and *Was-Customers* stocks, while the equilibrium value of *Non-Customers* decreases. Table 8 reveals the results of the *normal adoption fraction Non-Customers* after its sensitivity test:

Normal adoption fraction Non-Customers *[Dimensionless]* / Stock *[People]*	0.0294 (BAU)	0.0588	0.0882	0.1180	0.1470
Non-Customers	2 500	1 004	661	486	384
Occasional Attainable Customers	326	1 016	1 206	1 296	1 349
Regular Attainable Customers	163	508	603	648	674

Was- Customers	265	688	779	820	843

Table 8: Table 6: "normal adoption fraction Non-Customers" sensitivity testing results.

Extreme condition test

The initial values of *Occasional Attainable Customers* and *Regular Attainable Customers* represent the number of attainable customers who regularly or only sporadically visited the restaurant in 2015 when the simulation starts. However, in this test the stocks are initialized with no occasional customers and no regular customers. Further, individual stocks are initiated with extremely high values, but in the limit of *the total population of market demand*.

The behavior of four stocks, Non- Customers, Occasional Attainable Customers, Regular Attainable Customers, are Was- Customers is shown in Figure 24.

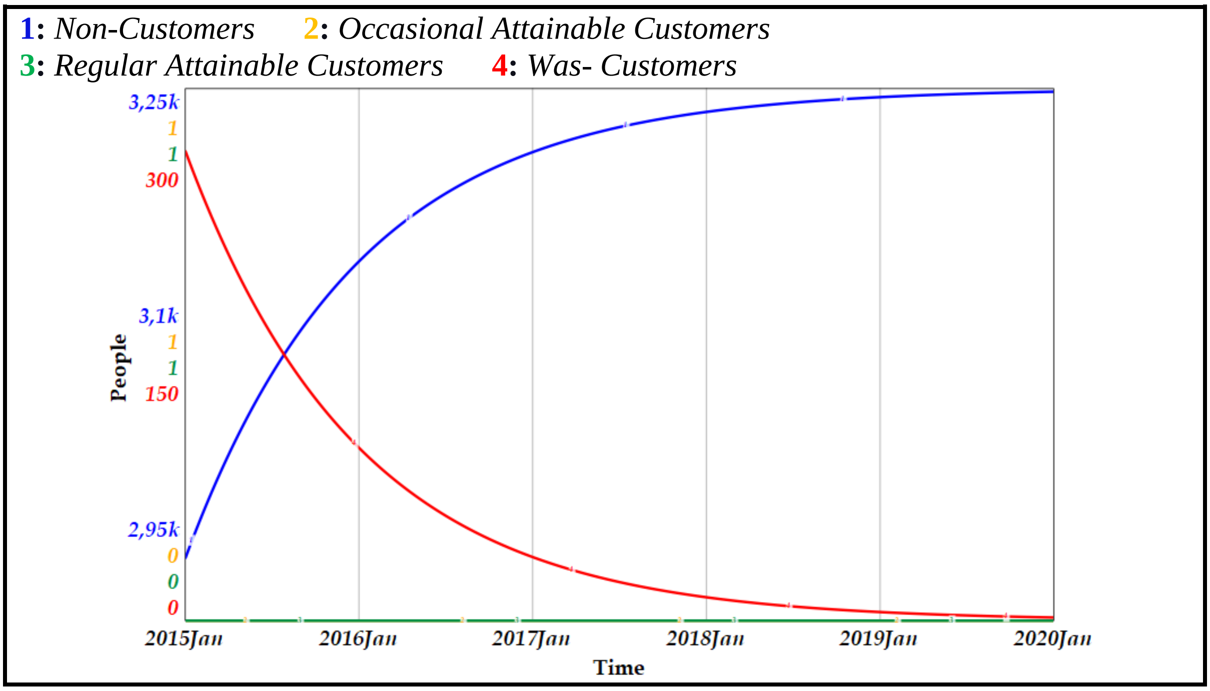


Figure 24: Extreme condition test with "Occasional Attainable Customers" and "Regular Attainable Customers" equal to zero.

Curves 2 and 3 depict the stocks initialized with zero: *Occasional Attainable Customers*, and *Regular Attainable Customers*. Throughout the entire simulation, all the people who are Was-Customers diffuse back to become Non-Customers again under the simulated extreme conditions of these stocks. Overall people in the *total population of market demand* do not become *Occasional Attainable Customers* or *Regular Attainable Customers*. This is obvious as if there are no *Occasional Attainable Customers*, or *Regular Attainable Customers*, the following parameters are equal to zero:

- *contacts Occasional Attainable Customers with Non-Customers,*
- *contacts Regular Attainable Customers with Non-Customers,*
- *contacts Occasional Attainable Customers with Was-Customers,*

- *contacts Regular Attainable Customers with Was-Customers.*

Thus, the *Non-Customers converted through WOM* and *Was-Customers converted through WOM* are also both equal to zero. As the advertising policy is not active in business as usual scenario, the flows *occasional creation rate* and the *customer retry rate* are equal to zero. Therefore, there must be at least one occasional or regular customer to increase the number of *Occasional Attainable Customers* and raise the number of *Regular Attainable Customers*.

Summarizing, only one person can produce a massive shift in the behavior of the system. A single person starts spreading referrals to others. A famous from reality example is a virus spreading through a population: only one sick person can enhance the tremendous growth of sick people.

Behavior validity

Figure 25 shows the simulated customers' behavior over time graph compared to the reference mode.

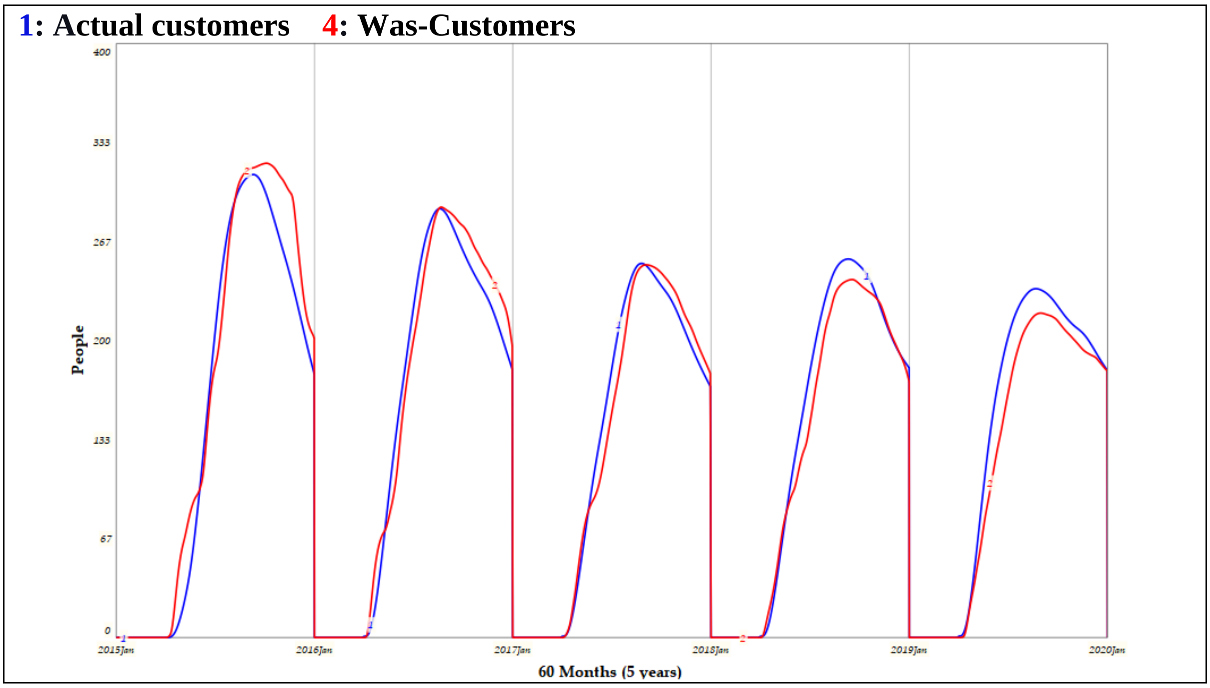


Figure 25: Behavior Pattern Prediction

Since the exact real number for customers had to be averaged to the degree where the results are satisfactory and produce real systems behavior (2015-2020), it was challenging to reproduce precise patterns that will match exactly match to each other.

However, the historical customers' behavior (Jan 2015-Jan 2020) was nearly re-created by the model's simulation. By rather precise replication of the behavior patterns, the model has passed the behavior-pattern prediction test.

Model runs

In this chapter, firstly, the behavior of the business model in the business as usual scenario is presented. Further, the different model's scenario runs based on two policies that were developed are presented and analyzed. Because the model comprises seven modules and 290 variables, only the most relevant variables are selected to be shown.

Base run

The base run relates to customers' historical behavior, to the reported number of employees, and the assumptions introduced in the *Dynamic Hypothesis* chapter. Data for the authentic number of customers and the number of employees (2015-2020) were collected from the company database and simplified to the extent that the model's behavior reflects the case-study system's real behavior. The base run simulation specifications are:

- Time Horizon: 5 years (2015- 2020)
- Time Step: 1/256
- Time Unit: Months
- Integration Method: Euler

Customers module

Total population of market demand

Figure 26 presented on the next shows the page behaavior over time graph (BOTG) of the *total population of market demand* disaggregated into four stocks: *Non-Customers*, *Occasional Attainable Customers*, *Regular Attainable Customers*, and *Was-Customers*.

1: Non-Customers **2: Occasional Attainable Customers**
3: Regular Attainable Customers **4: Was-Customers**

Figure 26:Base run of the customers' stocks.

After the *base run* simulation, the reported values of stocks: *Non-Customers*, *Occasional Attainable Customers*, *Regular Attainable Customers*, and *Was-Customers* are presented in table 9. The values are stocks levels in January 2015, January 2016, January 2017, January 2018, January 2019, and in January 2020.

Time / Stock [people]	*(initial)* ***2015 Jan***	***2016 Jan***	***2017 Jan***	***2018 Jan***	***2019 Jan***	***2020 Jan***
Non-Customers	2 500	2 590	2 690	2 790	2 860	2 900
Occasional Attainable Customers	326	278	228	187	163	147
Regular Attainable Customers	163	112	86	70	64	60
Was- Customers	265	272	245	203	167	143

Table 9: Reported values of "total population of market demand" disaggregated into four stocks of customers.

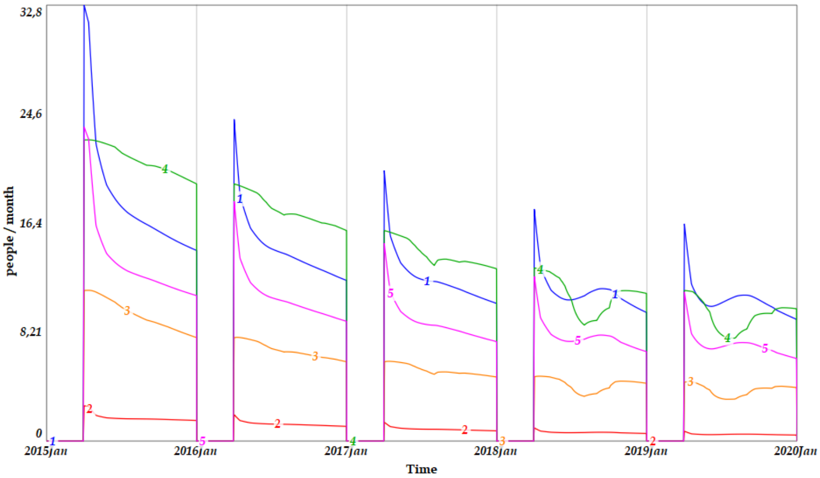
The behavior over time graph of the customers' stocks presented in Figure 26 shows that only *Non-Customers* stock was steadily increasing over the entire five years (Jan 2015-Jan 2020).

In contrast, the *Occasional Attainable Customers and Regular Attainable Customers* were steadily decreasing each year over the entire simulation period, when the restaurant was open from 1st April to 31st December each year (2015-2020).

However, when the restaurant was closed from 1st January to 31st March each year, the levels of stocks: *Occasional Attainable Customers* and *Regular Attainable Customers* did not change. The reason for this is that the inflows and the outflows for *Occasional Attainable Customers* stock and *Regular Attainable Customers* stock are assumed to not affect the model's behavior when the restaurant is closed; thus, they are equal to zero. The figure 28 shows the behavior over time graphs of flows for (a) *Occasional Attainable Customers* and (b) *Regular Attainable Customers*

a. BOTG: flow rates for Occasional Attainable Customers

INFLOWS:	*OUTFLOWS:*
1: occasional creation rate	**4: occasional leaving rate**
2: was customer retry rate	**5: occasional customer promotion rate**
3: regular customer demotion rate	



b. BOTG: flow rates for Regular Attainable Customer

INFLOWS:	*OUTFLOWS:*
1: occasional customer promotion rate	**2: regular customer demotion rate**
	3: was customer retry rate

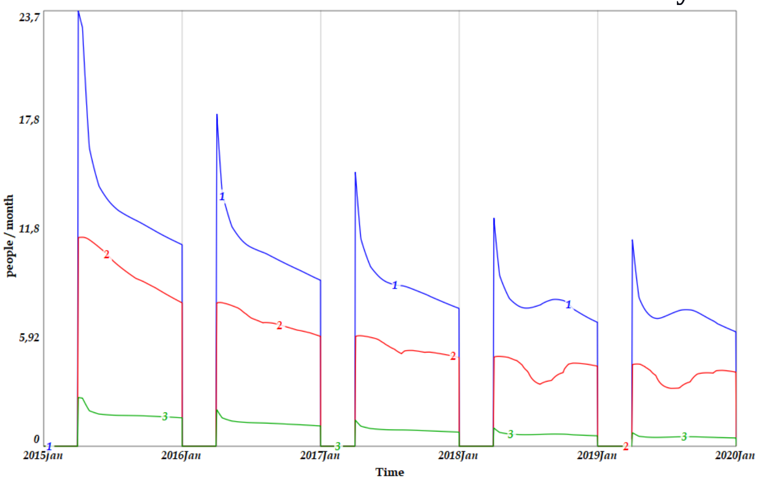


Figure 27: BOTG: base run of flow rates for: (a)" Occasional Attainable Customers" , (b)"Regular Attainable Customers" stocks.

While presented in Figure 27, six flow rates are equal to zero when the restaurant is closed each year; the flow *forgetting experience rate* is assumed to affect the model's behavior and does not equal zero. The Figure 28 presents the behavior over time graphs of inflows and outflows for stocks (a) Non-Customers, (b) Was-Customers.

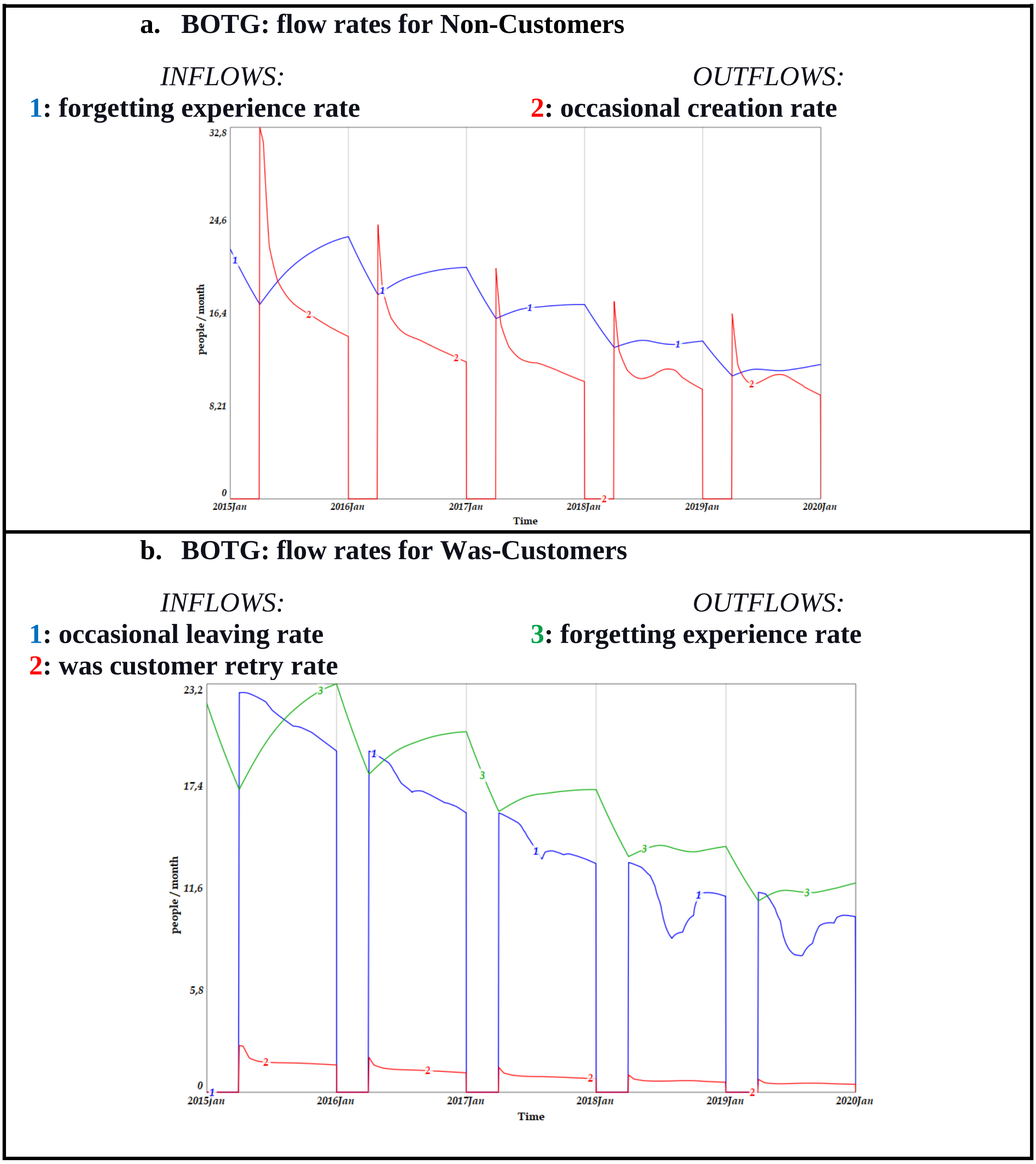


Figure 28: BOTG: base run of flow rates for: (a) "Non-Customers",(b) "Was-Customers".

Logically, all the presented six flows are assumed not to affect the model's behavior as all of them are affected by the *service failure rate* or by word-of-mouth. For example, word-of-mouth cannot influence customers' acquisition when customers cannot visit the restaurant as it is closed.

Opposite, the *forgetting experience rate* differs from other flows in the customers' structure as it is not affected by the *service failure rate*, nor by the word-of-mouth. This flow is an outflow from *Was-Customers'* stock, which brings people back to *Non-Customers*. Moreover, the *forgetting experience rate* is delayed with 12 months, and it is assumed that people might be forgetting their experience from visiting the restaurant also when the restaurant is closed.

Interesting is that the *Was-Customers* stock reached a higher value in January 2016 (272) than in the previous year in January 2015 (265). However, after 2016 it was decreasing, reaching lower values at the end of each year. That is because the delay time of this flow, as already mentioned, is 12 months, which is one year. Thus, while the stocks of *Occasional Attainable Customers* and *Regular Attainable Customers* were declining through *occasional leaving rate* and the *regular customer leaving rate* during the first year of simulation (Jan 2015- Jan 2016), the stock of *Was-Customers* increased from 265 to 272 (table 9).

See the section **SFD Customers module** in the **Dynamics Hypothesis** chapter for a more detailed definition and meaning of flows in the customers' module.

Accordingly, the customers' module presents the authentic customers' behavior observed in the real world. Below is a description of this real customer's behavior perceived and recognized by the author of this thesis.

Real- world system's overview

In the past (2015-2020), the only workable strategy in the case restaurant was to increase the schedule pressure when there was a massive influx of attainable customers than the restaurant's actual production capacity. Thus, the service failure rate also increased and affected the customers' churn (in the model through the *service failure rate effect on customers' churn*).

During the busiest time, the employees were trying to serve all *attainable customers*. They forgot about service quality and allowed for a higher *service failure rate* to catch the highest number of *attainable customers*. However, despite their enormous effort, they were not able to serve all *attainable customers,* and thus the *desired sales rate* was always higher than the *actual sales rate* The author of the thesis remembers so well the long customers' queues who were waiting for service on sunny days and other *attainable customers* who did not want to stand in such long queues and gave up on the purchase, finding other restaurants in the city.

Furthermore, at the beginning of each season, when there were large customer flows, employees were more productive, but while they were working overtime, they were feeling more and more stressed. By that, they were feeling overwhelmed and later burnt out at the end of each season.

The manager thought that by increasing schedule pressure, the employees would work quicker and be more productive. He was partly right. Here "partly" means that his strategy planning could be practical and workable, but only as a short-term solution, not as long one.

At the end of busy days, the revenue from sales was higher than on the ordinary days, which gave to manager misleading fictitious and false hope that his strategy is effective. The manager did not consider other unintended consequences of his strategy, which led to a higher service failure rate, leading to higher customers' churn through too high work pressure. Thus, the number of *attainable customers* was decreasing each year. The Figure 30 shows the behavior over time graph of attainable customers versus actual customers:

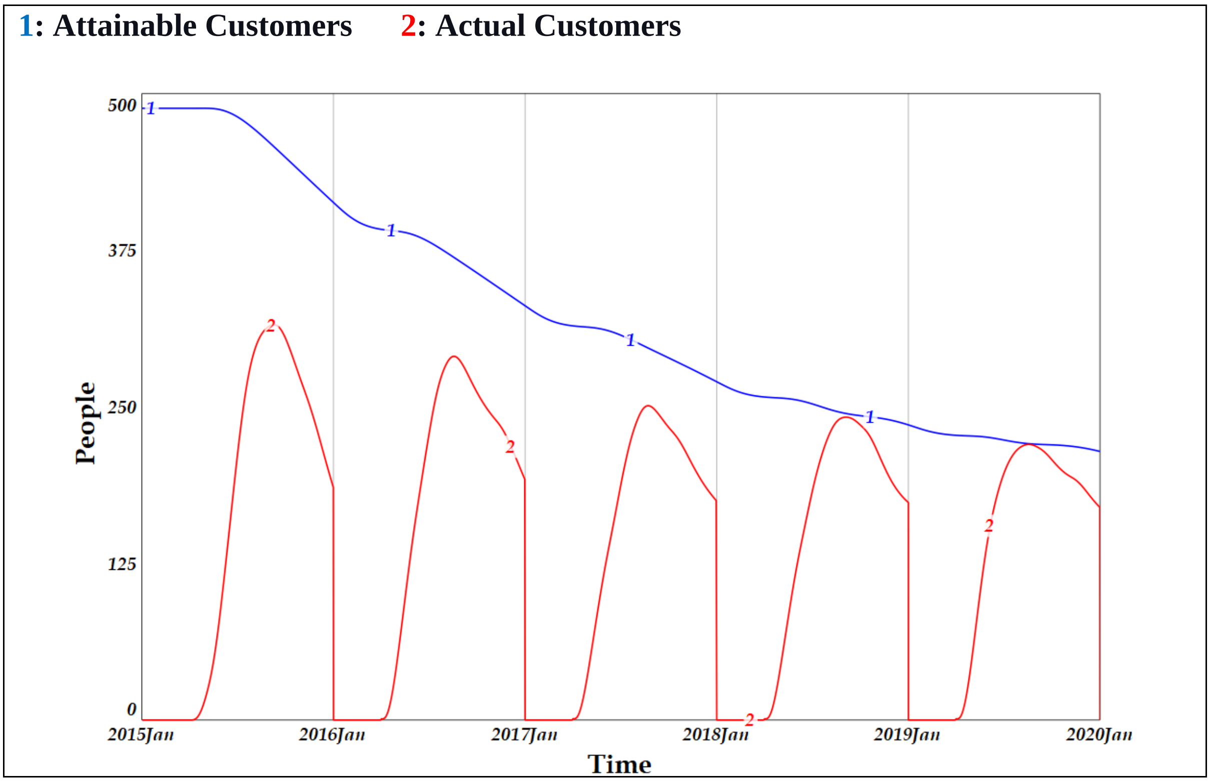


Figure 29: Base run of the "attainable customers" versus "actual customers".

The above graph displayed in Figure 29 shows that not all attainable customers (blue curve), became the restaurant's actual customers (red curve). The model shows the reality observed by the author of this study and the restaurant manager. The likely reason for the decreasing number of actual customers is the restaurant's reduced actual production capacity, which did not allow for serving all the *attainable customers*. Of course, the primary cause of that inadequate production capacity lies in the restaurant's management's strategy. That strategy led to the exponential decay of attainable customers, directing to a new equilibrium, in which the actual production capacity meets the demand of *attainable customers*.

The above description of the "Real-world system's overview" shows that the restaurant has potential; however, the existing strategy must change. An effective strategic plan is necessary to be implemented immediately.

Further, in this chapter, the Internal processes real module's behavior is analyzed to show the real roots of the customers' loss in the past five years (Jan 2015- Jan 2020). After that, policy runs shows projected custmers' behavior five years forward in time (Jan 2020-Jan 2025).

Internal processes real module

With aiming to find the roots of the problematic behavior of customers' loss, the behavior of the Internal processes-real module is analyzed. As the investigated system is a causal network of relationships created between people, it is highly influenced by forces that are difficult to measure, such as: schedule pressure, burnout, and service failure rate.

The model includes three "soft" variables: schedule pressure, burnout, and service failure rate that assumed to contribute to forming the dynamics of internal processes. By that, the simulated behavior of the model's structure, reflecting the real-world dynamics, differs from the assumed functioning of the system predicted by managers' mental model. As already mentioned, the manager did not consider the unintended consequences of his strategy, such as:

- the effect of schedule pressure on productivity
- the effect of schedule pressure on burnout
- the effect of burnout on productivity
- the effect of schedule pressure on service failure rate
- the effect of service failure rate on adoption fraction
- the effect of service failure on customers' churn

Thus, in the model, the three intangibles are presumed to affect the entire system's behavior profoundly. These "soft" variables are unforeseeable, and out of managers' control. As a result, the dynamic behavior of the system is different from the managers' mental model.

The "soft" variables actively influence the production capacity, customer base, and sales revenue. Below, the behavior of the most vigorous variables generated by the simulation model is presented and described.

The normal productivity vs. actual productivity

Figure 30 presents the behavior over time graphs of normal employees' productivity versus actual employees' productivity:

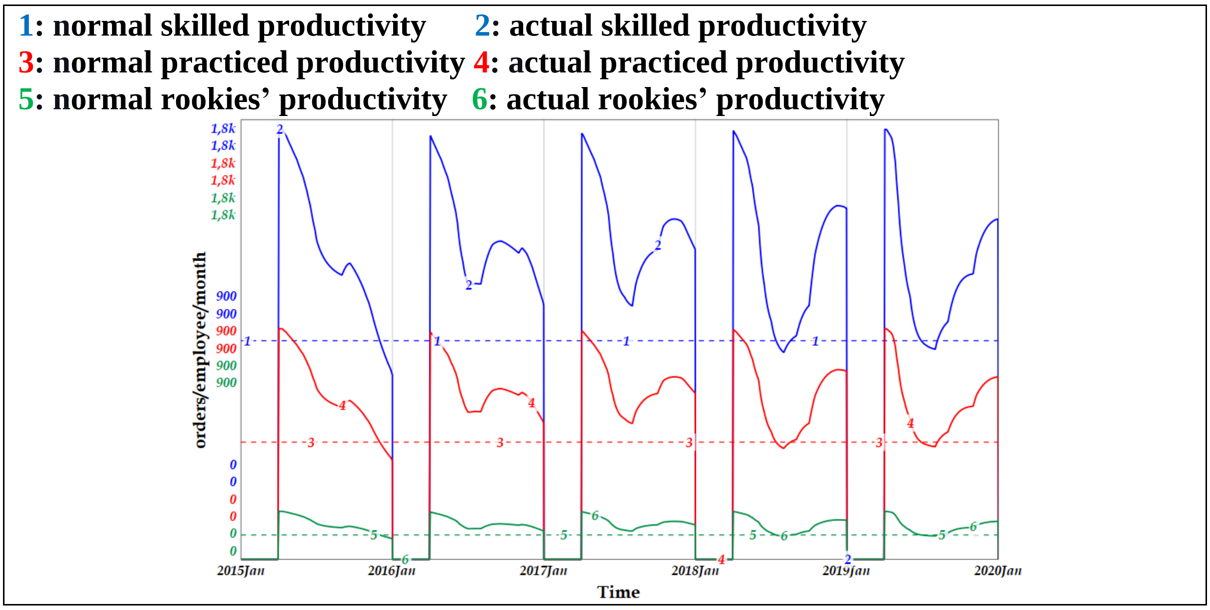


Figure 30: Actual productivity vs. normal productivity.

The presented graph shows that manager was partly right with his mind thinking that by increasing schedule pressure, the employees' productivity will increase. At the beginning of each year, the actual productivity for all three types of employees (*actual rookies productivity*, *actual practiced productivity*, and *actual skilled productivity*) is higher than corresponding to each type of employee the normal productivity (*normal rookies productivity*, *normal practiced productivity*, and *normal skilled productivity*). The table 10 below shows the numerical values of actual productivity versus the numerical values of normal productivity in the first month of the base run simulation (April 2015):

	Normal productivity [orders/employee/month]	**Actual productivity [orders/employee/month]**
Skilled	895	1 760
Practiced	480	944
Rookies	100	197

Table 10: Numerical values of normal productivity vs actual productivity (1st April 2015).

As table 10 shows, the *actual productivity* was almost twice of the n*ormal productivity* when the restaurant was reopened in April 2015. Moreover, as the behavior over time graph in Figure 31 displays, this event occurred each year. That is because of the massive customers' influx, which caused an increase in schedule pressure. In the model, when the schedule pressure is twice, the actual productivity is 1,976 times higher than its normal value.

However, as the graph in Figure 31 shows, the actual productivity after an increase on 1st April 2015 was rapidly decreasing until 31st December 2015. The pattern of behavior of employees' *actual productivity* is different in each year of the entire simulation. It depends on *schedule pressure*, determined by the *desired sales rate* and the *actual production capacity*, as already mentioned in the *Dynamic Hypothesis* chapter. While schedule pressure increases actual productivity, the burnout actively decreases it as employees' work under too much pressure. Moreover, the time for burnout to dissipate increases as burnout increases, which means higher burnout, and more time is needed for employees to recover. To understand more all that process, let us look at the graph in Figure 32, which shows how employees' productivity falls while burnout rises.

1: Total employees' productivity **2: Burnout**

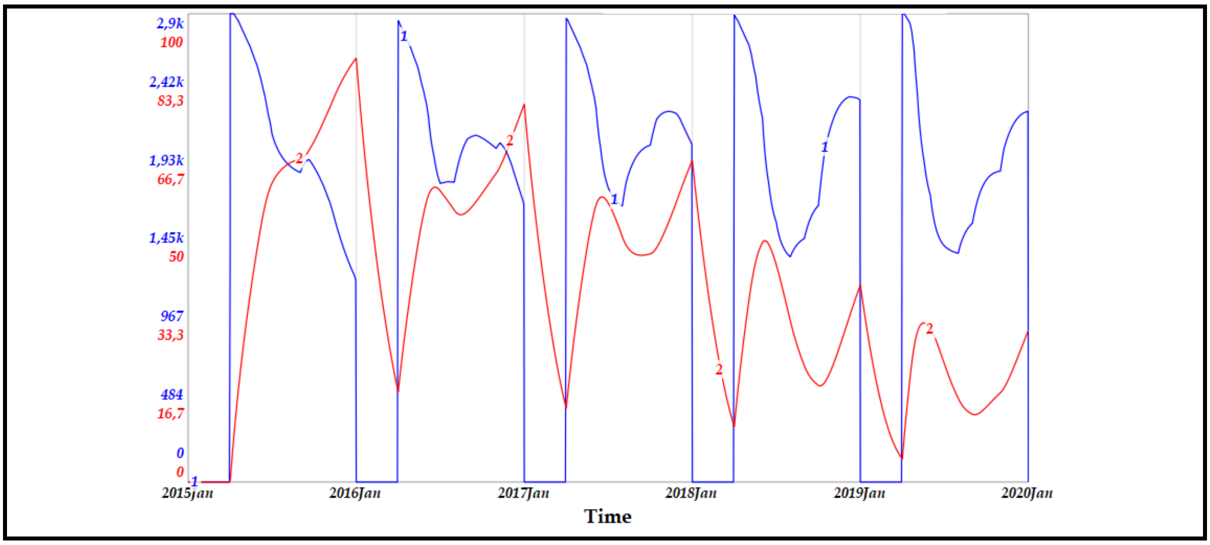


Figure 31: The base run of Total employees' productivity vs. "Burnout"

The behavior over time graph presented in Figure 31 shows that in April 2015, the total employees' productivity (blue curve) rapidly increased, and then it was falling. This pattern of behavior is slightly different for the years 2016- 2019. In 2015 there were a higher number of *attainable customers* (Figure 30), thus a higher *desired sales rate and a higher* discrepancy between attainable and *ac*tual customers.

The graph in Figure 31 also shows that when the restaurant was closed, the burnout was falling. That is reasonable, as when the employees were not at work, they had no pressure and could recover. Each year the *time to recover* was lower, and the burnout's maximum value was reaching lower maximum value each year over the entire simulation time (2015-2020).

The reason for the decreasing number of *attainable customers* is the *schedule pressure effect on service failure rate*. In the model, as the schedule pressure goes up, the service failure rate also increases. Moreover, the service failure rate affects the customers' adoption fraction and customers' churn, leading to a decrease of the *attainable customers* until the *actual production capacity* will match the customers' service demand, which in the model is revealed by the *desired sales rate*. Figure 32 presents how the customers' adoption fraction and customers' churn are affected by the *service failure rate*:

1: service failure rate **2: service failure rate effect on adoption fraction**
3: service failure rate effect on customers' churn

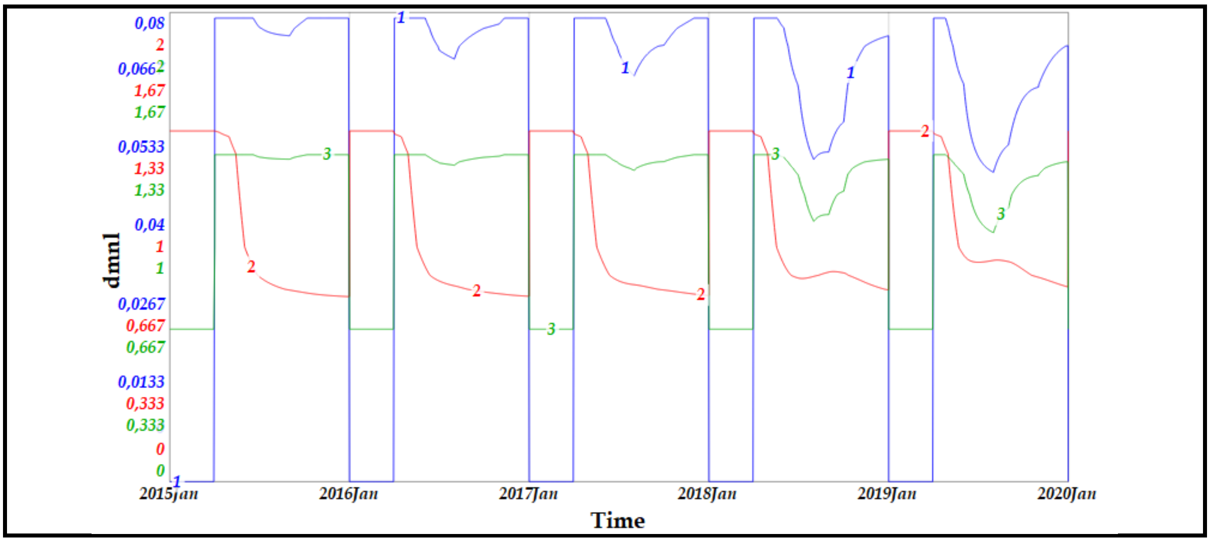


Figure 32: Service failure rate effect on adoption fraction and on customers' churn.

Figure 32 shows that when the *service failure rate* increases, *the service failure rate effect on adoption fraction* decreases, leading to a decrease in the overall force of the word-of-mouth on customers' acquisition, driven through referrals. On the other hand, while the *service failure rate* increases, the *service failure rate effect on customers' churn* also rises, leading to an increase in the churn of *attainable customers*.

In real-world dynamical systems, presented relationships between service failure rate, its effect on adoption fraction, and customers' churn are reasonable, as poor-quality service harms customers' experience. Therefore, even regular customers will leave if the quality suffers.

Policy runs and conclusion

With aiming of answering and resolving the second main question of this research: - How can a service-based business in a highly weather-dependent location raise revenue, increase their customer base, and eradicate the employees' burnout."- two policies were developed: hiring policy, and advertising policy.

These policies were formed based on the author's prime knowledge about the restaurant's system and its inadequacies and founded on learning gained during the model construction process. The policy run simulation specifications are:

- Time Horizon: 10 years (2015- 2025)
- Time Step: 1/256
- Time Unit: Months
- Integration Method: Euler

In the light of preceding policies, three leading scenarios were designed and considered as plausible solutions for the case restaurant:

- *Scenario 1:* The restaurant manager is assumed to implement only *Hiring Policy*
- *Scenario 2:* The restaurant manager is assumed to implement only *Advertising Policy*
- *Scenario 3:* The restaurant manager is assumed to implement *Mix of Policies,*

First, a brief description and meaningful assumptions of all three scenarios are described, and after that, the results of the most crucial variables after multiple policy runs are presented.

Scenario 1

Scenario 1 was developed to investigate the impact of hiring policy on customer base, employees' burnout, and sales revenue. That means this policy is primarily intended to meet the demand for customer service by hiring extra staff and increasing actual production capacity, along with improving workplace conditions by reducing stress and decreasing the need for employees' overtime. The anticipated results of scenario 1 include:

- An increase in the number of employees will increase *actual production capacity* and decrease the schedule pressure. That will lead to a lower service failure rate, and by that, to a more powerful impact of the force of word-of-mouth, which will have a more substantial impact on the customers' acquisition through referrals.
- As actual production capacity will increase, the actual sales will rise, leading to higher sales revenue.

Summarizing, an increase in referrals will boost the restaurant's customer base (*attainable customers)*. Moreover, reducing pressure on staff will increase their productivity and overall restaurant's production capacity. All that will contribute to a remarkable increase in profits, essential for the restaurant business to secure its growth and survival in highly competitive business industry.

In the model the structure of the Hiring Policy is embedded in the R&D Hiring Policy module. For more overview over the hiring policy structure, see the Appendix 2. The major assumptions of hiring policy are:

- The *extra staff needed* is determined by the desired sales rate and employees' total *actual productivity.* If the employees' actual productivity is below the *desired sales rate*, that means there are not enough employees, and the manager should hire extra staff.
- Both *rookies* and *practiced* might be hired at the same time. Rookies mean new employees who do not have any experience and need to learn from scratch. The *practiced* are employees who have the experience, but they need to know the working place to be more productive and become skilled. Skilled workers are those who work in the restaurant for a long time and have long experience and in-depth knowledge about workplace dynamics; thus, these are the most productive employees among other staff

- Pressure at work affects employees' attrition rates; the higher is the pressure at work, the higher are the attrition rates.

Scenario 2

Scenario 2: advertising policy investigates the effect of online advertisement and promotion on the customer base (in the model called: *attainable customers*), employees' burnout, and sales revenue. Advertising policy primarily is intended to increase the number of attainable customers, who might become actual customers, if actual production capacity is high enough.

In the model, advertising policy was developed to increase the number of *Occasional Attainable Customers* through an expansion of "*occasional creation rate,"* and the "*was customer retry rate"* and grow the number of *Regular Attainable Customers* by increasing the "*occasional customers' promotion rate."* Figure 33 shows the part of the customers' structure and flows affected by the advertising policy:

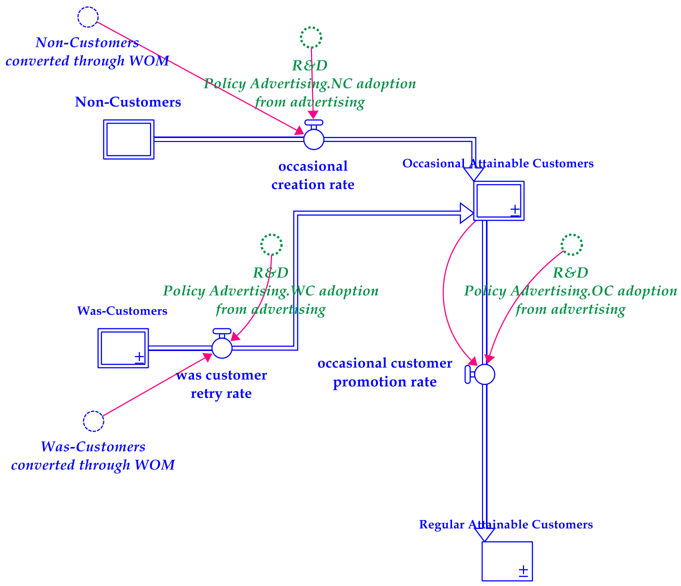


Figure 33: Advertising Policy affecting customers' diffusion flows.

The structure of the advertising policy is embedded in the *R&D Advertising Policy* module. For a more detailed overview of the structure, see the Appendix 3.The major assumptions of advertising policy are:

- Advertising effectiveness differs regarding the type of customers:

  NC advertising effectiveness= 0.004
  OC advertising effectiveness= 0.003
  WC advertising effectiveness= 0.002

This assumption is reasonable, as it is more challenging to gain “was-customers” again through advertising than the “non-customer” or “occasional- customer.” Moreover, this highest probability is that the “non-customers” will visit the restaurant from advertising. In the real world, most of us desire to explore new places, especially in the city we live in.

- As advertising is a policy, it does not affect the model’s behavior in the base run.

<u>Scenario 3</u>

Scenario 3 investigates the effect of a mix of hiring policy and advertising policy on customer base, employees' burnout, and sales revenue. This scenario seems to be the most plausible one; however, to judge which of the scenarios gives the best results, all three scenario runs will be presented and analyzed.

After a concise description of all three scenarios, the results from their runs are presented in the following order:

- Effect on customer base: behavior over time graphs of the crucial variables embedded in the **Customer module** are displayed. The *base run is* compared to *scenario 1: Hiring Policy, scenario 2: Advertising Policy scenario*, and *scenario 3: Mix of Policies* run results.
- Effect on employees’ burnout: behavior over time graphs of burnout and other crucial variables embedded in the **Internal Processes real module** are displayed. The *base run is* compared to *scenario 1: Hiring Policy, scenario 2: Advertising Policy scenario,* and *scenario 3: Mix of Policies* run results.
- Effect on sales revenue: behavior over time graphs of the crucial variables embedded in the **Financial module** are displayed. The *base run* is compared to *scenario 1: Hiring Policy, scenario 2: Advertising Policy scenario,* and *scenario 3: Mix of Policies* run results.

Customers module

The behavior over time graphs displaying distributed into four stocks "*total population of market demand"* are first presented in focus to give a more comprehensive overview of both base run and scenario runs results.

After that, a more extensive overview of *attainable customers* versus *actual customers* is given. By that, the reader will gain a deep understanding of the meaning and origin of *attainable customers* and *actual customers,* which is crucial to understand the entire system's behavior and further, the roots of the problem.

Total population of market demand

Figure 34 shows the behavior over time graphs of disaggregated into four stocks *total population of market demand.* Graphs show the *base run* compared to *scenario 1: Hiring Policy, scenario 2: Advertising Policy scenario, and scenario 3: Mix of Policies.*

a. Non-Customers

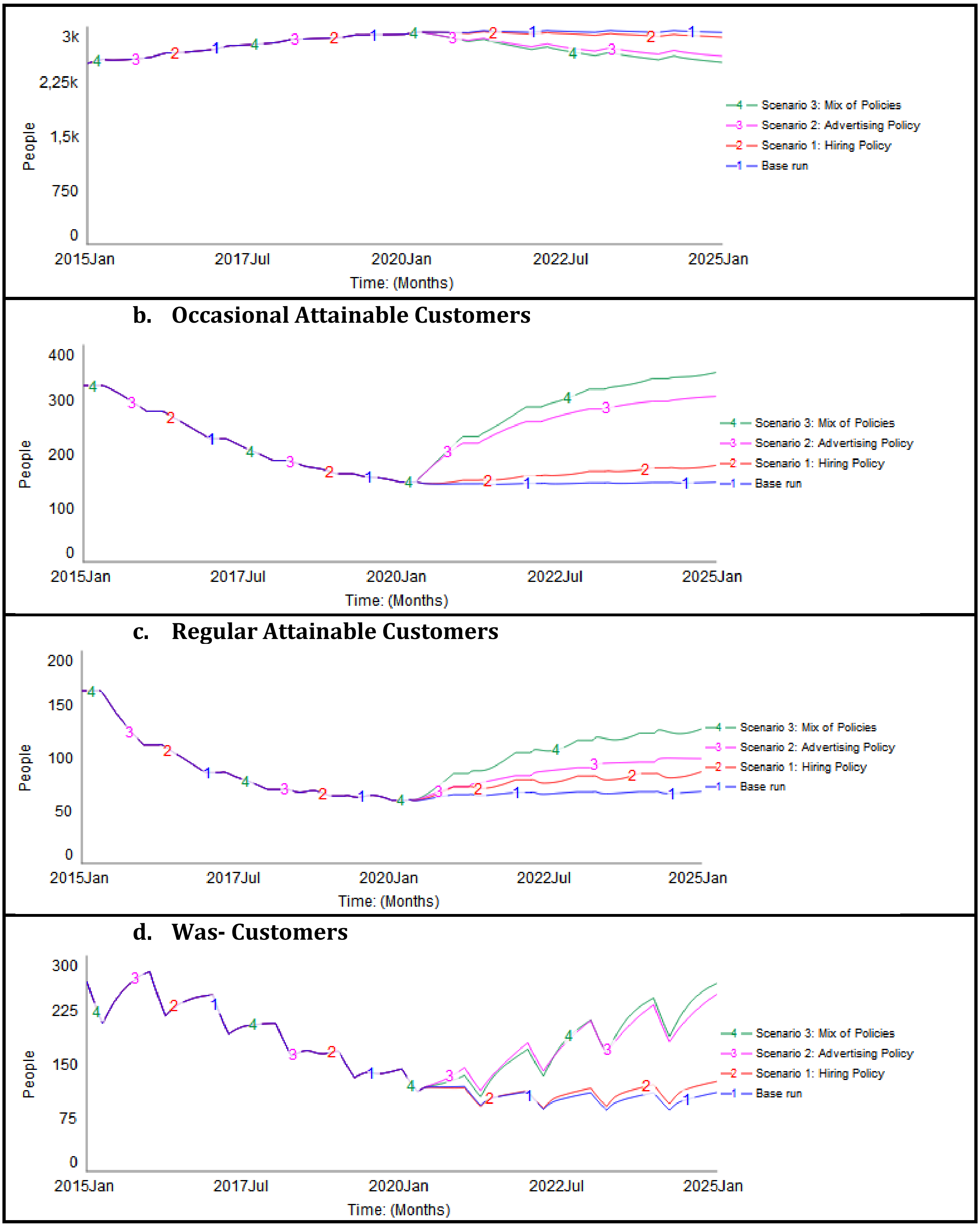


Table 11 presents the *base run* results compared to the *scenario 1: Hiring Policy*, *scenario 2: Advertising Policy*, and to the *scenario 3: Mix of Policies* run results of disaggregated into four stocks the *total population of market demand*: *Non-Customers, Occasional Attainable Customers, Regular Attainable Customers*, and *Was-Customers*. The results were reported at the end of the simulation time in December 2024:

Figure 34: Simulations of scenarios and base run of "total population of market demand" disaggregated into four distinct stocks: a. Non-Customers, b. Occasional Attainable Customers, c. Regular Attainable Customers, and d. Was-Customers.

	Base run		***Scenario 1: Hiring Policy***		***Scenario 2: Advertising Policy***		***Scenario 3: Mix of Policies***	
	[people]	[%]	[people]	[%]	[people]	[%]	[people]	[%]
Non-Customers	**2927**	90.06	**2861**	88.03	**2599**	79.97	**2511**	77.26
Occasional Attainable Customers	**146**	4.49	**178**	5.48	**305**	9.38	**350**	10.77
Regular Attainable Customers	**68**	2.09	**86**	2.65	**99**	3.05	**127**	3.91
Was-Customers	**109**	3.35	**125**	3.85	**247**	7.60	**262**	8.06

Table 11: Results of "Non-Customers", "Occasional Attainable Customers", "Regular Attainable Customers", and "Was-Customers" from scenarios and base run simulation.

The presented above table 11 shows the number of different types of customers and their percent regarding the *total population of market demand.* As already mentioned, *the total population of market demand* is assumed to be constant and equal to 3 250 people.

The results show that "scenario 3: a mix of policies" is the most effective to enhance the customer base (the sum of *Occasional Attainable Customers* and the number of *Regular Attainable Customers),* as in this scenario at the end of the simulation, the *Occasional Attainable Customers* are 10.77 % of the *total population of market demand*, and *Regular Attainable Customers* are 3.91 % of the *total population of market demand.* In comparison, in Scenario 1: Hiring Policy at the end of the simulation, the *Occasional Attainable Customers* constitute of 4.49 % of the *total population of market demand, and Regular Attainable Customers* are only 2.09 % of the total population of market demand. In scenario 2: Advertising policy, the *Occasional Attainable Customers* are 9.38% of the *total population of market demand*, and *Regular Attainable Customers* are 3.05%. Thus, *scenario 2: Advertising Policy* results are similar to *scenario 3: Mix of Policies*; however, scenario 3 wins in the percentage of *attainable customers* concerning all other scenarios.

Figure 35 presents the percentage distribution of customers created based on the results presented in table 11.

Percentage distribution of customers for Base run, Scenario 1,2, and 3.

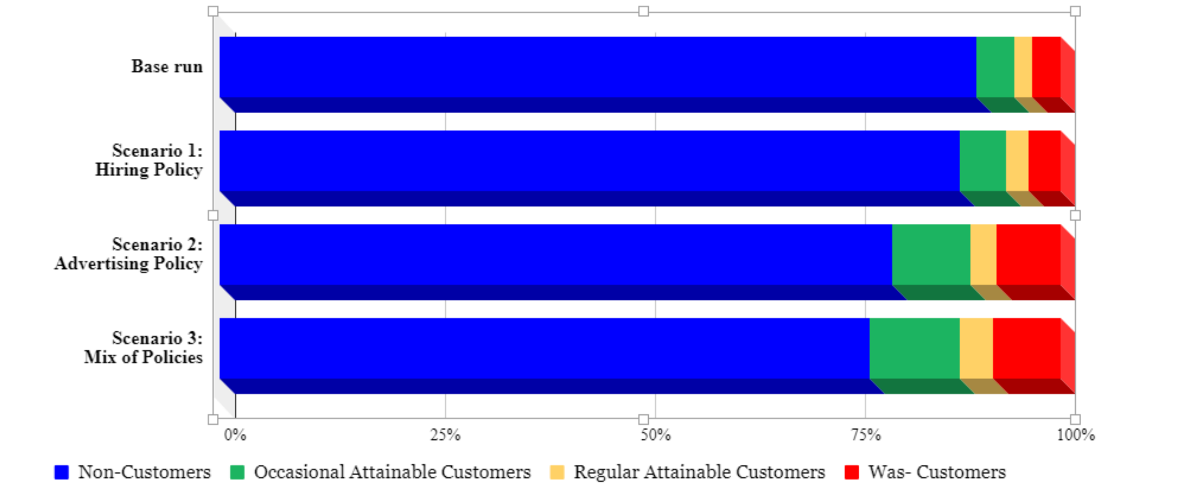


Figure 35: Percentage distribution of "total population of market demand" for simulation of base run and scenarios 1, 2, 3.

The percentage distribution of customers in the base run, scenarios 1,2, and 3 runs shown in Figure 35 give a precise, visual overview of projected customers' distribution for December 2024. Now, it is evident to view that *Scenario 3: Mix of Policies* compared to base run and scenarios 1 and 2 gives the most desired outputs of percentage distribution of the customers, as the customers base (sum of the Occasional Attainable Customers and Regular Attainable Customers) reaches the highest percentage with regard to the *total population of market demand*:

10.77% + 3.91%= 14.68%

Attainable customers vs. Actual customers

Figure 36 shows behavior over time graphs of (a) *attainable customers* and (b) *actual customers*. Graphs show the *base run* compared to *scenario 1: Hiring Policy, scenario 2: Advertising Policy scenario, and scenario 3: Mix of Policies*.

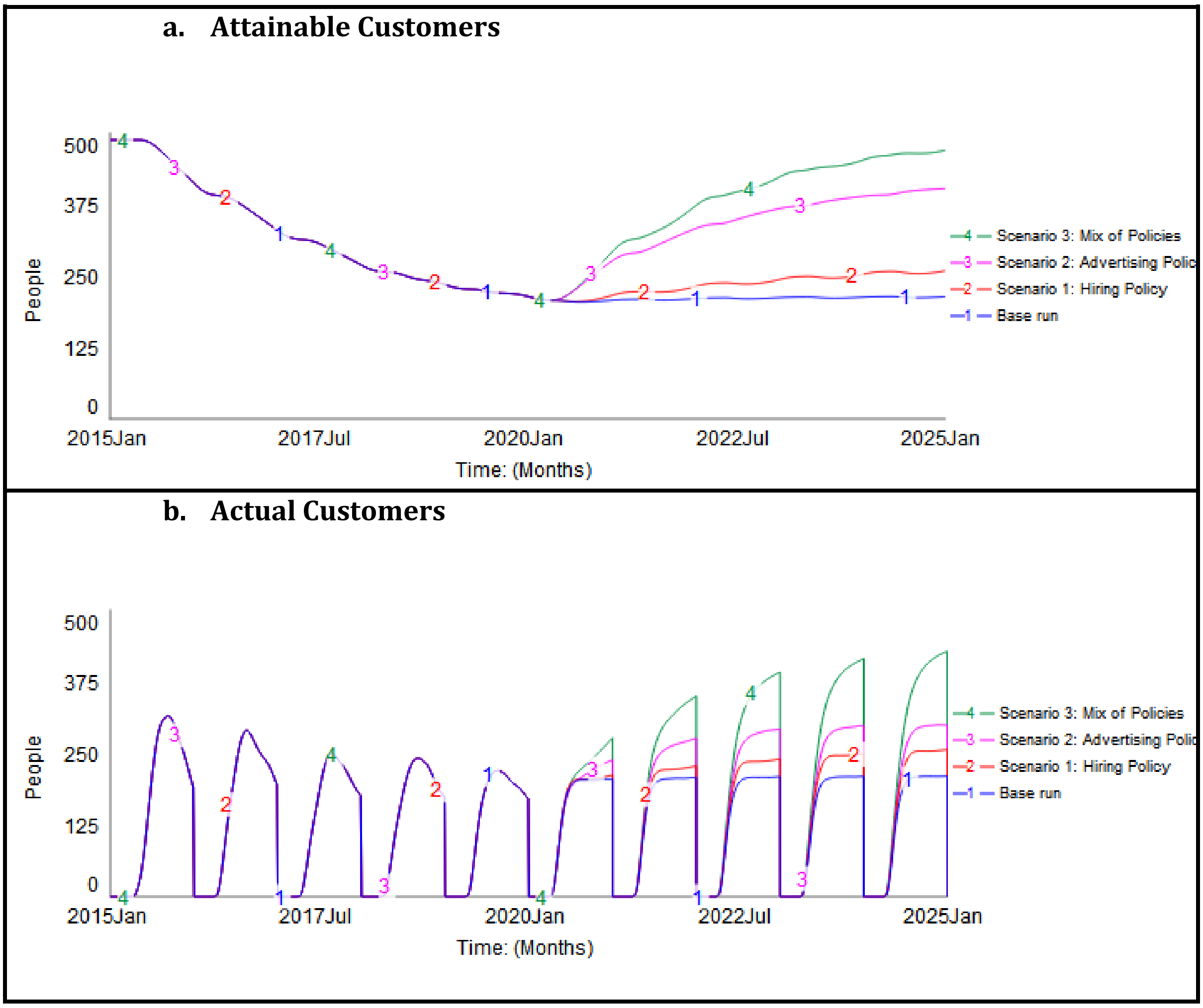


Figure 36: Scenarios 1,2, and 3 and base run of a. Attainable Customers, b. Actual customers.

As already mentioned in the model, the *actual customers* are the *attainable customers* who purchased at the restaurant. The graph (a) in Figure 36 confirms that scenario 3 is the most effective as the *attainable customers* (customer base) reach the highest peak in December 2024 (477 people). By looking at this graph, other scenarios predict the number of attainable customers in December 2024: *base run* forecasts 214 people, *scenario 1: Hiring policy* predicts 264 people, and *scenario 2: Advertising Policy* predicts 404 people.

Table 12 presents the *base run* results compared to the *scenario 1: Hiring Policy*, *scenario 2: Advertising Policy*, and to the *scenario 3: Mix of Policies* run results of *attainable customers* and *actual customers*. The results were reported at the end of the simulation time in December 2024:

	Base run		Scenario 1: Hiring Policy		Scenario 2: Advertising Policy		Scenario 3: Mix of Policies	
	[people]	[%]	[people]	[%]	[people]	[%]	[people]	[%]
Attainable Customers	**214**	6.58	**264**	8.12	**404**	12.43	**477**	14.68
Actual Customers	**210**	6.46	**257**	7.91	**300**	9.23	**427**	13.14

Table 12: Results "attainable customers" and "actual customers" from scenarios and base run simulation.

Figure 37 presents the percentage distribution of *attainable customers* and *actual customers*. The graph was created based on the results presented in table 12.

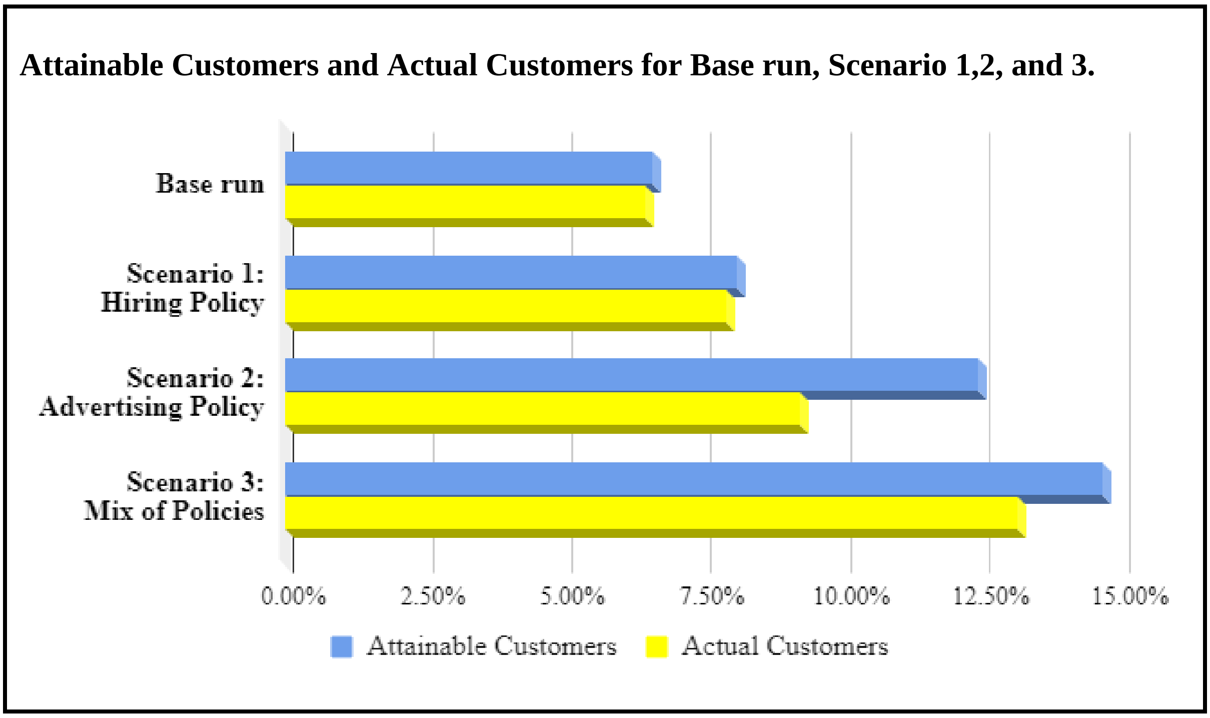


Figure 37: Percentage distribution of "attainable customers" and "actual customers" of base run, scenarios 1,2, and 3.

The percentage distribution of *attainable customers* and *actual customers* in the base run, and scenario 1,2, and 3 shown in Figure 38 gives an exact, visible summary of projected for future (December 2024) customer base. It is quite apparent to see that *Scenario 3: Mix of Policies* compared to base run and scenarios 1 and 2 again confirms its effectiveness as both *attainable customers* (customer base) and *actual customers* reach the highest percentages:

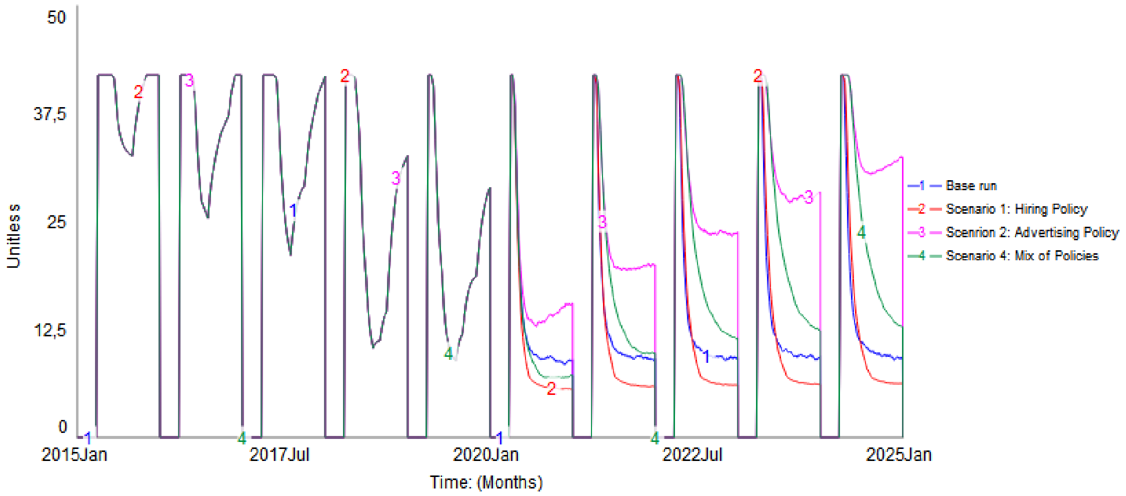
Attainable customers= 14.68%
Actual customers= 13.14%

The difference between attainable and *actual customers* is only 1,54%, which means future strategic planning might be even better adjusted to reduce this tiny discrepancy and reach all the *attainable customers*. By that, the restaurant manager will secure his service-based business and its sustainable growth. However, this might be future research to develop presented *scenario 3: Mix of Policies* strategic plan.

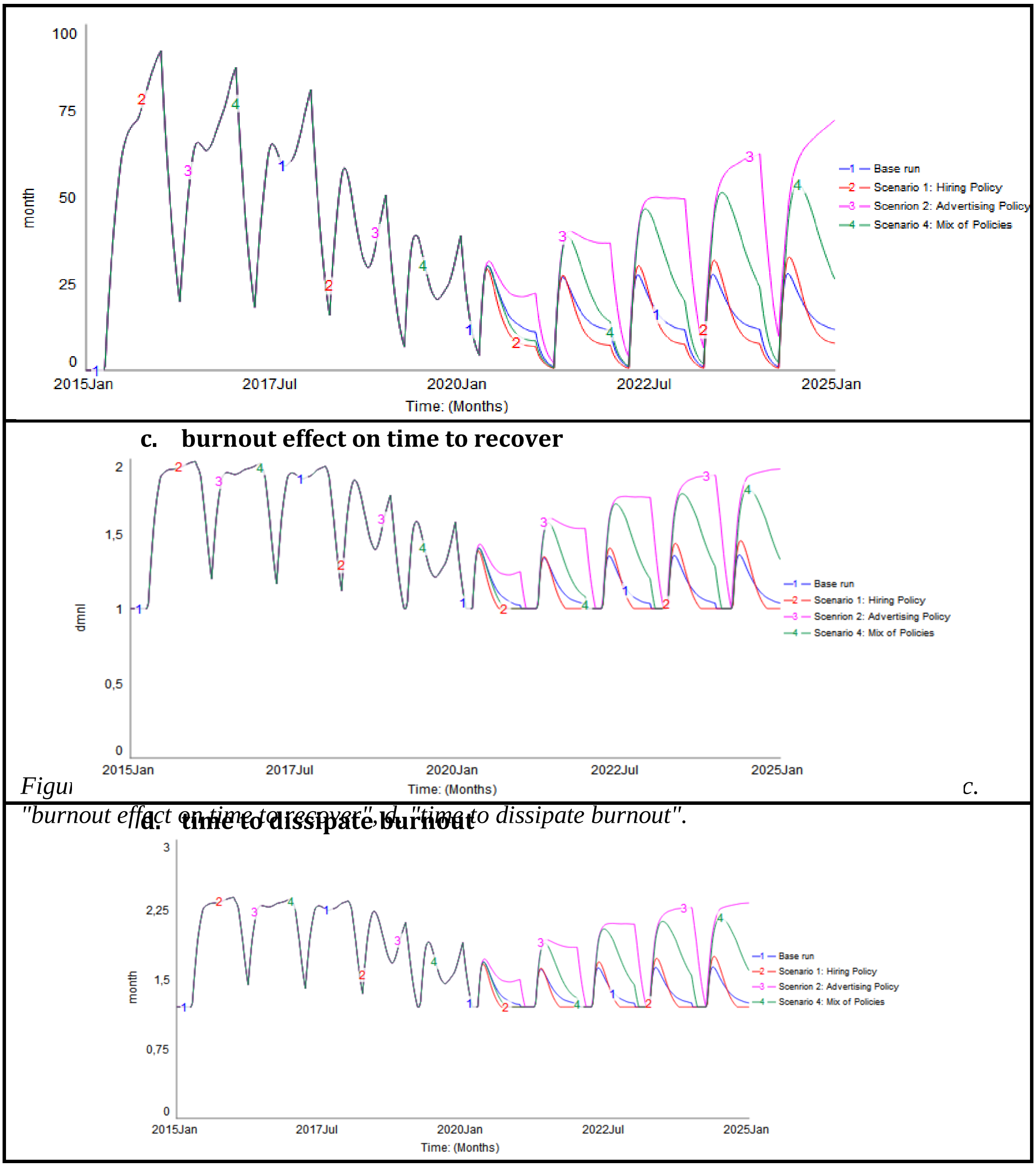
Internal processes real module

To investigate the effectiveness of different scenarios on depletion of burnout, the scenario 1,2, and 3 runs of the Internal Processes real module are compared to the base run. The behavior over time graphs of *building up burnout*, *burnout*, *burnout effect on time to recover* and *time to dissipate burnout* are presented in Figure 38:

a. building up Burnout



b. Burnout



Figu[...] c. "burnout effect on time to recover", d. "time to dissipate burnout".

By analyzing the graphs in Figure 38, the following findings are:

- *Scenario 1: Hiring policy* more than other scenarios diminish building up burnout. That is because a higher number of employees enhance the actual production capacity through higher total actual productivity. The simulation results confirm that the hiring policy was precisely developed to increase actual production capacity, not at the expense of burnout of employees and overtime, but through an appropriate higher number of employees, adjusted to the customers' service demand. The results confirm the accuracy of the Hiring Policy on diminishing employees' burnout.

- *Scenario 2: Advertising Policy* significantly increases building up burnout, burnout, burnout effect on time to recover, and time to dissipate burnout. Thus, the advertising policy does not meet the obligations to resolve the research question in this study.

- *Scenario 3: Mix of policies* raises burnout more than base run and more than scenario 1. However, it does not increase burnout as much as scenario 2; thus, it might be acceptable as the burnout increases slightly above 50 only for a very short time period. This scenario is acceptable to resolve the research question.

Financial module

To investigate the impact of different scenarios on revenue, the scenario 1,2, and 3 runs of the Financial module are compared to the base run. The behavior over time graph of *sales revenue* is displayed in Figure 39:

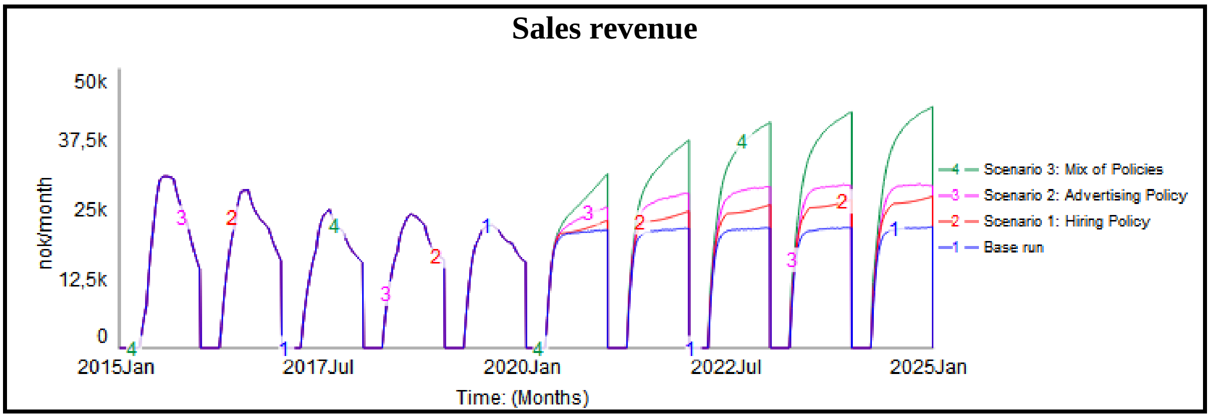


Figure 39: Scenarios 1,2, and 3 and base run of "Sales revenue".

By analyzing the graph presented in Figure 39, *scenario 3: Mix of Policies* forecasts the highest *sales revenue* for December 2024, which reaches its maximum peak at 31 100 NOK/month in 2024. There is no significant change in *sales revenue* in the base run because the *attainable customers* (customer base) did not grow, as presented above, policy runs showed. The outcomes of the *base run* of *sales revenue* reached its highest peak at 21 700 NOK/month in 2024. Further *scenario 1: Hiring Policy* reached its maximum peak at 27 200 NOK/month in 2024, while *scenario 2: Advertising Policy* 29 200 NOK/month.

The table presents the *base run* results compared to *scenario 1: Hiring Policy* run results, *scenario 2: Advertising Policy* run results, and *scenario 3: Mix of Policies* run results of *sales revenue*. Here, the results were reported at the end of the years 2020-2024. All results from running scenarios 1,2, and 3 were calculated regarding the *base run*. The results are presented in the table (*Scenario 1 to Base run Ratio, Scenario 2 to Base run ratio*, and *Scenario 3 to Base run ratio*). That gives a more precise overview of the increment of sales revenue concerning the base run.

Time	*Base run*	*Scenario 1: Hiring Policy*	*Scenario 1 to Base run ratio*	*Scenario 2: Advertising Policy*	*Scenario 2 to Base run ratio*	*Scenario 3: Mix of Policies*	*Scenario 3 to Base run ratio*
2020	**21200**	**22800**	107.55	**25000**	117.92	**31100**	146.70

2021	**21400**	**24500**	114.49	**27800**	129.91	**37300**	174.30
2022	**21500**	**25600**	119.07	**28900**	134.42	**40500**	188.37
2023	**21500**	**26500**	123.26	**29100**	135.35	**42200**	196.28
2024	**21700**	**27200**	125.35	**29200**	134.56	**43200**	199.08

Table 13: Results "Sales revenue" from scenarios and base run simulation.

By reading table 13, the restaurant manager can see the projected increment of *sales revenue* for 2020-2024. This information is beneficial and extremely useful as, based on that, the manager can make a higher investment in marketing and advertising to shape the future customer base. Alternatively, the manager can also invest in other parts of the business, such as renovation, new modern technology, hiring in anticipation, and training new staff, coaching, and market research. All these movements will actively impact the sustainable development of the seasonal and highly weather-dependent service-based business presented in this study.

Figure 40 shows the projected *sales revenue* (2020.2024) for base run, *scenario 1: Hiring Policy*, *scenario 2: Advertising Policy*, and *scenario 3: Mix of Policies*. The graph was created based on the results presented in table 13.

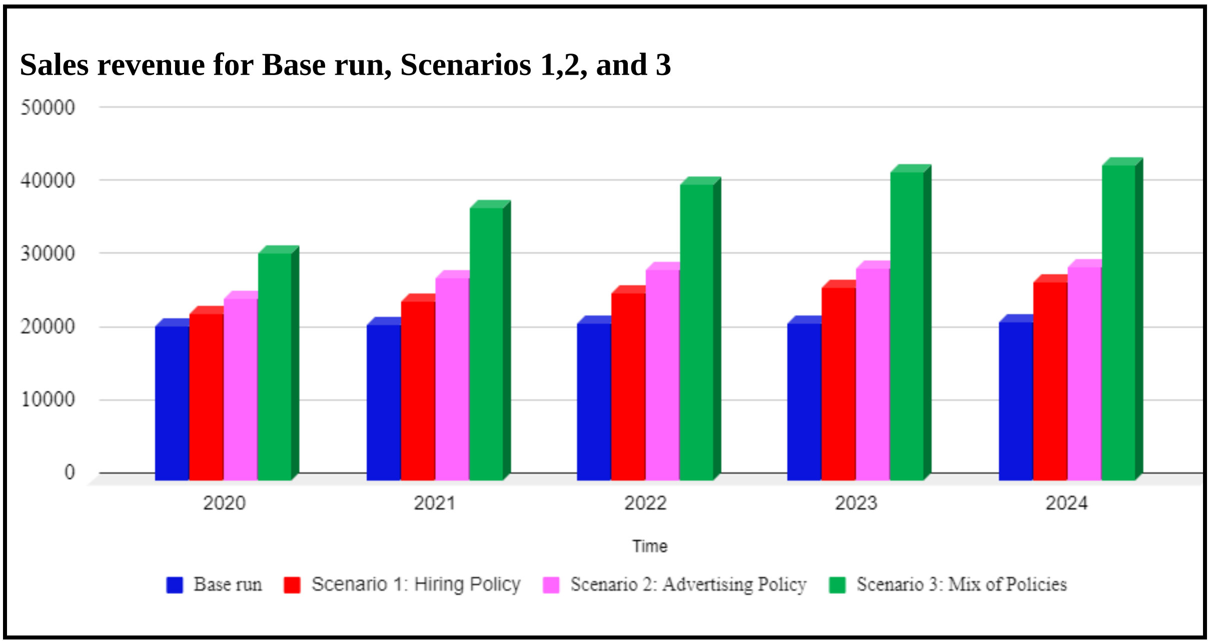


Figure 40:Sales revenue for Base run, scenarios 1,2, and 3.

Figure 40 gives an accurate, visual report of projected future sales revenue for *the base run* (colored with blue), *Scenario 3: Mix of Policies* (colored with green), *scenario 1: Hiring Policy* (colored with red) and *scenario 2: Advertising Policy* (colored with purple). The graph visually confirms the most substantial effectiveness of *scenario 3: Mix of Polices* as over years (2020- 2024), the forecasted *sales revenue* reaches the highest sales peak regarding the base run and scenarios 1 and 2 runs.

By visual presentation of anticipated results, the restaurant manager, and other stakeholders such as employees might clear understand and visualize the importance of the right strategic planning and its extraordinary impact on the whole system's behavior.

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Appendices

Appendix 1: Causal Loop Diagram for the entire model.

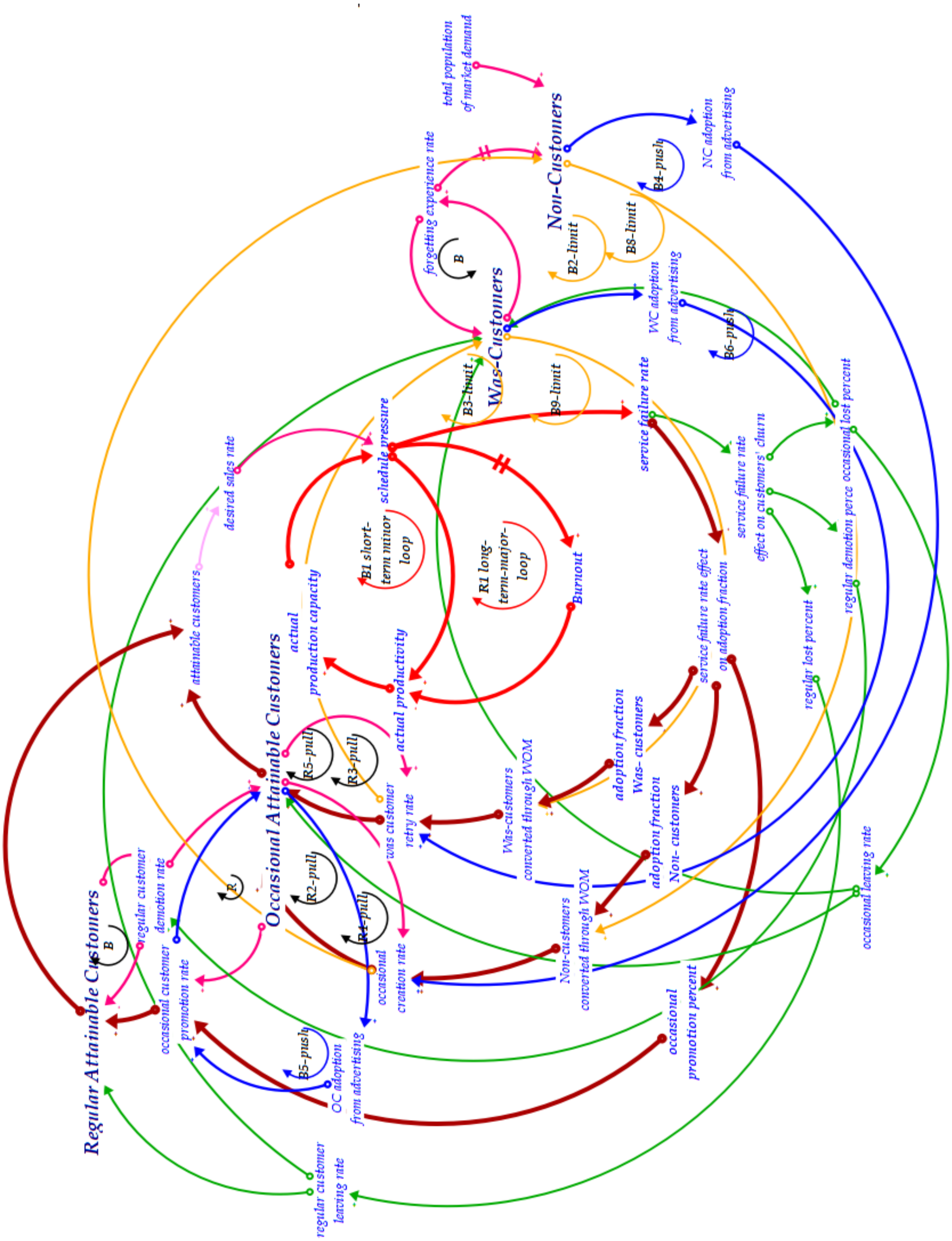

Figure 41: CLD Model overview.

Appendix 2: R&D Hiring Policy module

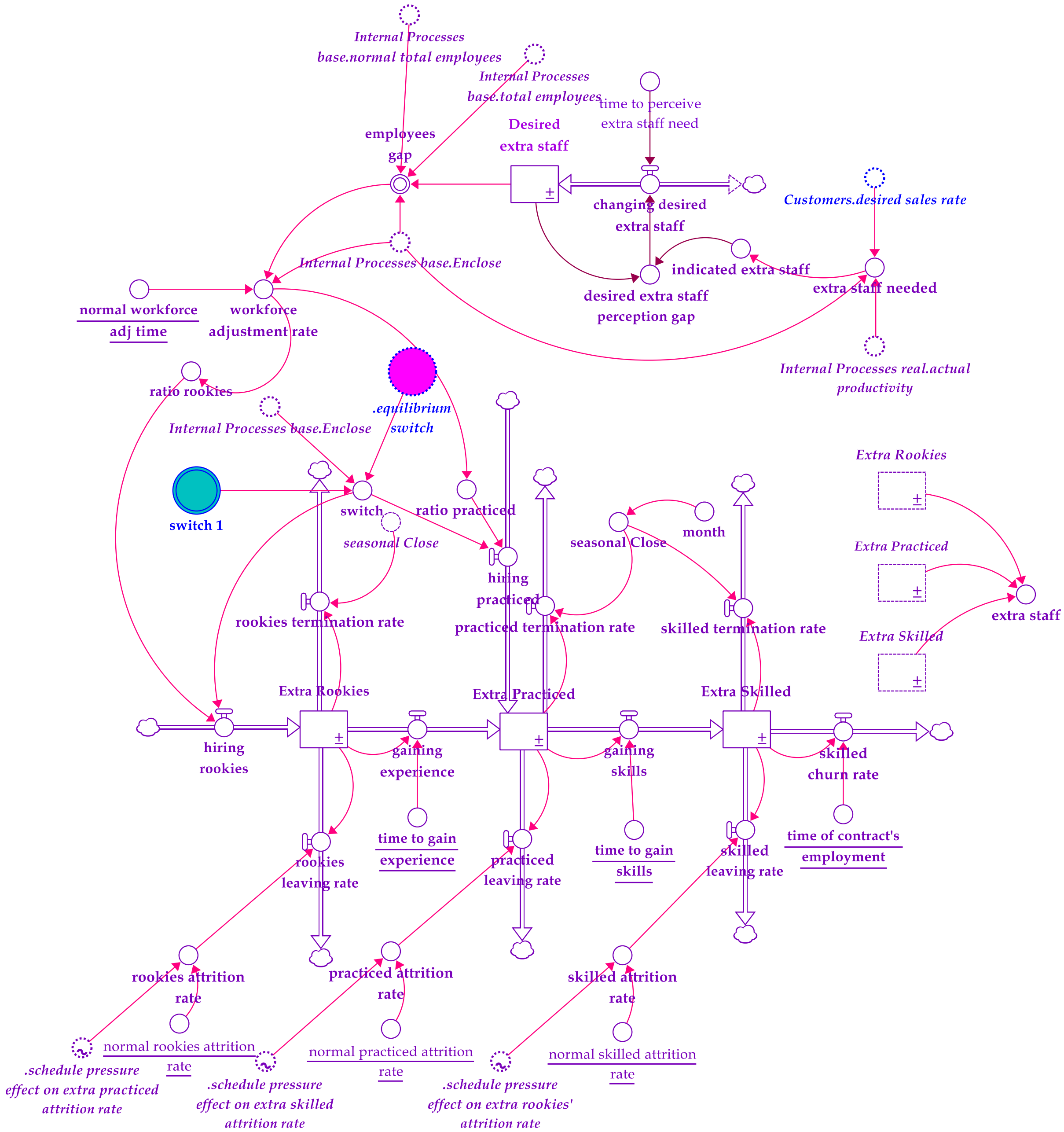

Figure 42: Hiring Policy module.

Appendix 3: R&D Advertising Policy module

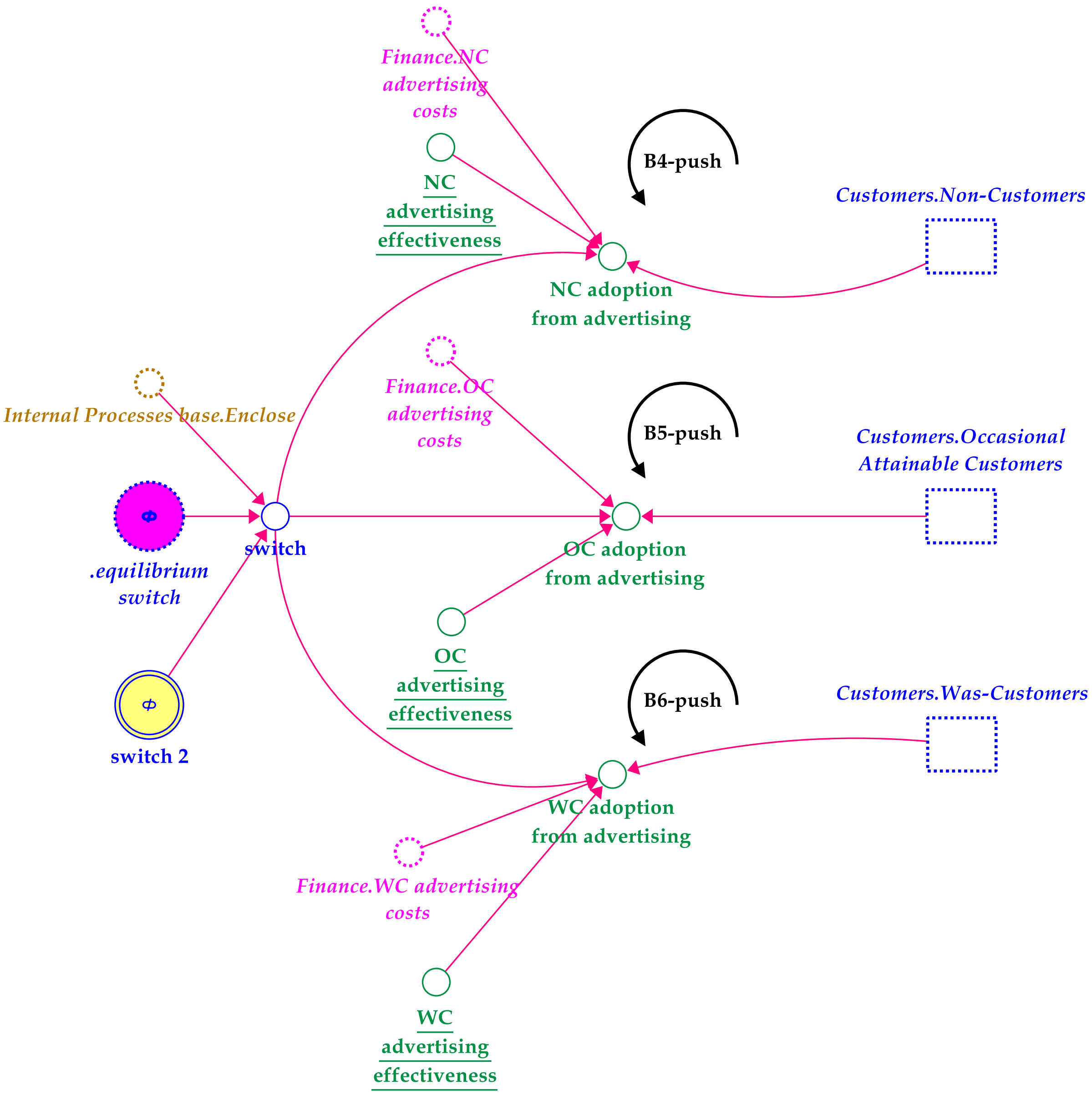

Figure 43: Advertising Policy module.

Appendix 4: Financial Module

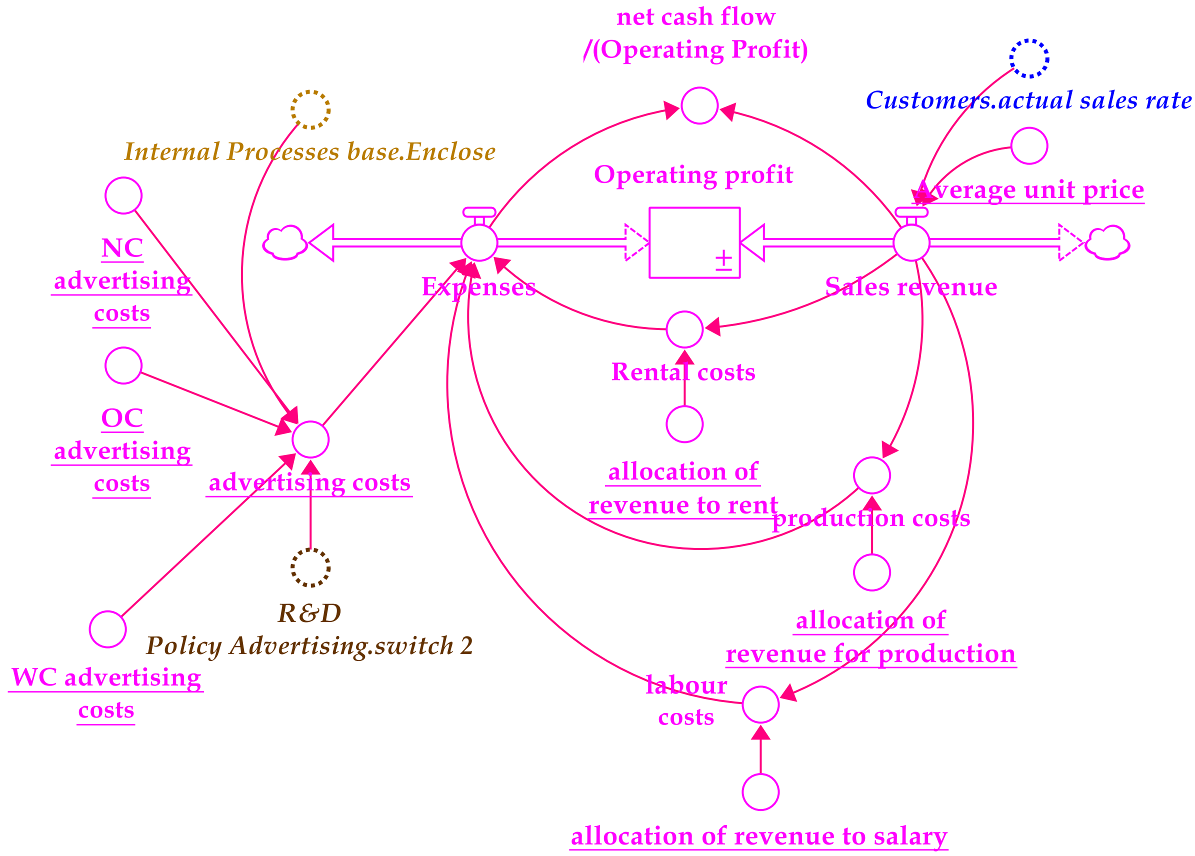

Figure 44: Financial Module

Appendix 4: Calculating equilibrium for the Customers' structure

Stocks:
NC -*Non-Customers*
OC -*Occasional_Attainable_Customers*
RC -*Regular_Attainable_Customers*
WC -*Was-Customers*

Flows:

A = forgetting_experience_rate
B = occasional_creation_rate
C = occasional_customer_promotion rate
D = regular_customer_demotion_rate
E =regular_customer_leaving_rate
F = occasional_leaving_rate
G = was _customer_retry rate

➤➤➤ Initial data

constants	complex constants	stock dependent variables
"6" = 0.02942 *adf = 0.02942* *dp = 0.05* *du = 2* *market_size = 65 000* *pr = 0.05* *t = 12* *x = 0.05* *z = 0.05* *.sf= 1 (in equilibrium)* *.sad= 1 (in equilibrium)* *ad.nad= 0 (in equilibrium)* *ad.oad= 0 (in equilibrium)* *ad.wad= 0 (in equilibrium)* *IP.opc= 1 (in equilibrium)*	fad = "6"*.sad*IP.opc h = z*.sf ms = market_size*0.05 op = pr*.sad rp = dp*.sf uh = .sad*adf*IP.opc up = x*.sf	"3" = (**WC**/ms) "12" = (**NC**/ms) i = **OC***du tu = **RC***du

"6"- "normal_adoption_fraction_Non-Customer" *adf - "normal_adoption_fraction_Was-Customers"* *dp - normal_regular_demotion_percent* *du- contact_rate* *pr- normal_occasional_promotion_percent* *t- time_to_forget_experience* *x = normal_regular_lost_percent* *z = normal_occasional_lost_percent* *ad.nad- NC_adoption_from_advertising* *ad.oad- OC_adoption_from_advertising* *ad.wad- WC_adoption_from_advertising* *.sad- .service_failure_rate_effect_on_adoption_fraction (in equilibrium is equal to 1)* *.sf- .service_failure_rate_effect_on_customers'_churn (in equilibrium is equal to 1)* *ad.nad- NC_adoption_from_advertising (in equilibrium is equal to 0)* *ad.oad- OC_adoption_from_advertising (in equilibrium is equal to 0)* *ad.wad- WC_adoption_from_advertising (in equilibrium is equal to 0)* *IP.opc- Enclose (in equilibrium is equal to1)*	*fad = "adoption_fraction_Non-Customers"* *h = occasional_lost_percent* *ms - total_population_of_market_demand* *op = occasional_promotion_percent* *rp = regular_demotion_percent* *up = regular_lost_percent* *uh- "adoption_fraction_Was-Customers"*	*"3"- "probability_of_contact_with_Was-Customer"* *"12"- "probability_of_contact_with_Non-Customers"* *i- total_Occasional_Attainable_Customers_contacts* *tu- total_Regular_Attainable_Customers_contacts*

complex stock dependent variables		
“5” =	"12"*i =	(**NC**/ms)***OC***du = $\frac{du}{ms}*NC*OC$
“7” =	"3"*tu =	(**WC**/ms)***RC***du = $\frac{du}{ms}*WC*RC$
“8” =	"3"*i =	(**WC**/ms)***OC***du = $\frac{du}{ms}*WC*OC$
“9” =	"12"*tu =	(**NC**/ms)***RC***du = $\frac{du}{ms}*NC*RC$
“NC-WOM” =	fad*("5"+"9") = fad*($\frac{du}{ms}*NC*OC + \frac{du}{ms}*NC*RC$) = $= \frac{fad*du}{ms}*NC*(OC+RC)$	
“WC-WOM” =	uh*("7"+"8") = $= \frac{uh*du}{ms}*WC*(OC+RC)$	uh*($\frac{du}{ms}*WC*RC + \frac{du}{ms}*WC*OC$) =

(all checked with diagrams)

➤➤➤ Initial system of equations - full version

(0) $NC = (ms - OC - RC - WC)$

(1) NC **A = B**

(2) OC B + G + D = C + F

(3) RC C = D + E

(4) WC E + F = G + A

A = (WC/t)
B = ("NC-WOM" + ad.nad)
C = ((OC*op) + ad.oad)
D = (RC*rp)
E = (RC*up)
F = (OC*h)
G = ("WC-WOM" + ad.wad)

Notice:

● equations (1) - (4) are always satisfied (because they are a "result of a closed diagram"), hence we have to swap one of them with equation (0). The equation (2) is the most complex one, hence I swap it for equation (0).

➤➤➤ Initial system of equations - official

(1) NC A = B

(2) OC $NC = (ms - OC - RC - WC)$

(3) RC C = D + E

(4) WC E + F = G + A

➤➤➤ System of equations - A, B, C… substituted

(1) (WC/t) = ("NC-WOM" + ad.nad)

(2) $NC = (ms - OC - RC - WC)$

(3) ((OC*op) + ad.oad) = (RC*rp) + (RC*up)

(4) (RC*up) + (OC*h) = ("WC-WOM" + ad.wad) + (WC/t)

➤➤➤ System of equations - all stock dependent variables substituted

(1) (WC/t) = ($\frac{fad*du}{ms} * NC*(OC+RC)$ + ad.nad)

(2) $NC = (ms - OC - RC - WC)$

(3) ((OC*op) + ad.oad) = (RC*rp) + (RC*up)

(4) (RC*up) + (OC*h) = ($\frac{uh*du}{ms} * WC*(OC+RC)$ + ad.wad) + (WC/t)

➤➤➤ System of equations - added fractions and deleted unnecessary brackets

(1) $$\frac{1}{t} * WC = \frac{fad * du}{ms} * NC * (OC + RC) + ad.nad$$

(2) $$NC = (ms - OC - RC - WC)$$

(3) $$OC * op + ad.oad = RC * rp + RC * up$$

(4) $$RC * up + OC * h = \frac{uh * du}{ms} * WC * (OC + RC) + ad.wad + \frac{1}{t} * WC$$

Notice:

- **equation (3) contains only OC and RC stocks, hence we can derive formula for OC in terms of RC**
- **equation (4) contains only OC, RC and WC stocks, hence we can derive formula for WC in terms of RC and OC**
- **after substituting OC in terms of RC to the formula for WC we can derive the formula for WC in terms of RC only**

➤➤➤ Equation (3) - deriving the formula for OC in terms of RC

(3) $$OC * op + ad.oad = RC * rp + RC * up$$

$$OC * op = RC * (rp + up) - ad.oad$$

$$OC = \frac{rp + up}{op} * RC - \frac{ad.oad}{op}$$

➤➤➤ Equation (4) - deriving the formula for WC in terms of RC

(4) $$RC * up + OC * h = \frac{uh * du}{ms} * WC * (OC + RC) + ad.wad + \frac{1}{t} * WC$$

separating the WC stock:

$$\frac{uh * du}{ms} * WC * (OC + RC) + \frac{1}{t} * WC = RC * up + OC * h - ad.wad$$

$$(\frac{uh * du}{ms} * (OC + RC) + \frac{1}{t}) * WC = RC * up + OC * h - ad.wad$$

substituting the formula for OC in terms of RC:

$$(\frac{uh * du}{ms} * (\frac{rp + up}{op} * RC - \frac{ad.oad}{op} + RC) + \frac{1}{t}) * WC =$$

$$= RC * up + (\frac{rp + up}{op} * RC - \frac{ad.oad}{op}) * h - ad.wad$$

simplifying:

$$(\frac{uh * du}{ms} * (\frac{rp + up + op}{op} * RC - \frac{ad.oad}{op}) + \frac{1}{t}) * WC =$$

$$= RC * up + \frac{(rp + up) * h}{op} * RC - \frac{ad.oad * h}{op} - ad.wad$$

$$(\frac{uh * du * (rp + up + op)}{ms * op} * RC - \frac{uh * du * ad.oad}{ms * op} + \frac{1}{t}) * WC =$$

$$= (up + \frac{(rp + up) * h}{op}) * RC - \frac{ad.oad * h}{op} - ad.wad$$

the formula for WC in terms of RC:

$$WC = \left((up + \frac{(rp + up) * h}{op}) * RC - \frac{ad.oad * h}{op} - ad.wad \right) /$$

$$\left(\frac{uh * du * (rp + up + op)}{ms * op} * RC - \frac{uh * du * ad.oad}{ms * op} + \frac{1}{t}\right)$$

➤➤➤ System of equations - current formulas

(1) $$\frac{1}{t} * WC = \frac{fad * du}{ms} * NC * (OC + RC) + ad.nad$$

(2) $$NC = (ms - OC - RC - WC)$$

(3) $$OC = \frac{rp + up}{op} * RC - \frac{ad.oad}{op}$$

(4) $$WC = \left((up + \frac{(rp + up) * h}{op}) * RC - \frac{ad.oad * h}{op} - ad.wad\right) / \left(\frac{uh * du * (rp + up + op)}{ms * op} * RC - \frac{uh * du * ad.oad}{ms * op} + \frac{1}{t}\right)$$

Notice:

- **equation (2) is a ready formula for NC in terms of OC, RC and WC, hence we can substitute it to the equation (1)**
- **after substituting formulas for OC and WC in terms of RC into the equation (1) we will receive equation with only one unknown (RC), which (probably and hopefully) be solvable**

➤➤➤ Equation (1) - substituting equation (2)

(1) $$\frac{1}{t} * WC = \frac{fad * du}{ms} * NC * (OC + RC) + ad.nad$$

$$\frac{1}{t} * WC = \frac{fad * du}{ms} * (ms - OC - RC - WC) * (OC + RC) + ad.nad$$

rearranging:

$$\frac{1}{t} * WC - ad.nad = \frac{fad * du}{ms} * (ms - OC - RC - WC) * (OC + RC)$$

$$\frac{1}{t} * WC - ad.nad = \frac{fad * du}{ms} * (ms - (OC + RC) - WC) * (OC + RC)$$

➤➤➤ Equation (1) - substituting equation (3) = formula for OC in terms of RC

(1) $$\frac{1}{t}*WC - ad.nad =$$

$$= \frac{fad*du}{ms}*(ms - (\frac{rp+up}{op}*RC - \frac{ad.oad}{op} + RC) - WC)*(\frac{rp+up}{op}*RC - \frac{ad.oad}{op} + RC)$$

simplifying:

$$\frac{1}{t}*WC - ad.nad =$$

$$= \frac{fad*du}{ms}*(ms - (\frac{rp+up+op}{op}*RC - \frac{ad.oad}{op}) - WC)*(\frac{rp+up+op}{op}*RC - \frac{ad.oad}{op})$$

$$\frac{1}{t}*WC - ad.nad =$$

$$= \frac{fad*du}{ms}*(ms + \frac{ad.oad}{op} - \frac{rp+up+op}{op}*RC - WC)*(\frac{rp+up+op}{op}*RC - \frac{ad.oad}{op})$$

$$\frac{1}{t}*WC - ad.nad =$$

$$= \frac{fad*du}{ms}*(\frac{ms*op+ad.oad}{op} - \frac{rp+up+op}{op}*RC - WC)*(\frac{rp+up+op}{op}*RC - \frac{ad.oad}{op})$$

multiplying the big brackets:

$$\frac{1}{t}*WC - ad.nad =$$

$$= \frac{fad*du}{ms}*(\frac{ms*op+ad.oad}{op}*\frac{rp+up+op}{op}*RC - \frac{ms*op+ad.oad}{op}*\frac{ad.oad}{op} - (\frac{rp+up+op}{op})^{2}$$

$$+ \frac{rp+up+op}{op}*\frac{ad.oad}{op}*RC - \frac{rp+up+op}{op}*RC*WC + \frac{ad.oad}{op}*WC)$$

rearranging and simplifying:

$$\frac{1}{t}*WC - ad.nad =$$

$$= \frac{fad*du}{ms}*(-\frac{ms*op+ad.oad}{op}*\frac{ad.oad}{op} + (\frac{ms*op+ad.oad}{op} + \frac{ad.oad}{op})*\frac{rp+up+op}{op}*RC +$$

$$+ \frac{ad.oad}{op}*WC - (\frac{rp+up+op}{op})^{2}*RC^{2} - \frac{rp+up+op}{op}*RC*WC)$$

$$\frac{1}{t} * WC - ad.nad =$$

$$= \frac{fad * du}{ms} * \left(- \frac{ms * op + ad.oad}{op} * \frac{ad.oad}{op} + \left(\frac{ms * op + 2 * ad.oad}{op}\right) * \frac{rp + up + op}{op} * RC + \right.$$

$$\left. + \frac{ad.oad}{op} * WC - \left(\frac{rp + up + op}{op}\right)^2 * RC^2 - \frac{rp + up + op}{op} * RC * WC \right)$$

multiplying both sides to get rid of the brackets:

$$\frac{ms}{fad * du * t} * WC - \frac{ms * ad.nad}{fad * du} =$$

$$= - \frac{ms * op + ad.oad}{op} * \frac{ad.oad}{op} + \left(\frac{ms * op + 2 * ad.oad}{op}\right) * \frac{rp + up + op}{op} * RC +$$

$$+ \frac{ad.oad}{op} * WC - \left(\frac{rp + up + op}{op}\right)^2 * RC^2 - \frac{rp + up + op}{op} * RC * WC$$

further simplifying:

$$0 = \frac{ms * ad.nad}{fad * du} - \frac{ms * op + ad.oad}{op} * \frac{ad.oad}{op} + \left(\frac{ms * op + 2 * ad.oad}{op}\right) * \frac{rp + up + op}{op} * RC$$

$$+ \frac{ad.oad}{op} * WC - \frac{ms}{fad * du * t} * WC - \left(\frac{rp + up + op}{op}\right)^2 * RC^2 - \frac{rp + up + op}{op} * RC * WC$$

$$0 = \left(\frac{ms * ad.nad}{fad * du} - \frac{ms * op + ad.oad}{op} * \frac{ad.oad}{op}\right) + \left(\frac{ms * op + 2 * ad.oad}{op}\right) * \frac{rp + up + op}{op} * R$$

$$+ \left(\frac{ad.oad}{op} - \frac{ms}{fad * du * t}\right) * WC - \left(\frac{rp + up + op}{op}\right)^2 * RC^2 - \frac{rp + up + op}{op} * RC * WC$$

➤➤➤ Equation (4) - simplifying into one fraction

(4) $$WC = \left(\left(up + \frac{(rp + up) * h}{op}\right) * RC - \frac{ad.oad * h}{op} - ad.wad \right) / \left(\frac{uh * du * (rp + up + op)}{ms * op} * RC - \frac{uh * du * ad.oad}{ms * op} + \frac{1}{t} \right)$$

changing formulas inside green brackets into fractions:

$$WC = \left(\frac{up * op + (rp + up) * h}{op} * RC - \frac{ad.oad * h + ad.wad * op}{op} \right) / \left(\frac{t * uh * du * (rp + up + op)}{t * ms * op} * RC - \frac{t * uh * du * ad.oad}{t * ms * op} + \frac{ms * op}{t * ms * op} \right)$$

$$WC = \left(\frac{(up * op + (rp + up) * h) * RC - (ad.oad * h + ad.wad * op)}{op} \right) / \left(\frac{t * uh * du * (rp + up + op) * RC - t * uh * du * ad.oad + ms * op}{t * ms * op} \right)$$

➤➤➤ Equation (1) - substituting equation (4) = formula for WC in terms of RC

(1)

$$0 = \left(\frac{ms * ad.nad}{fad * du} - \frac{ms * op + ad.oad}{op} * \frac{ad.oad}{op}\right) + \left(\frac{ms * op + 2 * ad.oad}{op}\right) * \frac{rp + up + op}{op} * RC +$$

$$+\left(\frac{ad.oad}{op} - \frac{ms}{fad * du * t}\right) * WC - \left(\frac{rp + up + op}{op}\right)^2 * RC^2 - \frac{rp + up + op}{op} * RC * WC$$

(4)

introducing auxiliary variables:

A = $\left(\frac{ms * ad.nad}{fad * du} - \frac{ms * op + ad.oad}{op} * \frac{ad.oad}{op}\right)$

B = $\left(\frac{ms * op + 2 * ad.oad}{op}\right) * \frac{rp + up + op}{op}$

C = $\left(\frac{ad.oad}{op} - \frac{ms}{fad * du * t}\right)$

D = $\frac{rp + up + op}{op}$

E = $t * ms * (up * op + (rp + up) * h)$

F = $t * ms * (ad.oad * h + ad.wad * op)$

G = $t * uh * du * (rp + up + op)$

H = $- t * uh * du * ad.oad + ms * op$

equations in simplified form:

(1) $$0 = A + B * RC + C * WC - D^2 * RC^2 - D * RC * WC$$

(4) $$WC = \frac{E * RC - F}{G * RC + H}$$

substituting equation (4) into the equation (1):

$$0 = A + B * RC + C * \frac{E * RC - F}{G * RC + H} - D^2 * RC^2 - D * RC * \frac{E * RC - F}{G * RC + H}$$

substituting RC = x and simplifying:

$$0 = A + B * x + C * \frac{E * x - F}{G * x + H} - D^2 * x^2 - D * x * \frac{E * x - F}{G * x + H}$$

$$0 = A + Bx + C * \frac{Ex - F}{Gx + H} - D^2x^2 - Dx * \frac{Ex - F}{Gx + H}$$

$$0 = A + Bx + \frac{CEx - CF}{Gx + H} - D^2x^2 - \frac{DEx^2 - DFx}{Gx + H}$$

Appendix 5: Model documentation

model.22.08 US.stmx
Top-Level Model:
equilibrium_switch = 1
UNITS: dmnl
normal_service_failure_rate = 0.05
UNITS: dimensionless
normalized_service_failure_rate = service_failure_rate/normal_service_failure_rate
UNITS: dmnl
schedule_pressure_effect_on_extra_practiced_attrition_rate =
GRAPH(Internal_Processes_real.normalized_schedule_pressure)
Points: (0,000, 0,600), (0,200, 0,650), (0,400, 0,680), (0,600, 0,700), (0,800, 0,800), (1,000, 1,000), (1,200, 1,283), (1,400, 1,450), (1,600, 1,550), (1,800, 1,600), (2,000, 1,650)
UNITS: dimensionless
schedule_pressure_effect_on_extra_rookies'_attrition_rate =
GRAPH(Internal_Processes_real.normalized_schedule_pressure)
Points: (0,000, 0,600), (0,200, 0,650), (0,400, 0,680), (0,600, 0,700), (0,800, 0,800), (1,000, 1,000), (1,200, 1,350), (1,400, 1,500), (1,600, 1,600), (1,800, 1,650), (2,000, 1,700)
UNITS: dimensionless
schedule_pressure_effect_on_extra_skilled_attrition_rate =
GRAPH(Internal_Processes_real.normalized_schedule_pressure)
Points: (0,000, 0,600), (0,200, 0,650), (0,400, 0,680), (0,600, 0,675), (0,800, 0,742), (1,000, 1,000), (1,200, 1,150), (1,400, 1,250), (1,600, 1,342), (1,800, 1,375), (2,000, 1,375)
UNITS: dimensionless
schedule_pressure_effect_on_service_failure_rate =
GRAPH(Internal_Processes_real.normalized_schedule_pressure)
Points: (0,000, 0,646), (0,200, 0,664), (0,400, 0,672), (0,600, 0,690), (0,800, 0,760), (1,000, 1,000), (1,200, 1,354), (1,400, 1,485), (1,600, 1,546), (1,800, 1,581), (2,000, 1,581)
UNITS: dmnl
service_failure_rate =
schedule_pressure_effect_on_service_failure_rate*normal_service_failure_rate
UNITS: dmnl
service_failure_rate_effect_on_adoption_fraction =
GRAPH(SMTH1(normalized_service_failure_rate, 2))
Points: (0,000, 1,495), (0,200, 1,490), (0,400, 1,480), (0,600, 1,471), (0,800, 1,398), (1,000, 1,000), (1,200, 0,880), (1,400, 0,820), (1,600, 0,780), (1,800, 0,750), (2,000, 0,720)
UNITS: dmnl
service_failure_rate_effect_on_customers'_churn =
GRAPH(normalized_service_failure_rate)
Points: (0,000, 0,650), (0,200, 0,650), (0,400, 0,700), (0,600, 0,800), (0,800, 0,900), (1,000, 1,000), (1,200, 1,223), (1,400, 1,336), (1,600, 1,400), (1,800, 1,480), (2,000, 1,474)
UNITS: dmnl

Customers:

"Non-Customers"(t) = "Non-Customers"(t - dt) + (forgetting_experience_rate - occasional_creation_rate) * dt {NON-NEGATIVE}
INIT "Non-Customers" = (total_population_of_market_demand-Occasional_Attainable_Customers-Regular_Attainable_Customers-"Was-Customers")
UNITS: People
DOCUMENT: The stock reveals the number of Non-Customers among total population of market demand, at any point in time.

1. Non-Customers can be people who NEVER were a customers in the case restaurant, or

2. Non-Customers can be people who were Occasional Attainable Customers, but

- they did not like place (e.g. the restaurant could be overcrowded and they could not be served), and became Non-Customers again, or like more service from competiotors, or

- these people were tourists, visitors or other people who cannot visit the restaurant regularly, thus they become Non-Customers again, or

- they got bad experience from service failure rate, and become Non-Customers again, or

3. Non-Customers can be people who were Occasional Attainable Customers, then Regular Attainable Customers, then Was-Customers and after delay time (time to forget experience=12 months) , they became Non- Customers again.

INFLOWS:
forgetting_experience_rate = ("Was-Customers"/time_to_forget_experience) {UNIFLOW}
UNITS: people / month
OUTFLOWS:
occasional_creation_rate = ("Non-Customers_converted_through_WOM"+R&D_Policy_Advertising.NC_adoption_from_advertising) {UNIFLOW}
UNITS: people / month
Occasional_Attainable_Customers(t) = Occasional_Attainable_Customers(t - dt) + (occasional_creation_rate + regular_customer_demotion_rate + was_customer_retry_rate - occasional_leaving_rate - occasional_customer_promotion_rate) * dt
INIT Occasional_Attainable_Customers = MAX(0.01, ((normal_regular_lost_percent + normal_regular_demotion_percent)/(normal_occasional_promotion_percent))*((-((-"normal_adoption_fraction_Non-Customers"*contact_rate*(normal_regular_lost_percent + normal_regular_demotion_percent) - normal_occasional_promotion_percent*"normal_adoption_fraction_Non-Customers"*contact_rate)*((normal_regular_lost_percent + normal_regular_demotion_percent)/(normal_occasional_promotion_percent)+1))*(total_population_of_market_demand*normal_occasional_promotion_percent) - ((-"normal_adoption_fraction_Non-Customers"*contact_rate +"normal_adoption_fraction_Was-Customers"*contact_rate)*(normal_occasional_promotion_percent + normal_regular_lost_percent + normal_regular_demotion_percent))*(time_to_forget_experience*total_population_of_marke

t_demand*normal_occasional_promotion_percent*normal_regular_lost_percent + time_to_forget_experience*total_population_of_market_demand*normal_occasional_lost_percent*(normal_regular_lost_percent + normal_regular_demotion_percent)) + ((total_population_of_market_demand*normal_occasional_lost_percent - "normal_adoption_fraction_Non-Customers"*contact_rate*total_population_of_market_demand)*(normal_regular_lost_percent + normal_regular_demotion_percent) + total_population_of_market_demand*normal_occasional_promotion_percent*(normal_regular_lost_percent - "normal_adoption_fraction_Non-Customers"*contact_rate))*(time_to_forget_experience*"normal_adoption_fraction_Was-Customers"*contact_rate*normal_occasional_promotion_percent + time_to_forget_experience*"normal_adoption_fraction_Was-Customers"*contact_rate*(normal_regular_lost_percent + normal_regular_demotion_percent)) - SQRT((((- "normal_adoption_fraction_Non-Customers"*contact_rate*(normal_regular_lost_percent + normal_regular_demotion_percent) - normal_occasional_promotion_percent*"normal_adoption_fraction_Non-Customers"*contact_rate)*((normal_regular_lost_percent + normal_regular_demotion_percent)/(normal_occasional_promotion_percent)+1))*(total_population_of_market_demand*normal_occasional_promotion_percent) + ((- "normal_adoption_fraction_Non-Customers"*contact_rate +"normal_adoption_fraction_Was-Customers"*contact_rate)*(normal_occasional_promotion_percent + normal_regular_lost_percent + normal_regular_demotion_percent))*(time_to_forget_experience*total_population_of_market_demand*normal_occasional_promotion_percent*normal_regular_lost_percent + time_to_forget_experience*total_population_of_market_demand*normal_occasional_lost_percent*(normal_regular_lost_percent + normal_regular_demotion_percent)) - ((total_population_of_market_demand*normal_occasional_lost_percent - "normal_adoption_fraction_Non-Customers"*contact_rate*total_population_of_market_demand)*(normal_regular_lost_percent + normal_regular_demotion_percent) + total_population_of_market_demand*normal_occasional_promotion_percent*(normal_regular_lost_percent - "normal_adoption_fraction_Non-Customers"*contact_rate))*(time_to_forget_experience*"normal_adoption_fraction_Was-Customers"*contact_rate*normal_occasional_promotion_percent + time_to_forget_experience*"normal_adoption_fraction_Was-Customers"*contact_rate*(normal_regular_lost_percent + normal_regular_demotion_percent)))^2 + 4*((- "normal_adoption_fraction_Non-Customers"*contact_rate*(normal_regular_lost_percent + normal_regular_demotion_percent) - normal_occasional_promotion_percent*"normal_adoption_fraction_Non-Customers"*contact_rate)*((normal_regular_lost_percent + normal_regular_demotion_percent)/(normal_occasional_promotion_percent)+1))*(time_to_forget_experience*"normal_adoption_fraction_Was-Customers"*contact_rate*normal_occasional_promotion_percent + time_to_forget_experience*"normal_adoption_fraction_Was-Customers"*contact_rate*(normal_regular_lost_percent + normal_regular_demotion_percent))*((total_population_of_market_demand*normal_occasional_lost_percent - "normal_adoption_fraction_Non-

Customers"*contact_rate*total_population_of_market_demand)*(normal_regular_lost_percent + normal_regular_demotion_percent) + total_population_of_market_demand*normal_occasional_promotion_percent*(normal_regular_lost_percent - "normal_adoption_fraction_Non-Customers"*contact_rate))*(total_population_of_market_demand*normal_occasional_promotion_percent))) / (2*((- "normal_adoption_fraction_Non-Customers"*contact_rate*(normal_regular_lost_percent + normal_regular_demotion_percent) - normal_occasional_promotion_percent*"normal_adoption_fraction_Non-Customers"*contact_rate)*((normal_regular_lost_percent + normal_regular_demotion_percent)/(normal_occasional_promotion_percent)+1))*(time_to_forget_experience*"normal_adoption_fraction_Was-Customers"*contact_rate*normal_occasional_promotion_percent + time_to_forget_experience*"normal_adoption_fraction_Was-Customers"*contact_rate*(normal_regular_lost_percent + normal_regular_demotion_percent)))))

UNITS: People

DOCUMENT: The stock reveals the number of Occasional Attainable Customers among total population of market demand, at any point in time.

Based on experience and observations it is assumed that Occasional Attainable Customers are people who purchase at store: {8 orders/person/month}, on average.

INFLOWS:

occasional_creation_rate = ("Non-Customers_converted_through_WOM"+R&D_Policy_Advertising.NC_adoption_from_advertising) {UNIFLOW}

UNITS: people / month

regular_customer_demotion_rate = Regular_Attainable_Customers*regular_demotion_percent {UNIFLOW}

UNITS: people / month

was_customer_retry_rate = ("Was-Customers_converted_through_WOM"+R&D_Policy_Advertising.WC_adoption_from_advertising) {UNIFLOW}

UNITS: people / month

OUTFLOWS:

occasional_leaving_rate = (Occasional_Attainable_Customers*occasional_lost_percent) {UNIFLOW}

UNITS: people / month

occasional_customer_promotion_rate = (Occasional_Attainable_Customers*occasional_promotion_percent)+R&D_Policy_Advertising.OC_adoption_from_advertising {UNIFLOW}

UNITS: people / month

Regular_Attainable_Customers(t) = Regular_Attainable_Customers(t - dt) + (occasional_customer_promotion_rate - regular_customer_demotion_rate - regular_customer_leaving_rate) * dt

INIT Regular_Attainable_Customers = (MAX(0.01, ((-((-"normal_adoption_fraction_Non-Customers"*contact_rate*(normal_regular_lost_percent + normal_regular_demotion_percent) -

normal_occasional_promotion_percent*"normal_adoption_fraction_Non-Customers"*contact_rate)*((normal_regular_lost_percent + normal_regular_demotion_percent)/(normal_occasional_promotion_percent)+1))*(total_population_of_market_demand*normal_occasional_promotion_percent) - ((-"normal_adoption_fraction_Non-Customers"*contact_rate +"normal_adoption_fraction_Was-Customers"*contact_rate)*(normal_occasional_promotion_percent + normal_regular_lost_percent + normal_regular_demotion_percent))*(time_to_forget_experience*total_population_of_market_demand*normal_occasional_promotion_percent*normal_regular_lost_percent + time_to_forget_experience*total_population_of_market_demand*normal_occasional_lost_percent*(normal_regular_lost_percent + normal_regular_demotion_percent)) + ((total_population_of_market_demand*normal_occasional_lost_percent - "normal_adoption_fraction_Non-Customers"*contact_rate*total_population_of_market_demand)*(normal_regular_lost_percent + normal_regular_demotion_percent) + total_population_of_market_demand*normal_occasional_promotion_percent*(normal_regular_lost_percent - "normal_adoption_fraction_Non-Customers"*contact_rate))*(time_to_forget_experience*"normal_adoption_fraction_Was-Customers"*contact_rate*normal_occasional_promotion_percent + time_to_forget_experience*"normal_adoption_fraction_Was-Customers"*contact_rate*(normal_regular_lost_percent + normal_regular_demotion_percent)) - SQRT((((- "normal_adoption_fraction_Non-Customers"*contact_rate*(normal_regular_lost_percent + normal_regular_demotion_percent) - normal_occasional_promotion_percent*"normal_adoption_fraction_Non-Customers"*contact_rate)*((normal_regular_lost_percent + normal_regular_demotion_percent)/(normal_occasional_promotion_percent)+1))*(total_population_of_market_demand*normal_occasional_promotion_percent) + ((-"normal_adoption_fraction_Non-Customers"*contact_rate +"normal_adoption_fraction_Was-Customers"*contact_rate)*(normal_occasional_promotion_percent + normal_regular_lost_percent + normal_regular_demotion_percent))*(time_to_forget_experience*total_population_of_market_demand*normal_occasional_promotion_percent*normal_regular_lost_percent + time_to_forget_experience*total_population_of_market_demand*normal_occasional_lost_percent*(normal_regular_lost_percent + normal_regular_demotion_percent)) - ((total_population_of_market_demand*normal_occasional_lost_percent - "normal_adoption_fraction_Non-Customers"*contact_rate*total_population_of_market_demand)*(normal_regular_lost_percent + normal_regular_demotion_percent) + total_population_of_market_demand*normal_occasional_promotion_percent*(normal_regular_lost_percent - "normal_adoption_fraction_Non-Customers"*contact_rate))*(time_to_forget_experience*"normal_adoption_fraction_Was-Customers"*contact_rate*normal_occasional_promotion_percent + time_to_forget_experience*"normal_adoption_fraction_Was-Customers"*contact_rate*(normal_regular_lost_percent + normal_regular_demotion_percent)))^2 + 4*((- "normal_adoption_fraction_Non-Customers"*contact_rate*(normal_regular_lost_percent + normal_regular_demotion_percent) - normal_occasional_promotion_percent*"normal_adoption_fraction_Non-

Customers"*contact_rate)*((normal_regular_lost_percent + normal_regular_demotion_percent)/(normal_occasional_promotion_percent)+1))*(time_to_forget_experience*"normal_adoption_fraction_Was-Customers"*contact_rate*normal_occasional_promotion_percent + time_to_forget_experience*"normal_adoption_fraction_Was-Customers"*contact_rate*(normal_regular_lost_percent + normal_regular_demotion_percent))*((total_population_of_market_demand*normal_occasional_lost_percent - "normal_adoption_fraction_Non-Customers"*contact_rate*total_population_of_market_demand)*(normal_regular_lost_percent + normal_regular_demotion_percent) + total_population_of_market_demand*normal_occasional_promotion_percent*(normal_regular_lost_percent - "normal_adoption_fraction_Non-Customers"*contact_rate))*(total_population_of_market_demand*normal_occasional_promotion_percent))) / (2*((- "normal_adoption_fraction_Non-Customers"*contact_rate*(normal_regular_lost_percent + normal_regular_demotion_percent) - normal_occasional_promotion_percent*"normal_adoption_fraction_Non-Customers"*contact_rate)*((normal_regular_lost_percent + normal_regular_demotion_percent)/(normal_occasional_promotion_percent)+1))*(time_to_forget_experience*"normal_adoption_fraction_Was-Customers"*contact_rate*normal_occasional_promotion_percent + time_to_forget_experience*"normal_adoption_fraction_Was-Customers"*contact_rate*(normal_regular_lost_percent + normal_regular_demotion_percent))))))

UNITS: People

DOCUMENT: The stock reveals the number of Regular Attainable Customers among total population of market demand, at any point in time.

Based on experience and observations it is assumed that Regular Attainable Customers are people who purchase at store regularly: {15 orders/person/month}, on average.

INFLOWS:

occasional_customer_promotion_rate = (Occasional_Attainable_Customers*occasional_promotion_percent)+R&D_Policy_Advertising.OC_adoption_from_advertising {UNIFLOW}

UNITS: people / month

OUTFLOWS:

regular_customer_demotion_rate = Regular_Attainable_Customers*regular_demotion_percent {UNIFLOW}

UNITS: people / month

regular_customer_leaving_rate = (Regular_Attainable_Customers*regular_lost_percent) {UNIFLOW}

UNITS: people / month

"Was-Customers"(t) = "Was-Customers"(t - dt) + (regular_customer_leaving_rate + occasional_leaving_rate - was_customer_retry_rate - forgetting_experience_rate) * dt

INIT "Was-Customers" = {(MAX(0, (time_to_forget_experience*market_size*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion*normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + time_to_forget_experience*market_size*normal_occasional_customer_lost_percent*effect_o f_customer_satisfaction_on_occasional_leaving_rate*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate)*((-((-adoption_fraction_Non_customer*contact_rate*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate) - normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion*adoption_fraction_Non_customer*contact_rate)*((normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate)/(normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion)+1))*(market_size*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion) - ((-adoption_fraction_Non_customer*contact_rate +adoption_fraction*contact_rate)*(normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion + normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate))*(time_to_forget_experience*market_size*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion*normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + time_to_forget_experience*market_size*normal_occasional_customer_lost_percent*effect_of_customer_satisfaction_on_occasional_leaving_rate*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate)) + ((market_size*normal_occasional_customer_lost_percent*effect_of_customer_satisfaction_on_occasional_leaving_rate - adoption_fraction_Non_customer*contact_rate*market_size)*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate) + market_size*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate - adoption_fraction_Non_customer*contact_rate))*(time_to_forget_experience*adoption_fraction*contact_rate*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion + time_to_forget_experience*adoption_fraction*contact_rate*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate)) - SQRT((((-adoption_fraction_Non_customer*contact_rate*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate) -

normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion*adoption_fraction_Non_customer*contact_rate)*((normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate)/(normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion)+1))*(market_size*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion) + ((-adoption_fraction_Non_customer*contact_rate +adoption_fraction*contact_rate)*(normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion + normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate))*(time_to_forget_experience*market_size*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion*normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + time_to_forget_experience*market_size*normal_occasional_customer_lost_percent*effect_of_customer_satisfaction_on_occasional_leaving_rate*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate)) - ((market_size*normal_occasional_customer_lost_percent*effect_of_customer_satisfaction_on_occasional_leaving_rate - adoption_fraction_Non_customer*contact_rate*market_size)*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate) + market_size*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate - adoption_fraction_Non_customer*contact_rate))*(time_to_forget_experience*adoption_fraction*contact_rate*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion + time_to_forget_experience*adoption_fraction*contact_rate*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate)))^2 + 4*((- adoption_fraction_Non_customer*contact_rate*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate) - normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion*adoption_fraction_Non_customer*contact_rate)*((normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate)/(normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion)+1))*(time_to_forget_experience*adoption_fraction*contact_rate*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion + time_to_forget_experience*adoption_fraction*contact_rate*(normal_regular_customer_lost_ percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate))*((market_size*normal_occasional_customer_lost_percent*effect_of_customer_satisfaction_on_occasional_leaving_rate - adoption_fraction_Non_customer*contact_rate*market_size)*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate) + market_size*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate - adoption_fraction_Non_customer*contact_rate))*(market_size*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion))) / (2*((-adoption_fraction_Non_customer*contact_rate*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate) - normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion*adoption_fraction_Non_customer*contact_rate)*((normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate)/(normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion)+1))*(time_to_forget_experience*adoption_fraction*contact_rate*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion + time_to_forget_experience*adoption_fraction*contact_rate*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate)))))/(market_size*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion + (time_to_forget_experience*adoption_fraction*contact_rate*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion + time_to_forget_experience*adoption_fraction*contact_rate*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate))*((-((-adoption_fraction_Non_customer*contact_rate*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate) - normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion*adoption_fraction_Non_customer*contact_rate)*((normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate)/(normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion)+1))*(market_size*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion) - ((-adoption_fraction_Non_customer*contact_rate +adoption_fraction*contact_rate)*(normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion +

normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate))*(time_to_forget_experience*market_size*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion*normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + time_to_forget_experience*market_size*normal_occasional_customer_lost_percent*effect_of_customer_satisfaction_on_occasional_leaving_rate*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate)) + ((market_size*normal_occasional_customer_lost_percent*effect_of_customer_satisfaction_on_occasional_leaving_rate - adoption_fraction_Non_customer*contact_rate*market_size)*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate) + market_size*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate - adoption_fraction_Non_customer*contact_rate))*(time_to_forget_experience*adoption_fraction*contact_rate*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion + time_to_forget_experience*adoption_fraction*contact_rate*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate)) - SQRT((((-adoption_fraction_Non_customer*contact_rate*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate) - normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion*adoption_fraction_Non_customer*contact_rate)*((normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate)/(normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion)+1))*(market_size*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion) + ((-adoption_fraction_Non_customer*contact_rate +adoption_fraction*contact_rate)*(normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion + normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate))*(time_to_forget_experience*market_size*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion*normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + time_to_forget_experience*market_size*normal_occasional_customer_lost_percent*effect_of_customer_satisfaction_on_occasional_leaving_rate*(normal_regular_customer_lost_percen

t*effect_of_customer_satisfaction_on_regular_leaving_rate +
normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate)) -
((market_size*normal_occasional_customer_lost_percent*effect_of_customer_satisfaction_on_occasional_leaving_rate -
adoption_fraction_Non_customer*contact_rate*market_size)*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate +
normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate) +
market_size*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate -
adoption_fraction_Non_customer*contact_rate))*(time_to_forget_experience*adoption_fraction*contact_rate*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion +
time_to_forget_experience*adoption_fraction*contact_rate*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate +
normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate)))^2 + 4*((-
adoption_fraction_Non_customer*contact_rate*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate +
normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate) -
normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion*adoption_fraction_Non_customer*contact_rate)*((normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate +
normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate)/(normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion)+1))*(time_to_forget_experience*adoption_fraction*contact_rate*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion +
time_to_forget_experience*adoption_fraction*contact_rate*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate +
normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate))*((market_size*normal_occasional_customer_lost_percent*effect_of_customer_satisfaction_on_occasional_leaving_rate -
adoption_fraction_Non_customer*contact_rate*market_size)*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate +
normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate) +
market_size*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate -
adoption_fraction_Non_customer*contact_rate))*(market_size*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion))) / (2*((-
adoption_fraction_Non_customer*contact_rate*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate +
normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate) -
normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_pro

motion*adoption_fraction_Non_customer*contact_rate)*((normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate)/(normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion)+1))*(time_to_forget_experience*adoption_fraction*contact_rate*normal_occasional_promotion_percent*effect_of_customer_satisfaction_on_occasional_promotion + time_to_forget_experience*adoption_fraction*contact_rate*(normal_regular_customer_lost_percent*effect_of_customer_satisfaction_on_regular_leaving_rate + normal_regular_demotion_percent*effect_of_customer_satisfaction_on_regular_demotion_rate)))))))}
{(Regular_Customers*normal_regular_customer_lost_percent+Occasional_Customers*normal_occasional_customer_lost_percent)*time_to_forget_experience}
{(Regular_Customers*normal_regular_customer_lost_percent+Occasional_Customers*normal_occasional_customer_lost_percent)*(time_to_forget_experience)} {IF equilibrium=1 THEN } {ELSE 100} 265

UNITS: People

DOCUMENT: The stock reveals the number of Was-Customers among the total population of market demand, at any point in time.

1. Was-Customers are people who were actual customers in the past, but they did not get a positive experience from service thus these people do not want come back to the restaurant.

It is assumed (based on experience and observations), that these people need time to forget experience 12 months. After that time they might totally forget about their negative experience and become Non-Customers.

Another possibilities are:

2. Was-Customers might be converted from word-of.mouth based on referrals from attainable customers (Occasional Attainable Customers and Regular Attainable Customers) and become Occasional Attainable Customers again.

3. Was- Customers might be encouraged by advertising and become Occasional Attainable Customers again., however.:

***advertising is a policy and in business as usual (BAU) scenario DOES NOT influences the behavior of customers'structure, thus the customers' behavior is primarily driven by word-of-mouth. ***

INFLOWS:

regular_customer_leaving_rate = (Regular_Attainable_Customers*regular_lost_percent) {UNIFLOW}

UNITS: people / month

occasional_leaving_rate = (Occasional_Attainable_Customers*occasional_lost_percent) {UNIFLOW}

UNITS: people / month

OUTFLOWS:

was_customer_retry_rate = ("Was-Customers_converted_through_WOM"+R&D_Policy_Advertising.WC_adoption_from_advertising) {UNIFLOW}
UNITS: people / month
forgetting_experience_rate = ("Was-Customers"/time_to_forget_experience) {UNIFLOW}
UNITS: people / month
actual_customers = (SMTH3(attainable_customers*sale_index, 1))*Internal_Processes_base.Enclose
UNITS: People
"actual_non-customers" = total_population_of_market_demand-actual_customers
UNITS: People
actual_sales_rate = MIN(desired_sales_rate, Internal_Processes_real.actual_production_capacity)*Internal_Processes_base.Enclose
UNITS: orders/month
DOCUMENT: This variable reveals the actual sales rate among the desired sales rate at any point in time.

The actual sales rate is limited by:

1. the actual production capacity, or
2. the desired sales rate

If the desired sales rate is above the actual production capacity , the actual sales rate will be limited by the actual production capacity and equal to actual production capacity.

If the desired sales rate is less than the actual production capacity , the actual sales rate will be limited by the desired sales rate and equal to the desired sales rate.

"adoption_fraction_Non-Customers" = "normal_adoption_fraction_Non-Customers"*.service_failure_rate_effect_on_adoption_fraction*Internal_Processes_base.Enclose
UNITS: dmnl
"adoption_fraction_Was-Customers" = .service_failure_rate_effect_on_adoption_fraction*"normal_adoption_fraction_Was-Customers"*Internal_Processes_base.Enclose
UNITS: dmnl
attainable_customers = SMTH3((Occasional_Attainable_Customers+Regular_Attainable_Customers), 2)
UNITS: People
DOCUMENT: This variable represents all reachable people in the market (part of the total population of market demand) and it is determined by the sum of Occasional Attainable Customers, and Regular Attainable Customers.

***The attainable customers (Occasional Attainable Customers, and Regular Attainable Customers) might have different origin. They could become attainable customers because of:

1. living in the near area, and being customer in past (the stocks of Occasional Attainable Customers and Regular Attainable Customers are not initialized with 0, but with numbers:

Occasional Attainable Customers= 326, and

Regular Attainable Customers = 162, which were taken from company's database and averaged to the degree to present the right behavior of the reference mode).

2. being persuaded by positive referrals from a third party,

3. being encouraged by advertising.

***If the restaurant was overcrowded, and they could not be served they still want to come back to the restaurant another day in the month, when the restaurant will no be full.

***Based on that number the manager of the restaurant can adjust to an appropriate level the strategic plan to gain all of the attainable customers, thus all attainable customers will become actual customers. This means all desired sales rate (from attainable customers) will be equal actual sales rate.

*** Advertising is a policy, and in business as usual (BAU) scenario DOES NOT influence the behavior of customers' structure; thus, the customers' behavior is primarily driven by word-of-mouth. ***

average_order_rate_per_occasional_customer_per_month = 8

UNITS: orders/person/month

DOCUMENT: The variable average order rate per occasional customer per month expresses how often, on a monthly base, Occasional Attainable Customers might visit the restaurant.

It is assumed (based on experience, observations, and numerical data from the company's database) that the Occasional Attainable Customers visit the restaurant 15 times monthly, on average.

{8 orders/person/month}, on average.

average_order_rate_per_regular_customer_per_month = 15

UNITS: orders/person/month

DOCUMENT: The variable average order rate per regular customer per month expresses how often, on a monthly base, Regular Attainable Customers might visit the restaurant.

It is assumed (based on experience, observations, and numerical data from the company's database) that the Regular Attainable Customers visit the restaurant 15 times monthly, on average.

contact_rate = 2

UNITS: people / people / month

DOCUMENT: The parameter defines how often attainable customers (Occasional Attainable Customers and Regular Attainable Customers) come into contact with their friends who are Non-Customers or Was-Customers each month.

"contacts_Occasional_Attainable_Customers_with_Non-Customers" = "probability_of_contact_with_Non-Customers"*total_Occasional_Attainable_Customers_contacts

UNITS: people / month

"contacts_Occasional_Attainable_Customers_with_Was-Customers" = "probability_of_contact_with_Was-Customers"*total_Occasional_Attainable_Customers_contacts
UNITS: people / month
"contacts_Regular_Attainable_Customers_with_Non-Customers" = "probability_of_contact_with_Non-Customers"*total_Regular_Attainable_Customers_contacts
UNITS: people / month
"contacts_Regular_Attainable_Customers_with_Was-Customers" = "probability_of_contact_with_Was-Customers"*total_Regular_Attainable_Customers_contacts
UNITS: people / month
desired_sales_rate = (potential_repeat_order_rate)*Internal_Processes_base.Enclose
UNITS: orders/month
DOCUMENT: It is determined by the potential repeat order rate.

It reveals potential sales at any point in time.

When the restaurant is closed for wintertime (1st January- 31st March) each year, the model automatically makes it equal to 0 multiplying the desired sales rate variable with Enclose variable, which is embedded in the Internal Processes base module.

equilibrium = .equilibrium_switch
UNITS: dmnl
market_size = 65000 {41000 population in Bergenhus and 24000 tourists/ visitors/ travels}
UNITS: People
DOCUMENT: The sum of

- people living in the area of Bergenhus in Bergen: 42,790 , and

- assumed number (based on available readings) of tourists/visitors/business travelers in the area of Bergenhus in the city Bergen : 22,210 people.

The sum is:

42,790 + 22,210 = 65 000 [people]
"Non-Customers_converted_through_WOM" = "adoption_fraction_Non-Customers"*("contacts_Occasional_Attainable_Customers_with_Non-Customers"+"contacts_Regular_Attainable_Customers_with_Non-Customers")
UNITS: people / month
"normal_adoption_fraction_Non-Customers" = 0.02942
UNITS: dmnl
DOCUMENT: The persuasiveness of the attainable customers (Occasional Attainable Customers and Regular Attainable Customers) when they meet the Non-Customers.

It is assumed based on available readings:
normal adoption fraction Non-Customers= 0.02942
"normal_adoption_fraction_Was-Customers" = 0.02942
UNITS: dmnl

DOCUMENT: The persuasiveness of the attainable customers (Occasional Attainable Customers and Regular Attainable Customers) when they meet the Was-Customers.

It is assumed based on available readings:
normal adoption fraction Was-Customers= 0.02942
normal_occasional_lost_percent = .05
UNITS: dmnl/month
normal_occasional_promotion_percent = .05
UNITS: dmnl/month
normal_regular_demotion_percent = .05
UNITS: dmnl/month
normal_regular_lost_percent = .05
UNITS: dmnl/month
occasional_lost_percent = normal_occasional_lost_percent*.service_failure_rate_effect_on_customers'_churn*Internal_Processes_base.Enclose
UNITS: dmnl/month
occasional_promotion_percent = normal_occasional_promotion_percent*.service_failure_rate_effect_on_adoption_fraction*Internal_Processes_base.Enclose
UNITS: dmnl/month
Potential_N&W_Customers = "Non-Customers"+"Was-Customers"
UNITS: People
potential_repeat_order_rate = potential_repeat_order_rate_OC+potential_repeat_order_rate_RC
UNITS: orders/month
DOCUMENT: It is determined by the sum of potential repeat order rate OC from Occasional Attainable Customers and potential repeat order rate RC from Regular Attainable Customers.
potential_repeat_order_rate_OC = Occasional_Attainable_Customers*average_order_rate_per_occasional_customer_per_month
UNITS: orders/month
DOCUMENT: It reveals potential repeat order rate of Occasional Attainable Customers at any point in time.

potential_repeat_order_rate_RC = Regular_Attainable_Customers*average_order_rate_per_regular_customer_per_month
UNITS: orders/month
DOCUMENT: It reveals potential repeat order rate of Regular Attainable Customers at any point in time.
"probability_of_contact_with_Non-Customers" = ("Non-Customers"/total_population_of_market_demand)
UNITS: dmnl
"probability_of_contact_with_Was-Customers" = ("Was-Customers"/total_population_of_market_demand)
UNITS: dmnl

regular_demotion_percent =
normal_regular_demotion_percent*.service_failure_rate_effect_on_customers'_churn*Internal_Processes_base.Enclose
UNITS: dmnl/month
regular_lost_percent =
normal_regular_lost_percent*.service_failure_rate_effect_on_customers'_churn*Internal_Processes_base.Enclose
UNITS: dmnl/month
sale_index = (SAFEDIV(actual_sales_rate, desired_sales_rate))
UNITS: dmnl
DOCUMENT: Sale index indicates the degree of actual sales rate in relation to desired sales rate.

The sale index indicates the degree of actual sales rate to the desired sales rate.
a.The sale index equals to 1.0 means that the actual sales rate is equal to the desired sales rate, and there are no lost sales (actual sales are top-notch).
b In case the value of the sale index dropped below 1.0, it indicates the company's poor performance and that the actual sales rate could be higher because, in reality, not all attainable customers were actual customers.

*** If value of ratio drops below 1, the restaurant manager wants catch all desired sales by increasing schedule pressure (BAU scenario.)
Schedule pressure leads to:
-an increase in the employee's productivity (normal practiced productivity, normal skilled productivity, and normal rookies' productivity),
-building up burnout, and
-an increase in service failure rate.

*Burnout decreases normal employees' productivity.
*service failure rate affects:
- the customers' adoption fraction (through service failure rate effect on adoption fraction): adoption fraction Was-Customers, adoption fraction Non-Customers, and occasional promotion percent.

- the customers' churn (through service failure rate effect on customers' churn): regular lost percent, regular demotion percent, and occasional lost percent.

time_to_forget_experience = 12
UNITS: months
total_Occasional_Attainable_Customers_contacts =
Occasional_Attainable_Customers*contact_rate
UNITS: people / month
total_population_of_market_demand = market_size*0.05
UNITS: people
DOCUMENT: The variable expresses market demand, in the district of Bergenhus, in Bergen, Norway. It is assumed to be 5% of market size:

65 000* 0.05= 3 250

The sum of Occasional Attainable Customers, Regular Attainable Customers, Non-Customers and Was-Customers is the total population of market demand.
total_Regular_Attainable_Customers_contacts = Regular_Attainable_Customers*contact_rate
UNITS: people / month
"Was-Customers_converted_through_WOM" = "adoption_fraction_Was-Customers"*("contacts_Regular_Attainable_Customers_with_Was-Customers"+"contacts_Occasional_Attainable_Customers_with_Was-Customers")
UNITS: people / month
DOCUMENT: The variable Was-Customers converted through WOM is affected by:

· contacts Occasional Attainable Customers with Was-Customers: defined by the probability of contact with Was-Customers, and the total Regular Attainable Customers contacts

· contacts Regular Attainable Customers with Was-Customers: defined by the probability of contact with Was-Customers, and the total Occasional Attainable Customers contacts

· adoption fraction Was-Customers.

Data_&_Reference_mode:
data_customers = GRAPH(TIME)
Points(15361): (0,00, 0,0), (0,00390625, 0,0), (0,0078125, 0,0), (0,01171875, 0,0), (0,015625, 0,0), (0,01953125, 0,0), (0,0234375, 0,0), (0,02734375, 0,0), (0,03125, 0,0), (0,03515625, 0,0), (0,0390625, 0,0), (0,04296875, 0,0), (0,046875, 0,0), (0,05078125, 0,0), (0,0546875, 0,0), (0,05859375, 0,0), (0,0625, 0,0), (0,06640625, 0,0), (0,0703125, 0,0), (0,07421875, 0,0), (0,078125, 0,0), (0,08203125, 0,0), (0,0859375, 0,0), (0,08984375, 0,0), (0,09375, 0,0), (0,09765625, 0,0), (0,1015625, 0,0), (0,10546875, 0,0), (0,109375, 0,0), (0,11328125, 0,0), (0,1171875, 0,0), (0,12109375, 0,0), (0,125, 0,0), (0,12890625, 0,0), (0,1328125, 0,0), (0,13671875, 0,0), (0,140625, 0,0), (0,14453125, 0,0), (0,1484375, 0,0), (0,15234375, 0,0), (0,15625, 0,0), (0,16015625, 0,0), (0,1640625, 0,0), (0,16796875, 0,0), (0,171875, 0,0), (0,17578125, 0,0), (0,1796875, 0,0), (0,18359375, 0,0), (0,1875, 0,0), (0,19140625, 0,0), (0,1953125, 0,0), (0,19921875, 0,0), (0,203125, 0,0), (0,20703125, 0,0), (0,2109375, 0,0), (0,21484375, 0,0), (0,21875, 0,0), (0,22265625, 0,0), (0,2265625, 0,0), (0,23046875, 0,0), (0,234375, 0,0), (0,23828125, 0,0), (0,2421875, 0,0), (0,24609375, 0,0), (0,25, 0,0), (0,25390625, 0,0), (0,2578125, 0,0), (0,26171875, 0,0), (0,265625, 0,0), (0,26953125, 0,0), (0,2734375, 0,0), (0,27734375, 0,0), (0,28125, 0,0), (0,28515625, 0,0), (0,2890625, 0,0), (0,29296875, 0,0), (0,296875, 0,0), (0,30078125, 0,0), (0,3046875, 0,0), (0,30859375, 0,0), (0,3125, 0,0), (0,31640625, 0,0), (0,3203125, 0,0), (0,32421875, 0,0), (0,328125, 0,0), (0,33203125, 0,0), (0,3359375, 0,0), (0,33984375, 0,0), (0,34375, 0,0), (0,34765625, 0,0), (0,3515625, 0,0), (0,35546875, 0,0), (0,359375, 0,0), (0,36328125, 0,0), (0,3671875, 0,0), (0,37109375, 0,0), (0,375, 0,0), (0,37890625, 0,0), (0,3828125, 0,0), (0,38671875, 0,0), ...
UNITS: Customers
data_practiced = GRAPH(TIME)
Points(15361): (0,00, 0,0), (0,00390625, 0,0), (0,0078125, 0,0), (0,01171875, 0,0), (0,015625, 0,0), (0,01953125, 0,0), (0,0234375, 0,0), (0,02734375, 0,0), (0,03125, 0,0),

(0,03515625, 0,0), (0,0390625, 0,0), (0,04296875, 0,0), (0,046875, 0,0), (0,05078125, 0,0), (0,0546875, 0,0), (0,05859375, 0,0), (0,0625, 0,0), (0,06640625, 0,0), (0,0703125, 0,0), (0,07421875, 0,0), (0,078125, 0,0), (0,08203125, 0,0), (0,0859375, 0,0), (0,08984375, 0,0), (0,09375, 0,0), (0,09765625, 0,0), (0,1015625, 0,0), (0,10546875, 0,0), (0,109375, 0,0), (0,11328125, 0,0), (0,1171875, 0,0), (0,12109375, 0,0), (0,125, 0,0), (0,12890625, 0,0), (0,1328125, 0,0), (0,13671875, 0,0), (0,140625, 0,0), (0,14453125, 0,0), (0,1484375, 0,0), (0,15234375, 0,0), (0,15625, 0,0), (0,16015625, 0,0), (0,1640625, 0,0), (0,16796875, 0,0), (0,171875, 0,0), (0,17578125, 0,0), (0,1796875, 0,0), (0,18359375, 0,0), (0,1875, 0,0), (0,19140625, 0,0), (0,1953125, 0,0), (0,19921875, 0,0), (0,203125, 0,0), (0,20703125, 0,0), (0,2109375, 0,0), (0,21484375, 0,0), (0,21875, 0,0), (0,22265625, 0,0), (0,2265625, 0,0), (0,23046875, 0,0), (0,234375, 0,0), (0,23828125, 0,0), (0,2421875, 0,0), (0,24609375, 0,0), (0,25, 0,0), (0,25390625, 0,0), (0,2578125, 0,0), (0,26171875, 0,0), (0,265625, 0,0), (0,26953125, 0,0), (0,2734375, 0,0), (0,27734375, 0,0), (0,28125, 0,0), (0,28515625, 0,0), (0,2890625, 0,0), (0,29296875, 0,0), (0,296875, 0,0), (0,30078125, 0,0), (0,3046875, 0,0), (0,30859375, 0,0), (0,3125, 0,0), (0,31640625, 0,0), (0,3203125, 0,0), (0,32421875, 0,0), (0,328125, 0,0), (0,33203125, 0,0), (0,3359375, 0,0), (0,33984375, 0,0), (0,34375, 0,0), (0,34765625, 0,0), (0,3515625, 0,0), (0,35546875, 0,0), (0,359375, 0,0), (0,36328125, 0,0), (0,3671875, 0,0), (0,37109375, 0,0), (0,375, 0,0), (0,37890625, 0,0), (0,3828125, 0,0), (0,38671875, 0,0), ...

UNITS: Employees

data_rookies = GRAPH(TIME)

Points(15361): (0,00, 0,0), (0,00390625, 0,0), (0,0078125, 0,0), (0,01171875, 0,0), (0,015625, 0,0), (0,01953125, 0,0), (0,0234375, 0,0), (0,02734375, 0,0), (0,03125, 0,0), (0,03515625, 0,0), (0,0390625, 0,0), (0,04296875, 0,0), (0,046875, 0,0), (0,05078125, 0,0), (0,0546875, 0,0), (0,05859375, 0,0), (0,0625, 0,0), (0,06640625, 0,0), (0,0703125, 0,0), (0,07421875, 0,0), (0,078125, 0,0), (0,08203125, 0,0), (0,0859375, 0,0), (0,08984375, 0,0), (0,09375, 0,0), (0,09765625, 0,0), (0,1015625, 0,0), (0,10546875, 0,0), (0,109375, 0,0), (0,11328125, 0,0), (0,1171875, 0,0), (0,12109375, 0,0), (0,125, 0,0), (0,12890625, 0,0), (0,1328125, 0,0), (0,13671875, 0,0), (0,140625, 0,0), (0,14453125, 0,0), (0,1484375, 0,0), (0,15234375, 0,0), (0,15625, 0,0), (0,16015625, 0,0), (0,1640625, 0,0), (0,16796875, 0,0), (0,171875, 0,0), (0,17578125, 0,0), (0,1796875, 0,0), (0,18359375, 0,0), (0,1875, 0,0), (0,19140625, 0,0), (0,1953125, 0,0), (0,19921875, 0,0), (0,203125, 0,0), (0,20703125, 0,0), (0,2109375, 0,0), (0,21484375, 0,0), (0,21875, 0,0), (0,22265625, 0,0), (0,2265625, 0,0), (0,23046875, 0,0), (0,234375, 0,0), (0,23828125, 0,0), (0,2421875, 0,0), (0,24609375, 0,0), (0,25, 0,0), (0,25390625, 0,0), (0,2578125, 0,0), (0,26171875, 0,0), (0,265625, 0,0), (0,26953125, 0,0), (0,2734375, 0,0), (0,27734375, 0,0), (0,28125, 0,0), (0,28515625, 0,0), (0,2890625, 0,0), (0,29296875, 0,0), (0,296875, 0,0), (0,30078125, 0,0), (0,3046875, 0,0), (0,30859375, 0,0), (0,3125, 0,0), (0,31640625, 0,0), (0,3203125, 0,0), (0,32421875, 0,0), (0,328125, 0,0), (0,33203125, 0,0), (0,3359375, 0,0), (0,33984375, 0,0), (0,34375, 0,0), (0,34765625, 0,0), (0,3515625, 0,0), (0,35546875, 0,0), (0,359375, 0,0), (0,36328125, 0,0), (0,3671875, 0,0), (0,37109375, 0,0), (0,375, 0,0), (0,37890625, 0,0), (0,3828125, 0,0), (0,38671875, 0,0), ...

UNITS: Employees

data_skilled = GRAPH(TIME)

Points(15361): (0,00, 0,0), (0,00390625, 0,0), (0,0078125, 0,0), (0,01171875, 0,0), (0,015625, 0,0), (0,01953125, 0,0), (0,0234375, 0,0), (0,02734375, 0,0), (0,03125, 0,0), (0,03515625, 0,0), (0,0390625, 0,0), (0,04296875, 0,0), (0,046875, 0,0), (0,05078125, 0,0), (0,0546875, 0,0), (0,05859375, 0,0), (0,0625, 0,0), (0,06640625, 0,0), (0,0703125, 0,0), (0,07421875, 0,0), (0,078125, 0,0), (0,08203125, 0,0), (0,0859375, 0,0), (0,08984375, 0,0),

(0,09375, 0,0), (0,09765625, 0,0), (0,1015625, 0,0), (0,10546875, 0,0), (0,109375, 0,0), (0,11328125, 0,0), (0,1171875, 0,0), (0,12109375, 0,0), (0,125, 0,0), (0,12890625, 0,0), (0,1328125, 0,0), (0,13671875, 0,0), (0,140625, 0,0), (0,14453125, 0,0), (0,1484375, 0,0), (0,15234375, 0,0), (0,15625, 0,0), (0,16015625, 0,0), (0,1640625, 0,0), (0,16796875, 0,0), (0,171875, 0,0), (0,17578125, 0,0), (0,1796875, 0,0), (0,18359375, 0,0), (0,1875, 0,0), (0,19140625, 0,0), (0,1953125, 0,0), (0,19921875, 0,0), (0,203125, 0,0), (0,20703125, 0,0), (0,2109375, 0,0), (0,21484375, 0,0), (0,21875, 0,0), (0,22265625, 0,0), (0,2265625, 0,0), (0,23046875, 0,0), (0,234375, 0,0), (0,23828125, 0,0), (0,2421875, 0,0), (0,24609375, 0,0), (0,25, 0,0), (0,25390625, 0,0), (0,2578125, 0,0), (0,26171875, 0,0), (0,265625, 0,0), (0,26953125, 0,0), (0,2734375, 0,0), (0,27734375, 0,0), (0,28125, 0,0), (0,28515625, 0,0), (0,2890625, 0,0), (0,29296875, 0,0), (0,296875, 0,0), (0,30078125, 0,0), (0,3046875, 0,0), (0,30859375, 0,0), (0,3125, 0,0), (0,31640625, 0,0), (0,3203125, 0,0), (0,32421875, 0,0), (0,328125, 0,0), (0,33203125, 0,0), (0,3359375, 0,0), (0,33984375, 0,0), (0,34375, 0,0), (0,34765625, 0,0), (0,3515625, 0,0), (0,35546875, 0,0), (0,359375, 0,0), (0,36328125, 0,0), (0,3671875, 0,0), (0,37109375, 0,0), (0,375, 0,0), (0,37890625, 0,0), (0,3828125, 0,0), (0,38671875, 0,0), ...
UNITS: Employees
data_total_employees = data_practiced+data_rookies+data_skilled
UNITS: Employees
data_total_employees_smth3 = SMTH3(data_total_employees, 0.25)
UNITS: Employees
expected_clients = GRAPH(TIME)
Points(15361): (0,00, 0,0), (0,00390625, 0,0), (0,0078125, 0,0), (0,01171875, 0,0), (0,015625, 0,0), (0,01953125, 0,0), (0,0234375, 0,0), (0,02734375, 0,0), (0,03125, 0,0), (0,03515625, 0,0), (0,0390625, 0,0), (0,04296875, 0,0), (0,046875, 0,0), (0,05078125, 0,0), (0,0546875, 0,0), (0,05859375, 0,0), (0,0625, 0,0), (0,06640625, 0,0), (0,0703125, 0,0), (0,07421875, 0,0), (0,078125, 0,0), (0,08203125, 0,0), (0,0859375, 0,0), (0,08984375, 0,0), (0,09375, 0,0), (0,09765625, 0,0), (0,1015625, 0,0), (0,10546875, 0,0), (0,109375, 0,0), (0,11328125, 0,0), (0,1171875, 0,0), (0,12109375, 0,0), (0,125, 0,0), (0,12890625, 0,0), (0,1328125, 0,0), (0,13671875, 0,0), (0,140625, 0,0), (0,14453125, 0,0), (0,1484375, 0,0), (0,15234375, 0,0), (0,15625, 0,0), (0,16015625, 0,0), (0,1640625, 0,0), (0,16796875, 0,0), (0,171875, 0,0), (0,17578125, 0,0), (0,1796875, 0,0), (0,18359375, 0,0), (0,1875, 0,0), (0,19140625, 0,0), (0,1953125, 0,0), (0,19921875, 0,0), (0,203125, 0,0), (0,20703125, 0,0), (0,2109375, 0,0), (0,21484375, 0,0), (0,21875, 0,0), (0,22265625, 0,0), (0,2265625, 0,0), (0,23046875, 0,0), (0,234375, 0,0), (0,23828125, 0,0), (0,2421875, 0,0), (0,24609375, 0,0), (0,25, 0,0), (0,25390625, 0,0), (0,2578125, 0,0), (0,26171875, 0,0), (0,265625, 0,0), (0,26953125, 0,0), (0,2734375, 0,0), (0,27734375, 0,0), (0,28125, 0,0), (0,28515625, 0,0), (0,2890625, 0,0), (0,29296875, 0,0), (0,296875, 0,0), (0,30078125, 0,0), (0,3046875, 0,0), (0,30859375, 0,0), (0,3125, 0,0), (0,31640625, 0,0), (0,3203125, 0,0), (0,32421875, 0,0), (0,328125, 0,0), (0,33203125, 0,0), (0,3359375, 0,0), (0,33984375, 0,0), (0,34375, 0,0), (0,34765625, 0,0), (0,3515625, 0,0), (0,35546875, 0,0), (0,359375, 0,0), (0,36328125, 0,0), (0,3671875, 0,0), (0,37109375, 0,0), (0,375, 0,0), (0,37890625, 0,0), (0,3828125, 0,0), (0,38671875, 0,0), ...
UNITS: Customers
expected_customers = SMTH1(expected_clients, 0.6, 0.8)*Internal_Processes_base.Enclose
UNITS: Customers

Finance:
Operating_profit(t) = Operating_profit(t - dt) + (Sales_revenue - Expenses) * dt

```
INIT Operating_profit = 0
   UNITS: nok
   INFLOWS:
      Sales_revenue = Customers.actual_sales_rate*Average_unit_price
         UNITS: nok/month
   OUTFLOWS:
      Expenses = Rental_costs+production_costs+labour_costs+advertising_costs
         UNITS: nok/month
advertising_costs =
(NC_advertising_costs+OC_advertising_costs+WC_advertising_costs)*Internal_Processes_b
ase.Enclose*R&D_Policy_Advertising.switch_2
   UNITS: nok/ month
allocation_of_revenue_for_production = 0.28
   UNITS: unitless
allocation_of_revenue_to_rent = 0.1
   UNITS: unitless
allocation_of_revenue_to_salary = 0.5
   UNITS: unitless
Average_unit_price = 10
   UNITS: nok/orders
labour_costs = Sales_revenue*allocation_of_revenue_to_salary
   UNITS: nok/ month
   DOCUMENT: Workforce*avg_wages

   USD/month
NC_advertising_costs = 1 {thousand nok }
   UNITS: nok/ month
"net_cash_flow_/(Operating_Profit)" = Sales_revenue-Expenses
   REPORT IN TABLE AS FLOW
   UNITS: nok/month
   DOCUMENT: revenues-expenses
OC_advertising_costs = 1{  thousand nok }
   UNITS: nok/ month
production_costs = Sales_revenue*allocation_of_revenue_for_production
   UNITS: nok/month
   DOCUMENT: 100000

   USD/month
Rental_costs = Sales_revenue*allocation_of_revenue_to_rent
   REPORT IN TABLE AS FLOW
   UNITS: nok/ month
WC_advertising_costs = 1{  thousand nok }
   UNITS: nok/ month

Internal_Processes_base:
cut_back_and_saving_effect = GRAPH(TIME*0)
Points: (60,00, 1,0000), (61,00, 1,0000), (62,00, 1,0000), (63,00, 1,0000), (64,00, 1,0000),
(65,00, 0,9079), (66,00, 0,8794), (67,00, 0,6500), (68,00, 0,6000), (69,00, 0,5500), (70,00,
0,5000), (71,00, 0,4000), (72,00, 0,3000), (73,00, 1,0000), (74,00, 1,0000), (75,00, 1,0000),
```

(76,00, 1,0000), (77,00, 0,8640), (78,00, 0,7982), (79,00, 0,6500), (80,00, 0,6000), (81,00, 0,5500), (82,00, 0,5000), (83,00, 0,4000), (84,00, 0,3000), (85,00, 1,0000), (86,00, 1,0000), (87,00, 1,0000), (88,00, 1,0000), (89,00, 0,8311), (90,00, 0,7741), (91,00, 0,6500), (92,00, 0,6000), (93,00, 0,5500), (94,00, 0,5000), (95,00, 0,4000), (96,00, 0,3000), (97,00, 1,0000), (98,00, 1,0000), (99,00, 1,0000), (100,00, 1,0000), (101,00, 0,6974), (102,00, 0,6645), (103,00, 0,6360), (104,00, 0,6000), (105,00, 0,5500), (106,00, 0,5000), (107,00, 0,4000), (108,00, 0,3000), (109,00, 1,0000), (110,00, 1,0000), (111,00, 1,0000), (112,00, 1,0000), (113,00, 0,8377), (114,00, 0,5987), (115,00, 0,5636), (116,00, 0,5263), (117,00, 0,5175), (118,00, 0,5000), (119,00, 0,4000), (120,00, 0,3000)

UNITS: dmnl

DOCUMENT: This graphical function shows the current manager's policy "save money"- which means fewer employees at work to decrease staff costs. As the model shows, this policy is very ineffective. It has a tremendous impact on the real internal processes, where schedule pressure affects the employees' productivity, and it affects building up employees' burnout. By that, the actual production capacity first increases and then depletes.

Moreover, it affects the service failure rate, leading to a lower number of attainable customers.

This graphical function is active after 60 months of model' simulation when there is no data for employees (the data was available from 2014 to 2019). It makes it possible to predict the future scenario, what will the situation looks like if the manager will practice the current strategy for the next five years.

This graphical function is crucial to reveal the reality of the restaurant's internal processes and it was make based on author's experience and observations (2014-2019).

Enclose = IF(.equilibrium_switch=1) THEN 1 ELSE IF(OPEN=1) THEN 1 ELSE seasonal_Open&Close

UNITS: dmnl

DOCUMENT: (1st January- 31st March)

CLOSED

The variable Enclose resets the model's variables which normally do not affect the state of the system when the restaurant is closed for wintertime (1st January- 31st March) each year.

(1st April-31st December)

OPEN

The variable Enclose does not affect the model's behavior when the restaurant is open (1st April-31st December)

month = INT(TIME MOD 12) + 1

UNITS: month

normal_practiced = IF(.equilibrium_switch=1) THEN 1 ELSE IF .equilibrium_switch=0 AND TIME <= 60 THEN Data_&_Reference_mode.data_practiced ELSE (Data_&_Reference_mode.data_practiced+1)*RANDOM(1, 2) *Enclose*cut_back_and_saving_effect

UNITS: Employees

normal_practiced_production = normal_practiced*normal_practiced_productivity

UNITS: orders/month
normal_practiced_productivity = 480
UNITS: orders/employee/month
normal_production_capacity =
normal_skilled_production+normal_practiced_production+normal_rookies'_production
UNITS: orders/month
normal_productivity =
(normal_skilled_productivity+normal_practiced_productivity+normal_rookies'_productivity)
UNITS: orders/employee/month
normal_rookies = IF(.equilibrium_switch=1) THEN 1   ELSE IF .equilibrium_switch=0
AND TIME <= 60 THEN Data_&_Reference_mode.data_rookies ELSE
(Data_&_Reference_mode.data_rookies+1)*RANDOM(0, 1)
*Enclose*cut_back_and_saving_effect
UNITS: Employees
normal_rookies'_production = normal_rookies*normal_rookies'_productivity
UNITS: orders/month
normal_rookies'_productivity = 100
UNITS: orders/employee/month
normal_skilled = IF(.equilibrium_switch=1) THEN 2 ELSE IF (.equilibrium_switch=0)
AND TIME <= 60 THEN Data_&_Reference_mode.data_skilled ELSE
(Data_&_Reference_mode.data_skilled+1)* RANDOM(1, 2)
*Enclose*cut_back_and_saving_effect
UNITS: Employees
normal_skilled_production = normal_skilled*normal_skilled_productivity
UNITS: orders/month
normal_skilled_productivity = 895
UNITS: orders/employee/month
normal_total_employees = normal_skilled+normal_practiced+normal_rookies
UNITS: Employees
OPEN = 0
UNITS: dmnl
practiced = normal_practiced+R&D_Policy_Hiring.Extra_Practiced
UNITS: Employees
practiced_production = normal_practiced_productivity*practiced
UNITS: orders/month
production_capacity = (skilled_production+practiced_production+rookies'_production)
UNITS: orders/month
rookies = normal_rookies+R&D_Policy_Hiring.Extra_Rookies
UNITS: Employees
rookies'_production = normal_rookies'_productivity*rookies
UNITS: orders/month
seasonal_Open&Close = IF (month < 4)THEN 0 ELSE 1
UNITS: dmnl
skilled = normal_skilled+R&D_Policy_Hiring.Extra_Skilled
UNITS: Employees
skilled_production = normal_skilled_productivity*skilled
UNITS: orders/month
total_employees = (skilled+practiced+rookies)
UNITS: Employees

Internal_Processes_real:
Burnout(t) = Burnout(t - dt) + (building - dissipating) * dt {NON-NEGATIVE}
INIT Burnout =
normal_burnout*normal_time_dissipate_burnout*Internal_Processes_base.Enclose
UNITS: month
INFLOWS:
building = schedule_pressure_effect_on_burnout*normal_burnout {UNIFLOW}
UNITS: Unitless
OUTFLOWS:
dissipating = Burnout/time_to_dissipate_burnout {UNIFLOW}
UNITS: Unitless
Workload(t) = Workload(t - dt) + (piling_up - actual_working_rate) * dt {NON-NEGATIVE}
INIT Workload = actual_production_capacity*Internal_Processes_base.Enclose
{Customers.desired_sales_rate*Internal_Processes_base.Open&Close}
UNITS: orders/month
INFLOWS:
piling_up = {IF(equilibrium_switch=1) THEN
PRODUCTIVITY_&_PRODUCTION_CAPACITY.normal_production_capacity*PRODUCTIVITY_&_PRODUCTION_CAPACITY.Open&Close ELSE}
Customers.desired_sales_rate*Internal_Processes_base.Enclose/workload's_time
{UNIFLOW}
UNITS: orders/month/Months
OUTFLOWS:
actual_working_rate =
Customers.actual_sales_rate*Internal_Processes_base.Enclose/workload's_time
{UNIFLOW}
UNITS: orders/month/Months
actual_practiced_production =
actual_practiced_productivity*Internal_Processes_base.practiced
UNITS: orders/month
actual_practiced_productivity =
Internal_Processes_base.normal_practiced_productivity*schedule_pressure_effect_on_productivity*burnout_effect_on_productivity
UNITS: orders/employee/month
actual_production_capacity =
(SMTH1(actual_skilled_production+actual_practiced_production+actual_rookies'_production,time_for_workload_to_affect_capacity,
Internal_Processes_base.production_capacity))*Internal_Processes_base.Enclose {DELAY CONVERTER}
UNITS: orders/month
DOCUMENT: This reveals actual production capacity, the sum of actual skilled production, actual practiced production, and actual rookies' production.
actual_productivity =
actual_skilled_productivity+actual_practiced_productivity+actual_rookies'_productivity
UNITS: orders/employee/month
actual_rookies'_production = actual_rookies'_productivity*Internal_Processes_base.rookies
UNITS: orders/month

actual_rookies'_productivity = Internal_Processes_base.normal_rookies'_productivity*schedule_pressure_effect_on_productivity*burnout_effect_on_productivity
UNITS: orders/employee/month
actual_skilled_production = actual_skilled_productivity*Internal_Processes_base.skilled
UNITS: orders/month
actual_skilled_productivity = Internal_Processes_base.normal_skilled_productivity*schedule_pressure_effect_on_productivity*burnout_effect_on_productivity
UNITS: orders/employee/month
burnout_effect_on_productivity = GRAPH(Burnout*Internal_Processes_base.Enclose)
Points: (0,0, 1,000), (10,0, 1,000), (20,0, 0,984126984127), (30,0, 0,95873015873), (40,0, 0,930158730159), (50,0, 0,888888888889), (60,0, 0,825396825397), (70,0, 0,726984126984), (80,0, 0,600), (90,0, 0,44126984127), (100,0, 0,200)
UNITS: dmnl
burnout_effect_on_time_to_recover = GRAPH(Burnout)
Points: (0,0, 1,000), (10,0, 1,000), (20,0, 1,200), (30,0, 1,400), (40,0, 1,600), (50,0, 1,750), (60,0, 1,880), (70,0, 1,930), (80,0, 1,950), (90,0, 1,980), (100,0, 2,000)
UNITS: dmnl
normal_burnout = 7
UNITS: dmnl
normal_schedule_pressure = INIT(schedule_pressure)
UNITS: dmnl
normal_time_dissipate_burnout = 1.2
UNITS: month
normalized_schedule_pressure = (schedule_pressure/normal_schedule_pressure)*Internal_Processes_base.Enclose
UNITS: dmnl
schedule_pressure = (SAFEDIV(Customers.desired_sales_rate, actual_production_capacity, 1))
UNITS: dmnl
DOCUMENT: It is defined itself by the desired sales rate and actual production capacity; desired sales rate divided by actual production capacity shows what the schedule pressure is, and if desired sales rate will be equal the actual production capacity, the value will be 1 which means there will be not schedule pressure.
schedule_pressure_effect_on_burnout = GRAPH(normalized_schedule_pressure)
Points: (0,000, 0,000), (0,200, 0,000), (0,400, 0,0507936507937), (0,600, 0,15873015873), (0,800, 0,444444444444), (1,000, 1,000), (1,200, 2,70476190476), (1,400, 4,09523809524), (1,600, 5,06666666667), (1,800, 5,69523809524), (2,000, 6,000)
UNITS: dmnl
schedule_pressure_effect_on_productivity = GRAPH(normalized_schedule_pressure)
Points: (0,000, 0,000), (0,200, 0,0190476190476), (0,400, 0,0571428571429), (0,600, 0,171428571429), (0,800, 0,457142857143), (1,000, 1,000), (1,200, 1,42222222222), (1,400, 1,71428571429), (1,600, 1,89206349206), (1,800, 1,94920634921), (2,000, 1,967)
UNITS: dmnl
DOCUMENT: An increase in the schedule pressure above 1 leads to an increase in the productivity. If the schedule pressure is below 1, there is a decrease in the productivity. This effect of schedule pressure on employees' productivity leads to counteracting feedback loop.
time_for_workload_to_affect_capacity = 2

UNITS: Months
time_to_dissipate_burnout = burnout_effect_on_time_to_recover*normal_time_dissipate_burnout
UNITS: month
DOCUMENT: burnout looses over time (it is a disspiation process)
workload's_time = 1
UNITS: month

R&D_Policy_Advertising:
NC_adoption_from_advertising = IF(switch=1) THEN (NC_advertising_effectiveness*Customers."Non-Customers"*Finance.NC_advertising_costs) ELSE 0
UNITS: people/ month
NC_advertising_effectiveness = 0.004
UNITS: 1/nok
OC_adoption_from_advertising = IF(switch=1) THEN (Finance.OC_advertising_costs*OC_advertising_effectiveness*Customers.Occasional_Attainable_Customers) ELSE 0
UNITS: people/ month
OC_advertising_effectiveness = 0.003 { per thousand nok }
UNITS: 1/nok
switch = IF .equilibrium_switch=1 THEN 0 ELSE IF .equilibrium_switch=0 AND TIME >60 THEN switch_2*Internal_Processes_base.Enclose ELSE 0
UNITS: dmnl
switch_2 = 0
UNITS: dmnl
WC_adoption_from_advertising = IF(switch=1) THEN (Finance.WC_advertising_costs*WC_advertising_effectiveness*Customers."Was-Customers") ELSE 0
UNITS: people/ month
WC_advertising_effectiveness = 0.002 { per thousand nok }
UNITS: 1/nok

R&D_Policy_Hiring:
Desired_extra_staff(t) = Desired_extra_staff(t - dt) + (changing_desired_extra_staff) * dt
INIT Desired_extra_staff = indicated_extra_staff
UNITS: Employees
DOCUMENT: 40

{workers}
INFLOWS:
changing_desired_extra_staff = desired_extra_staff_perception_gap/time_to_perceive_extra_staff_need
UNITS: employee/month
DOCUMENT: desired_workforce_perception_gap/time_to_perceive_workforce_needs

{workers / month}

Extra_Practiced(t) = Extra_Practiced(t - dt) + (gaining_experience + hiring_practiced - gaining_skills - practiced_leaving_rate - practiced_termination_rate) * dt
    INIT Extra_Practiced = {(time_to_gain_skills*(((hiring_rookies / ((1/time_to_gain_experience)+rookies_attrition_rate))/time_to_gain_experience)+(hiring_practiced)) / (1+time_to_gain_skills*practiced_attrition_rate))}+0
    UNITS: Employees
    INFLOWS:
        gaining_experience = (Extra_Rookies/time_to_gain_experience) {UNIFLOW}
            UNITS: employee/month
        hiring_practiced = IF switch=1 THEN ratio_practiced ELSE 0 {UNIFLOW}
            UNITS: employee/month
    OUTFLOWS:
        gaining_skills = (Extra_Practiced/time_to_gain_skills) {UNIFLOW}
            UNITS: employee/month
        practiced_leaving_rate = Extra_Practiced*practiced_attrition_rate {UNIFLOW}
            UNITS: employee/month
        practiced_termination_rate = (Extra_Practiced/DT)*seasonal_Close {UNIFLOW}
            UNITS: employee/month
Extra_Rookies(t) = Extra_Rookies(t - dt) + (hiring_rookies - gaining_experience - rookies_leaving_rate - rookies_termination_rate) * dt
    INIT Extra_Rookies = {(hiring_rookies / ((1/time_to_gain_experience)+rookies_attrition_rate))}+0
    UNITS: Employees
    INFLOWS:
        hiring_rookies = IF switch= 1 THEN ratio_rookies ELSE 0 {UNIFLOW}
            UNITS: employee/month
    OUTFLOWS:
        gaining_experience = (Extra_Rookies/time_to_gain_experience) {UNIFLOW}
            UNITS: employee/month
        rookies_leaving_rate = Extra_Rookies*rookies_attrition_rate {UNIFLOW}
            UNITS: employee/month
        rookies_termination_rate = (Extra_Rookies/DT)*seasonal_Close {UNIFLOW}
            UNITS: employee/month
Extra_Skilled(t) = Extra_Skilled(t - dt) + (gaining_skills - skilled_churn_rate - skilled_leaving_rate - skilled_termination_rate) * dt
    INIT Extra_Skilled = {((time_of_contract's_employment*((time_to_gain_skills*(((hiring_rookies / ((1/time_to_gain_experience)+rookies_attrition_rate))/time_to_gain_experience)+(hiring_practiced)) / (1+time_to_gain_skills*practiced_attrition_rate))/time_to_gain_skills))/(1+(time_of_contract's_employment*skilled_attrition_rate)))}+0
    UNITS: Employees
    INFLOWS:
        gaining_skills = (Extra_Practiced/time_to_gain_skills) {UNIFLOW}
            UNITS: employee/month
    OUTFLOWS:
        skilled_churn_rate = (Extra_Skilled/time_of_contract's_employment) {UNIFLOW}
            UNITS: employee/month
        skilled_leaving_rate = skilled_attrition_rate*Extra_Skilled {UNIFLOW}

UNITS: employee/month
skilled_termination_rate = (Extra_Skilled/DT)*seasonal_Close {UNIFLOW}
UNITS: employee/month
desired_extra_staff_perception_gap = indicated_extra_staff-Desired_extra_staff
UNITS: Employees
DOCUMENT: indicated_desired_workforce-Desired_Workforce

{workers}
employees_gap = (Desired_extra_staff-(Internal_Processes_base.total_employees-Internal_Processes_base.normal_total_employees))*Internal_Processes_base.Enclose
UNITS: Employees
DOCUMENT: (Desired_Workforce-Workforce)

workers
extra_staff = Extra_Rookies+Extra_Practiced+Extra_Skilled
UNITS: Employees
extra_staff_needed = {IF(actual_productivity=0) THEN 0 ELSE (potential_sales_rate/actual_productivity)*PRODUCTIVITY_&_PRODUCTION_CAPACITY.Open&Close} (SAFEDIV(Customers.desired_sales_rate, Internal_Processes_real.actual_productivity))*Internal_Processes_base.Enclose
UNITS: Employees
indicated_extra_staff = extra_staff_needed
UNITS: Employees
DOCUMENT: job_contract_signing_rate/productivity

workers
month = INT(TIME MOD 12) + 1
UNITS: month
normal_practiced_attrition_rate = 0.1
UNITS: dmnl/month
normal_rookies_attrition_rate = 0.1
UNITS: dmnl/month
normal_skilled_attrition_rate = 0.1
UNITS: dmnl/month
normal_workforce_adj_time = 1
UNITS: months
practiced_attrition_rate = .schedule_pressure_effect_on_extra_skilled_attrition_rate*normal_practiced_attrition_rate
UNITS: dmnl/month
ratio_practiced = workforce_adjustment_rate
UNITS: Employees/month
ratio_rookies = workforce_adjustment_rate
UNITS: Employees/month
rookies_attrition_rate = normal_rookies_attrition_rate*.schedule_pressure_effect_on_extra_practiced_attrition_rate
UNITS: dmnl/month
seasonal_Close = IF (month < 4)THEN 1 ELSE 0
UNITS: dmnl

```
skilled_attrition_rate =
.schedule_pressure_effect_on_extra_rookies'_attrition_rate*normal_skilled_attrition_rate
    UNITS: dmnl/month
switch = IF .equilibrium_switch = 1 THEN 0 ELSE IF  .equilibrium_switch = 0 AND TIME
>60   THEN switch_1*Internal_Processes_base.Enclose  ELSE 0
    UNITS: dmnl
switch_1 = 0
    UNITS: dmnl
time_of_contract's_employment = 6
    UNITS: months
time_to_gain_experience = 1
    UNITS: month
time_to_gain_skills = 1
    UNITS: month
time_to_perceive_extra_staff_need = 1
    UNITS: months
    DOCUMENT: 1

    months
workforce_adjustment_rate = Internal_Processes_base.Enclose*(SAFEDIV( employees_gap,
normal_workforce_adj_time))
    UNITS: employees/month
{ The model has 292 (292) variables (array expansion in parens).
  In root model and 7 additional modules with 7 sectors.
  Stocks: 11 (11) Flows: 25 (25) Converters: 256 (256)
  Constants: 42 (42) Equations: 239 (239) Graphicals: 24 (24)
  There are also 45 expanded macro variables.
  }
```