Agent-based Modeling for Scenario Analysis in Management Consulting

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Abstract

This paper investigates the modernization of a corporate practice called scenario analysis. It is widely used across the globe, originating from World War II, helping companies to gain a better understanding of potential future outcomes. In order to modernize scenario analysis, this paper will explore the novel approaches; of a hybrid development between Agent-Based Modeling (ABM) and scenario analysis, the utilization of bottom-up and industry-view approaches and introducing elements of human social behavior. All these features are integrated in a single scenario analysis, ABM, that will model the fundamental philosophy behind the daily operations of a large corporation, such as Deloitte.

This paper addresses more natural evolutions for scenarios, by looking at the firm's fundamental building blocks, rather than just an objective view based on the firm's financial statements. This model will focus on accurate representations of the daily interactions of an enterprise, especially improving the explainability and transparency of causality in scenario analysis generated by the models, in order to achieve enduring agreements among executives about the firm's future.

With this novel approach to scenario analysis, the modeling of a firm with the use of an ABM, there is the potential to provide more in-depth micro-observations of the future, rather than the conventional scenario analysis methods performed today.

Keywords

Agent-based modeling, scenario analysis, management consulting, group model building, functional approximators, Deloitte LLP, Simudyne SDK

1 Introduction

With constant improvements in technology in both hardware potential and software applications, many new forms of market analysis have developed that leverage greater computational capability. This paper will look at the union of a relatively new technological approach in the form of agent-based modeling within the context of the more traditional tool of scenario analysis.

This paper aims to investigate the novel approach in the modernization process of utilizing scenario analysis, with the use of Agent-Based Modeling (ABM). The general application of scenario analysis is to generate best-, base-, and worst-case scenario analysis of a firm's financial outcome, based on potential financial and economic inputs, or future corporate decisions. For example, this paper will focus on people-driven services, such as consulting, where some of the key variables are the number of available consultants, more specifically the total availability (count), their billable hour rate, working hours, utilization rate (expected downtime), current running contracts, future contracts and expected contracts, in order to derive expected revenue. This topic is explained in further detail in Section 3, Tables 1 and 2; however, the standard approach to scenario analysis is simply to organize mathematical equations to solve for the best-, base-, and worst-case scenarios and, consequently, there is a lot of information lost throughout the natural evolution of the company to achieve the derived causality, leaving an opening for further innovation, which this paper will explore with the use of ABMs.

The first innovative procedure comes from the hybrid development between agent-based modeling and scenario analysis, where the two systems complement each other in order to provide a more in-depth explanation of the causality (not prediction) of a scenario, by building on the transparency and explainability.

Transparency is a key aspect of the new approach of scenario analysis with ABMs and is why many practitioners refer to ABMs as a "glass box" approach, in contrast to a "black box" approach commonly used in reference to machine learning. It is essential to provide the users with a clear understanding and representation of the model's development and interactions with each operation, as compared to standard approaches, which simply provide an input-output method without explicitly expressing the approach to the solution, which can be seen in Section 2.3. Consequently, utilizing ABMs provides the unique opportunity to generate a scenario analysis solution via a bottom-up and industry-view, rather than a conventional top-down profit and loss (P&L) or cash-flow approach. Furthermore, the model also allows for the unconventional feature of introducing aspects of irrationality generated by human behavior. As it will be further investigated in Sections 2.2 and 5, it allows the model to evolve through its scenarios more realistically and naturally.

The goal is to accentuate the strengths of standard scenario analysis models by building on the transparency and explainability of causality. Furthermore, these strengths allow the model freedom to naturally adapt to its irrational environment. This paper will focus on the applications of the ABM for scenario analysis, particularly in management consulting, as it was developed in collaboration with Dr Weston from Deloitte UK, Dr Luk from Imperial College London, and Simudyne Ltd. A notable thanks to Dr Guo from Imperial College London and from Simudyne, Mr Babaie-Harmon and Dr Krishnen Vytelingum, for their contribution to the publication of this paper.

There are a variety of challenges to overcome, however; the most notable of which is the representation of the dynamics of human behavior and internal relationships naturally found within the firm. As a consequence, the following arguments are the development focal points:

1. Understanding the strengths, weaknesses and union of both scenario analysis and ABM.
2. Developing a model capable of respecting the complex innerworkings of a human capital-dependent organization, such as a consulting firm.
3. Introduction of a human-orientated model, capable of evolving and implementing behavioral properties, such as unexpected irrational decisions that would be generally ignored during a company-wide scenario analysis.

This paper will begin with an in-depth view of agent-based modeling, scenario analysis, and their applications. Additionally, it will investigate their corresponding benefits and limitations over conventional approaches to scenario analysis. It will then continue with the ABM model design and implementation, with a focus on the different agents, interactions, and model behavior in order to simulate a large consulting firm. The paper will tackle the three main challenges incurred and an overview of how these were overcome. At the end, there will be a discussion on current limitations and availability for future development.

2 Background and literature review

2.1 Literature review method

The boundaries set for the literature review have purposely been broad. The reasoning for this approach is the fact that the paper's pioneering approach in utilizing agent-based modeling for scenario analysis is still rather unique and, consequently, there isn't a lot of available sources to draw upon. There is a focus on the two approaches as separate entities and on the benefits that can be extracted from them. Furthermore, it was important to include the expected behavior of the two models and how the results might affect the user. Much of the information and ideas used in the approach are based on subject matter expertise of the co-authors providing valuable insights into common behavior found within a management consulting firm. Consequently, the literature review's primary focus is to gain appreciation for the application and combination of ABM and scenario analysis. It is important to analyze the strengths and weaknesses present within the model and how they are currently applied in their respective industry.

2.2 Scenario analysis and agent-based modeling

Based on a questionnaire by the GARP Risk Institute (GRI), 70% of the 78 companies (collectively holding US$48 trillion in assets) utilize some form of scenario analysis (Jaeger, 2021). With "no surprise, scenario (analysis) has its roots in military strategy, with the use of scenario (analysis) in business pioneered by Shell" (Safarova, 2020). The idea behind the use of scenario analysis is the process of calculating the expected future revenue of a company, depending on the outcome of various future scenarios. Generally speaking, these scenarios are preselected either to mirror past experiences, such as 9/11, the oil crises in the 1970s, or more recently the Covid-19 pandemic, in order to give a forecastable indication of what would happen to the current business profile should similar scenarios arise. Some of these analysis techniques can be used to model unforecastable future scenarios, such as the future value of the US dollar, or the widespread implementation of digital contracts on blockchain technology. These pre-imposed scenarios are then modeled to impact certain areas of the business in different ways and to generate an aggregate revenue change for each.

The integration of an agent-based model to develop and generate scenario analysis is a new concept, especially in the management consulting space. Consequently, there is little known work on the subject. However, ABMs have been utilized for a while and have been very successful in their corresponding fields. These topics follow similar principles involving the utilization of scenario analysis and agent-based models.

In recent years, ABM "has emerged as a new research and management paradigm" (Wall, 2016). Achieved thanks to its ability to model scenarios with a high level of detail, with the capability of extending the models to investigate different aspects of the system. ABMs have been utilized in diverse business areas, providing senior staff with the possibility of preparing and anticipating future market developments, and may help with understanding or adapting the decision process to overcome an unprecedented scenario (Baxter *et al.*, 2003). "The leading market analysts worldwide are using ABMs to gain deeper insight into the market dynamics and to elaborate optimal strategies for their companies" (Garifullin *et al.*, 2007). An example of this, explained by Baxter *et al.* (2003), is found in the retailer Sainsbury's collaboration with SimWorld Ltd to model their customers in their stores. This simulation helped to gain insight into the design of the ideal floor layout, thus avoiding potential bottlenecks and improving their revenue (Baxter *et al.*, 2003). Additionally, there was a collaboration between Macy's and PricewaterhouseCoopers. Their goal was to utilize ABM techniques to find the optimal location for the service desk and cash registers (Bonabeau, 2002a). In this case, ABMs have the ability to "explore the key drivers of customer behavior" and provide feedback with regard to their current strategies (Baxter *et al.*, 2003). The ABM allows clients to further test their model, by altering different input parameters, in order to achieve their desired outcome (Baxter *et al.*, 2003).

However, there are drawbacks with the utilization of ABMs. These models are known to leave users complacent with the reliability of the outcomes. As Roxburgh explains, once a developing scenario analysis has been made, a sense of security

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may spread across the management (Roxburgh, 2009). Furthermore, ABMs are computationally intensive and "therefore may hit limits of today's desktop" (Garifullin *et al*., 2007). Nevertheless, this comment was written back in 2007. Since then there have been major strides in hardware development and today's technology has finally caught up with an excellent medium and has a lot of potential, going forward.

2.3 Behavioral management and functional approximators

Functional approximators are often utilized in both mathematics and computer science. These can be best described as "approximation functions of several variables by the superposition and sums of functions of one variable" (Gorban, 1998). This will help to synthesize several variable functions into a single functional approximator. A well-known example of this approach, and currently a growing trend, is the use of artificial neural networks, that, in essence, are devices that compute superpositions of single variable functions to derive a solution (Gorban, 1998).

It is important to note that functional approximators are utilized "to consider approximate, non-accurate representations" (Gorban, 1998). This theory is applicable in the context of this paper, since it would be impossible to imitate the accurate representation and operations of every aspect of a firm, more specifically the representation of human behavior within the model. Consequently, the model should be considered as a functional approximator to the real-life behavior represented.

In this paper, the functional approximator is the agent-based scenario analysis model. Not only will it represent the overall complexity of a multibillion-dollar consulting firm, but will also focus on its impact on the behavioral management decision process of its agents in order to introduce aspects of real-life behavior and aid with the decision process of high-level executives.

The results of a scenario analysis model are often analyzed during important board decisions, not only as preventives, but also for forecasting potential outcomes of strategies taken. As described by Rodney James Scott, in a paper explaining how group model building (GMB) supports enduring agreement, "looking at the best methods for bringing conflicting parties to consensus agreements" (Scott, 2017). Offering a "five best-supported hypotheses: the cognitive bias mechanism, the boundary object mechanism, the operator logic mechanism, the argument structuring mechanism, and the persuasion mechanism" (Scott, 2017). A detailed explanation of each mechanism can be found in Scott's publication. The interesting aspect is how the utilization of agent-based modeling within scenario analysis has the ability to comply with most of the five best-supported mechanisms for an enduring agreement.

Although the ABM does not exactly meet all the requirements in GMB, it does tick some very important boxes when it comes to building enduring agreements with regard to analysis and understanding the procedures to be taken in future scenarios. As Dr Scott explains, the conceptual integrated model of the five mechanisms can be broken down into four layers; from the foremost layer, consisting of exogenous elements, to mechanisms, persuasiveness, and the innermost level of the impact enduring agreement.

The outermost layer is mainly focused on the described design features, complexity, portrayal of dependencies, and producing tangible artefacts (Scott, 2017). During the development process of an ABM for scenario analysis, there should be a strong relationship between the developer and the clients in order to develop a model meeting their main requirements and, importantly, designing the initialization process to allow users free rein modify key parameters of the model to achieve the desired scenarios. The freedom to modify key parameters of the model, in order to develop a variety of different scenarios, helps with the cognitive bias mechanism and the boundary object mechanism, where the users are able to build personalized models and respectively modify the agent's interactions (Scott, 2017).

The third layer, categorized as the mechanisms, looks at the conditions for argument structuring mechanism, reflecting a structured argument, predisposition to supporting conclusions, and mutual trust (Scott, 2017). The ABM makes it very simple for the users to view and understand the interaction between agents. This can be seen in Figure 2, clearly displaying the network of the model.

The second-to-last layer, before theoretically achieving enduring agreements within the group, is persuasiveness. This layer is very similar to the previous, however, focusing on the results or ability to process information, motivation to process information, persuasive content, and argument quality (Scott, 2017). This directly reflects the key asset of utilizing an agent-based scenario analysis model. As elaborated on later, the model is completely transparent when it comes to the interactions and decisions performed across the scenario; since it is computer generated, each interaction between the agents is recorded and graphed for the user in a clear interface. Consequently, improving on the persuasion mechanism, as Dr Scott states, it is important that "group model building integrates and structures the available information into discrete logical steps" (Scott, 2017), which is exactly how the data is returned to its user.

With the introduction of ABM for scenario analysis, it is now possible to use an approach that captures the non-linear dynamics, more specifically, introducing human behavior to each agent, and being able to uphold the main characteristics to help generate enduring agreements in group model building. Compared to standard differential equations, this can be achieved in an ABM, since as Dr Bonabeau explains, "individual behavior is nonlinear and can be characterized by thresholds, if-then rules, or nonlinear coupling. Describing discontinuity in individual behavior is difficult with differential equations" (Bonabeau, 2002b). However, it would be impossible to develop a model based solely on the actions and decisions performed by single individual. Nevertheless, as the firm becomes bigger, so would the accuracy of the model, as it would follow the law of large numbers. This entails that with a large enough sample source, it would be possible to model human behavior in corporations, such as the big four consulting firms. Ergo, with the appropriate assumptions (acting as functional approximators to their general behavior), it allows for a unique opening in the world of scenario analysis, where we may also consider human behavior.

The union of ABMs and traditional scenario analysis can be very successful. A standard scenario analysis model is excellent at portraying the state of a company at the end of a particular occurrence; however, it lacks the narration and derivation of the solution. The new ABM-based scenario analysis tackles the problem slightly differently by generating "emergent phenomena from the bottom-up" (Bonabeau, 2002b), which becomes very important as highlighted in Section 3. Furthermore, additional responsibilities are given to the model, allowing it to alter the firm as seen appropriate to match the evolving environment. Lastly, thanks to the ease of extensibility of ABMs, there is also the possibility of introducing an element of natural behavior within the model. Overall, the model shows each stage of the company as it evolves through its scenarios.

2.4 Model operations

Ultimately, the final result of the two approaches should be very similar but not identical. The main difference is the way data is presented, making the agent-based scenario analysis significantly more descriptive and transparent with its approach.

Fundamentally, the two models should be homogeneous, as they are both interpretations of the final outcome of the firm or cooperation during a particular scenario. However, due to the difference in modeling, utilizing a bottom-up approach versus a top-down approach, and having the ability to naturally evolve alongside with its environment, the ABM will offer a more detailed result compared to standard approaches. The ABM-based scenario analysis will perform better at rebalancing the company as the scenario evolves; however, as it has parameters based on probability, such as the acceptance rate of a contract, or the probability of an employee quitting, there may be minor differences between the results of the model after it has been run multiple times. On the other hand, a standard scenario analysis is purely based on a mathematical model, therefore deriving consistent generalized results of the firm's outcome. Nevertheless, being unable to restructure the company and reallocate the resources as an ABM with its agents, makes its solutions more generalized.

The main difference and consequently the key advantage, lies in the fact that the two models differentiate with their approach to transparency and explainability. Because of the novel approach of generating scenario analysis with the use of an ABM, the technique to how data is analyzed and portrayed to its users is very different compared to a standard scenario analysis model. What is notable of the new approach is that the model recreates the most important interactions occurring in the firm in order to recreate the company's cashflow and P&L. These exchanges can be followed by the user as the model progresses through time. An example of the connections can be seen in Figure 2.

The transparency is clearly depicted, as the model registers each interaction, node, and generates graphs of each progression for the user to analyze, thus showing the evolutionary process of the model at each interval and providing a purely see-through reasoning to the derivation of the analysis, unprecedented by alternative techniques.

The explainability of the model, on the other hand, is comprehensive thanks to an extensive record of every exchange. Since each interaction of the model is recorded and, if desired, portrayed to the user, this makes it very easy to illustrate and explain, with supporting evidence, the consequence of different market impacts or managerial decisions on the firm. As mentioned, the overall results of a standard scenario analysis and the new ABM scenario analysis should be the same (assuming the market moves at constant rates), but the clear difference is the recorded growth of the model showing the evolution of the firm's causality and its departments, in line with a particular market, and how to reallocate resources effectively.

As specified by Dr Scott in the group model building decision-making, the novel approach will outshine a standard scenario analysis, as it helps with the "persuasion mechanism" having the ability to carefully follow the returns of the algorithm, understand its outcome and the decisions performed. The ABM can publish any data desired by the user; consequently, decision-makers are able to derive more profound conclusions with supporting evidence of the expected outcome depending on different scenarios.

3 ABM for management consulting

As mentioned, this paper was developed in collaboration with Deloitte London and Simudyne. Consequently, it is primarily focused on people-driven services and, in particular, consulting. However, with the appropriate adjustments, the approach is applicable to all industries.

At the time of writing, Deloitte utilizes a two-pronged approach for its scenario analysis. A bottom-up analysis and an industry-view analysis. The bottom-up approach is people-oriented and focuses on looking at the total number of consultants available and calculates the total potential revenue they would be able to generate (also referred to as headcount-driven approach). The top-down, or industry-view approach, focuses on the current contracts in progress, future contracts that are in the pipeline, and the potential future contracts that may be won with a certain degree of probability (also referred to as demand-driven approach). A better representation of this approach is shown in fictional representations of the firm in Tables 1 and 2.

The first representation is achieved by calculating the expected performance of a consulting firm based on the total maximum utilization of its employees. This can be seen in the fictitious representation of the company, see Table 1.

Based on 20 senior consultants and 80 junior consultants and an assumed utilization rate of 70%, it becomes clear that there is an expected net profit potential of 10 million. To complete the scenario analysis, the base model will be set up to allow for worst-case and best-case scenarios. To generate different outcomes, one can either increase or decrease the utilization rate or hours of work.

The second parameter utilized is the Industry View Plan. As the name suggests, it is based on an industry-focus view or a company-specific view. The idea behind this model is to look at the industry as a whole, and analyze sector by sector, in order to provide an estimate of the potential expenditure on consulting fees. With this method, the firm considers which contracts are already safe, such as signed but not billed contracts (Backlog), and which are expected new contract agreements for the coming year (Pipeline). An example of these parameters can be seen in the following table of imaginary client companies across various industry sectors:

Table 2 shows how the Industry View Plan provides a further representation of the scenario analysis of the company. Table 2 also shows the estimated expected revenue from each company A, B, C, is 11.5m, 8.9m, and 33.5m, respectively. Again, the scenario approach simulates other market developments, affecting each client company and allowing for a greater appreciation of the expected potential revenue.

Lastly, both models are compared, as seen in the bottom right of Table 2. This shows the discrepancy between the potential billable income and the estimated client/industry revenue. This provides a guideline for the company to assess future actions needed to match the estimated demand with sufficient service offer. This example shows how the expected revenue from the industry view would be higher than the potential revenue from the total workforce. Consequently, to balance the business model in this example, the firm would have to either hire more consultants to meet the demand or would have to shift focus towards more profitable sectors and relationships, to maximize its potential revenue.

Table 1: Bottom-Up Scenario Analysis representation.

Number of Available Consultants					
	Count	**Billable**	**Hours**	**Utilization**	**Total Revenue**
Senior	20	500	1760	70%	12,320,000
Junior	80	300	1760	70%	29,568,000
				Total	41,888,000
				Gross Margin	50%
				EBITDA	20,944,000
				Profit Margin	50%
				Net Profit	10,472,000

Table 2: Industry View Scenario Analysis representation & Discrepancy Table.

Company A				
Sector Financial				
Previous Year Revenue				20,000,000
Backlog				5,000,000
Pipeline	5,000,000	30%	Conversion	1,500,000
Other				5,000,000
Estimated Revenue				11,500,000
Presumed Retained Fees				58%

Company B				
Sector Industrial				
Previous Year Revenue				10,000,000
Backlog				3,000,000
Pipeline	3,000,000	30%	Conversion	900,000
Other				5,000,000
Estimated Revenue				8,900,000
Presumed Retained Fees				0.89

Company C				
Sector Technology				
Previous Year Revenue				50,000,000
Backlog				20,000,000
Pipeline	28,000,000	30%	Conversion	8,400,000
Other				5,000,000
Estimated Revenue			33,400,000	
Presumed Retained Fees			67%	

Industry View Plan			
Expected Revenue		**Discrepancy**	
Company A	11,500,000	Potential	41,888,000
Company B	8,900,000	Industry View	53,800,000
Company C	33,400,000	Net Discrepancy	11,912,000
Total Revenue	53,800,000		

Sector Revenue	
Financials	11,500,000
Industrial	8,900,000
Technology	33,400,000

Compared to conventional applications of scenario analysis, such as the one described above, an ABM scenario analysis would have the ability not only to show the derivation of net profit over time, but, more importantly, also show the performance of each division. For example, the model would be able to show which department or employee had the highest utilization rate during the scenario. Therefore, it might show if there were any increases in personnel in order to supplement the increased demand or vice versa. Alternatively, it could also show why one sector performed better than another among its client base. Each interaction between the model and the environment is carefully analyzed and graphed for the user to maximize its explainability and transparency.

In order to achieve a bottom-up representation, the ABM will integrate the two approaches described above. The ABM will be able to automatically calibrate itself in order to maximize company growth by optimizing its resources and workforce appropriately. This is further expanded on below.

4 Apply ABM to scenario analysis

In order to maximize the effectiveness of an ABM-based scenario analysis model, it is important to be able to represent the corresponding firm and industry with as much accuracy as possible. Consequently, for each model, it is crucial to get a thorough understanding of the relationships present and deriving a simpler network, while maintaining the fundamental structure.

To achieve this, the focus of the model will be to primarily take a bottom-up approach to scenario analysis to simulate a corporation. A bottom-up approach entails focusing on the fundamental building blocks of the firm, such as employees, individual clients, contracts, and to slowly build up the daily operations of the firm. This is compared to standard scenario analysis approaches, which have a top-down perspective, similar to how a cash-flow statement is prepared, focusing on the accounting of each department, such as the overall revenue and costs per department, rather than what actually comprises the organization in question. Once the agent-based model has been developed, it should therefore allow for the generation of quantitative insights of the potential changes in the firm, or market environment and structure, allowing C-suite executives to plan and prepare for the unexpected.

Conceptually, however, once one ABM model has been designed, there are a lot of similarities between the different firms and industries, and the majority of parameters may be re-utilized. Each company however has a fundamental distinguishing factor that allows it to differentiate itself from competitors, making it perform differently. This discerning factor is what makes it very difficult to design a 'one-size-fits-all' model. Consequently, the key principle to abide by while developing the ABM model is to keep the concept of the model as simple as possible to avoid getting caught up in the details of the model, but rather to focus on the general behavior.

The approach found to be effective during the development of the agent-based scenario analysis model is the use of an iterative design approach, often applied in electrical engineering and a common technique utilized in all industries during a research and development (R&D) project. In computer science, this approach is referred to as agile software development, where one begins with a skeleton structure and sets up the agents and environment in its most primitive state, with no parameters. The idea being that at each iteration you have a functional model, and you layer in complexity slowly, testing and validating each addition in small increments. One then develops the complexity of characteristics over iterations, starting from the simplest interaction, validating the results, and layering in complexity once the previous iteration is stable. The developer will learn from testing each update and amend the model if necessary. This process is repeated in a loop until completion of the ABM model. Lastly, it helps to maintain a sense of modularity in the model, developing the code in an object-orientated manner, which is critical to facilitate additional development, introducing a new department, or company regulations. Thus, allowing the model to be further developed with higher levels of flexibility for future industrial developments and evolutions in the market.

As described earlier, and in line with Scott's publication, since the model is highly modular, the ABM has the ability to constantly alter its input parameters and scenarios at the initialization of each model. Consequently, it allows its participants to contribute and provide input, thus strengthening the decision process the company may face down the road.

5 Agent definitions and interactions

An ABM is composed of agents, the model's environment, and the interactions between agents and their environment. More specifically, an agent is an autonomous decision entity that can be designed with its own unique behavior and attributes (Rand, 2013). It is also simple to manipulate the initialization of different models once one has been developed. It is possible to add or delete agents by simply altering the initialization parameters, without having to modify the backend (Gomez-Cruz *et al.*, 2017). Consequently, to facilitate different applications to the ABM model, based on the company's needs, it is still very important to maintain the code as self-contained as possible. This will allow for the possibility of future extension within the agents, or the environment. This approach to ABMs will allow the user to develop some intricate interactions between agents and, consequently, lead to a novel approach to scenario analysis.

This leads to one of the most fascinating utilizations of an ABM. The fact that compared to standard modeling techniques, an ABM allows the developer to specify human characteristics to its agents and initialize them to have heterogenous properties. Thus, introducing an element of irrational behavior not only with the employees but also the market. As the economist John Maynard Keynes famously said, the market can remain irrational longer than you can remain solvent. This is a fascinating aspect of ABM simulations, as it provides the opportunity to examine how humans would naturally react to changes in their environment and, consequently, how it would affect the company.

A clear example of natural behavior implemented within the model is the employee's ability to resign. The complete analysis of the process will be seen in Section 5.2; however, the base case is the fact that employees have project preferences and, consequently, a tolerance for undesirable project assignments. If the employee is unhappy with the current work environment, they may leave the firm. This becomes relevant if the market model evolves and the employees specialized in a specific economic sector, which is shrinking, may be assigned to different department projects. If continued, the employee will become unhappy and resign. This is an important aspect that general scenario analysis would be unable to convey. However, utilizing ABM, it is possible to model.

5.1 Utilized agent classes

Table 3: ABM Agents.

Agent	Description	Action
Employees	Workforce of the company. Each level in the hierarchy would have to be developed as its own agent. Introduces an element of risk of employee turnover and or retention.	They are the main source of revenue, based upon the number of projects they are working on. Have the possibility to quit if their needs aren't met.
Client Company	Clients currently represented by the firm. Introduces potential revenue for the firm.	Generates contracts. They are allowed to leave the consulting services if it's no longer desirable, and if all existing contracts are completed.
Running Contracts	Ongoing contracts at the firm. Introducing a finite number of resources available at the home company.	Utilized by the home company as a record of contracts but do not have an action applied.
Home Company	The entity responsible for tracking the profit and loss P&L of the firm, and responsible for the correct allocation of resources.	These have the ability to manage the company resources, either hiring/discharging employees, assigning the correct employees to a project, or accepting/rejecting client contracts.
Market Environment	This acts as the environment of the home company. Allows the user to set the desired scenario, then responsible for generating or de-allocating clients in the environment.	Based upon a randomization algorithm, this agent will force, at a variety of percentages, the number of clients joining or leaving the home company.

5.2 Agent-based modeling interactions

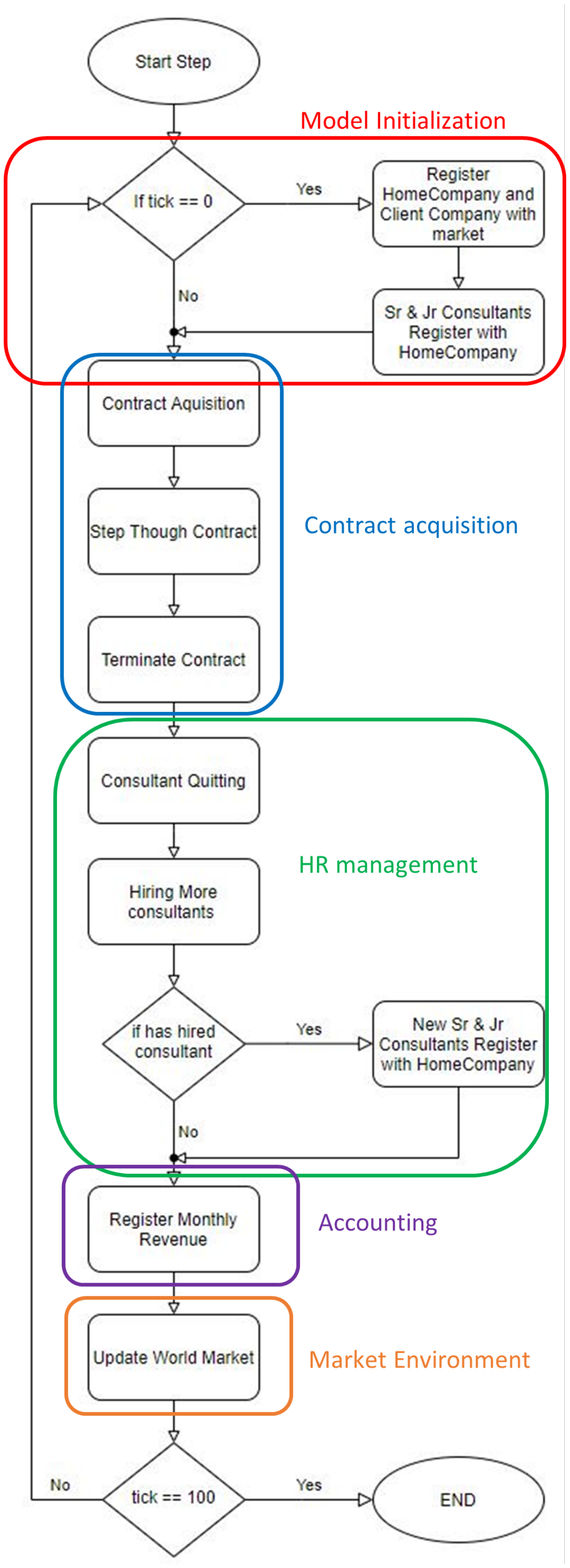
Having designed the key components for the model to be built around, it is fundamental to capture the characteristics of the model as concisely as possible, while maintaining a realistic behavior. The main characteristics can be condensed in five main categories (as seen in Figure 1):

Model initialization, Contract Acquisition and Termination, Human Resource (HR) Management, Accounting, and the Market environment.

Model Initialization: The model allows for ample customization within its starting parameters in order to customize different starting scenarios and calibrate the model to the firm's current operational structure. During the initialization process the model will generate the necessary agents and set up the links between agents as seen in Figure 1.

Contract Acquisition and Termination: This is the main operation performed by the home company where, depending on the availability, will choose to either accept a new contract from a client or not. Consequently, it will also terminate and release the assets allocated upon termination.

Figure 1: ABM general algorithm flow chart.



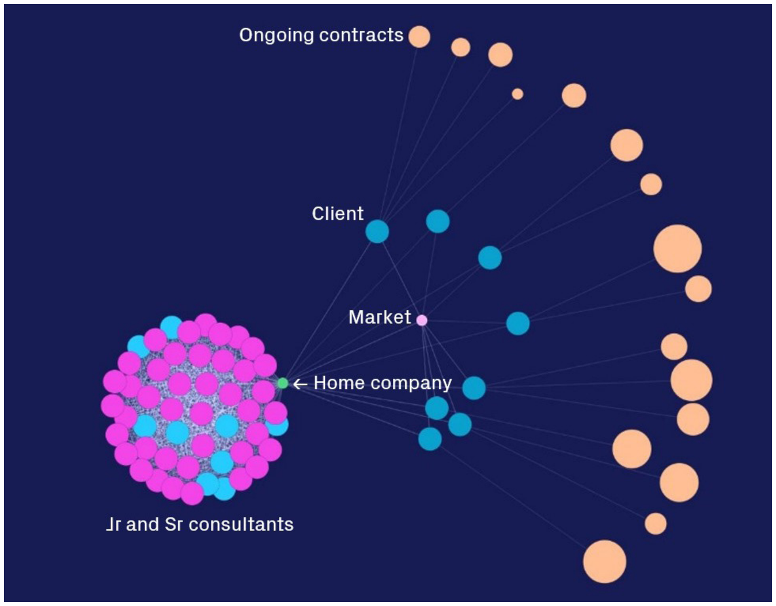
Human Resource Management: An important property of an ABM simulation, compared to standard scenario analysis, is the fact that the model is not static, having the ability to grow and contract naturally following the demands of the market. Subsequently, if there is a sudden increase in the number of contracts, the ABM will attempt to recalibrate by hiring additional employees, or vice versa. Additionally, an element of human nature is introduced to the model, where the employees assigned to a project outside of their scope may feel resentment towards the firm and potentially leave. This functionality can be further expanded on to meet the workforce needs.

Accounting: This operation is perfomed by the home company agent, which is capable of keeping track of the P&L of the firm, and of each division, on a monthly interval (which can be regulated depending on the different industires), providing a powerful and detailed representation of the current operations of the company.

Market Environment is responsible for managing the interactions between the home company and client companies. This is achieved by carefully modeling and simulating market behaviors. For the developement of the ABM described in this paper, the market can be toggled between two different scenarios; in the first, the market follows a simple randomized business cycle with a 2% average annual growth (which can be altered by the user) to portray the responsiveness of the model to changes in the environment. Additionally, there is the possibility to have an exponential contraction or expansion to the market, utilized to stress test the market and analyze potential weak areas in the home company.

The communication process between the different agents is achieved with a messaging system, which passes information to the next agent. This system will call a function of the next agent that performs an operation based on the message received, that could in turn send another message, until the operational branch has completed and returns back to the main (file responsible for controlling the program execution). Consequently, unless an agent is defined to perform an action written in *super class* (*AgentBasedModel.java*), it will remain dormant until a message is received.

Figure 2: ABM Agent network map.



5.3 ABM network representation in management consulting

Figure 2 is a graph generated by the Simudyne SDK and shows the links between the different agents generated and their interactions with one another.

The combination of these parameters allows for a much more detailed representation of the scenario analysis, not only with regard to the final outcome, but also the journey followed by the firm along the way. This in turn allows the firm's executives to further store, observe, understand, and analyze the effect of potential alterations in the market and generate a record of appropriate responses. Minimizing the risk of being unprepared and in a reactive state.

What is really exiting is the fact that the model was able to represent such a complex mechanism in detail and allow the user to have a lot of freedom to alter and modify each parameter, achieving the exact scenario or situations they would like to investigate, which is further discussed in the Appendix.

An interesting feature is the fact that the ABM may be used to back test one's previous management decisions, as it would be able to re-evolve from the past into the current environment and would allow management to evaluate the effectiveness of its decisions.

5.4 ABM example run

In order to fully capture the benefits of an ABM model compared to a standard scenario analysis approach, an example run of the Deloitte UK consulting firm was conducted. The aim was to highlight the behaviours and the improved explainability and transparency that conventional models have difficulty capturing.

The full ABM scenario analysis run can be found in the Appendix; however, this paper will primarily focus on a very important topic in consulting, which is the utilization rate of the employees. As mentioned, this ABM scenario analysis is based on a people-driven service, and thus the key form of revenue is deploying consultants on a variety of different projects and generating billable hours. If an employee is not actively working on a project, then the company is running a loss in that specific case with the employee. Consequently, this example run will focus on the utilization rates of the two agent categories *SrConsultants* (considered partners) and *JrConsultants* (general consultants) and how the model allows attempts to optimize the company's returns and provide feedback to the user about potential optimization opportunities that would be much harder, or missing, from standard scenario analysis models.

Figures 3 and 4 represent the utilization period of the consulting firm between December 2017 and May 2026. The economic environment during this period follows a random business cycle with an average 2% growth rate. The full derivation can be seen in the Appendix, Figures a.4-a.5.

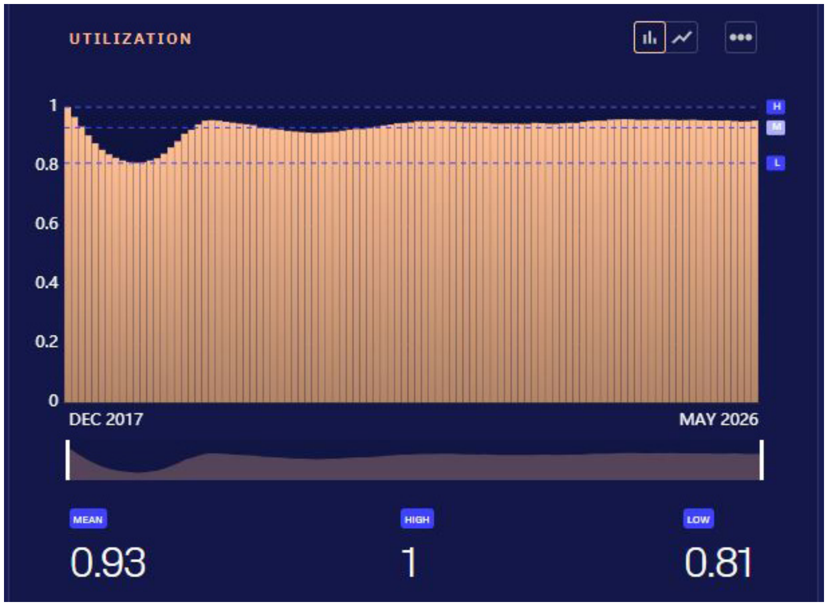
5.4.1 Utilization rate discussion

The utilization rate achieved in the model is very high. For the partners, it is almost 100%. There was an agent which dropped in utilization which can be seen in the lower bar below the chart in Figure 3. However, the graph represents the mean and it is too small to be portrayed, whereas for the employees, the mean is about 93%. From a financial point of view, this would be a phenomenal achievement and would be ideal for Deloitte, as it would maximize its bottom-up approach in its scenario analysis, seen previously in Table 1. However, a more realistic utilization follows a similar pattern to a sine wave, with a more realistic average utilization rate of approximately 69% (Consultancy, 2020). The reasoning for this is that people tend to work in bursts, where they may have high utilization rates, followed by periods of low utilization rates, such as going on vacation. This will generally end up following a wave similar to a sine wave. Whereas in the ABM model, the agents don't require and aren't given permission to take vacation and breaks between contracts, which may be an interesting functionality to add to the future model. This also is a cause of the increased revenue, compared to Deloitte's actual financial statement seen in the Appendix, since all the consultants are utilized to a higher capacity.

The utilization rate of the ABM, however, may be too lenient, as it does not take into consideration how many projects the employees may work on simultaneously. The partners (Senior), within the ABM algorithm, are currently set by the user to

Figure 3: SrConsultants Utilization rate.

Figure 4: JrConsultants Utilization rate.



[AQ: Should this be Figure 6?]

Figure 5: Number if missed contracts by the consulting firm.

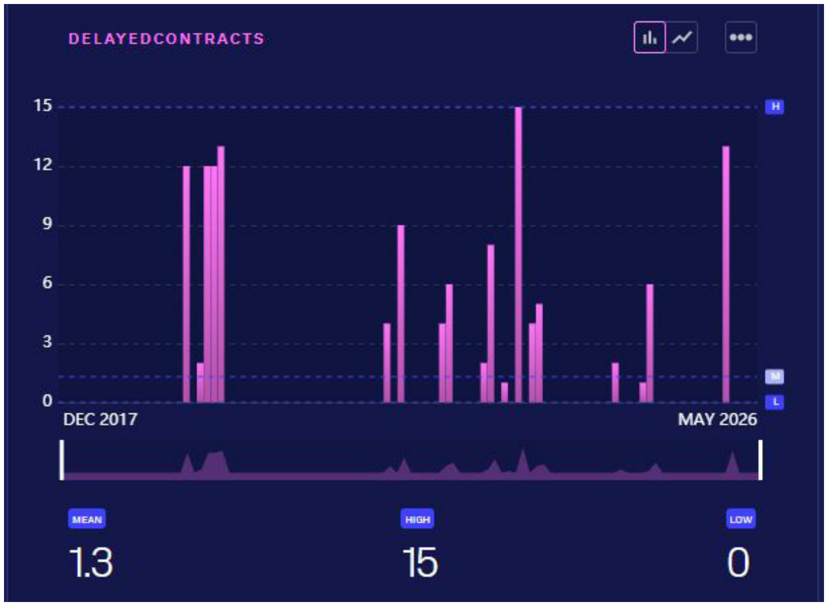
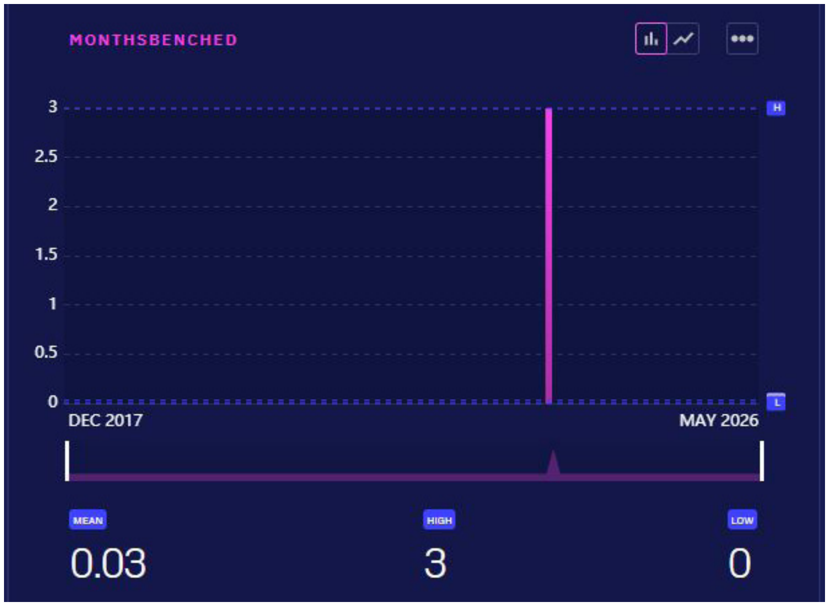


Figure 3: Total months benched by SrConsultants (sum).



be allowed to work on average 12 simultaneous projects, whereas the employees are allowed to work on 1.5 simultaneous projects on average. However, the utilization rate simply looks at whether the employee was active over the last 25 months, irrespective of the number of contracts involved.

5.4.2 Resource management discussion

However, compared to standard scenario analysis, crucial information can be derived by the ABM models, especially when the utilization rates are partnered with Figure 5 on *delayed* (skipped) *contracts*, the *months benched* (Figures 6 and a.7), and the *missing consultant's* graph in Figures 7 and 8. The *delayed contract* chart represents all the contracts which were refused by the consulting firm due to the lack of resources. Whereas the *months benched* graph, Figure 6 (aggregator), as the name suggests, keeps a monthly track of the total number of months agents have not been actively working. The final set of charts show the exact number of agents requested but were unavailable in a particular month. It may be misleading, however, as there might have been a particularly large contract requested, and the model would still count it.

From these graphs, it is clear that, to some degree, there is a shortage of consultants. Having just looked at the *SrConsultants Utilisation rate*, Figure 3, it is clear that there is opportunity loss and, as a consequence, the model will attempt to hire additional employees to prevent the loss of additional opportunities.

This shows that in the current model, there is a lack of SrConsultants; consequently, there is a slight loss in potential revenue. Consequently, the ABM model will react to its current environment and hire additional SrConsultants, as seen in Figure 7. On reoccurring occasions, there was a lack of resources, thus missed opportunities in Figure 5, which the ABM model had overcome by hiring additional consultants.

This operation can be seen in the increase in the salary graph, Figure a.1 in the Appendix, which had a mean of £32.2m and a high of £33m, showing that the model was reacting to the increase in demand and started hiring additional consultants. This demonstrates how an ABM of this kind can provide additional insight into scenario analysis compared to more traditional methods, as it highlights detailed output, such as the need for SrConsultants (Partners), that a standard model would not pick up on.

6 Conclusion

The world is under constant evolution, looking for new approaches to common problems, in the constant pursuit of efficiency and profits. Scenario analysis modeling is highly applied, and this paper looked at the potential process of modernization of such models. The process selected was to utilize agent-based modeling, as it is able to complement the returns of a traditional scenario analysis model.

With the integration of an ABM, the model is now designed from the bottom-up, emphasizing the fundamental building blocks of a company, rather than looking at the returns from a purely accounting point of view. Additionally, the implementation of an ABM allows to not only simulate the operational interactions within the firm, but it also provides the opportunity to introduce some elements of natural behavior among its employees in order to introduce an additional element of realism within the model.

Objectively, the results should not be very different between the two approaches, other than the fact that an ABM-based scenario analysis may offer more focused results, based on the given scenario. It is the transparency and explainability of the model that is the key factor, as an ABM model allows the user to follow the entire evolutionary process of the model to arrive at its results, allowing management to optimize their decision process with more evidence and ultimately more confidence. Consequently, it can also be represented as an extension for the ABM during scenario analysis decisions, providing the user with the capability of interacting and initializing the model as desired, showing the clear architecture of the model's development and, most importantly, providing clarity between each decision process through the evolution of the model until it reaches its goal state.

It is important to note that the output will never be an exact prediction of the future, as the paper would have otherwise been called an introduction to wizardry.

Figure 7: Missing SrConsultants.

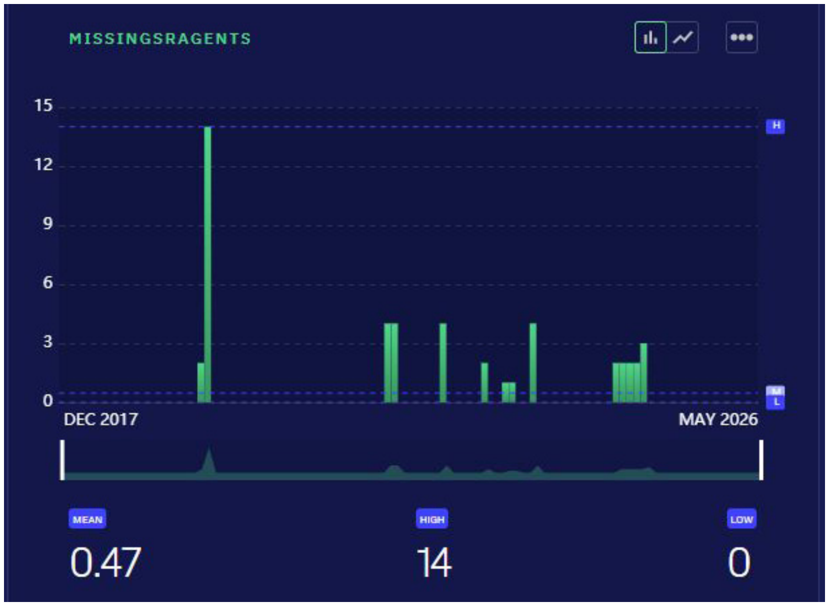


Figure 8: Missing JrConsultants.

However, the derivation of the model is that it acts as a functional approximator to the resultant outcome, a sophisticated and evidence-based guess to a potential future and its implications. The outcome is the result of a variety of different variables and decisions made to imitate the firm in as much precision as possible with the current state of technology. It is an unprecedented approach to introduce human behavior in a purely mathematical model, such as scenario analysis, and to allow the model to make decisions based on the imposed parameters; however, it does allow to provide a new bottom-up unique insight into one's company.

6.1 Model limitations

Unfortunately, large simulations of companies can still encounter hardware limitations while running the model. Based on the hardware available to me, when initializing the model with 5,000+ employees, it was discovered that the program was running out of allocated heap space in order to accommodate the 5,000+ agents present in the model. This problem could have been avoided with better hardware, as at the time of testing the model, the computer utilized was an 8-core processor, 16GB RAM. Scaling the model would be an availability of hardware limitation and not a model or tool limitation. It was struggling to manage all the links between the agents, as it required 25+ million links alone, only for the ~5,000 employees, showing that there are still hardware challenges to the experimental size of the model. However, the constant growth in simple personal computing power over the years allows for standardized approaches to be challenged and re-examined in all simple office environments, which is the purpose of this paper.

Furthermore, there are some limitations to the current model design, primarily in the lack of human behavior. There is an infinite combination of parameters that may be added to the model's employees, and further research will have to be conducted in order to select the best main characteristics. Additionally, the utilization of employees in the model is a little excessive and unrealistic. Furthermore, it would be wise to introduce team chemistry among agents. This could certainly be achieved with higher computational power. Lastly, in the current setup of the model, there is a bit of initialization lag in the model, as it takes a couple of weeks to stabilize the firm and, consequently, affecting some of the scenario analysis average returns.

6.2 Future development

A lot of the features highlighted above, however, may be avoided with additional future development. As per the development of ABMs, they allow for considerable expandability. This may entail adding additional agents, additional traits, and multiple environments (possibly for each economic platform) and perform in a variety of ways depending on the surrounding circumstances. There are still numerous possibilities for expansion with such a model.

Possible implementations to integrate with the model to improve the realism, or additionally to expand the environment, should be investigated further, such as providing *improvements to behavioral factors and the initialization process*. The introduction of additional basic needs, such as break periods between contracts for the employees, could have an additional effect on the efficiency, depending on how rested the employees are. Introducing relationships between employees, depending on their personality, and how this might affect the teamwork performance. Lastly, to help with the initialization process, is to have the firm set-up with already ongoing contracts, rather than from a clean slate.

Additionally, it would be beneficial to look at *improvements on resource management*. This could be achieved with the utilization of ML algorithms, either by utilizing historical data to initialize the model or utilizing the historical data and potential futuristic solutions generated by the ABM to generate conclusions about future scenarios and, alternatively, to implement ML algorithms to improve the decision process of each agent within the ABM, as investigated by a paper from W. Rand (2006). An alternative method is to introduce an optimization algorithm, which through trial-and-error assigns different weights to the decision process, in the pursuit of reaching a global maximum revenue of the ABM.

In order to provide further realism, there would be the need for the *implementation of outsourced work*. In the current stages of development, the model is only

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reliant on internal resources available to the firm. In a real-life scenario, a lot of projects and contracts end up being outsourced to external contractors and improving on the ability to predict third-party outgoing contracts, allowing the firm to collaborate with a higher number of clients, taking on more complicated projects while optimizing costs.

Lastly, a very intriguing proposition would be the implementation of competing firms to the model. The current ABM model has a good framework to allow the implementation of additional competing consulting firms into the environment. For example, this would allow to simulate the Big 4, competing with each other, generating better deals for clients, and poaching agents between competing consulting firms. This would generate very interesting interactions between the firms, having to implement a sense of strategy among them. A mathematical interaction between the consulting firms may be simulated with the utilization of game theory. This is a mathematical model to implement a sense of imperfect competition (the market is the same, but each company strives on having its own small unique difference, to differentiate itself from the competition). Utilizing game theory would allow for "real-world scenarios for such situations as pricing competition" (Hayes, 2021), which would allow for simulating the competitiveness within the market, providing insight on picking their next strategy for the quarter.

About the Authors

After earning an International Baccalaureate at TASIS, an international school in Switzerland, **Christopher A. Stanford** went on to Exeter University in the UK, where he earned a BEng in electronic engineering. Fueling his passion, he pursued an MSc in Computing Science with a focus on machine learning and agent-based modeling at Imperial College London, solidifying his expertise in emerging technologies. This paper was written while pursuing his degree at Imperial. Since then, he has continued his work in alternative modeling approaches with ABMs and is currently working in quantitative risk analysis within the financial industry. His main research interests reside in alternative modeling approaches, investigating the use of ABMs, and machine learning techniques to recreate representations of the complex dynamics observed in the real world.

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Dr Krishnen Vytelingum is Simudyne's Chief Scientist. He joined Simudyne from J.P. Morgan's Market Risk team. Prior to that, Krishnen had a similar role at Sungard Systems, modeling Market and Credit Risk. These were roles for which he was well-suited, having spent five years researching agent-based models for the financial and energy markets. With over 30 peer-reviewed publications and over 3,000 citations, Krishnen has a Master's degree from Imperial College London and a PhD in Artificial Intelligence from the University of Southampton.

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Appendix

A. Presentation of experimental or analytical data and results

This Appendix is dedicated to run through examples of an ABM scenario analysis model, specifically in a people-driven agency within management consulting. This example run provides insight into the level of detail in the explainability and transparency of causality referred to multiple times throughout the paper. Furthermore, this is the complete trial run and discussion, explaining the calibration process, assumptions, and derivation of input values used to discuss the utilization rate explained in the "Example run utilization rates" section.

A.1 ABM experimental data compared to Deloitte

Since this model is designed for the Deloitte UK consulting subsidiary, the ABM is compared to its profit and loss (P&L) table. Table a.1 represents the P&L for the year 2020, and its conversion to the inferred consulting P&L. The aim of the model is to achieve similar results to Deloitte's financial report.

The first step is to carefully calibrate the ABM with the parameters from Deloitte. The first parameter is to specify the number of employees. The ABM scenario analysis model was developed with only two ranks, *Sr* and *JrConsultants*. Therefore, the Members (Partners) will be assigned as *SrConsultants*, while the employees are assigned as *JrConsultants*. By looking at Table a.2 below, there are approximately 250 Partners, and 5,000 employees working at Deloitte Consulting in the UK. The next step is to calculate their monthly salary. From Table a.4, the monthly staff costs are derived to be £31m for the consulting group. This is calculated by taking the published yearly revenues for the consulting division of £910m and applying the same Staff costs/Revenue ratio of the published group financials of 41%. This results in £373m yearly staff costs for the consulting arm, or £31m monthly. An average salary for Partners in the UK is assumed to be £250,000, whereas for employees it is approximately £65,000 a year, according to industry averages (Glassdoor, 2021a; 2021b). Consequently, an approximation to the daily salary for each agent is £1,040 and £270, respectively.

Additionally, there is also the need to calculate the revenue generated by the members and employees of Deloitte. After multiple interactions with industry professionals, a reasonable assumption of £2,750 and £1,000 for SrConsultants and JrConsultants was made, respectively.

Lastly, there was an assumption about the number of clients Deloitte currently has and the number of consultants per contract. Unfortunately, the total number of clients was not published, consequently an assumption of 250 clients with a randomized maximum of 10 contracts each was made as a starting point.

Table a.1: (Deloitte 2020) £ million.

Deloitte LLP Profit and Loss for the year 2020

Continuing Operations 2020 (£m)		Yearly		Yearly Consulting	
Revenue		2,627	~35%	–>	910
Operating Expenses			*(Ratio to Revenue)*		
	Staff costs	1,081	41%		373
	Depreciation and amortization	119	5%		41
	Other Operating Expenses	816	31%		283
Operating Profit		611			213
Investment Income		80	3%		28
Financial cost		75	3%		26
Profit of the Year (before tax)		616			215

Table a.2: Derivation of employee's salary for the ABM calibration

Employees Salary Estimation (Total Employees)		Ratio of Partners	Staff cost	Salary	Total (£m)	Daily (individual)
Members (Partner)	249	0.05	1.5	250,000	5.1	1,041
Employees	4,860	0.95	29.6	65,000	26.3	270
Total	5,109	1.00	31.1		31.4	

Table a.3

£m	Revenue	Salary	Gross Profit	EBIT	Net Profit
Mean	80.64	32.26	48.37	23.62	18.90
High	90.63	32.99	57.79	32.79	26.23
Low	0.00	0.00	–6.79	–31.79	25.43

Table a.4: Conversion of yearly P&L to a monthly format.

Continuing Operations 2020 (£m)		Yearly		Monthly		Gross Operating Profit	
Revenue		910		76			
Operating Expenses							
	Staff costs	373	41%	31	41%		
(User Input)	Depreciation and Amortization	41	5%	3			
	Other Operating Expenses	283	31%	24		(Minus Staff cost Only)	
Operating Profit (EBIT)		213		18		45	59%
Investment Income		28	3%	2			
Financial cost		26	3%	2			
Profit of the Year (before tax)		215		18	24%		

Figure a.1: Revenue on the right and Salary on the left.

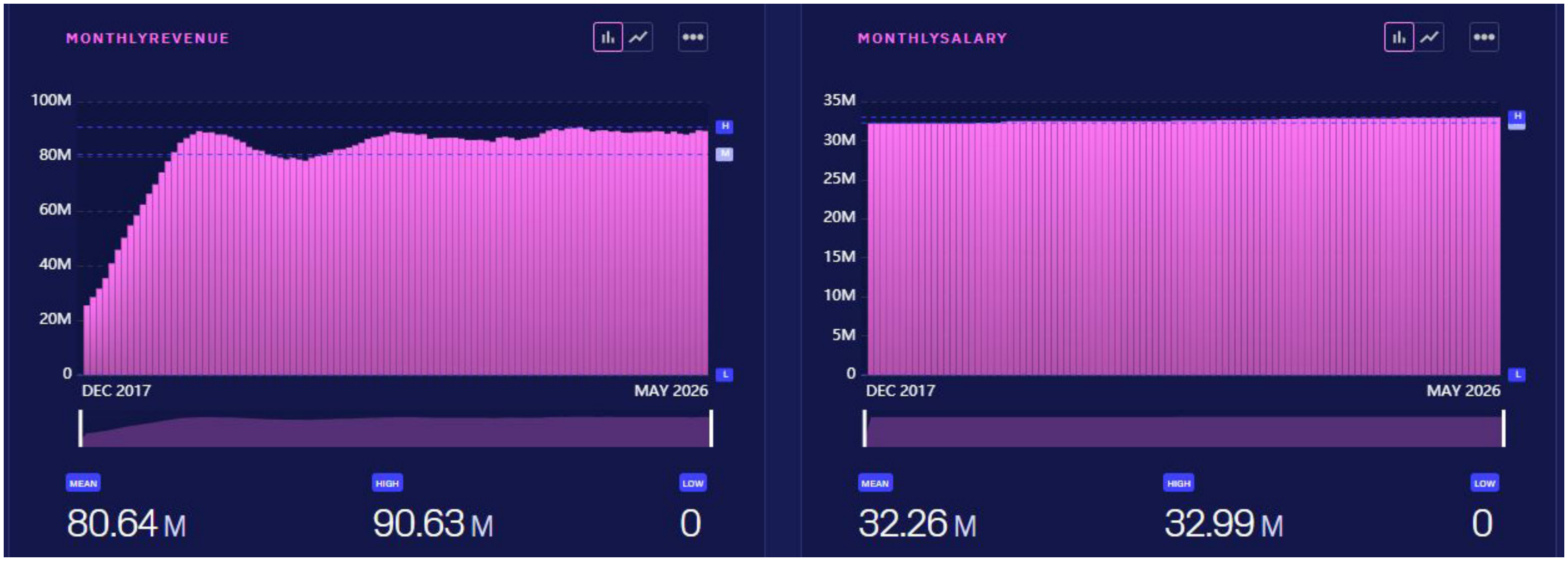
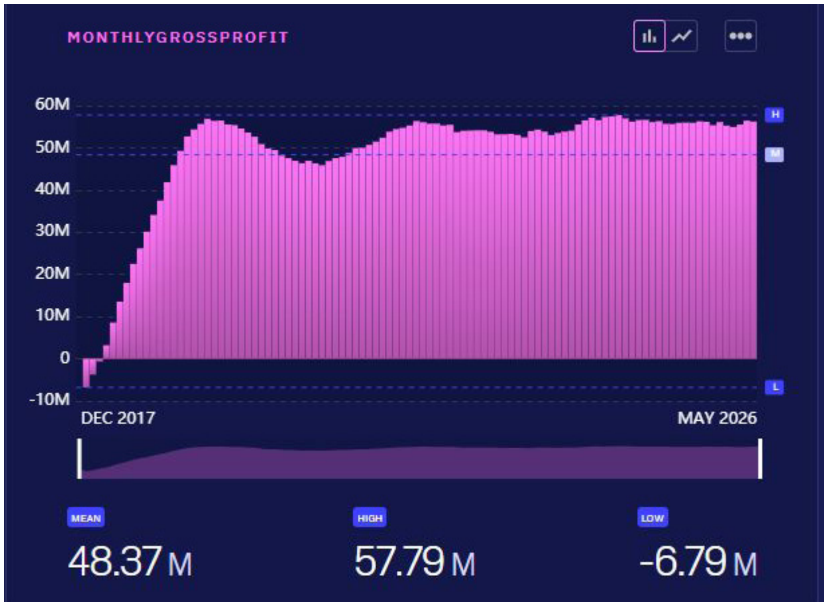


Figure a.2 Gross profit (Revenue - Staff Cost)



A.1.1 Simulation profit and loss

The following Figures (a.1-a.3) are the printed outputs from the ABM model showing the monthly revenue, salary, profit, earnings before interest tax (EBIT), and the net profit.

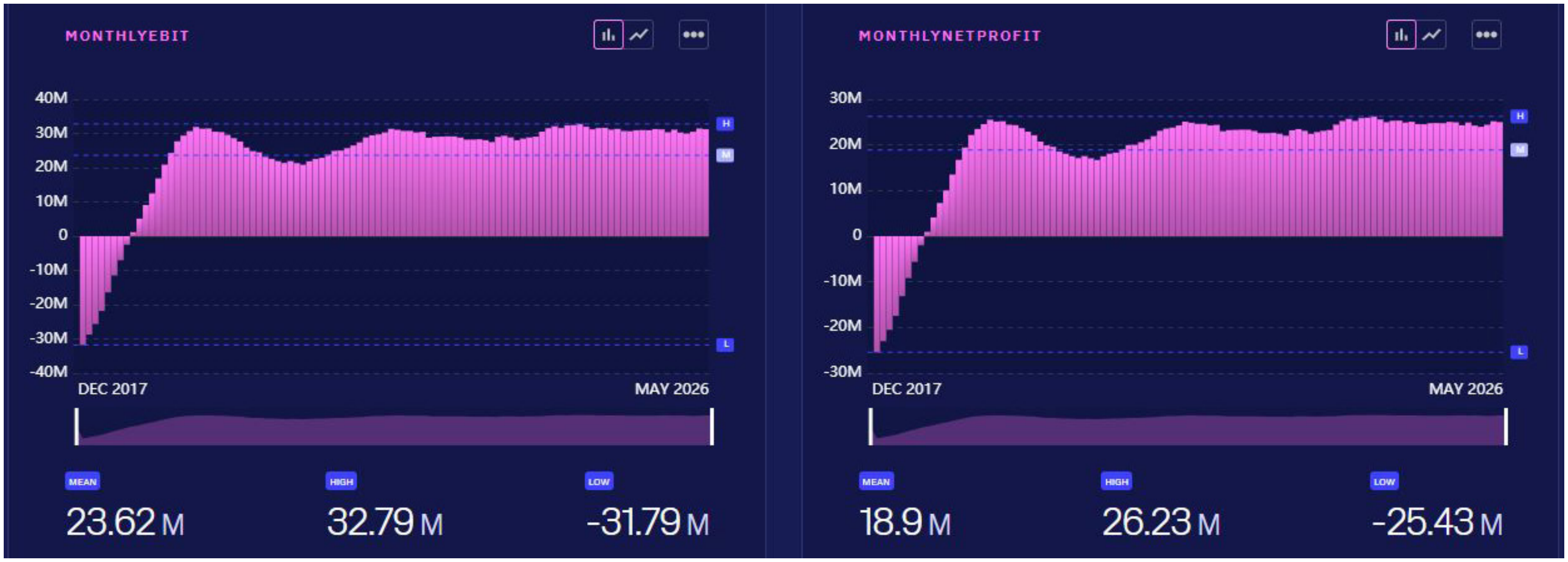
A summary of the produced data generated by the ABM can be seen in Table a.3.

An important factor to note is that the gross profit generated by the ABM does not follow the standard formula. In this scenario, the gross profit represents exclusively the difference between revenue and staff cost (salary). This is because the other operating expenses, such as depreciation and amortization, are set up as a fixed input to the model called FixedCosts. These parameters in the future could be tailored to fit different user's preferences.

In order to match the results generated by the ABM model, it is important to also calibrate Deloitte's P&L to correspond to the same format as the model. This is because the ABM model iterates in monthly steps. The following Table a.4 shows the conversion from the yearly to the monthly financials.

An additional field was added to the table called gross operating profit. This value shows the pure operating profit by adding back depreciation and amortization and other expenses.

Figure a.3: EBIT on the left and Net Profit on the right.



Comparing the two tables, it is clear that the ABM model can generate relatively similar data to the Deloitte report. The mean revenue generated was slightly elevated at £80m compared to the £76m monthly reported by Deloitte. Likewise, the mean salary is £32m compared to the £31m reported. In order to compare the model more accurately, gross operating profit was used, which was £45m compared to the £48m generated in the ABM. There is a bit more of a difference between the EBIT and the profit for the year, which should be the same value, which are £23m compared to the £18m published. Lastly, the ABM also calculated the net profit, which was not published by Deloitte.

Although a large number of assumptions were made during the initialization of the model, when comparing to the ratios between the various inputs, such as revenue and staff costs, one can notice a relatively uniform pattern.

Comparing the ratios between the revenue and all other inputs, the difference is minimal. The ratio between revenue and salary is 40% compared to Deloitte's 41%. Furthermore, the ratio between revenue and the staff cost is 60% compared to the 59% derived by the Deloitte financial statement and lastly, the ratio of revenue to EBIT is 29% to 24% for the Profit of the Year as seen in Table a.4. The increase in the difference at the end is again caused by an estimation error. During the simulation of the model, the selected input for fixed costs (depreciation, amortization and other operating expenses) was set to £25m rather than the £27m reported. This number was simplified in order to make it easier to interpret the returns generated by the ABM.

A.1.2 Discussion about ABM calibration

At first glance, there seems to be a lot of similarities between the mean values generated by the ABM model and the reported statistics form the Deloitte 2020 financial statements. However, in reality, the mean in the ABM seems to be skewed down. Looking at Figures (a.1-a.3), one can notice an initialization period in the model. Thus, lowering the overall mean. By focusing on the revenue, it seems like the mean is in fact closer to £85m rather than the suggested £80m.

On the other hand, by carefully looking at the revenue, it is clear that there is a trending growth in the model. This is because during the nine years the model has been running, the environment has been constantly shifting, with an average growth rate of 2% a year.

This is a consequence of the initialization process. The model is initialized with the correct number of companies, although the *HomeCompany* does not have any running contracts upon initialization. It takes about a year to come up to speed. However, if the ratio between revenue and salary was calculated with the better approximation, the ratio drops from ~40% (32/80) to ~38% (32/85).

As seen in Figure a.4, the market, originally initiated at 1, has been constantly fluctuating. Looking at the mean, one can see that on average the market has been growing. Consequently, by looking at Figure a.5 there has been a net growth in the number of clients.

As mentioned, the model started with about 250 clients, but ended with 280 clients with an average of 3 contracts each. This means that there were approximately 90 new contracts to fulfil congruently. This would explain the steady growth and increase in the revenue seen in Figure a.1.

However, there is another interesting observation made with regard to the P&L returns, as seen in Figures a.1–a.3. It seems that the model, while running, caused dampening oscillation and the frequency seems to be present throughout the graphs. Originally, I thought that this phenomenon was caused by the market, as it seemed to be somewhat aligned to the recession and expansion of the market, as seen in Figure a.4, during the same time as the first dip, there were clients leaving Deloitte due to the recession. However, because of the way the model was developed, there is a bit of a lag from the moment a client decides to leave and when they actually leave, since they have to complete their ongoing contracts.

Therefore, it seems more likely that the model has its own unique natural frequency. Hence, looking at either the *utilization* rate in Figures 3 and 4, or especially at the *months benched* in Figure a.7, for junior consultants, the oscillation is quite obvious. Consequently, it seems that even though the model is highly randomized, there is still a baseline which must be followed by the model, and it

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Figure a.4: Market value.

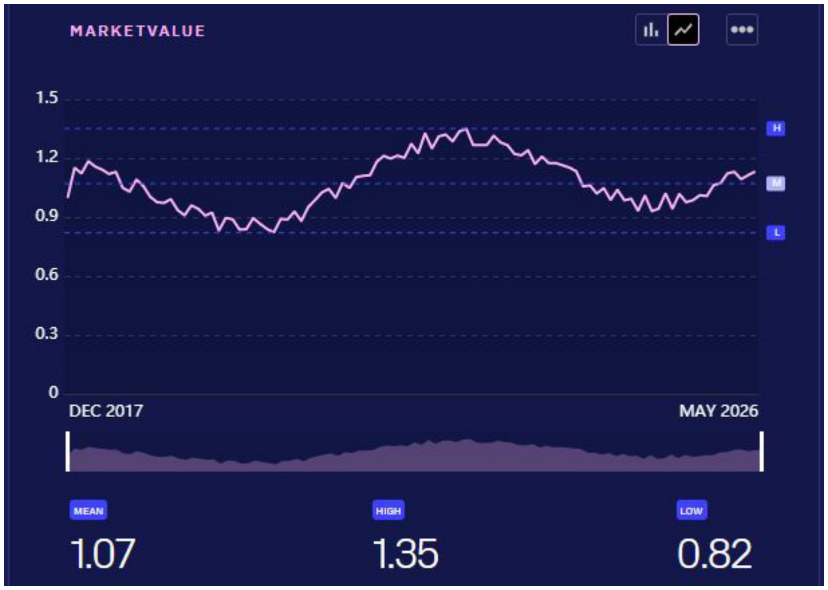


Figure a.5: Number of client companies.

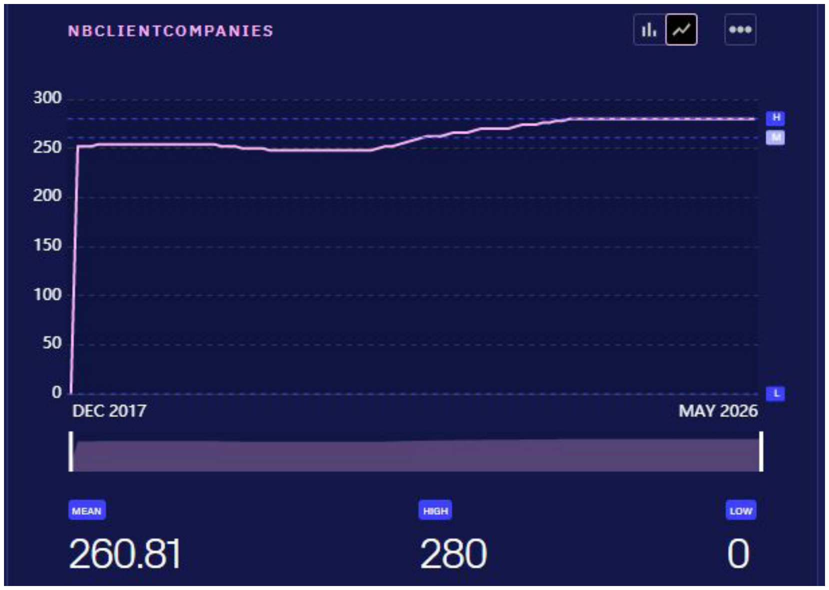


Figure a.6: Number of clients in the process of leaving.

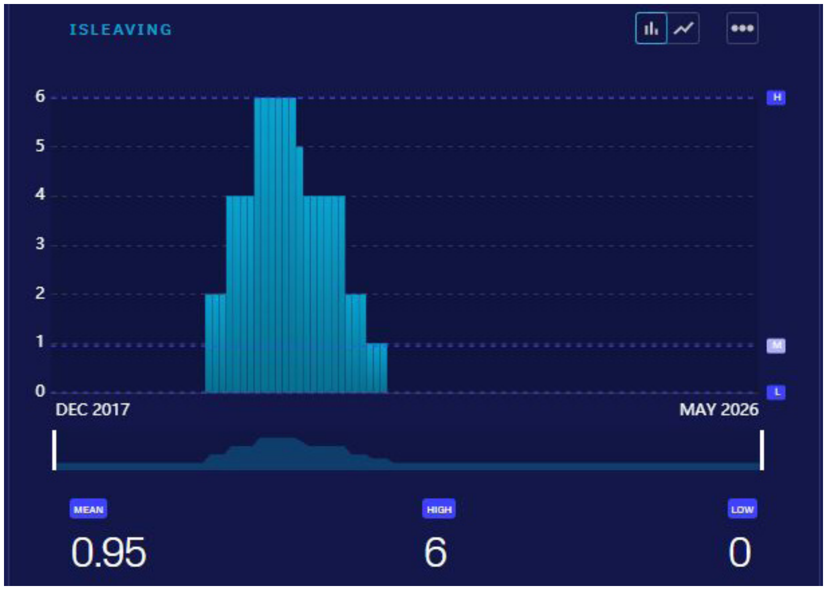
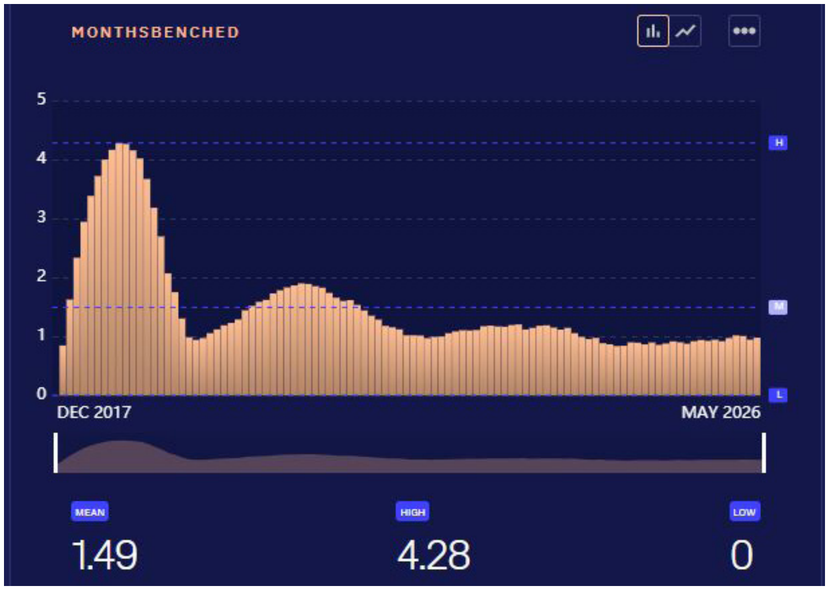


Figure a.7: Mean representation for the months benched for Jr Consultants.



seems to have come through in the simulation. This unexpected development in the model, however, can be either seen as a glass half-full or half-empty. The oscillation may reduce the precision of the model, as the user might become uncertain whether the dip in the results was intentional or a by-product created by the oscillation. On the other hand, there is some representation to what happens in real life. People tend to follow others' initiative known as the bandwagon effect (Kelly, 2020). Not to the same extent as seen in the model; however, one could interpret the oscillation as human behavior, where one client might approach Deloitte with a contract and others might follow.

However, there is a way to eliminate the oscillation created by the model. This would be achieved by initiating the model with pre-existing contracts already running. This would prevent the sudden influx of contracts, removing the catalyst to the initialization of the wave. Proof of this can already be seen in the model. Looking at the revenue in Figure a.1, the oscillation quickly phases out. This behavior would be expected by the ABM when initialized with pre-existing running contracts. Unfortunately, the model was developed with much smaller numbers and consequently the phenomenon wasn't caught until a later date, but it would certainly be an interesting part of the future development of the ABM.