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# The supply chain as a complex adaptive system: hybrid simulation modelling

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## Abstract

Complex adaptive systems (CAS) are constituted by large number of components called agents, wich learn, adapt and interact. Supply chain has been conceptualized, modelled and simulated as CAS by many authors. Despite the existing studies on simulation of supply chain as CAS the present study aims to fill a gap, because it proposes a hybrid simulation model of supply chain as CAS (Discrete-Event Simulation and Agent-Based Modelling and Simulation) using Anylogic™ software to analyze the micro mechanisms that influence on the service time measured at macro level. Although previous researchers conducted simulation studies into the supply chain as CAS, they all focused on applying agent-based simulation approach only. First, the literature review on modelling and simulation of supply chain as CAS is developed. Second, a hybrid simulation model of supply chain as CAS (Discrete-Event Simulation and Agent-Based Modelling and Simulation) is implemented using Anylogic™ software and presented. Third, the simulation results are analyzed in Section 4. Finally, the concluding remarks are drawn in Section 5. Results gave us the opportunity to observe and measure impact of limited capacity of facilities and its dynamics depending on demand flows.

**Keywords:** CAS; supply chain; hybrid simulation; e-commerce; service time.

## 1. Introduction

Complex adaptative systems (CAS) term was first introduced by Walter Buckley in 1968. In his publication named *Society as a complex adaptative system*, Buckley explained that CAS are open internally as well as externally, therefore assumes that the interactions among their main components can change their own nature with a significant effect on system as a whole. So, CAS are constituted by large number of components called agents, that learn, adapt, and interact (Holland, 2006). For making decisions, CAS does not search on huge solution tables, instead regularities compress into schemes. Applying schemes into real life components results as feedback, that defines their position and reputation to compete showing fitness as an emergent property of the system (Gell-Mann, 1994).

From the cybernetics point of view (Rosenblueth *et al.*, 1943), CAS are complex effectors organized and self-regulated to subtract themselves or one of their effects, within certain limits, from contingency, from increased entropy, or from both (Lara-Rosano, 2016). The environment of a CAS sends different types of signals, such as messages, electromagnetic waves, mechanical pressures, emanations of chemical substances, etc., so, when they can be detected and analyzed by any CAS, can provide information about that environment for example, spatial dimensions, shapes, its nature. etc. so that, in the face of a contingency or a change caused by the environment, it can respond homeostatically in the most appropriate way, without losing its fitness (Lara-Rosano, 2016). Considering that homeostasis is based on feedback loops that come from the environment, in which the corresponding information is processed, and an adaptation response is given, for homeostasis to occur, three elements are needed: (Lara-Rosano 2016).

1. Receptors or sensors: they are responsible for detecting signals from the external environment that can provide information about it.

2. Processor or homeostatic controller: it is the cybernetic center of the CAS and the one that, through the function of perception, interprets the sensations that come from the receptors and determines what the system must do to fulfill its purposes.

3. Effectors: their function is to execute the decision sent by the homeostatic processor through the efferent conductors.

Also, supply chain has been conceptualized as a CAS by many authors: Choi *et al.* (2001), Dunne (2004), Surana (2005), Seuring (2013), Brandenburg (2014), Huerta -Barrientos and Flores de la Mota (2017) among others. Considering the cybernetics point of view, Figure 1 shows the receptors or sensors, the processor or homeostatic controller and the effectors of a supply chain conceptualized as CAS.

Despite the existing studies on simulation of supply chain as complex adaptive system the present study aims to fill a gap because it proposes a hybrid simulation model of supply chain as CAS (Discrete-Event Simulation and Agent-Based Modelling and Simulation) using Anylogic™ software to analyze the micro mechanisms that influence on the service time measured at macro level. Although previous researchers conducted simulation studies into the supply chain as complex adaptive system, they all focused on applying agent-based simulation approach only.

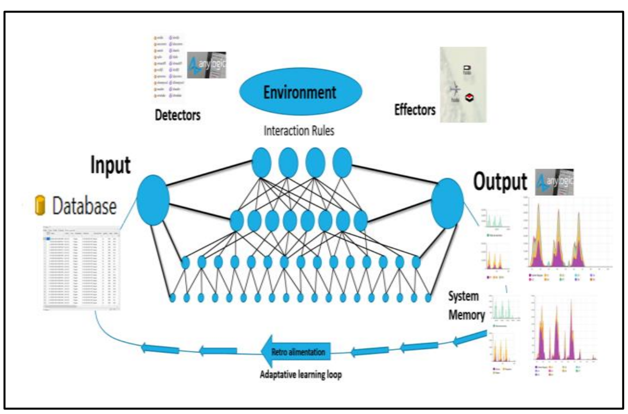


**Figure 1.** Supply chain conceptualized as CAS.

**Table 1.** Relevant paper on supply chain as CAS, 2001-2010.

| Authors | Contribution on Supply chain as CAS | Year |
|---|---|---|
| Choi *et al.* (2001) | "Supply networks and complex adaptive systems: control versus emergence". Describes supply chain as a complex adaptive system instead of observing it only as a system. Supply chain properties and behavior are explained as a CAS together with problem solving trends. | 2001 |
| Dobson (2004) | "Complexity Science Will Transform Logistics". Presents applications of agent-based modelling and potential for RFID technology controlling. | 2004 |
| Surana *et al.* (2005) | "Supply-chain networks: a complex adaptive systems perspective". Describes supply chain as a CAS and number different technics for its study and modelling. Includes Agent based modelling and system dynamics. | 2005 |
| Nilsson and Darley (2006) | "On complex adaptive systems and agent-based modelling for improving decision-making in manufacturing and logistics settings: Experiences from a Packing company". Describes complex adaptative systems together with agent-based modelling. Shows an application on a manufacturing company. Distinguish advantages a bottom up and bottom down analysis. | 2006 |
| Wycisk *et al.* (2008) | "Smart parts. supply networks as complex adaptive systems: analysis and implications". Describes and compare supply chain with CAS and their properties. Uses term of logistics complex adaptative systems and stans out the necessity for including "smart parts" management on a supply chain. | 2008 |
| Ivanov and Sokolov (2010) | "Adaptative Supply Chain Management". Mentions different solutions approach like optimization, simulation control theory, heuristics and complex adaptative systems. | 2010 |

**Table 2.** Relevant paper on supply chain as CAS, 2011-2017.

| Authors | Contribution on Supply chain as CAS | Year |
|---|---|---|

| | | |
|---|---|---|
| Nair and Vidal (2011) | "Supply network topology and robustness against disruptions – an investigation using multi-agent model". Presents an agent-based modelling together with small world network analysis. Focuses on how topology network helps on system robustness. | 2011 |
| Haghnevis and Askin (2012) | "A Modeling Framework for Engineered Complex Adaptive Systems". Proposes a framework of a complex adaptive system to model engineering systems. Uses an example of an electric network. Incorporates social interactions. | 2012 |
| Wojtusiak *et al.* (2012) | "Machine learning in agent-based stochastic simulation: Inferential theory and evaluation in transportation logistics". Proposes an agent-based modelling and machine learning system called PLASMA and Q21 system for transportation traffic rules learning. | 2012 |
| Long (2015) | "Three-dimensional-flow model of agent-based computational experiment for complex supply network evolution". Implements an evolutive based on agents' model. Investigation is grounded on supply chain complexity dynamics in terms of materials, information, and time flows. | 2015 |
| Huerta Barrientos and Flores de la Mota (2017) | "Modeling Sustainable Supply Chain Management as a Complex Adaptive System: The Emergence of Cooperation". Implements a game theory evolutive model for cooperation. | 2017 |
| Reyes Levalle and Nof (2017) | "Resilience in supply networks: Definition, dimensions, and levels". Describes resilience levels on supply chain and describes complex adaptative systems. | 2017 |

The paper relies on the modelling and simulation of supply chain as CAS, but we make a novel application in the field of hybrid modelling and simulation of an e-commerce supply chain in the context of Mexico. We obtained an average indicator of backlog and the period of recovery. By comparing backlog data with capacity bottlenecks can be understood in two dimensions, first to dimension volume impact and then to ponder if recovery time is according to business service requirements.

The paper is prepared as follows: the literature review on modelling and simulation of supply chain as CAS is developed in Section 2. A hybrid simulation model of supply chain as CAS (Discrete-Event Simulation and Agent-Based Modelling and Simulation) is implemented using Anylogic™ software and presented in Section 3. The simulation results are analyzed in Section 4. Concluding remarks are drawn in Section 5.

## 2. Systematic literature review

In this section, we present the literature review on modelling and simulation of supply chain as CAS. We followed the literature review process proposed by Machi and McEvoy (2009). The Figure 2 shows the steps for conducting the systematic literature review. Modelling and simulation of supply chain as CAS

#### 2.1.1. *Step 1. Select a topic*

In this case, the topic was simulation of supply chain as complex adaptive system.

#### 2.1.2. *Step 2. Search the literature*

For each manuscript, preliminary relevance was determined by title. We searched Scopus database, accessed on April 11, 2022. We limited the publication date from 2017 and 2021, so that we can build the review on the literature published in the past five years. We started the literature search by using the keywords: *supply chain* AND *complex* AND *adaptive* AND *system*. We found a total of 33 relevant articles.

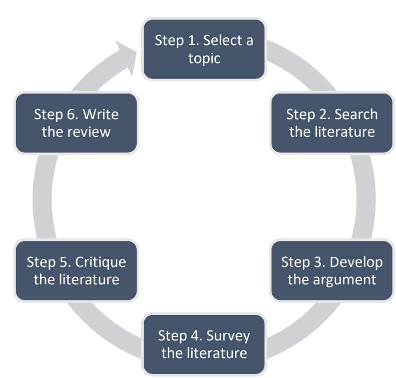


**Figure 2.** The literature review model, Machi and McEvoy (2009).

#### 2.1.3. *Step 3. Develop the argument*

The main objective of the search was to find the contributions where the CAS approach has been applied to study supply chain.

### *2.1.4. Step 4. Survey the literature*

We downloaded the bibliographical information and analyzed it using VOSviewer™ software (Van Eck and Waltman, 2010; Van Eck and Waltman, 2014), which is a software tool for constructing and visualizing bibliometric networks based on citation, bibliographic coupling, co-citation, or co-authorship relations.

We conducted two types of analysis: co-authorship, with authors as the unit of analysis, and co-occurrence with keywords as unit of analysis. Figure 3 presents the visualization of the co-authorship network constructed using full counting technique. Each circle represents an author, we counted 98 different authors. The size of a circle reflects the number of publications of the corresponding author. The distance between two circles indicates the relatedness of the authors (Van Eck & Waltman, 2014). Colors represents clusters of authors with strong co-authorship links. Table 3 provides the top-ten authors in this case.

On the other hand, the visualization in Figure 4, based on full counting, shows the co-occurrence network, distinct groups of keywords can be easily distinguished. Each circle represents a keyword. The size of a circle reflects the number of ocurrences of the corresponding keyword. Colors represents clusters of keywords with strong co-occurrence links. We note that supply chain relates to complex adaptive system, adaptive systems, and complex networks.

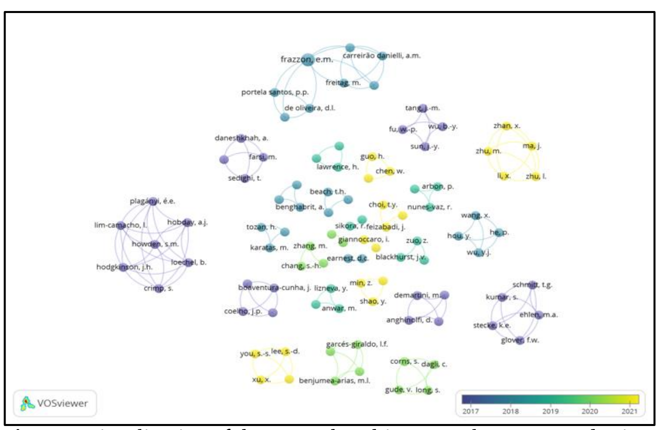


**Figure 3**. Visualization of the co-authorship network constructed using full counting technique by VOSviewer™ software.

**Table 3.** Number of co-authors of top-ten authors.

| Author | Co-authors |
|---|---|
| Frazzon, E. M. | 7 |
| Crimp, S. | 6 |
| Hobday, A.J. | 6 |
| Hodgkinson,J.H. | 6 |
| Howden, S.M. | 6 |
| Lim-Camacho, I. | 6 |
| Loechel, B. | 6 |
| Plagányi, E. E. | 6 |
| Carreirao Danielli, A.M. | 4 |
| Ehlen, M.A. | 4 |

Importantly, the visualization in Fig. 5 indicates the co-occurrence network over line-of-time from 2017 to 2021. Dynamic evolution, adaptive control systems, stochastic systems, automotives and competition are the topics recently used in the context of supply chain and CAS. Figure 6 provides the density visualization and Table 4 lists the top-ten keywords by number of occurrences.

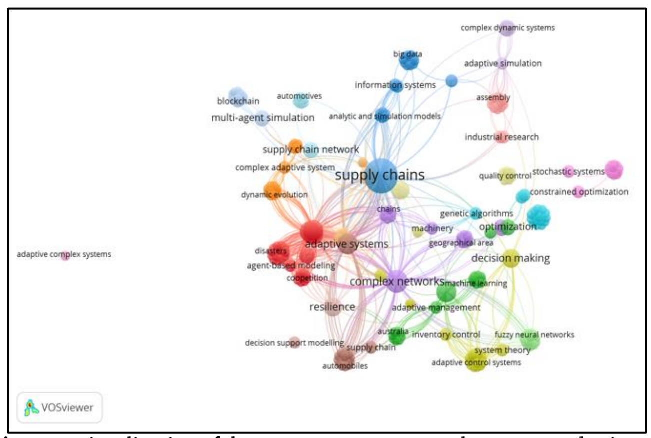


**Figure 4**. Visualization of the co-occurrence network constructed using full counting technique by VOSviewer™ software.

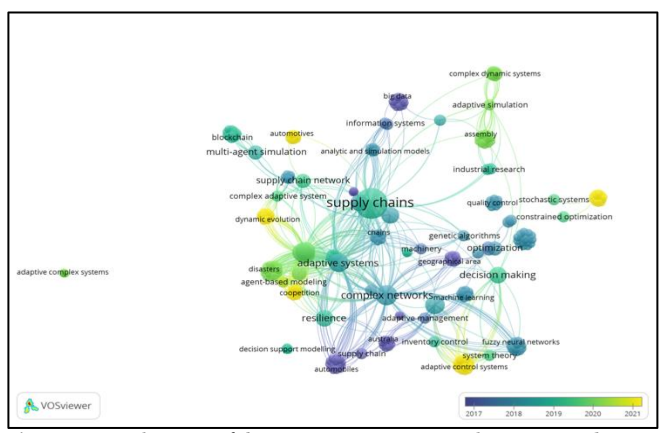


**Figure 5**. Visualization of the co-occurrence network constructed using full counting technique by VOSviewer™ software, evolution over line-of-time.

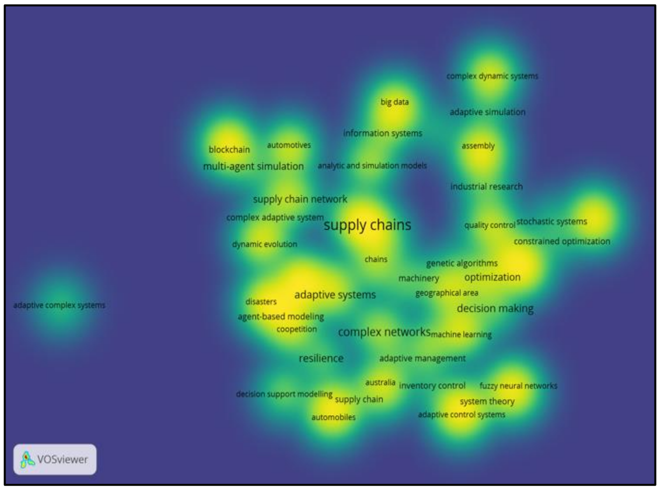


**Figure 6**. Visualization of the co-occurrence network constructed using full counting technique by VOSviewer™ software, density visualization.

**Table 4**. Number of occurrences of top-ten keywords.

| Keywords | Occurrences |
|---|---|
| Supply chains | 14 |
| Complex networks | 6 |
| Adaptive systems | 5 |
| Agent-based model | 5 |
| Autonomous agents | 5 |
| Computational methods | 5 |
| Supply chain management | 5 |
| Decision making | 4 |
| Resilience | 4 |
| Simulation | 4 |

#### *2.1.5. Step 5. Critique the literature*

Based on the analysis of the contributions more relevant, it is important to indicate that simulation studies have been conducted into the supply chain as CAS, however they all focused on applying agent-based modelling approach, multi-agent simulation, and combine analytical and simulation models. In the last five years, the study of supply chain as CAS has been focused on micro level only.

## 3. Methods

### 3.1. Methods

In this section, we implement a hybrid simulation model of supply chain as CAS (Discrete-Event Simulation and Agent-Based Modelling and Simulation).

#### *3.1.1. A novel hybrid modelling and simulation methodology*

We present a novel methodology for integrating top-down and bottom-up approaches using synthetic microanalysis, of an e-commerce and covid 19 pandemic influenced supply chain to perform simulation experiments and to find natural emergent properties at certain levels as result of the interactions between the constituent parts. The conceptual modeling and communication hybrid simulation phases are based on Eldabi (2019) using complexity sciences tools. Our main contribution is to adapt recognized knowledge for a complex adaptative parcel delivery supply chain.

The 3.2 Section describes in general methodology and a brief description of elements to proceed with 3.3 section where we use examples based on case study to land and show specific implications and concepts. On every phase, advantages of hybrid M&S and CAS approach are described and highlighted.

#### *3.1.2. Phase 1: Conceptual modelling*

In short, Phase 1 mainly focuses on problem source definition and objectives identification. Working on a complexity science framework, we assumed that the main objective will be to find emerging patterns due to interactions among the components of the system. Then analysis and behavior understanding will be also helped by an additional complexity science theorical framework proposed by Auyang (2019). Same as typical system modelling, inputs are considered to obtain certain outputs. It is also included a feedback adaptative learning loop and a system learning memory. In our case this loop is implemented by users looking for what if scenarios and understand their emerging patterns.

Different to *black box* system diagrams, in our approach, system interactions play the most relevant role. That's why we needed a software with capabilities including not only to process an input and return an output like a typical DES simulation. After a software analysis, we found that Anylogic™ is one of the simulation leading platforms found in the market, native Anylogic™ software's features enables users to integrate DES, ABMS and SD on a single integrated model that can dynamically read and write data to spreadsheets or databases during a simulation run and is capable to develop spatially explicit models integrating GIS functionality (Ma *et.al.*, 2021). Then, the possibility to build hybrid simulation models on Anylogic™ is not only possible, but it is also many times implied on software's applications. In our case study and methodology, we took advantage of DES and ABMS technology by declaring supply chain facilities vehicles and as agents that have their own DES processes. Therefore, demand agents can travel along supply chain processes being influenced by specific job time. CAS components of our proposed modelling are briefly described below:

**Input** including typical on hand information about supply chain:

a) Historical or forecasted demand
b) Objective service level
c) Product characteristics
d) Number of facilities and location
e) Number of vehicles and scheduling
f) Processing and traveling time

**Detectors** aided by **Anylogic™'s** features

a) The counter variables.
b) The statistics Blocks.
c) Time DataSet blocks and plots.
d) Time histogram blocks and plots effectors.
e) Agent indoor facilities with DES processes.
f) Agent transportation network.

**Output** suited for micro and macro system analysis

a) Specific time Bottle necks
b) Nodes behavior
c) Temporarily Exceeded and maximum capacity
d) End to end product system life.
e) Specific time (process, travel, waiting) per agents or facility.
f) Backlog indicators.
g) Bottle necks

Last but not least, **Effectors** are agents interacting on simulation, in this case, are the ones who process demand an also in charge of performing logistics.

### *3.1.3. Phase 2: Simulation modelling*

In the simulation models, interaction rules are governed by programmed business rules and a predesigned a supply network. Every agent is created based on historical demand, from a source block and then travel to different facilities. On every facility, demand agents could change their attributes or lifetime due to DES processes, and then wait for a vehicle that match the next step or destination. Hybrid simulation models are integrated by agents working as effectors of our CAS as following:

1. Main Agent
2. Demand Agent
3. Facility Agent
4. Transportation Agent
5. Agent Waiting Areas

Without being exhaustive saving a more specific description of agents and their actions by presenting the model on study case, in general *Main agent* is who hosts everyone in a GIS geospatial environment, then demand agents enter *facilities* to accomplish certain job governed by DES simulations. By modelling agent-based interactions, transportation agents announce their departure or arrival based on their schedules and take agents from facilities waiting areas to their own loaded product areas, achieving to carry demand agents to next destination.

### *3.1.4. Phase 3: Model communication*

Once DES processes agents are created, communication phase includes simulation programming to link variables, identify interactions and then to execute model scenarios. Here is where we identified the most relevant advantage of analyzing and modelling supply chain with a complex adaptative system perspective. Being aware of dynamics, and to analyze outputs as emerging system patterns, upgraded the results of our methodology. On the same way, synthetic micro analysis gave us the opportunity to understand the most micro level interactions that drive to model better business decisions. *Linking variables* and identified interactions are mainly built by product flows and flows are followed by database driven decisions. The following diagram explains how demand agents flow through the simulation model.

Figure 7 shows product and demand flows inside Anylogic™ software, every box represents different states of demand agents preforming processes. It assumes a traditional DES flow along described agents who also are interacting and communicating between each other. On every step, outputs are programmed considering special attention on simulation time and different products behavior. Normally output values are shown in dynamic plots during simulation. Now that CAS behavior is programmed on simulation software, adaptative learning loop depends on user experience and iterative what-if scenarios. Every iteration stored output on computer will conform our system memory, and retro alimentation will be sustained proposing different agent network paths or capacity.

*Model execution and data Exchange* is not complicated after modelling agent interactions, first step is to run the model, follow interesting interactions and wait for the result. After every iteration, recorded statistics and indicator calculations, are exported to a consolidated Microsoft Excel spreadsheet. The relevance of this step is not only to obtain results and record them, but objective is also to identify the influence of every interaction at micro level that are shown at macro level as emergent patterns of the complex adaptative system, in our case these emergent patterns coincide with supply chain performance indicators.

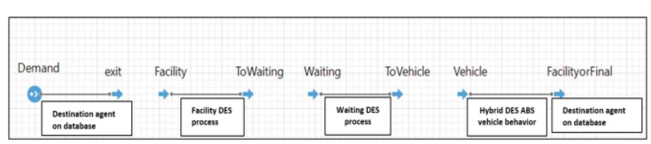


**Figure 7:** Simulation flow diagram.

*On Evaluation of outputs phase,* we analyze results recorded and programmed on software, accordingly, we take advantage of datasets blocks along with time plots on agent processes simulation. Examples of outputs could be demand behavior, transportation travel time and utilization, bottleneck understanding using backlog statistics at micro level and at macro level, and facilities utilization. Even when performance is enough for accomplishing demand requirements at macro level, interactions at micro mechanisms should be understood to get a better result. It is important to highlight again that this is a general description of analysis to be more specific of how this was implemented on one of our case selected studies.

### 3.2. The case study: Parcel delivery supply chain influenced by e-commerce

Adoption of new consumer habits due to the increase of ecommerce before, after and during covid 19 pandemic, resulted on an unexpected need for last mile delivery. Parcel delivery companies have had difficulties to plan their operations and to understand different scenarios. With more than 12,000 collaborators and about 130 hubs connected by 300 hundred trucks and 5 airplanes comprising its primary network, our case study company planning analysts, needed a tool to run demand scenarios with the objective of discovering alternatives for limited capacity in certain hours that could extend facility lifetime and at the same time to improve customer service.

Taking advantage of the development of a hybrid model methodology based on CAS taken of PHD studies protocol along with Mexican *VP consulting* business knowledge, an Anylogic™ DES, ABM simulation provided a platform for testing and analyzing company situation. It is important to mention that model focuses on HUBS locations and primary network, leaving last mile delivery only as a process without considering vehicles and final customer location.

#### *3.2.1. Phase 1: Conceptual modelling*

Due to the characteristics of our case study involving a large number of constituents that learn and adapt, showing and dynamic behavior, our simulation model was built based on CAS approach. Components of simulation are described below:

**Input**

a) Historical demand of parcels including origin, destination, type of packaging, type of customer, time and day of collection and promised service time
b) Logistic hubs locations, taking into account processing capacity
c) Transportation ground and aerial number of assets considering schedules and capacities
d) Business sorting rules for every demand combination

**Detectors** on every agent

a) Dataset blocks, for customer, service and package type demand behavior, and time plots
b) Capacity backlog and utilization of facilities datasets and time plots

**Output** suited for micro and macro system analysis and specific business questions

Exported Excel spreadsheet with all collected data and statistics during the model.

a) Customer aggrupation data of total demand
b) Parcels sorted by hub
c) Parcels delivery by hub
d) HUB capacity and utilization behavior
e) HUB Backlog behavior
f) Transportation Assets utilization

**Effectors** are the set of HUBS including their sorting and delivery process together with transportation vehicles who are in charge to collect and deliver parcels from each place to another during simulation run.

#### *3.2.2. Phase 2: Simulation modelling*

All the options indicated before, were programed on a hybrid simulation model using historical data as an input looking for improvements on certain moments in time. Before starting to describe simulation inputs and outputs, it is important to remember the relevance and advantages of our methodology, that not only implies to program a hybrid model. It is also important to recognize how these steps can be useful to describe a real life complex adaptative e-commerce supply chain system. CAS are recognized mainly by their nonlinear behavior and a large number or constituents interacting at the same time, so every parcel is conceived as an agent and is processed on every logistic agent node until transportation agents take it to their final destination. By following data base driven rules, package show complex behavior at micro level on hub processes and at macro level by understanding limited capacity and demand behavior. Emergent patters were identified due to several runs and output recompilation. First step of simulation is to set up agents and their processes on a GIS environment (see Fig. 8). Database includes every parameter and business rule to give life to agents and its way of behaving. Main agent not only contains agents but also plots of demand behavior by product or customer type. They are all fed by the collection of information saved on dataset blocks after refreshing counter variables.

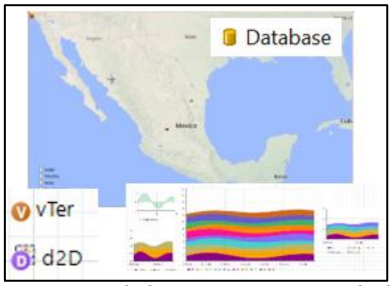


**Figure 8:** Main agent including GIS maps HUBs Vehicles and Plot outputs.

Processes of sorting and delivery are on purpose not complicated, so they are only composed by delay blocks, queues, and seized resources forming a typical DES model. To achieve the objective, where we programed complex behavior, is in the way the packages travel to different places choosing a business rule logistics path or a vehicle depending con their capacity and schedule. Then on every DES exit block a database query is executed, telling the agent its corresponding agent waiting area that also lives inside facilities as a sub agent. On this step, a waiting area works as a stagging real-life zone where products are hold until the right vehicle is ready to be loaded. By filling array collections when transportation assets arrive to the facility, waiting area agents receive the message to decide, depending on product and reported capacity, if the demand agents must travel on a faster vehicle like van or an airplane instead of a truck. Same as main agent, indoor facility processes and waiting areas sub agents, are enabled with data collection and plots to follow micro level behavior.

It is relevant to mention that none of the agents are governed at a central level, everyone follow their own simple rules and the result we obtain is complex system behavior. An example of this behavior could be found in the nature, where insects or birds manage to build complicated structures by only following the closest element of its population. Being consistent with the argument, *transportation assets* have their own agent-based logic, where everyday schedule events trigger their departures and arrivals. Basic rules stored on data base, indicate them where to go each day of the week. By far transportation assets where the more difficult to program.

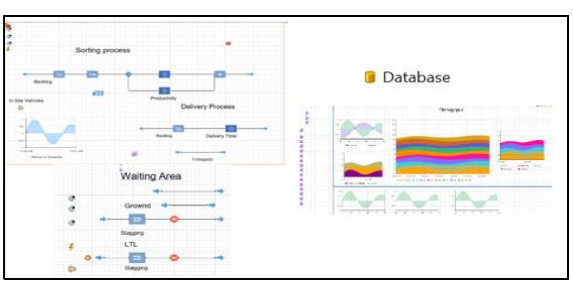


**Figure 9:** HUB processes and output plots.

Difficulty presented consisted first on incorporating schedules, since Anylogic™ standard blocks do not allow to use parameters taken from database, schedule API was used to programmatically run schedules on model simulation. Then, every stop was programmed inside agent states to report arrivals and departures to HUBs waiting areas and manage to pick up products (see Fig. 9).

On this step and on every DES modelling phase, it is important to highlight the role of JavaScript programming, typical DES logic is included in Anylogic™ and even statechart logic for agents modelling is useful for models escalating, but where we found a real breakthrough, is in allowing the ability to the programmer to enable model communications by incorporating real life rules on different blocks and states using structured text programming language (see Fig. 10).

### *3.2.3. Phase 3: Model communication*

In a consistent way, final phase of our case suty model, contains mentioned four steps by T. Eldabi (2019) tutorial on means of simulation, *identifying linking variables*, *identifying the interactions type, model execution and data exchange and evaluation of outputs.* In this case novelty is about complex adaptative approach together a specific type of business.

After explaining modeling and role of agents, linking variables between DES and ABM models are easy to figure out. Most are linked by demand, because of parcels traveling along processes. There is also an implicit link since DES models born inside logistics agents.

Interactions are understood due to the behavior of supply chain as *parallel*, because DES models are mutually transferring packages during simulation run. *Model execution* is all about starting flow of demand and read the influenced variables. That is why on this text section our focus is on *outputs and their evaluation.*

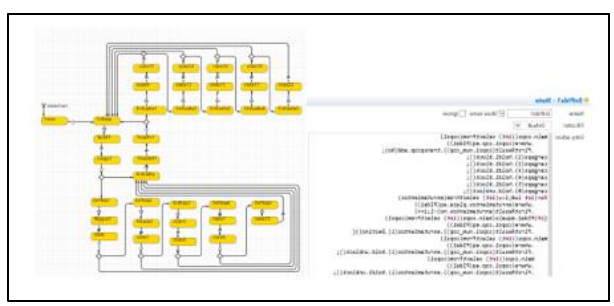

**Figure 10:** Transportation Agent ABM logic and JavaScript code.

Our first output is about demand behavior, not only about total collected demand. We analyzed every facility to identify who has the most collected, delivered or sorted parcels over time. As an example, it can be observed on Figure 11 how model allowed us to analyze behavior at a certain day of the week and even during daytime using time stack charts divided customer types.

This is a perfect example of emergent patterns that can be observed on the system caused by dynamics complex behavior. Even when interactions of regular customers and their volume seems to be more relevant, it is important to notice how e-commerce demand could impact business in certain moment in certain place reducing capacity of the system to respond appropriately. Here is where efforts can be made for it to be worth. Same as demand behavior, capacity behavior was analyzed as an emergent pattern of the supply chain complex adaptative system (see Fig. 12).

The interesting part of analyzing capacity, is to notice that emergent pattern of limitations is presented only on certain hours. Therefore, analyzing agent interactions that cause these effects, is what makes the difference between a static traditional optimization model based on averages of some period in time. By this type of analysis that not only identify the problem but relevant interactions, implementing solutions were simpler and more possible to reach.

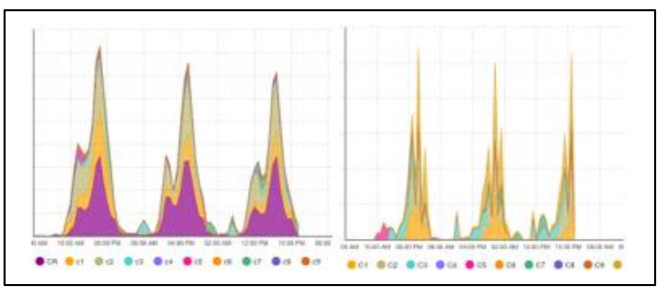

**Figure 11:** Demand and package sorting example plots.

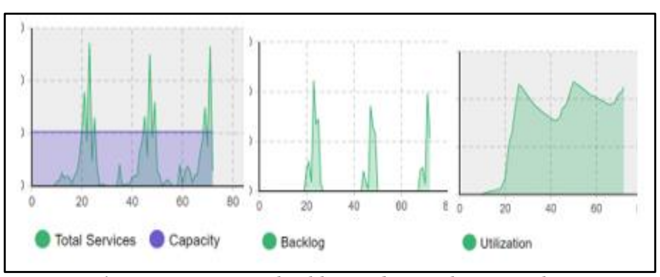


**Figure 12:** Capacity, backlog and HUB plot example.

## 4. Results and Discussion

Simulation results are analyzed in two ways, the first is to confirm what we expected about methodology, and the second about business benefits.

On the one hand, we manage to confirm benefits of assuming supply chain as a CAS. CAS approach helped us to focus on agent interactions and dynamics instead of trying to solve the problem from every hub and asset one by one in a reductionistic way. By understanding complex emerging patterns at macro level and obtaining capacity and demand outputs, we reached to find the causes at micro level and take actions to improve service level. Our contribution at last was to implement this already existing approach and tools proposing a novel methodology defined for an specific real life business.

On the other hand, by identifying specific customers that are collected in certain places at certain time asking for a particular delivery promise, business analysts got to prioritize processes. Short term benefits are to know how to act in a high season to maintain service level and log term are to delay major investments by increasing facility utilization. Advantage of this modelling is not only to know what to do but also the right time and circumstances.

## 5. Conclusions

We conclude that methodology can be implemented on a computer hybrid model simulation but more important to help a company to take better decisions. Even when supply chain had been assumed as a CAS potential of this approach is enormous and could help to manage with current logistics problems caused by constant change sin the environment. We want to emphasize that companies are still needed for operation research specialists. Currently, even solutions based on static models, are not within the reach of a large part. This lag difficult even more to implement new approaches.

On the other hand, future work could be also the study of the CAS learning loop not only based on what if scenarios and user understanding. CAS perspective gives us the opportunity to look for fitness system sizing and improvement using genetic algorithms as for example.

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