Proceedings of the 2022 Winter Simulation Conference
B. Feng, G. Pedrielli, Y. Peng, S. Shashaani, E. Song, C.G. Corlu, L.H. Lee, E.P. Chew, T. Roeder, and P. Lendermann, eds.

ENTERPRISE DIGITAL TWINS FOR RISK FREE BUSINESS EXPERIMENTATIONS

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ABSTRACT

While Digital Twin technology is a proven cost-effective experimentation aid for analyzing physical systems, its effective exploitation is yet to be seen in the enterprise space. Enterprises that are operating in a dynamic uncertain environment still address critical business problems like product redesign, improvement of customer satisfaction, enhancement operational efficiency and business transformations through intuition-based trial-and-error approach. Being not grounded in precise scientific laws as physical systems, the system of system nature, inherent uncertainty, inadequate and fragmented data, and increasingly dynamic operating environment make it difficult for existing enterprise modelling techniques to serve as digital twin of enterprise. We developed a pragmatic and robust *Enterprise Digital Twin* (EDT) as an aid to "in-silico" simulation-driven business experimentation for evidence-backed decision-making with possible tradeoffs. This paper presents our approach, key considerations of EDT and their rationales. It also demonstrates the efficacy of EDT with an illustrative business case of a telecom organization.

1 INTRODUCTION

Enterprises are complex system of systems that aim to continue achieving their business goals while operating in a dynamic and uncertain environment where changes can occur along multiple dimensions in unforeseen ways (Marchau et al. 2019). They typically run a host of business processes to deliver value to their customers in terms of fit-for-purpose products and services to maximize user experience. They also need to continuously reinvent product & services offerings, channels of customer engagement, pricing, and promotional strategy to satisfy evolving customer needs. However, a change comes with certain degree of risk and non-reversable business consequences in addition to cost. As a result, enterprises are often trapped into ambidexterity dilemma (Brix 2019) while establishing the right balance between required business changes and associated business risks.

Decision makers are tasked to analyze the context and business objectives to identify potential change options, evaluate their efficacies and associated risks, and select the best option for achieving the desired objectives. While arriving at a robust decision calls for detailed information and analyses along multiple dimensions, enterprises are often forced to make decisions with partial information. This is principally due to the large size and complex interdependecies of enterprise as well as limitations of human experts. Current upward trend, irrespective of business domains, is to analyze historical data using sophisticated statistical analytics or AI techniques. However, the efficacy of a decision that is solely based on historical data largely depends on its quality and adequacy. Fragmented and partial data typically leads to inadequate solution – survival bias (Mangel and Samaniego 1984). Pure intuition-based decision-making is prone to human-bias thus leading to myopic decisions (Hinson et al. 2003). To overcome these limitations, an approach that captures domain knowledge in the form of simulatable models and amenable to rigorous what-if analysis seems promising. Such an simulation-based approach has been extensively used for physical

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systems governed by scientific laws such as law of physics, chemistry, and thermodynamics (Enders and Hoßbach 2019). For example, NASA adopts the concept of digital twin that captures domain knowledge in a multi-physics multi-scale probabilistic model so as to perform what-if analysis on the digital twin to arrive at the right decision in an evidence-backed manner (Glaessgen and Stargel 2012). While digital twin centric simulation based approach to decision-making has been found effective for physical systems, its adoption in enterprise space is still in infancy. This is principally because enterprises are not governed by well-defined scientific laws. Effective modelling of enterprises for decision-making needs to be cognizant of high degree of contextual uncertainty (fuzziness), system of systems nature with multiple conflicting and evolving goals, and the emergent nature of enterprise behaviour (Teece et al. 2016). With existing modelling techniques falling short on these counts and inadequacy of quality data describing entire enterprise constitute further hurdles for effective utilization of digital twin in enterprise space.

To overcome these limitations, we integrate and build further upon the proven concepts from Modeling & Simulation, Probabilistic modelling and Artificial Intelligence to support risk-free experimentation-driven evidence-backed decision-making in the face of uncertainty. At the heart of our proposed approach is the concept of an *Enterprise Digital Twin* (EDT) – a purposive hi-fidelity simulatable model of the enterprise. The approach uses *agent* (Hewitt 2010) as the core modelling abstraction at the right level of granularity augmented effectively by probabilistic modelling, the perceptron concept (Rosenblatt 1958), and multi-criteria decision-making (Aruldoss et al. 2013). Our agent abstraction supports composition as a first-class concept to cater to the *system of systems* nature of enterprises and supports a wide variety of agents to address uncertainty and ambiguity, *i.e.*, *known known*, *known unknown* and *unknown known* situations (Rumsfeld 2011). More precisely we support: (i) canonical deterministic agent that captures the static *known known* behaviour, (ii) stochastic agent that models probabilistic *known unknown* behaviour, and (iii) machine-learnt agent that represents the behaviour learnt from past data for *unknown-known* characteristics.

Through fine-grained agent-based "what-if" simulation, EDT supports an "in silico" experimentation aid to: (i) Understand why the system is behaving the way it is, (ii) Evaluate efficacy of an intervention to nudge system in the right direction, and (iii) Explore possible better states for the enterprise. From methodological perspective, we adopt and combine three established validation techniques from simulation research namely: data validity, conceptual validity and operational validity (Robinson 1999; Sargent 2010) to establish the desired faithfulness of constructed digital twin. The culture of experimentation-centric innovation is promoted by demonstrating the effective use of EDT as an aid for quantitative simulation-based evidence-backed decision-making. We addressed several tough business-critical problems across multiple domains to evaluate the utility and efficacy of our approach. The key contribution of this paper are to a) present a pragmatic modelling and simulation approach to capture and analyze complex business systems, and b) illustrates its efficacy through a representative real-world business case study.

Rest of the paper is organized as follows: Section 2 discusses state of the art and practice of enterprise decision-making in the face of uncertainty. Section 3 presents our digital twin approach for business systems and enterprises. We illustrate the efficacy and utility of our approach using a business case in Section 4 and conclude with our future plans in Section 5.

2 STATE OF THE PRACTICE

Traditionally, enterprise decision-making relies heavily on human expertise and experience wherein the decision-maker qualitatively analyzes the current state with respect to the stated goals in order to arrive at the best possible change/interventions – *e.g.*, experimentation on new products, new offerings, customized services, and process changes – that would help reach the desired state. These experimentations are typically done in a sandboxed environment involving limited customers, i.e., A/B testing (Kohavi and Longbotham 2017). Still, this calls for the candidate changes to be introduced in the real system to comprehend their efficacy – a cost-, effort-, and time-intensive endeavor requiring iteration over multiple unsuccessful attempts before a "good enough solution" can be reached. Enhanced dynamics, shortening window of opportunity, and increasing uncertainty are making this intuition-based ideate-build-experiment approach ineffective.

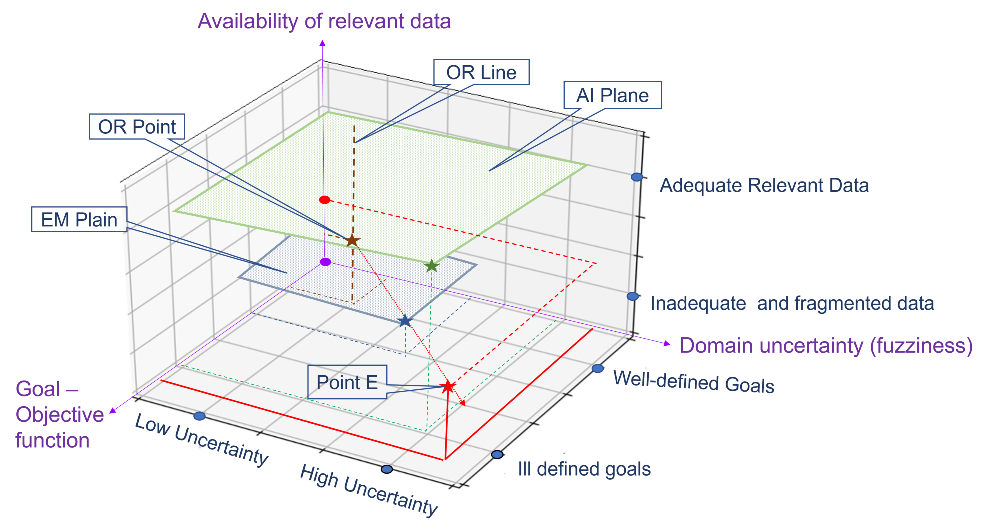


Figure 1: Complexities and state of the art analysis techniques.

Enterprises are looking for a better approach to evaluate the efficacy of candidate strategies to remain innovative, agile and resilient in the face of deep uncertainty (Marchau et al. 2019). Exploitation of digital twin concept as witnessed for mission-critical systems and physical systems over a decade address (Glaessgen and Stargel 2012; Enders and Hoßbach 2019) is becoming a necessity in enterprise space too (Kerremans and Kopcho 2019) where the expectation is to create a purposive faithful replica of an enterprise on which decision-makers can iteratively ideate the candidate interventions and evaluate them in a quantitative manner before selecting the most appropriate. In this section, we evaluate the state-of-the-art modelling, analysis and simulation techniques for supporting a quantitative evidence-backed approach to decision-making in enterprises.

2.1 Modelling and Analysis Requirements

Reflecting on our experience to apply existing modelling & simulation techniques for industry scale business and societal systems, we visualize the complexity of enterprise along three broad dimensions as shown in Figure 1, – a) uncertainty of the domain of interest, b) nature of the objectives function or goals, and c) availability of relevant data. Conceptually, Enterprises are socio-techno-economic systems, and they are not governed by any scientific laws – a clear contrast with respect to physical systems that are ruled by the law of physics, thermodynamics, and so on. Enterprises are prominently characterized by high degree of uncertainty or fuzziness. A large enterprise comprises multiple (power) units, thus taking the form of a *system of systems*, where these units (or systems/subsystems) focus on individual objective function that may conflict with objective functions of other units. As a result, identification of the most appropriate change is a multi-objective satisfaction endeavor that may involve tradeoffs. Available historical data of an enterprise typically exists in distributed fragments and is rarely comprehensive / complete for the purpose. Moreover, it depicts behaviours that have manifest, but, provides no clue for possible behaviours in future. Figure 1 depicts the three-dimensional space for enterprise decision-making. A majority of enterprises are at `Point E` in Figure 1.

2.2 Modelling and Analysis Techniques

Analysis approaches based on Artificial Intelligence (AI) and machine learning (ML) models solely rely on historical data and hence are effective for the systems that are having comprehensive and relevant data as shown using green surface, *i.e.*, `AI plain` in Figure 1. Distance between the `AI plain` and `Point E`

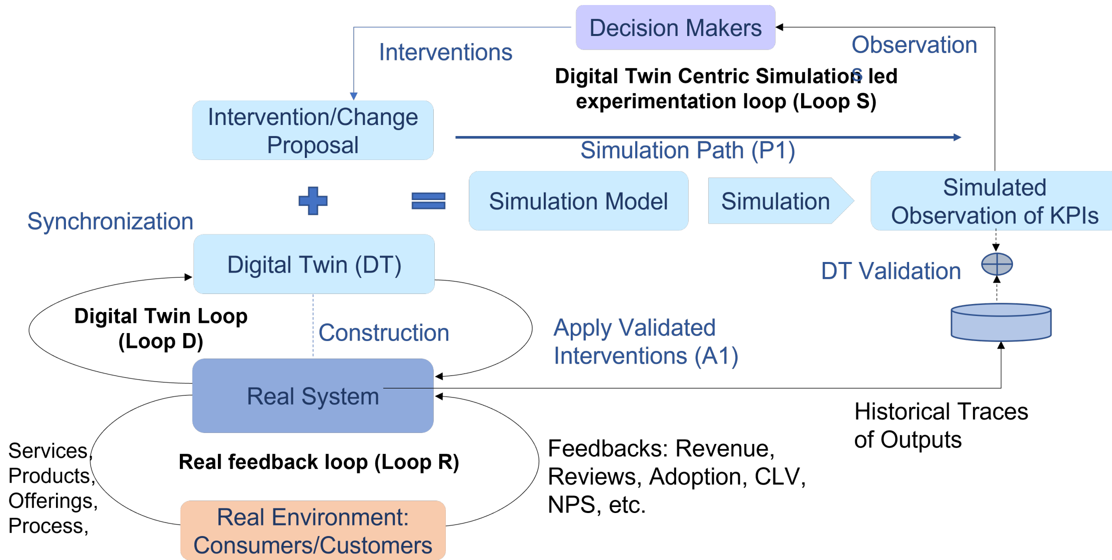
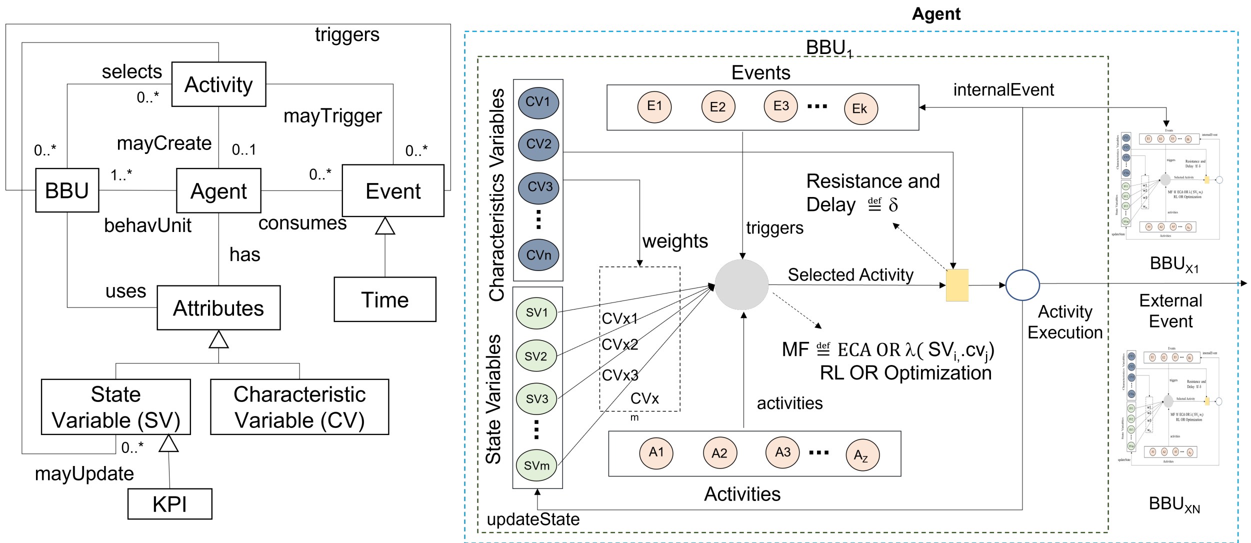


Figure 2: Simulation based business experimentation environment.

indicates the degree of inefficacy of pure historical data centric approach for an enterprise. High flux and dynamism of the operating environment of the enterprise displace the `Point E` away from `AI plain`.

Models that can capture core characteristics and behaviours of the constituent elements of enterprise along with its environment reduce the heavy dependency on relevant historical data for precise understanding and decision-making. Operational Research (OR) and associated techniques, such as linear programming and mixed integer programming, are extensively used in the context where data is inadequate (Kobbacy et al. 2007). However, the OR technique is effective for a situation (*i.e.*, `OR Line`), which is characterized by less uncertainty and precise objective function. Traditionally OR based approaches are effectively used for systems where historical data is inadequate, objective function is limited to few KPIs, and less uncertainty (*i.e.*, for `OR Point`). For enterprise context, the utilization of OR techniques are limited to derive local optimum solutions (*i.e.*, for a system within a system of systems) as opposed to predict enterprise-wide ramifications of a solution or guaranteeing the global robustness of a solution. For example, OR techniques can be used to minimize cycle time of a service fulfilment process of a telecom company or define optimum resource utilization schedule in a fulfilment process. However, whether the value proposition offered to the customers will generate sustainable value over a period on the backdrop of evolving customer context, Customer Lifetime Value (CLV), is beyond the realms of OR techniques as large number of KPIs influence CLV and domain is characterized by high uncertainty and fuzziness.

Enterprise Modelling community has proposed a wide range of modelling and simulation techniques to model and analyze enterprises. They belong to two broad paradigms: top-down or bottom-up (Thomas and McGarry 1994). A top-down paradigm begins by visualizing an enterprise as a whole and relies on a reductionist view to decompose the large problem into smaller parts to be addressed in isolation. The enterprise models (EMs), such as ArchiMate (Iacob et al. 2012), i* (Yu et al. 2006), BPMN (White 2004), and System Dynamics (SD) (Meadows 2008), are the examples of top-down models. A bottom-up approach, in contrast, starts from the parts or micro-behaviours and arrives at a holistic view of a system through composition. The bottom-up approach uses agent and actor (Hewitt 2010) based technologies, such as Akka (Allen 2013), for modelling and analyzing system of systems with limited uncertainty. State of the art enterprise modelling techniques are capable of addressing the plane (highlighted as `EM plane` in Figure 1) that is characterized by low data requirements, limited uncertainty and limited number of conflicting KPIs. However, they found wanting on uncertainty and tradeoffs (Vernadat 2020). In short, the coarse-grained models fail to capture the notion of system of systems having conflicting goals, and the



(a) Structural Representation (b) Behavioural Representation

Figure 3: Agents and core modelling abstraction.

fine-grained models are found inadequate to capture desired fuzziness and often fail to scale so as to be able to analyze large enterprises. Therefore, it can be said that the state of the art modelling, analysis and simulation techniques is found wanting to meet the decision-making needs of large enterprises.

3 APPROACH: ENTERPRISE DIGITAL TWIN

Enterprises need an effective experimentation environment to explore possible changes and understand their efficacies along multiple (conflicting) KPIs in the face of deep uncertainties and inadequate relevant data. To address this need, we use digital-twin (Grieves and Vickers 2017) as an "in silico" experimentation aid as shown in Figure 2. We further integrate and extend multiple modelling techniques to model enterprises as complex system of systems and exploit prior art in simulation-led experimentation, validation (Sargent 2010), and confidence on simulation outcome (Robinson 1999).

3.1 Modelling an Enterprise

We follow bottom-up modelling paradigm where an extended form of *agent* (Hewitt 2010) constitutes the core modelling abstraction to model enterprise as a system of systems at the desired level of granularity, *i.e.*, a digital twin of an enterprise. To specify behaviour, we extend the *Event-Condition-Action* (ECA) paradigm (Alferes et al. 2006) to support: (i) Probabilistic behaviour to specify uncertainty through non-determinism (ND), (ii) Machine learnt (ML) model to effectively utilize fragmented data, (iii) Multi-criteria decision-making approach (MCDM), such utility function (Triantaphyllou 2000) and TOPSIS (Behzadian et al. 2012), to mimic micro-level decision-making, and (iv) a notion of Time event for temporal behavioural patterns and relationships.

An agent behavioural specification using the combination of ECA, MCDM, ND, and ML technique is schematically represented in Figure 3. An agent can interact with other agents through events, internally it has a set of State Variables (SV) and a set of Characteristic Variables (CV), and it can perform a set of activities (A). An activity can update state variables, send events to other agents and/or create a new agent as shown in Figure 3 (a). The behaviours of an agent can be depicted using a connected or independent perceptron like structure, *Basic Behavioural Unit* (BBU), as illustrated in Figure 3 (b). These BBUs consider the state variables and incoming events are inputs, activities as outputs and a range of computation

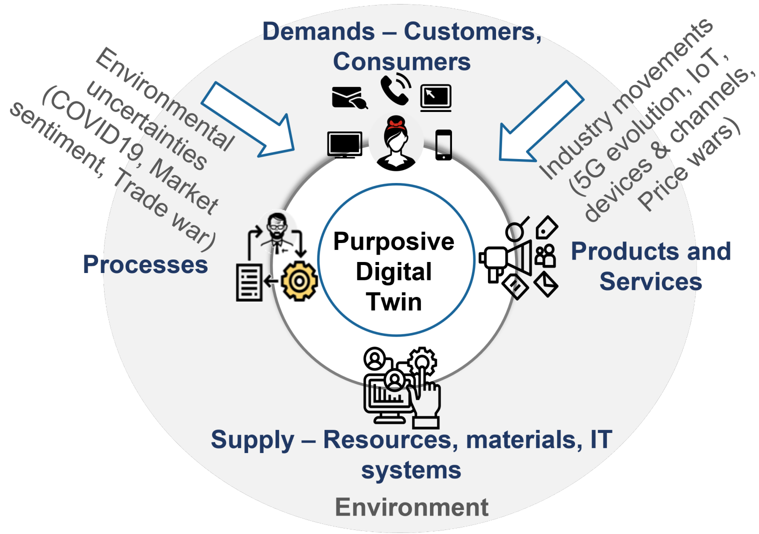


Figure 4: A purposive enterprise digital twin.

specification techniques for input to output mapping (*i.e.*, activity selection for a situation). Appropriate computation specification can be chosen by considering available domain understanding and/or available relevant data. An input to output mapping function (MF) can be specified: a) using pure rules (*i.e.*, ECA) to choose appropriate activities, wherein domain experts define the rules for agents, b) the rules can be further augmented with probabilistic affinities to introduce stochasticity (*i.e.*, *known unknown* behaviour), c) it can be a function over weighted sum of input values (*i.e.*, a utility function) with an optional temporal delay, where characteristic variable describes the weights and possible delay, and d) a complex MCDM formula involving inputs and weights to rank candidate activities and choose an activity with highest computed utility value or randomly choose one of the top ranked activities – a fuzzy MCDM (Dursun and Karsak 2010). The characteristics variables, *i.e.*, weights for input values and resistance function, of an agent can be specified by the domain expert (from their experience) or it can be learnt from historical data if behaviour is not precisely known but relevant data exist (*i.e.*, existence of partial and fragmented data) – a *unknown known* behaviour. An agent can have a connected BBU with/without temporal delay as shown in Figure 3 (b). This interconnected BBUs helps to capture several pragmatic scenarios: a) an incoming event as input makes an agent reactive, b) a state variable as input to BBU promotes autonomy, and c) an ability to specify weights (*i.e.*, the value of characteristic variables) by domain experts or learn from historical data helps to combine data-centric approach and model-based approach in a seamless manner. Probabilistic affinities and temporal delays within BBU topology help to mimic micro-level fuzziness and non-linearities in a pragmatic manner. Here, we differ from the traditional application of MCDM and AI based techniques by applying the core concept from both the techniques at micro-level to decide the best activity that an agent can perform as opposed to understand marco-trends and system as a whole. For example, MCDM technique is traditionally used to predict best-selling product from a set of product options, but here it is used for selecting an activity of an agent in a situation run.

3.2 Construction and Contextualization of Digital Twin

In line with Gartner's Digital Twin of the organization (Kerremans and Kopcho 2019), we developed a configurable digital twin of enterprise, termed as *Enterprise Digital Twin* (EDT). Established management frameworks for strategic decision-making of enterprise, including Porter's five forces (Grundy 2006), is considered to define generic purpose, scope and aspects that need to be sufficiently capture in EDT. Broadly we focus on five concerns of interest: *Demands* (*e.g.*, customers, consumers), *Supply* (*e.g.*, resources, raw materials, hardware/software infrastructure and other inputs), *Processes* (*e.g.*, operational processes, enablement processes), *Products* (that includes Services, offerings, *etc*. based on the industry under consideration) and *Environment*, as shown in Figure 4. Business domains, such as Telecom, Retail, Banking and Finance, contextualize these generic concepts and elaborate them by reflecting on the established knowledge from respective domain and problem under consideration.

In construction phase, the domain experts identify relevant domain concepts and capture them using *agents* and their interactions. The Characteristic Variables (CV) of agents and their mapping with BBUs are established. As the values of CV are either specified by domain experts or learnt from historical data using AI/ML techniques, the desired richness of a digital twin can be attained either through effective utilization of fragmented enterprise data or through active involvement of domain experts. The situations where both domain knowledge and relevant data are inadequate lead to uncertainty about enterprise and its environment. Such situations are specified using probabilistic behaviours and fuzzy MCDM where both are typically specified as ranges by the domain experts and/or learnt from historical events.

After construction, the EDT needs to be periodically synchronized by initializing State Variables (CVi) of all agents from real system to make state of the EDT same as real system as shown in Figure 2.

3.3 Simulation

Simulation of purposive EDT, as shown in Figure 2, is supported by introducing a periodic Time event that mimics a primitive time unit, *i.e.*, minute, hour, day, year, *etc.* of a problem statement. A simulation produces traces/trends of KPIs, *i.e.*, projection of state variables (*refer* Figure 3 (a)). Repetition of EDT simulation incorporating various environmental situations provides a justification why enterprise is behaving the way it is. Simulation of EDT with specific change/intervention incorporated (*e.g.*, introduction of a new product, replacement of resources in a care service, or change in an operational process) thus leading to new values for KPIs and trace over time. Examination of the two can evaluate the efficacy of the intervention. An iterative process helps arrive at the most appropriate intervention or a sequence of interventions required to achieve the stated goals with possible tradeoffs.

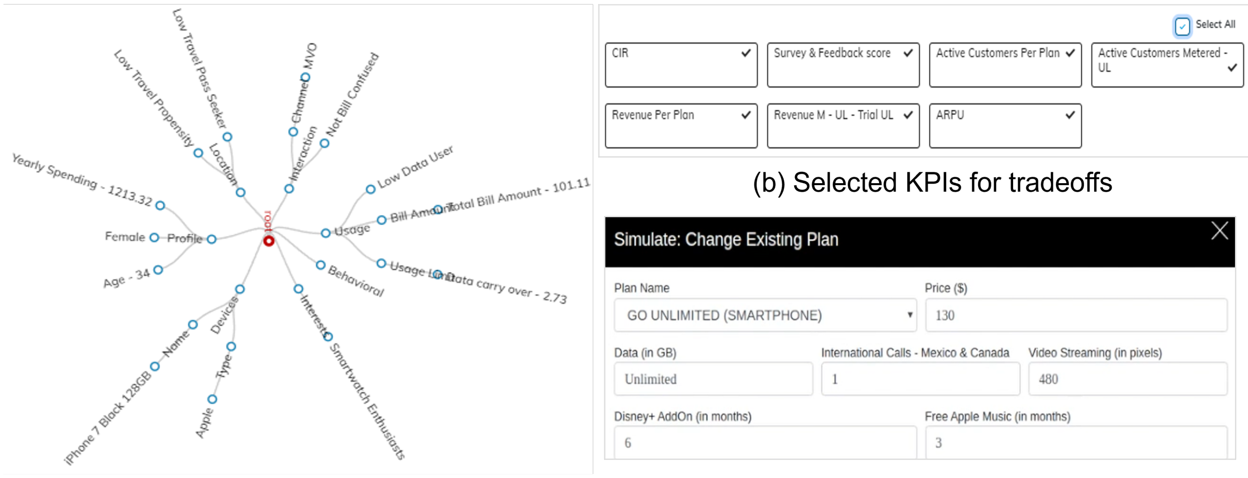
EDT simulation enables stakeholders across the board to ideate candidate adaptation/design options, roll out experimentations using simulation, generate data (*e.g.*, KPI trends) from the experiments and use it in combination with real data for evidence based decision making as shown in Figure 2. This human-in-the-loop experimentation expects decision-makers to come up with the adaptation/design alternatives.

3.4 Methodology

From methodological perspective, we combine three established validation techniques from simulation research namely, data validity, conceptual validity and operational validity (Sargent 2010), and adapt them to agent-based modelling paradigm. During the construction phase, the domain expert ensures all relevant business concepts are adequately captured in the form of agents in EDT thus ensuring conceptual validity. Instantiation of state variables from real system and their periodic synchronization (as shown in Figure 2) help to ascertain data validity. The operational validity is established by comparing results of simulating for a set of known past situations with the real data as shown in Figure 2. Here, we expect simulation outcome may differ with real outcome to an extent (within a tolerable range) due to multiple micro-level stochastic behaviours.

Moreover, we simulate a scenario multiple times and consider normalized KPI trends to predict future trends – this helps to improve the confidence level (Robinson 1999) of observed simulation trends over stochastic behaviours of the agents. We follow below steps, in line with repetitive stochastic guestimation (Agapie and Bratianu 2010), to allow KPI trends to converge:

Simulate EDT for N times and compute average of all KPIs ($KPIs_{Avg}$) // We consider N = 5
While all KPIs haven't converged
Simulate and compute new average ($KPIs_{New}$) from all simulation runs



(a) Relevant customer attributes

(b) Selected KPIs for tradeoffs

(c) Intervention - Configurable product attributes

Figure 5: EDT workbench for Telco case study.

For all KPI
If ($(|KPIs_{Avg}$ - $KPIs_{New}|$) $< \delta$) // (deviation is within a tolerable range)
Converged = $True$
Else
$KPIs_{Avg} = KPIs_{New}$

We use the trends of KPIsAvg to comprehend multiple simulation outcomes. Our in-house agent-based modelling language, ESL (Clark et al. 2017; Clark et al. 2022), is extended to support the modelling abstraction, iterative simulation and experimentation methodology discussed in this section.

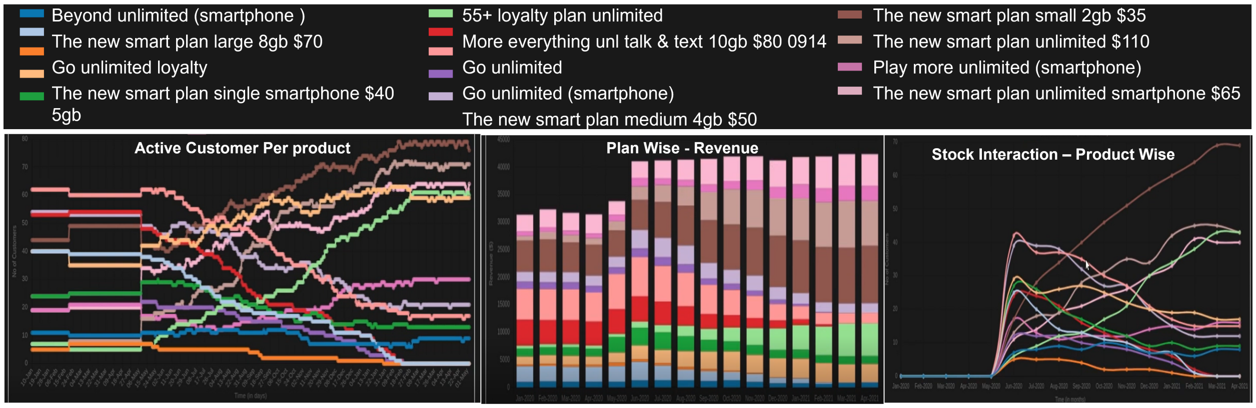
4 IMPACT CASE STUDY: EDT AS AN IN SILICO EXPERIMENTATION AID

We experimented EDT across a wide span of business functions, such as Customer Experience Management, Business Process Optimization, New Product/Process launches, Stakeholder Value Management, Business/Technology Advisory and industry verticals, such as Telecom, Banking, Postal service providers, and Retail. Here, we illustrate the efficacy of EDT using a notable scenario from telecom domain where a leading Telecom company used EDT to understand customer behavioral dispositions at a granular level towards launch of various unlimited plans before and after the impact of the Covid-19 pandemic.

4.1 Problem Statement

With the onset of Covid-19 in early 2020, Government bodies across the globe enacted movement restrictions to contain the spread of the virus and reduce the impact on people. This led to millions of citizens being locked in their homes round the clock, where they were forced to adapt a new normal using telecom connectivity services to continue to work, access entertainment etc. The demand for mobile connectivity was expected to shoot-up exponentially in the upcoming months. However, the analytics showed *Average Revenue per User* (ARPU) of metered customers (*i.e.*, pay per use) was 40-45% lower than unlimited plan customers. Initially, major Telcos offered free extra GBs of data usage to their metered customers to help citizens adapt to the new normal with the eventual objective of nudging customers toward Unlimited plans for all metered customers.

For the Telco we worked with, around 16% were metered customers which constituted a significant revenue growth opportunity by converting them to Unlimited plan subscribers. The marketing team also realized that it is not enough to have good ‘take rates’ during the free trial period, the customers need to



(a) Trends on Active Customer per Product (b) Overall and product specific revenue (c) Load on customer care service

Figure 6: EDT simulation dashboard.

retain the offer post trial period to contribute to revenue and ARPU uplift. But the pertinent question was how to nudge maximum number of metered customers – what should be the ideal product offerings and whom to target when?

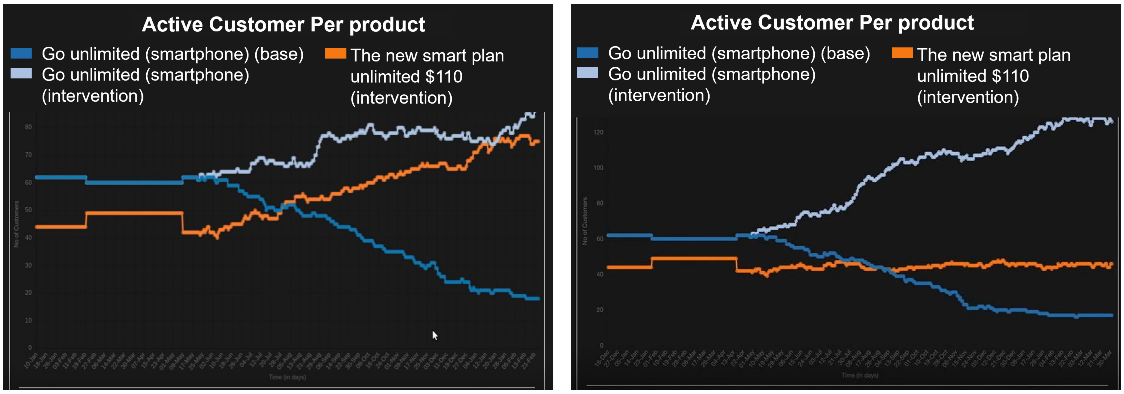
4.2 Enterprise Digital Twin

As an "in silico" experimentation aid, we constructed an EDT for Telco with its 374K Customers (targeted for the trial period), a set of Products that include all Unlimited and metered plans, the trial rollout Process and all channels and technology Resources involved in supporting and measuring the success of the trial unlimited campaign. Relevant customers attributes were modelled based on the interactions with Marketing Team and the Product Owners – attribute set is shown in Figure 5 (a). The state variables capture information about Device, Customer Profile and Locations. Characteristics variables indicate various affinities about preferred Channels for offer related communication, Usage patterns, and behavioural patterns, such as brand consciousness, data usage, and other interests. The entire customers are segmented into 109 architypes to define appropriate probability ranges of identified characteristic variables – an approximation for convenience. The probability ranges are determined by applying ML models on historical customer data and adjusted by domain experts to replicate evolving situations and usage patterns. Environmental factors including lockdown and phased relaxations during Covid-19 are considered as time bound stochastic behaviours while conceptualizing customer behaviours. Meaningful KPIs are identified (depicted in Figure 5 (b)) to understand the efficacies of the interventions, *e.g.*, product features, as illustrated in Figure 5 (c).

Constructed EDT and its configuration capability were used to run "in-silico" experimentations, as opposed to A/B testing, to understand which features of the Unlimited Products would have maximum positive impact or negative influence on specific customer architypes and their behavioral dispositions.

4.3 Validation

Contextualized EDT with precise as-is product definitions and environment situation is simulated from January 2020 and the simulation results are compared till April 2020 for validation. Illustrative KPI values are shown in using EDT dashboard in Figure 6 (actual results are not depicted due to confidentiality). While the initial hypothesis was that the usage of mobile data would significantly upsurge with the implementation of movement restrictions, the real trend was not indicating so – detailed analysis on data usage reveled that the most of data traffic being routed through fiber broadband based high speed home internet. Further, the buying power of the target customers was diminished during the pandemic largely due to business environment uncertainty and week on week increase in number of unemployed people in the geography.



(a) Trend for as-is product vs Configuration 1

(b) Trend for Configuration 2

Figure 7: Comparative analysis and tradeoffs.

These adjustments had to be made into our EDT as part of validation and correction – a combination of conceptual validity and operational validity is leveraged for required adjustments.

4.4 Experimentations

Validated EDT was considered to carry out experimentations. The impacts of various situations that mimic the lockdown period and thereafter phased relaxation on KPIs were predicted using simulation as shown in Figure 6. Results indicate trends on a) customers movements across products portfolios addressing their evolving needs, (b) marginal revenue improvement for Telco from June 2020 due to increase usage of metered plans, and (c) significant increase in the load of call service assistance chiefly for bill explanation (due to disproportionate usage pattern and limited period of offers). Further experimentations were carried out by changing product features (using a product definition workbench as shown in Figure 5 (c)) and their impacts in terms of number of customers, revenue, load on call service and other KPIs (as listed in Figure 5 (b)) are predicted by simulating EDT with altered feature definition. As an illustration, the KPI trends on active number of customers of two products, namely `Go Unlimited` and `The New Smart Plan Unlimited $ 110`, is shown in Figure 7 (a). Simulation results indicate that the product `The New Smart Plan Unlimited $ 110` (shown using orange line) would cannibalize the product `Go Unlimited` (shown using dark blue line) starting from May 2020. However, the Marketing team had an perception that the `Go Unlimited` has better growth potential for the environmental situation at that point of time – but, they were not sure about product features that would perform better for customer group under consideration. EDT helped them to experiment various product features and arrive at best combination. For example, a configuration of `Go Unlimited` (configuration 1), with altered price point from $100 to $130 and two potential value add - a) allowance of international call to Mexico and Canada, and b) more video streaming capacity, is shown better prospect than the existing configuration (shown using light blue line). For the new configuration, the number of customers is increasing moderately without cannibalizing the product `The New Smart Plan Unlimited $ 110`. However, the further increase in price point from $130 to $140 with more streaming capacity (configuration 2) can limit the growth business potential of `The New Smart Plan Unlimited $ 110` as shown in Figure 7 (b). In reality, several experiments are conducted to generate sufficient experience and quantitative explanations to decide appropriate product offerings. For example, they carried out with and without offering OTT service add-ons, such as Disney+ or Apple Music to understand the their influence to overall product uptake. In this case, the offer acceptance decisions were not significantly impacted by additional offers to these services. These “in-silico” experimentations helped Telco to save additional subscription cost during the offer period as it would not impact their overall revenue growth.

4.5 Business Impact

EDT based business experimentation helped Marketing team to arrive at had four Unlimited plans a choice for their trial, in contrast launching multiple products with differential pricing and product features to the target group. The actual campaigns of Trial Unlimited were rollout out in parallel to the digital twin experimentations. Start Unlimited was offered in the first month of the trial and the conversion ratio (take rate * retention rate) for the target group. EDT based prediction exhibited a result within 20 basis points of reality. Experimentation helped them 2X improvement in overall take rate than expected otherwise and approximately 1% reduction in churn rate. Following this success, we have worked with a major Telco in Malaysia and an Information Service Provider in North America to model Marketing Mixes using our EDT. We applied EDT to other business functions in Telecom and also to other domains that include Banking & Financial Services, Insurance and Retail – development of a product, TwinX$^{\text{TM}}$ (Tata Consultancy Services 2022), is a significant testimony of the business impact of our research.

5 CONCLUSION

We presented a pragmatic as well as robust enterprise digital twin based exploration aid for decision-making in the face of uncertainty. We showed that our approach overcomes some of the limitations of the state-of-the-art modelling and simulation techniques. We proposed Agent as the core modeling abstraction to capture the system of systems nature of the enterprise. An ability to specify behaviour using multiple paradigms, *i.e.*, ECA, MCDM, and machine learnt model helps address the limitation of partial information in a pragmatic manner. A provision to capture micro uncertainties in the form of stochastic models and fuzzy MCDM helps model uncertainty and fuzziness within the enterprise and environment. Human guided iterative simulation helps to explore multiple adaptation/design alternatives. Simulatable purposive EDT acts as experience generator to support an evidence based decision-making and tradeoffs in human-in-loop manner. Our pragmatic model validation methodology that includes conceptual validation from domain experts in combination with operational validity and data validity helps to establish high fidelity of the digital twin with respect to real system. Methodological support to simulate a configuration (*i.e.*, adaptation/design alternative) till all KPIs converge helps to improve the confidence level of the analysis.

We developed a product, TwinX$^{\text{TM}}$ (Tata Consultancy Services 2022), for business experts from multiple domains to enable digital-twin based simulation-led evidence-driven decision-making as opposed to intuition-based business decisions. An open–source version of ESL (Clark et al. 2022) is available to explore our research capabilities for academic purposes. As a next step of our research, we would like to focus on supporting decision-making for societal problems, such as smart city, e-mobility and sustainability.

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