Digital Twin as Risk-Free Experimentation Aid for Techno-socio-economic Systems

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ABSTRACT

Environmental uncertainties and hyperconnectivity force techno-socio-economic systems to introspect and adapt to succeed and survive. Current practice is chiefly intuition-driven which is inconsistent with the need for precision and rigor. We propose that this can be addressed through the use of digital twins by combining results from Modelling & Simulation, Artificial Intelligence, and Control Theory to create a risk free 'in silico' experimentation aid to help: (i) understand why system is the way it is, (ii) be prepared for possible outlier conditions, and (iii) identify plausible solutions for mitigating the outlier conditions in an evidence-backed manner. We use reinforcement learning to systematically explore the digital twin solution space. Our proposal is significant because it advances the effective use of digital twins to new problem domains that have greater impact potential. Our novel approach contributes a meta model for simulatable digital twin of industry scale techno-socio-economic systems, agent-based implementation of the digital twin, and an architecture that serves as a risk-free experimentation aid to support simulation-based evidence-backed decision-making. We also discuss validation of this approach, associated technology infrastructure, and architecture through a representative sample of industry-scale real-world use cases.

KEYWORDS

Digital Twin, Decision Making, Simulatable Model, Agent Model

1 Introduction

Today's techno-socio-economic systems, such as enterprises, ecosystems and society, need to achieve the desired goals while operating in a dynamic, uncertain and hyperconnected environment [23]. They continuously need to adapt in a manner to effectively respond to a variety of environmental disruptions possibly leading to unanticipated outlier conditions. However, deciding an effective response to a change is a difficult task. It requires precise understanding of system structure & behavior, goals, and the operating environment. Unique techno-socio-economic characteristics such as nonlinearity, uncertainty and emergentism further exacerbate the task [11]. Moreover, introduction of an intervention in a system that operates in an uncertain and dynamic environment comes with certain degree of risk and non-reversable consequences in addition to the cost of change. Therefore, decision-makers often face *ambidexterity dilemma* [7] while balancing required adaptations and risk mitigation to achieve resilience.

For decision-making, a system can be viewed as a transfer function from *Input* value space to *Output* value space with some assumptions about the operating *Environment* with an intention to meet the desired *Goals* as shown in Figure 1. The system *Goal* is an objective function over *Measures* that are derived from *Traces*, *i.e.*, a history of *Output* and *State* of the system. Decision-Making becomes necessary when the system is not able to meet the desired *Goal*. It is an act of identifying appropriate intervention or *Lever*, *i.e.*, introducing a change in *Input* space and/or in transfer function, to produce the desired *Output* thus achieving the stated *Goals*. Thus, robust decision-making calls for a detailed understanding of system transfer function, input & output value spaces, and dynamics of the environment.

Digital twins have a history of use as a decision-making aid a key example of which is the digital twin of a flying vehicle created by NASA including a probabilistic model that used fleet history to ascertain fidelity. The twin was used to explore better design alternatives and to identify interventions necessary so as to respond suitably when faced with environmental changes. These simulations led to several benefits such as better understanding of aircraft structure leading to better design, better fleet management, and evidence-backed help to make the vehicle future ready [16]. Since then, digital twins have been widely used in physical systems space [14].

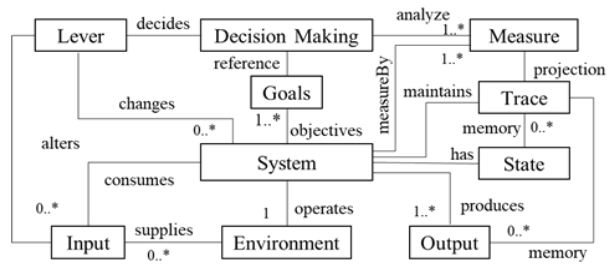


Figure 1: A meta-model for decision-making

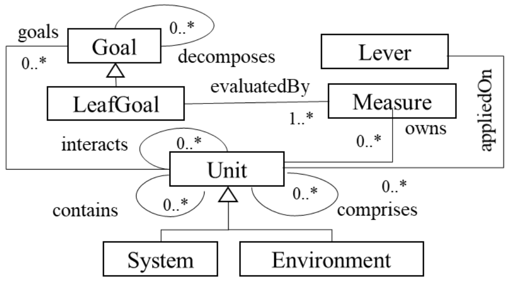


Figure 2: Meta-model to visualize complex system

Similar rigor is needed for decision-making in organizational and societal contexts [21]; however, a digital twin based approach is yet to emerge. This is principally because techno-socio-economic systems are not governed by well-defined scientific laws like physical systems, chemistry and thermodynamics. Rather, transfer function and environment of techno-socio-economic systems exhibit high degree of contextual uncertainty, system of systems nature with multiple conflicting goals, and emergent behavior arising from the complex nonlinear interactions involving constituent elements [31]. Existing modelling techniques fall short of capturing these distinguishing characteristics effectively. Moreover, the lack of high-quality data pertaining to structure and behavior of techno-socio-economic system presents an additional barrier for using the digital twin based approach.

With an aim to introduce digital twin as risk-free experimentation aid for techno-socio-economic systems, we critically evaluate the lacunae of the existing modelling & analysis techniques and address these lacunae by building further upon proven concepts from Modeling & Simulation (M&S), Artificial Intelligence and Control Theory. At the heart of the approach is a purposive hi-fidelity simulatable model of techno-socio-economic system – a Digital Twin (SDT) [17]. The proposed approach uses *agent/actor* [18] as the core modelling abstraction at the right level of granularity augmented effectively by probabilistic modelling, the perceptron concept [28], and multi-criteria decision-making [3]. 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*, *unknown known* situations [27]. More precisely, we support: (i) deterministic agent leveraging *Event-Condition-Action* (ECA) [1] paradigm to capture the static *known known* behavior, (ii) stochastic agent that augments nondeterminism to model *known unknown* behavior, and (iii) machine-learnt agent that represents behavior learnt from past data to model *unknown-known* situations.

A SDT serves as an "in silico" experimentation aid to: (i) understand system behavior, (ii) evaluate behavioral modifications, and (iii) explore possible better states for the system reducing the gap between expectation and reality. An ability to understand the efficacy of an intervention coupled with iterative simulation capability helps assess the risk of an intervention. From a methodological perspective, we adopt and combine two established validation techniques from simulation research namely: conceptual validity and operational validity [26, 29] in an agent-based modelling paradigm. Several tough business-critical and social

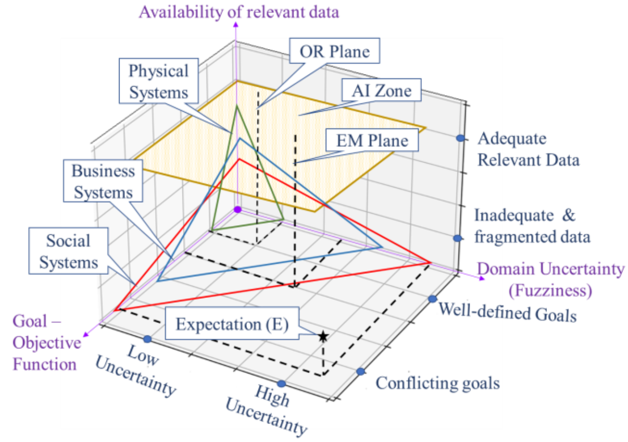


Figure 3: System complexities and state of the art modelling techniques

problems across are addressed to evaluate the utility and efficacy of our approach.

The rest of the paper is organized as follows: section 2 presents inherent complexities of techno-socio-economic system and evaluate existing modelling and analysis techniques. Section 3 discusses our approach and section 4 presents four industrial case studies. The paper concludes with future work in Section 5.

2 Background

The state-of-the-practice of organizational decision-making [11] is predominantly qualitative where decision-makers intuitively analyze various performance indicators, *i.e.*, *Measures*, compare them with the desired *Goals*, and reflect on expertise and past experience to arrive at the required change/interventions. Risk associated with intuition-driven decisions is typically mitigated through controlled experimentation in a sandboxed environment e.g., *A/B testing* [22]. However, experimentation involving real system is a time-, effort- and cost-intensive endeavor that typically requires iteration over multiple unsuccessful attempts before reaching a "good enough solution". Enhanced dynamics, shrinking window of opportunity, and increasing uncertainty are making this intuition-based ideate-build-experiment approach risky and ineffective. In this section, we critically analyze contextual complexities of techno-socio-economic systems, and evaluate adequacy of state-of-the-art modelling & analysis techniques to support decision-making for techno-socio-economic space.

2.1 Contextual Complexities

A large business system or social system can be decomposed ad infinitum into a set of interacting subsystems, *i.e.*, *Units*. On the contrary, one may take a constructionist view wherein the atomic *Units* are composed ad infinitum to realize the complex system as shown in Figure 2. These units may interact with each other in order to achieve individual as well as system level *Goals*. The system level goals typically follow a top-down hierarchical decomposition structure, where the leaf level goals are mapped to *Measures* that are owned by specific units. Scale, complex interactions, and partial information make it quite difficult to adhere solely to either reductionist or constructionist view. Instead, pragmatism suggests use of both.

We describe the complexity of techno-socio-economic systems along three broad dimensions shown in Figure 3: a) inherent uncertainty of the domain of interest, b) the objective function or goals, and c) availability of relevant data. Techno-socio-economic systems are often inherently uncertain or fuzzy in terms of the unit behaviors and unit interactions thus leading to uncertainty in emergent behaviour. More the constituent elements, greater is the uncertainty. Therefore, specification of business systems tends to be more complex than physical systems, and specification of societal systems is even more complex – refer the green, blue and red colored triangles of Figure 3.

The lack of precise mapping from top-down goal decomposition structure to unit [de]composition structure results in a complex and fuzzy objective function. Multi-criteria decision making with conflicting goals requires special attention to tradeoffs.

Historical data of techno-socio-economic systems is a cause of concern. Typically, this data exists in a distributed and fragmented form which calls for significant integration effort to come up with a single holistic view. Currency of data is another concern as system operates in a dynamic environment. Majority of techno-socio-economic systems are at point *Expectation (E)* in three-dimensional hyperspace of Figure 3.

2.2 Modelling and Analysis Techniques

The modeling and analysis techniques for decision-making are broadly classified as: data centric and domain-model centric. The former relies on analysis of past data using statistical and/or machine learning techniques to identify the appropriate interventions. Availability of relevant high-quality data is a prerequisite for this approach - the yellow colored surface, i.e., *AI Zone* in Figure 3. Distance between the *AI Zone* and *Point E* indicates the degree of inefficacy of pure data centric approach to decision-making for techno-socio-economic systems. High flux socio-technical characteristics and dynamism of the operating environment displace the *Point E* away from *AI Zone*.

Domain-model centric approaches represent the transfer function and environment of the system using a variety of analyzable models. These models are further categorized into two types: mathematical models and enterprise models (EM). Mathematical models, such as linear programming, can specify the complex system of systems in terms of lumped-up mathematical formulae thus enabling formulation of decision-making problem as a multi-variate optimization problem. However, this approach is vulnerable to data inadequacy *i.e.*, *survival bias* [24]. Over the years, Simulink and MATLAB are extensively used for modelling and analyzing systems where relevant data is inadequate, domain understanding is less ambiguous, and the objective function is well formed, i.e., devoid of conflicting goals (highlighted as *OR Plane* in Figure 3). These techniques can be used to derive an optimal solution in a local context. However, they are found inadequate in predicting system-wide ramifications of introducing intervention in a locality and hence incapable of guaranteeing global robustness.

Whilst less rigorous than mathematical models,

Enterprise Models (EMs) fall into two broad categories: top-down coarse-grained and bottom-up fine-grained where the majority adopt top-down view and support coarse-grained modelling abstraction to specify large complex business enterprises. EMs are spread across a wide spectrum where some provide sophisticated graphical representation of enterprise that's also somewhat amenable to automated analysis *e.g.*, ArchiMate [20], and some support machine interpretable and/or simulatable specifications that help analyze a range of system aspects, for instance, BPMN [34] for modelling the process aspect, i* [19] for modelling enterprise goals, and System Dynamic (SD) [25] model for modelling enterprise behavior in an aggregated form. The multi-modelling and co-simulation environments, such as DEVS [8] and MEMO [15], demonstrate further advancement in EM that support analysis of multiple aspects.

A bottom-up approach, in contrast, starts from the parts or micro-behaviors and derives macro behavior of a system through composition of micro-behaviours specified commonly using Erlang [2] and agent/actor [18].

To sum up, coarse-grained models fail to capture the notion of system of systems characterized by conflicting goals, individualistic behavior of fine-grained units, and emergent behavior. While fine-grained models are useful in supporting a constructionist view of modelling complex system of systems, they often fail to scale in order to analyze large business and social systems. The state-of-the-art EM techniques work best when uncertainty is limited and few goals conflict (highlighted as *EM Plane* in Figure 3) [33]. Thus, it can be said that current state of modelling practice is inadequate in supporting decision-making for techno-socio-economic systems.

3 Proposed Approach

We propose an approach that innovatively integrates and builds further upon proven ideas from modelling & simulation, artificial intelligence, and control theory. At the heart of this approach is the concept of System Digital Twin (SDT) – a purposive virtual faithful simulatable model. Here, we present a meta model for SDT, agent-based realization of SDT, and an architecture that enables risk-free "in-silico" experimentation to support evidence-backed decision-making in the face of dynamism and uncertainty. The concept of iterative exploration-centric decision-making is introduced by reflecting on the management perspective of decision-making in the face of deep uncertainty [11, 23]. We use reinforcement learning to reduce analysis & synthesis burden on human experts in the iterative decision-making process. We take inspiration from model reference adaptive control paradigm [30] to bring together the techno-socio-economic system, SDT, and the reinforcement learning agent in an architecture capable of dynamic adaptation.

Management perspective of decision-making considers complex decision-making as three steps process: *decision framing*, *strategy evaluation*, and *tradeoffs*. Decision framing step focuses on precise definition of *Goals*, goal decomposition structure, *Measures* that help determine to what extend a goal is achieved, and potential options/interventions (i.e., *Levers*) that can be introduced to achieve the desired goals. We use GML structure as described in Figure 4 to frame the decision-making problem in a structured way.

Strategy evaluation step aims to understand the influence of candidate *Levers* on *Measures*. We use SDT as a faithful representation of the system to explore a candidate set of *Levers* for

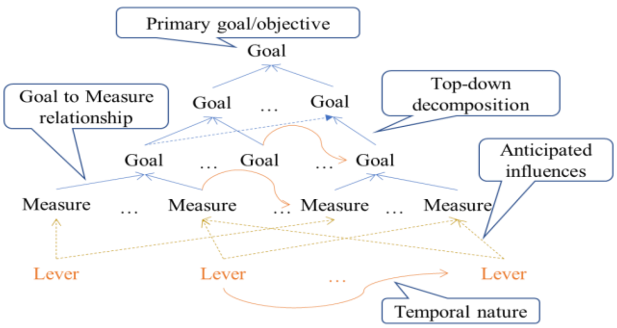


Figure 4. Decision Framing - Goals, Measures and Levers (GML)

their potential impact on *Measures*. SDT simulation using what-if scenarios supports the exploration "in-silico" and in a risk-free manner. We adopt a bottom-up fine-grained modelling paradigm where extended agent abstraction [18] is used to specify techno-socio-economic systems. Chiefly, we extend the deterministic *Event-Condition-Action* (ECA) centric behavioral specification paradigm with: probability model to address uncertainty, AI model to effectively utilize fragmented micro-level data, and multi-criteria decision-making approach (MCDM) to mimic micro-level decision-making. For evidence-driven tradeoff, we simulate multiple *Levers* and compare the simulated traces of *Measures* to identify a *Lever* capable of achieving the desired *Goals* in best possible way.

3.1 Extended Agent Model

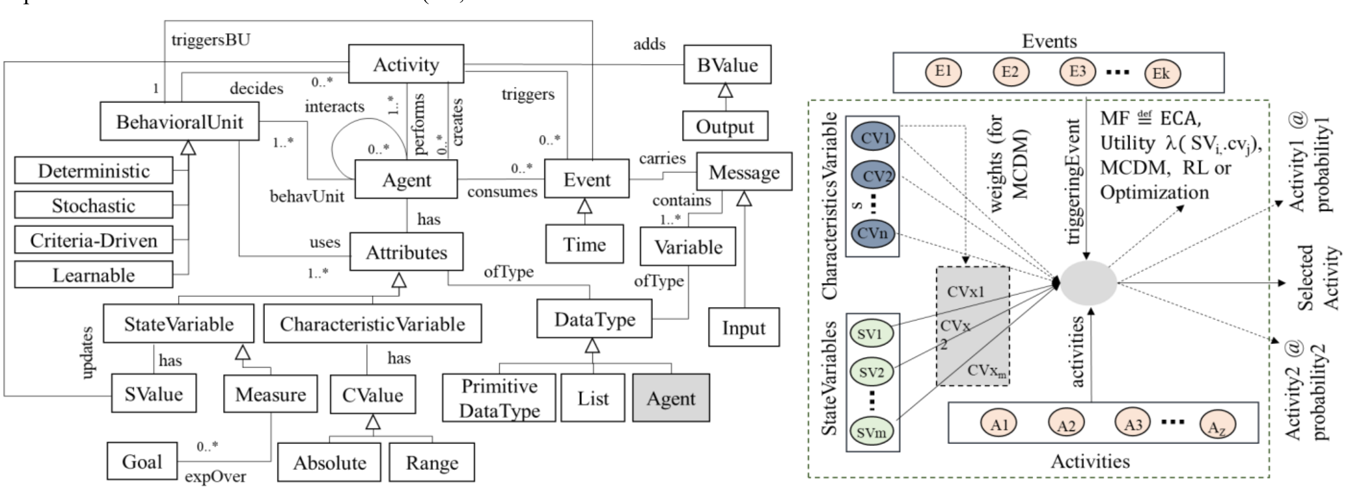
A techno-socio-economic system comprises of composable interacting *Units* as shown in Figure 2. We use an extended *Agent* abstraction to model *Units*. As shown in Figure 5 (a), our agent encapsulates two kinds of typed attributes, namely *StateVariable* (SV) and *CharacteristicVariables* (CV). The SVs represent state information using *SValues,* whereas CVs represent characteristics such as various affinities and biases of the unit using *CValues*. We consider *Agent* as a *DataType*, in addition to primitive types and list, to support desired composition and decomposition structure. A *CValue* can either be singleton or a range where the latter represents nondeterministic characteristics (*i.e.*, a *known unknown* situation). A domain expert can specify *CValues* based on experience, or it can be learnt from history if relevant data exists.

An agent can interact with other agents by raising *Events* and sending relevant data as *Message*. The simulation is driven through Time events. The behavior of an *Agent* is defined using different types of *BehavioralUnit* (BU) and *Activities*. An activity may update state variables (SVs), send events to other agents and/or create a new agent as shown in Figure 5 (a). The BU of an agent can be conceptually visualized as a singleton perceptron like structure as shown in Figure 5 (b). A BU of an agent comprises a triggering event, subset of SVs, subset of CVs, and a subset of activities of the agent. A canonical agent uses *Deterministic* BUs that define behavioral specification as ECA rules. That can include probabilities to capture *Stochastic* BU. A Stochastic BU defines nondeterminism as below (also shown in Figure 5 (b)):

```
on event {
 if conditions on SVs and CVs are true
 then do {
  activity1 @ probability1 (from CVx) or
  activity2 @ probability2 (from CVy) …
 }
}
```

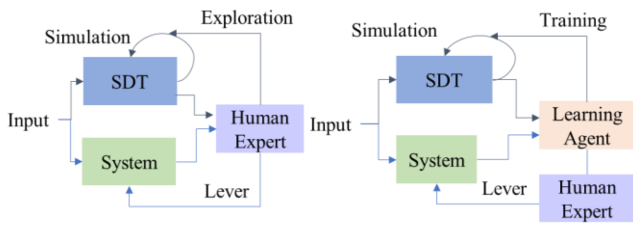
For *Criteria Driven* BU, we introduce multi-criteria decision making (MCDM) technique [32] to choose an activity from a set of options by considering triggering Event and SVs as inputs, CVs as weights to the inputs and Activities as outputs. A simple utility function [32] or a complex MCDM technique, e.g., TOPSIS [6], can be used to compute utility values of all involved activities of a BU. Here, an activity with highest utility value in given moment is a response to the triggering event, alternatively an activity can be randomly chosen from a set of Activities with high utility values – a fuzzy MCDM [13]. Important to note here that response can change over time as the state variables of agent change over time. *Learnable* BU is conceptually a layered neural network, where the triggering event and SVs of BU are input, and activities of the BU are outputs. Learnable BUs need to be trained with relevant dataset to learn behavior from the history.

These BU types help to capture several pragmatic scenarios, thus our agent abstraction is suitable for capturing elements of techno-



(a) Agent meta-model (b) Structure for specifying behavioral unit

Figure 5: Agent specification



(a) Case 1: Human-in-the-loop experiment (b) Case 2: RL based experiments
Figure 6. Digital Twin centric approach to decision-making

socio-economic elements: a) an incoming event as triggering event makes an agent reactive, b) a state variable as input to BU promotes autonomy, and c) an ability to specify characteristic variables (affinities and biases) by domain experts or learn from historical data helps to combine data-centric approach and domain model centric approach in a seamless manner. The existence of multiple interconnected BUs as triggers & response augmented with temporal delay in between and nondeterminism in an agent 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 concepts from both the techniques at micro-level to decide the best activity that an agent can perform at given moment as opposed to use AI and MCDM to predict macro behavior of a system.

We further extend agent abstraction to introduce GML structure at varying level of granularity as shown in Figure 5 (a). The Measures are computed from SVs and *Goals* are expression over *Measures*. The *Levers* are combination of a) replacement of *CValues*, replacement of BUs honoring activity compliance (i.e., a BU can be replaced with other when both consider same set of activities), and replacement of Agent honoring event interaction pattern.

Since we consider *Environment* as a singleton or a set of units (see Figure 2) and thus realize as *Agents*, the *Messages* from agents that represent environment constitute the system *Inputs* and the *Values* in terms of *Measures* that system agents produce while performing activities form the system *Output*.

3.2 Enabling Technology and Methodology

An SDT of a system represents the elements and environment of the system as agents as shown in Figure 5 (a). We use the agent-based Enterprise Simulation Language (ESL) [10] as a realization mechanism and follow well-defined methodologies to validate its faithfulness.

Construction and contextualization: In this phase, domain experts identify relevant units and their composition, decomposition and interaction patterns (see Figure 2). All identified units are specified using ESL agents, interactions are represented as Events, and behavioral aspects are captured using BUs and activities. The CVs of all agents and their mapping with BUs are established. In situations where both domain knowledge and relevant data are inadequate, they are represented using probabilistic behaviors and fuzzy MCDM. After construction, the SDT needs to be periodically synchronized by initializing SVs of all agents from real system to sync up SDT state with system state.

Ensuring faithfulness: We adopt the established technique of operational validity [29] to ensure faithfulness of the digital twin - historical situations are simulated using the digital twin and simulation results are compared with real observations to ensure faithfulness. We have developed a pattern language to specify and match the desired patterns in the simulation trace [9] to ensure operational validity. The use of agent-based modelling abstraction with finer level of granularity helps to capture the relevant aspects of interest as close as the reality – this helps to ensure the conceptual validity [29].

Managing uncertainty: Stochastic characteristics and behaviors of the constituent elements help support validity. However, it poses a unique concern – each situation of same configuration may emerge differently. As opposed to predicting future Measure trends based on a single simulation run, we simulate a scenario multiple times so as to cover as broad a spectrum of the nondeterminism as possible thus limiting extreme emergent behaviors to a tolerable range while also leading to convergent normalized behavior to emerge. This helps to improve the confidence level as discussed in [26]. We follow below steps to allow Measure trends to converge.

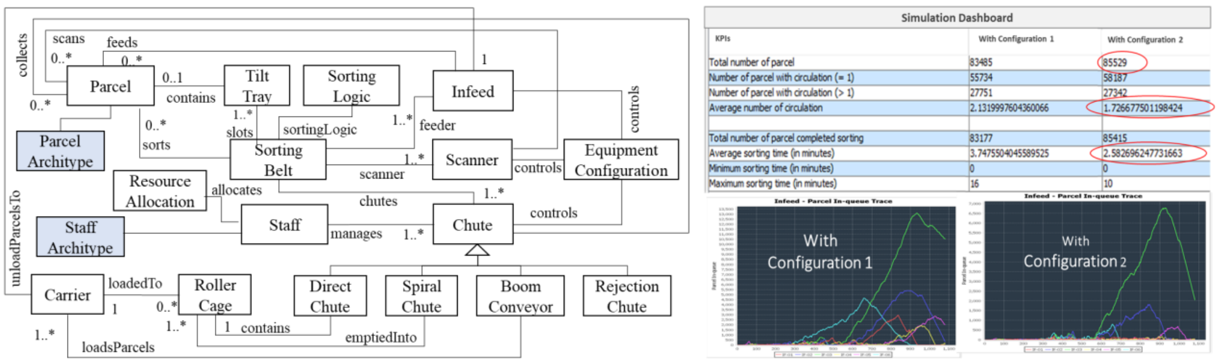
Simulate **N** times & compute average of all *Measures* (M_{Avg})
// we consider N = 5
While all *Measures* haven’t converged
Simulate & compute new average (M_{New}) from simulation runs
For all **Measures**
If (($|M_{Avg} - M_{New}|$) < δ)
// (deviation δ is within a tolerable range)
Converged = True
Else
$M_{Avg} = M_{New}$

Managing Heterogeneity: Techno-socio-economic systems contains large number of elements, such as millions of customers and people, each having individual characteristics and behavior. Specifying each of them is not a pragmatic consideration. We use the concept of “architype” with characteristic variables (CVs) having range of values to capture the heterogeneity of the problem domain – number of architypes for an element is a tradeoff between specification complexity and richness. We establish a balance based on domain complexity and expected prediction precision.

3.3 Simulation led learning aided experimentation

Simulation of purposive SDT is supported by introducing a periodic Time event that mimics a primitive time unit of a problem statement. A simulation produces traces/trends of Measures as a projection of state variables. Repetition of SDT simulation incorporating various environmental situations helps understand real-world behavior. Simulation also helps understand the impact of *Levers* on *Measures*. The two together can evaluate efficacy of Levers. An iterative process helps arrive at the most appropriate *Lever* or a sequence of *Levers* required to achieve the desired goals with possible tradeoffs. Therefore, SDT simulation enables stakeholders across the board to ideate candidate adaptation/design options, roll out experimentations using simulation, generate data (i.e., *Measure* trends) from the experiments and use it in combination with real data for evidence-based decision making as shown in Figure 6 (a).

A digital twin does not reduce the intellectual burden on human experts who still need to identify candidate what-if scenarios, interpret the simulation results, compute how far the current state



(a) Key units and actor topology (b) An illustration of SDT led in-silico experimentation

Figure 7. Overview of sorting terminal case study

is from the desired state, and identify candidate set of levers to bridge the gap. To this end, we use an AI technique called as Reinforcement Learning (RL). Basically, we use digital twin as an "experience generator" from which the reinforcement learning agent (RL agent) learns what action to perform when to achieve the overall goals as shown in Figure 6 (b).

4 Real World Case Studies

The proposed approach and associated technology support are validated for utility and efficacy on a set of real-world problems spanning a wide spectrum of business and social scenarios. A representative sample from cyber-physical, business and social systems are presented below.

4.1 Case Study on Cyber-physical system

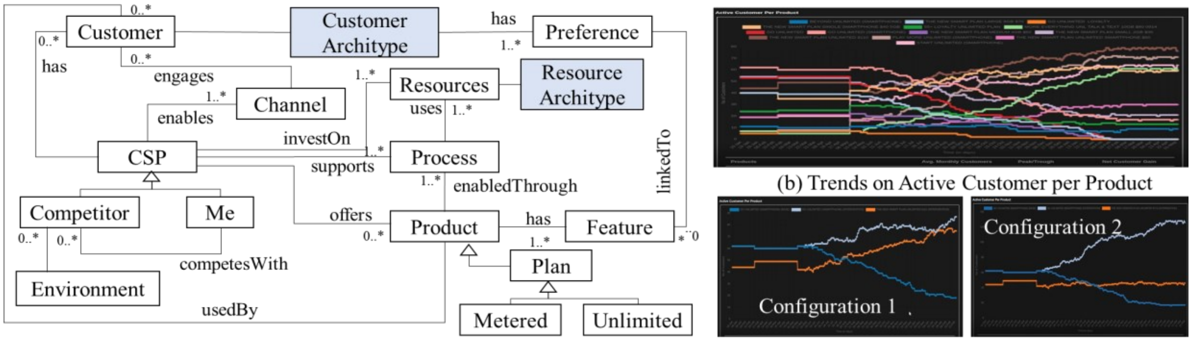
Delivering increasingly large volume of parcels of different size and characteristics across the globe in a dynamic and uncertain world is a significant challenge for Courier, Express and Parcel (CEP) companies. To meet this demand, CEP companies rely on a largely static network comprising collection centers, sorting terminals, transportation means, and last-mile connectivity. The global e-commerce market is expected to reach USD 55.6 Trillion by 2027 from USD 13 Trillion in 2021[1]. To meet the consequent surge in parcel delivery demand in a fast-shrinking time window, CEP companies are trying to improve along three dimensions: optimum vehicle management, efficient last-mile delivery, and greater throughput of the sorting terminals. Here, we present an application of SDT to improve the throughput of sorting terminals of a Nordic postal company.

Context: Sorting Terminal is a human-in-loop automated cyber-physical system that aims to effectively route a wide range of heterogeneous parcels to their appropriate destinations. Error-free and efficient sorting is a pre-requisite for faster delivery of parcels. Figure 7 (a) depicts schematic of a typical sorting terminal comprising: *Carriers* that bring parcels for sorting, *Infeeds* that put parcels onto sorting belt, *Sorting belt* (along with *Tilt tray*) that carries the parcels to be sorted, *Scanner* for identifying the destination address written on the parcels, *Chutes* to collect the parcels, and *Roller* cage to send the sorted parcels to outbound carriers. Chutes are of different types and a chute has a dedicated team that collects the parcels, puts them into roller cages, and takes them to the designated loading stations. For maximal throughput (*i.e.*, a *Goal*) of sorting terminal, the following conditions must hold (*i.e.*, *Measures* to be satisfied): parcels should spend as less time on the *Sorting belt* as possible, *Chutes* should get emptied as quickly as possible, *Chute* blockage should be minimum, no parcel should remain unsorted beyond the prescribed rotations (*i.e.*, circulation count) on the sorting belt thus leading to manual handling of the package (inside rejection chute) which is time and cost expensive. Three broad levers exist to achieve this objective namely, *Sorting logic*, *Resource allocation* and *Sorting terminal configuration* as shown in Figure 7 (a). Sorting logic is about defining parcels destined for which region should get collected in which chute. Resource allocation is about defining team size (and composition) to be assigned to a chute. Sorting terminal configuration is about making fit-for-purpose choices on the various components of this cyber-physical system.

Problem statement: Current practice takes a call on these levers using data-centric AI-based approach, optimization techniques in a localized context (e.g., sorting logic, resource allocation, *etc.*), and/or relying solely on intuition of domain experts. Given the high uncertainty, there is a high probability of these decisions turning out to be sub-optimal if not outright incorrect. For example, it is very difficult to know a-priori about inbound parcel flow in terms of number of parcels, destination, average parcel size, and the sequence they come up for sorting. This leads to ad-hoc addressing of the ensuing outlier conditions which perpetuates further outlier conditions. Moreover, other uncertainties pertaining to machine breakdown, staff availability, and staff productivity collectively lead to a situation that's far away from the desired situation.

SDT led exploration: To overcome this problem, we constructed a digital twin of the sorting terminal by capturing necessary concepts defined in Figure 7 (a) using ESL agents. In particular, the digital twin of sorting terminal contains a sorting belt with 522 tilt trays, 6 infeeds, 2 scanners, 18 chutes (4 direct chutes, 8 spiral chutes, 5 boom conveyor chutes and 1 rejection chute), 100 roller cases and 30 staffs. The agents that represent machines, such as sorting belt, infeed and scanner, are implemented as determinist BUs with failure propensity captured as stochastic BUs. The agent to represent staffs is implemented as stochastic BUs. The container types, such as chutes and roller cages, do not have their own

[1] https://www.imarcgroup.com/e-commerce-market



(a) Actor topology of CSP

(b) Trends on Active Customer per Product

(c) Trend for Configuration 1 and Configuration 2

Figure 8. Overview of sorting Telecom Case Study

behavior, however, they are involved in phenomena, such as parcel blockage and parcel overflow that influence the throughput. These agents having *unknown known* behavior are implemented as learnable BU.

We validated the SDT by simulating historical payloads and comparing simulated results with past results. The validated SDT serves as an "in silico" experimentation aid where a wide range of what-if simulations can be performed. Apart from helping arrive at the right sorting terminal configuration, these experiments also help identify possible outlier conditions where the desired Measures/KPI are not met. The Measures we focused on were: number of parcels processed, time taken to clear chutes, number of chute blockages, average time to get collected in a chute, number of parcels that stayed unsorted, and queue buildup on infeeds. We also simulated for different parcel payloads to check for bottlenecks if any. Simulation results of two configurations involving different sorting logic and circulation count are shown in Figure 7 (b).

Sorting terminal SDT enabled decision space exploration through what-if scenario playing using representative workload. This not only helped arrive at appropriate configuration of the sorting terminal for the given workload, but also helped in identifying the right resource allocation strategies for delivering 'good enough' throughput when working with fewer chutes and reduced staff.

4.2 Case Study on Business System

The core telecom space can be viewed along two broad dimensions – a) telecom network infrastructure, which is primarily a collection of physical systems, and b) business system that offers products to their customers by utilizing network infrastructure. This case study focuses on the latter dimension for a North American Communication Services Providers (CSP).

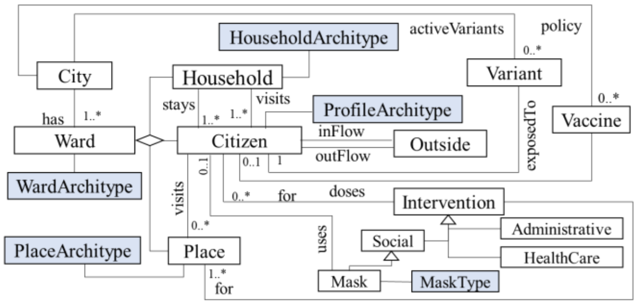
Context: Onset of Covid-19 resulted in steep surge in demand for internet connectivity as practically the whole world switched to work-from-home mode. Among CSP, the general belief was that *Unlimited Plans* (*i.e.*, fixed charge regardless of usage) will do far better than *Metered Plans* (*i.e.,* pay as you go). Moreover, Unlimited Plans have very low post-sale cost to CSPs compared to Metered Plans. As a result, CSPs were keen on diverting much of the network infrastructure to service Unlimited Plans. Here, we used SDT to explore the following questions for Unlimited Plans: What features should it have? At what price point? Will it grow at the cost of our other products?

Problem Statement: We considered two Unlimited Plan products namely Product A and Product B – both stable revenue earners at low cost to CEP. We want both products to do well after onset of Covid-19. Therefore, the problem is: What new features to add at what price point such that both products continue to do well. Current practice is to define new products by anticipating customer needs and evaluating the product in a sandbox environment using A/B testing. This is a time-, cost-, and effort-intensive endeavor as the new product needs to be built and rolled out to a sample set of customers. Moreover, this requires multiple iterations especially when the customer base is very large and highly heterogeneous in terms of its communication needs.

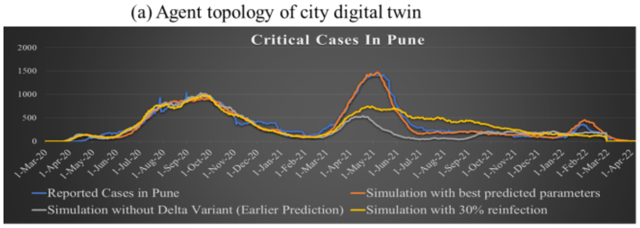
SDT led Exploration: To enable "in silico" experimentation, we constructed an SDT for CSP with its 374K Customers, 14 *Products* that include Unlimited and Metered plans, the trial rollout *Process*, the required *Channels* to take plans to customers, and *Resources* involved in supporting the campaign as shown in Figure 8 (a). We classified the existing customers into 109 architypes where the probability ranges are determined by applying ML models on historical customer data and further refined by domain experts in the light of evolving and uncertain situations. The buying decision of each individual is determined by TOPSIS method [6] (*i.e.*, a criteria-driven BU) where offers constitute the triggering event, product features and state variables of the individuals constitute the inputs, and affinities constitute the weights to select who can buy which product. Uncertain environmental factors such as lockdowns / phased relaxations constitute time-bound stochastic behaviors. Product uptake and product retention constitute the measures for evaluating the candidate set of interventions.

We set up CSP SDT appropriately to simulate business as usual scenario and subjected it to onset of pandemic in February 2020 as an event of interest. As seen from Figure 8(b), all products continue almost unaffected till April 2020 after which they show significantly high turbulent behaviour.

Consider Figure 8(c) configuration 1 that depicts performance of Product A (dark blue line) and Product B (orange line). Both products are seen performing stably till April 2020 after which Product B does noticeably better (as expected of an Unlimited Plan product) whereas Product A is seen doing pretty bad. We have two levers to salvage its performance: new features and price point. We consider two options for the former: (a) increasing free international calls to Canada & Mexico and video streaming capacity, and (b) providing subscription for Disney+ and Apple



(a) Agent topology of city digital twin



(b) An illustration of SDT led in-silico experimentation

Figure 9. Overview of Covid case study

Music; and for the latter: (i) price range USD 100 - 120, and (ii) price USD 140. We simulate CSP SDT for *configuration 1* (providing increased free international calls to Canada & Mexico and video streaming capacity at USD 100 – 120) to predict performance of Products A and B. As shown in Figure 8(c) *Configuration 1*, performance of Product A improves considerably (light blue line) without affecting performance of Product B (orange line). We simulate CSP SDT for configuration 2 (providing subscription for Disney+ and Apple music at USD 140). As shown in Figure 8(c) *Configuration 2*, performance of Product A improves considerably (light blue line) but at the cost of Product B (orange line). Therefore, configuration 1 turns out to be the right intervention to achieve the desired goal.

Experimentation helped CSP design the product and arrive at a price point that led to 2X improvement in overall take rate 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. A product, TwinX[2], based on SDT for enterprise is developed and launched to address a wide range of Telco needs.

4.3 Case Study on Social System

The Covid19 pandemic has impacted public health safety, economy and social well-being for more than two years. This prolonged yet evolving situation has put forth a perpetual challenge for the policy makers and administrators to understand the evolution of the pandemic in the face of emerging variants and decide effective interventions to control situations if necessary.

Context: The Covid19 pandemic has affected more than 500 million of population globally over past two years and the number is still going up in many parts of the world as we write this paper. Multiple waves of varying amplitude due to several virus strains have adversely affected the world in many ways *e.g.*, death count has crossed 6 million, economy is crippled, and social wellbeing is heavily compromised. Some of the variants, such as Alpha and Delta, have stayed on for a prolonged period resulting in large number of severe infections and deaths. Variants like Omicron and its descendent lineage have been quite infectious but significantly milder in comparison to earlier variants. It is expected that the mutation of Covid19 virus will continue and may turn into more or less infectious and severe with other characteristics, such as higher reinfection propensity, in the future. Going forward, extended lockdown cannot be a preferred option from socio-economic standpoint. Therefore, we need better understanding of the pandemic evolution for (existing/new) variants to explore effective interventions for return to new normalcy without compromising public health safety.

Problem Statement: We believe that exploring effective Nonpharmaceutical interventions (NPIs) for entire country is not a pragmatic proposition. Instead, localized NPIs considering the unique characteristics of the locality can be more effective. However, deciding effective NPIs for a city or locality is not easy due to: a) increasing uncertainty about various influencing factors such as emergence of new variants, vaccines & their efficacies, and waning of immunity, b) wide heterogeneity in demographic characteristics of people and noncompliance possibilities by people, and c) poor quality and corpus of relevant data due to low testing uptake and underreporting. In absence of pragmatic means to overcome these issues, most of the pandemic control decisions tend to be intuition-driven, and therefore, less effective.

Modelling considerations: We construct a purposive SDT to manage Covid19 pandemic in a city. The city SDT helps predict evolution of Covid19 pandemic and explore efficacy of candidate set of NPIs for controlling the pandemic in a quantitative manner. We visualize a city as a collection of administrative wards with in- and outflow of people from outside. A ward is a bottom-up composition of different types of places (*e.g.*, school, college, market, offices, and restaurant), household structures (e.g., small congested house with many household members, large house with less members), and citizens with unique set of socio-economic strata (*e.g.*, office goer, shop keepers, students, worker, etc.). The behaviour of containers such as wards, places and households evolve over time based on visitor/member footfall thus exhibiting emergentism (*e.g.*, contact propensity emerges based on gathering of people leading to super-spreader event). Citizens have their own state variables (*e.g.*, age, gender, comorbidity), characteristics variables (*e.g.*, affinity to comply with Covid-appropriate behaviors and tendency to violate non-pharmaceutical interventions, and vaccine hesitancy) and a set of spatiotemporal nondeterministic behaviors. Behaviors are bounded by who they are (*i.e.*, a student or an office goer), where they are (*i.e.*, at home, in office/school/clinic or in a restaurant) and the time of the day. Behavioral nondeterminism is primarily due to movements within and around the places. The infection transmission and infection progression for an individual emerge based on virus variant (when they get exposed), vaccines (if administered) and mask (if used). The virus transmission from one individual to another represents a nonlinear probabilistic phenomenon (*i.e.*, similar type of contact may result in different outcomes depending on the micro-situation), and the progression of infected case (*i.e.*, exposed to infectious,

[2] https://www.tcs.com/tcs-twinx-digital-twin-technology

Table: 1: Summary of Case studies

	Sorting Terminal	Telco case Study	Covid Case Study	Supporting SDT concept
Structural Composition & Decomposition	Mostly static hierarchical decomposition	Fairly static composition and decomposition	Dynamic composition and decomposition	Agent
Heterogeneity	Less	Moderate	High (need simplification)	Architype with CharacteristicVariable with Range of values
Behavior	Less fuzzy	Highly Nondeterministic	Nondeterminist & Spatiotemporal	BehavioralUnit (BU)
Goals	Well defined	Conflicting	Ill-defined and conflicting	Human-in-loop exploration & RL Technique
Existing data	Useful	Need update considering current situation	Inadequate	Agent abstraction helps to use fragmented data effectively
Uncertainty	Limited	High	Exceedingly High	StochasticBU
Emregentism	Less	Moderate	High	Agent composition stucture
Number of elements	Not too many (in Thousands)	Large (in Million)	Exceptionally large	Scalable ESL technology
Validation	Operational validity serve the purpose	Need operational and conceptual validity	Existing validation technique are inadequate	Validation Technique

Sufficiently supported in SDT; Addressed adequately with moderate approximation; Supported but need improvement

infectious to asymptomatic, mildly symptomatic or severe, etc.) of an individual is dependent on infection history, vaccination details and the infecting variant.

We modelled necessary entities using a configurable agent topology and their interactions as highlighted in Figure 9 (a). A fine grained model captures the heterogeneity in terms of: a) 13 household architypes that range from two-member family to twelve-member family, b) 20 place architypes representing relevant places of a city where people frequently visit, spend time and make contacts, such as office, school, restaurants & pub, clinics, mall, market-place, worship place and representative commuting means, c) 5 ward architypes to represent different mix of well-to-do localities, slums and market area, d) 25 profile architypes, including child, college student, senior citizen, and office goer, to represent professions with different behavioral patterns, e) 3 intervention architypes (administrative, healthcare-related, and social). The vaccines and variants are introduced as configurable agents where their characteristics are specified based on research published in reputed journals like Lancet.

SDT led Exploration: We constructed city specific SDT for Indian city of Pune[3] having 4 million population. The utility and efficacy of city SDT to manage the first of wave of Covid19 pandemic by choosing NPIs in a locality-specific manner is presented in [5]. Our prediction about the second wave, several months before its appearance, was very close with respect to the reality (see grey curve of Figure 9(b) – taken from Figure 21 of [5]).

We used this city SDT to predict evolution of pandemic at the backdrop of several parameters that were not fully known *e.g.*, infection characteristics of Delta variant, loss of immunity post-vaccination, reinfection probability, adherence to Covid19 appropriate behavior *etc*. This was an iterative process that involved playing around with plausible values of these parameters to project best case and worst-case situations measured along the key indices such as death count, number of patients requiring hospitalization, and number of patients requiring isolation. Figure 9(b) shows these projections – orange for worst case and grey for best case. Characteristics of Delta and Omicron variants, available vaccines, 5% reinfection possibility and moderate noncompliance of NPIs, shown using orange line, closely matches with the reported cases (shown using blue line) till end of third wave in Pune. Our conceptualization that considers vaccine and variants as configurable agents help to explore different hypothetical scenarios such as new variants with different epidemiological characteristics and exploring vaccine strategies, *e.g.*, booster doses for the future.

4.4 Discussion

Three industrial case studies with varying complexities demonstrate the efficacy of the proposed SDT for representing and analyzing techno-socio-economic systems.

Sorting terminal case study illustrates how hierarchically decomposed structures (or a system of systems) of a cyber-physical system can be modelled and analyzed. The key challenge here is to effectively operate, engage and orchestrate machines and human operators to achieve optimal throughput of the sorting terminal for a given configuration and team size. Here, the uncertainties pertain to parcel inflow, machine failure, staff productivity and staff availability at right place at right time. Some of these uncertainties can be gauged by analyzing historical data such as machine failure records, productivity charts for a specific activity and so on. Our agent abstraction that’s amenable to: (i) augmentation of nondeterminism (i.e., stochastic BU), (ii) wrapping a model learnt from data as an agent, and (iii) hierarchical [de] composition helps to specify such systems with precision.

The telco case study illustrates how a business system (*see* Figure 3) that comprises large number of fuzzy and evolving entities (*i.e.*, customers) having widely varying and uncertain affinities/preferences can be modelled. It demonstrates simulation-based approach to arrive at appropriate business interventions in response to a disruption like Covid19 pandemic. The key characteristics are: a wide range of heterogeneity (*i.e.*, 109 customer architypes with several conflicting preferences), nondeterminism, and dynamism *(e.g*., change in preference and behavior due to lockdown). Our agent abstraction capable of supporting non-deterministic behavior (*i.e.*, stochastic Bus), behavior learnable from data (*i.e.*, learnable Bus) and Criteria-Driven BUs *(i.e*., use of MCDM and fuzzy MCDM at micro-level). Iterative SDT based simulations help arrive at suitable tradeoff in case of conflicting goals such as revenue growth, product portfolio rationalization, customer satisfaction, customer care optimization. and other conflicting criteria. Here, we used SDT as experience generator to support an evidence-based decision-making in human-in-loop manner. A Reinforcement Learning (RL) agent can used with SDT to explore product features and price that can attract maximum number of customers while achieving higher revenue target. Elsewhere [4], we demonstrated the utility of SDT as an environment to train RL for a business system – in particular, for optimum stock replenishment of a large retail supply-chain. Business study for competition, collaboration and establishing pareto optimality are the possibility using SDT led exploration.

City SDT is a case where bottom-up modelling, behaviors with degree of uncertainty and spatiotemporal characteristics, nonlinearity and emergent behavior of a system of system are

[3] https://en.wikipedia.org/wiki/Pune

demonstrated. It also shows how simulation-based synthetic environment can produce useful evidence for hypothesis evaluation where existing data is inconsistent and hard to believe.

Table 1 summarizes inherent characteristics of three case studies and maturity of SDT along those characteristics. As shown in the table, we need further improvement in SDT to support the inherent characteristics of social systems. Validations often require multiple repetitions to establish operational validity and more importantly it demands significant involvement of domain experts for conceptual validity. This is an area for improvement of our work.

5 Conclusion

Existing modelling techniques provide limited support for techno-socio-economic system decision-making. We propose that this can be improved using digital twin based simulations supported by a meta model for the digital twin and an agent-based realization of the meta model in the form of an executable specification capable of modelling uncertainty through non-determinism. We showed how the ability to specify agent behavior using multiple paradigms, i.e., ECA, MCDM, and machine learnt model can effectively overcome the limitation of partial information in a pragmatic manner. We presented how the provision to capture micro uncertainties in the form of stochastic models and fuzzy MCDM helps model uncertainty and fuzziness. Our pragmatic model validation methodology that includes conceptual validation from domain experts in combination with operational validity helps to establish high fidelity of the digital twin with respect to the real system. We discussed associated technology infrastructure to support decision-making in a dynamic and uncertain environment. Methodological support to simulate a configuration (i.e., adaptation/design alternative) till all Measures converge helps to improve the confidence level of the analysis. Human guided iterative simulation helps to identify which amongst the candidate set of interventions is most suitable.

Reinforcement learning can be used to reduce the analysis & synthesis burden on human experts where the SDT acts as an “experience generator” to support data-driven evidence-backed decision-making in a human-in-control manner. An SDT can also be used to train RL agent thus reducing the intellect burden on human expert while also leading to efficient exploration of decision space. Here we also discussed utility and efficacy of the approach on real world industry scale use cases spanning across cyber-physical (sorting terminal case study) business (telecom case study), and societal (Covid19 case study) domains. Almost everywhere the proposed approach has fared better than current practice. Adoption of our approach as a product, TwinX[2], is a testimony of business impact of our research. We believe proposed system digital twin with sufficient support for all characteristics as highlighted in Table 1 can be effectively utilized to address emerging socio-techno-economic challenges such as sustainable enterprise, smart city, and wellness & healthcare.

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