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HYBRID MODELS WITH REAL-TIME DATA: CHARACTERISING REAL-TIME SIMULATION AND DIGITAL TWINS

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ABSTRACT

Real-time Simulation (RtS) and Digital Twins (DT) are terms generally associated with hybrid models that use real-time data to drive computational models. Additionally, in the case of DTs, real-time data is often used to create virtual replicas of the physical system as it progresses through real-time. There is an increasing volume of literature on RtS and DT; however, the field of OR/MS is yet to coalesce on accepted definitions and conceptualisations. This has arguably led to the cascading usage of these terms. The objective of the paper is threefold: (1) distinguish between RtS and DT, (2) present RtS-DT conceptualisation in four dimensions, and (3) present methodological and technical insights on developing RtS with limited data. We argue that the evolution of conventional simulation models to fully-fledged hybrid DTs may necessitate a focus on a transitional stage; namely, RtS models primarily driven using historical distributions with limited real-time data feeds.

Keywords: Real-time Simulation, Digital Twin, Hybrid Modelling, Conceptualisation

1 INTRODUCTION

A defining characteristic of the present Millennium is the exponential increase in data availability, made possible through advances in data acquisition technologies such as sensors, Global Positioning System (GPS)-enabled devices and Radio-frequency identification (RFID) chips and the underlying network and communication, storage, and computing infrastructures. Developing novel ways of making sense of this explosion of data, often referred to as data deluge (Bell et al., 2009), presents a contemporary challenge to researchers.

Modelling and simulation (M&S) techniques predates the era of Big Data (Taylor, 2019). The data requirements of such conventional simulation models were often limited to distributions computed from historical data and observational data, the latter necessary to model the system of interest using an overarching M&S methodology. With the increase in both the volume and velocity of data, the challenge to our community is to develop hybrid modelling approaches that combine the traditional M&S methods (and their reliance on historical distributions) with updated data streams. An example of such a hybrid approach is the application of M&S approaches with methods from Data Science, for example, machine learning with DES (Elbattah and Molloy, 2016), process mining with DES (Abohamad et al., 2017) and neural networks with SD (Abdelbari and Shafi, 2017). However, hybridisation could also be achieved by using values from historical distributions with real-time data and using it to drive computer simulations (Powell and Mustafee, 2017). In the M&S community, Real-time Simulation (RtS) and Digital Twins (DT) are generally recognised as computational models using real-time data feeds. However, the lack of common definitions and conceptualisation has, arguably, given rise to cascading usage of these terms. To address this gap, the objective of this paper is, ***first***, to distinguish between RtS and DT based on the literature; ***second***, to present a conceptualisation of RtS and DT based on the following four dimensions of a simulation study – *modelling objectives*, *data requirements*, *implementation*, and *experimentation*.

The paper also draws on the authors' experiences in developing a platform that publishes real-time data from several NHS Trusts in the South West of England – *NHSQuicker* (Mustafee and Powell, 2020) – and using data from NHSquicker in an Accident & Emergency (A&E) model developed using AnyLogic™. A conventional Discrete-event Simulation (DES) is used as the core computational model (Harper, 2021). The core model is being incrementally developed to integrate "limited" real-time data feeds available to the authors. The ***third*** objective of the paper is thus to present methodological and technical insights from our experience in developing RtS with limited real-time data.

For the remainder of the paper, the terms Operations Research/Management Science (OR/MS) DT and DT are used as synonyms for digital twins. Similarly, the terms "computational models", "conventional models" and OR/MS M&S are used interchangeably and refer to conventional simulation models. Finally, RtS refers to OR/MS simulations with limited real-time data feeds.

2 HYBRID MODELS WITH REAL-TIME DATA STREAMS

A simulation study comprises several well-defined stages. The model implementation stage concerns the development of a computer model using programming languages/libraries and software packages. However, prior to implementation, conceptualisations of the system must be developed and translated into modelling artefacts. Abstractions built on constructs specific to M&S techniques often lead to single-technique implementations. For example, an abstraction of a service delivery system viewed through the lens of queues and servers would often lead to a DES implementation; the same system could be modelled in agent-based simulation (ABS) if the conceptualisation draws on agent classes, inter-agent communication and the concept of emergence. Distinct from such single-technique DES and ABS implementations, *Hybrid Simulation* uses multiple simulation techniques in the context of a single simulation study. As reported by Brailsford et al. (2019), since 2000, there has been rapid growth in publications that have used combined approaches, such as the use of hybrid agent-based DES (Viana et al., 2020), DES with system dynamics (Xu et al., 2018) and mixed DES-ABS-SD modelling (Roemer and Strassburger, 2019).

The combined application of simulation with frameworks, methods, tools, and techniques that have been developed outside the field of M&S is referred to as Hybrid Modelling (Tolk et al., 2021). Unlike hybrid simulation, which mainly focuses on the model implementation stage, there are opportunities to leverage cross-disciplinary methods in conceptual modelling, verification and validation (V&V), scenario development, experimentation, and other stages of an M&S study (Powell and Mustafee, 2017). Mustafee et al. (2020) present several examples of hybrid models from the literature that have combined OR/MS simulations with approaches from applied computing, for example, distributed simulation, parallel computing, cloud computing, and real-time computing.

DT and RtS are hybrid models that use real-time data streams. They are considered hybrid models since their execution necessitates integration with backend data acquisition systems using distributed computing approaches such as socket programming and web application programming interfaces (APIs). Database-centric methods (including spreadsheets) could also be used wherein real-time data stored in the backend system is accessed using the *Open Database Connectivity (ODBC)* interfaces (Microsoft ODBC, 2022) to specific database management systems. Yet another approach is through the development of database triggers which access APIs defined in DT and RtS. A trigger is a code snippet stored in a database and executed following a defined database event, for example, an arrival of a patient in a hospital or a trigger executed at pre-defined intervals. The triggers are developed using procedural languages such as *PL/SQL* (Oracle) and *PL/pgSQL* (PostgresSQL). Flat-file-based systems (e.g., data from a data acquisition system (DAS) dumped in a shared directory) are yet another option, although this often requires parsing the data before being used by DT and RtS.

Our discussion has assumed that the front-end DASs were primarily developed to meet an organisation's data requirements and that they provide APIs, flat files, ODBC interfaces, etc., for external applications to access data. However, our experience working with multiple A&E patient flow systems has shown that this may not always be the case. A DAS could be a "closed" system in cases where primitive data structures are written in binary format using languages such as C/C++, and thus only accessible to program code (other programs cannot decipher records from these data files). On the opposite end of the spectrum, bespoke DAS and DT/RtS systems may be developed, which motivates the need for strong coupling in the design phases. In such cases, some of the complexities of real-time data communication are abstracted through higher-level libraries and API calls.

3 DEFINITIONS: DIGITAL TWINS AND REAL-TIME SIMULATION

VanDerHorn and Mahadevan (2021) reviewed 46 definitions of DTs and proposed the following generalised definition: *"(DT is) ... a virtual representation of a physical system (and its associated environment and processes) that is updated through the exchange of information between the physical and virtual systems"*. Arguably, the authors' definition rests on the characterisation of DT originally proposed by Michael Grieves (Grieves, 2014, as cited in VanDerHorn and Mahadevan, 2021), which necessitated the existence of a **physical system** in the real world, the **virtual representation** of the real system, and **communication channels** between the real and the virtual systems for information exchange and synchronisation. In the following paragraphs (including Tables 1 and 2), we critique DT and conventional M&S models, as applied to OR/MS, based on Grieves' characterisation of the definition of digital twins. Through this critique, we lay the foundation for the definition of real-time simulation, or RtS, which is introduced in Section 3.1.

Physical Reality: A fundamental difference between M&S and DT is whether the system being modelled exists in the real world. For OR/MS simulations, this could be a system that does not yet exist. Here the purpose of the simulation study is to experiment with system configurations before implementing the physical infrastructure. The work conducted by British Airways' Operations Research department is a good example. They developed generic simulation models to assess infrastructure requirements, such as the number of check-in counters for the new Heathrow Terminal 5 (Beck, 2011).

A physical system, a physical environment and physical processes are identified by VanDerHorn and Mahadevan (2021) as the three essential elements of the physical reality and which a DT must model. When a physical system does not exist, a DT implementation cannot be realised as there are no entities, no physical environment for the entities to reside and interact in, and no existing physical processes exist.

Virtual Representation: The five definitional elements associated with virtual representation are presented in Table 1 (column one). The definition presented by VanDerHorn and Mahadevan (2021) is a very broad and encompassing definition of DT. Thus, we assessed the definitions from the standpoint of OR/MS researchers. We consider both the traditional OR/MS simulations of physical systems that exist in reality (Table 1; column two) and DTs that include an OR/MS focus (Table 1; column three).

Table 1 *A comparison of conventional OR/MS simulation and OR/MS DT based on VanDerHorn and Mahadevan (2021) definition of Virtual Representation*

Definitional elements of virtual representation	Conventional OR/MS Simulation of a Physical System	OR/MS DT
Idealised representation of physical reality	For conventional OR/MS simulation, the conceptual modelling stage helps develop an abstraction of the system of interest based on factors such as the objectives of the simulation study.	The idealised representation of physical reality often has to consider the real-time data available to model the abstraction of the physical system in the DT model.
System states and parameters	A simulation model of a physical system often requires a modeller to observe the real-world system or develop familiarity through interaction with the problem stakeholders, reading literature, etc. The modeller then relies on this understanding	A key element of an OR/MS DT is to monitor the physical reality as it transitions through time (also referred to as the wall clock time). The terms system states and parameters are concepts that are

	and uses technique-specific constructs available to implement a computer model. The computer model will include system states which will transition through time and various parameters, all of which are defined based on the modeller's understanding of the system in question.	used in state space modelling; state estimation methodology is frequently used in DTs to change information between physical reality and virtual representation (VanDerHorn and Mahadevan, 2021).
Virtual system: The virtual system consists of data and models of the entities from the physical system at the chosen level of abstraction.	*Data:* For conventional models, the sources of data include primary and secondary data, observational data, estimates from the literature, hypothetical values, expert opinion, or a combination. *Models of Entity:* For detailed-level DES/ABS modelling, individual entities can be modelled as work units and agents. SD can provide a higher level of abstraction using stocks and flows. Hybrid simulation can provide different levels of abstraction.	*Data:* Generally acquired from the physical reality, e.g., manufacturing facility, using data acquisition systems. *Models of Entity:* Generally, represent the flow of real-world entities through physical reality. For example, in a manufacturing facility for mobile phones, every unit of the phone could be modelled as a virtual entity that interacts with entities that represent manufacturing sub-processes.
Virtual environment: Virtual representation of the physical environment at a chosen level of abstraction. The objective is for the virtual environment to mimic the physical system's interaction with the physical environment (if the latter affects the former).	Certain aspects of the physical environment (if they are deemed important) can be modelled through the conventional OR/MS models. For example, virtual representation could be spatial in nature. They may include the dimensions of a factory floor, machines, and conveyor belts. Commercial, off-the-shelf DES packages often provide options for 2D and 3D visual displays (Akpan and Brooks, 2012). The use of Virtual Reality (VR) in DES is also an active area of research (Turner et al., 2016). Spatial aspects can also be modelled in a conventional way. For example, the placement of inventory of semi-finished goods may affect the travel time associated with moving items from the store for further processing. Some packages like Simul8™ can include distance travelled which affects the overall processing time.	Sensors can monitor aspects of the physical environment like occupancy level and air quality. Sensor data can thus be used to create a virtual environment at the chosen level of abstraction. However, it is arguable that the inclusion of a virtual environment may only be necessary if its physical counterpart affects either the entities or the processes in the physical reality. For example, monitoring air quality in high-precision manufacturing facilities may be considered important. However, occupancy levels at the same facility may not have a bearing on the physical processes and may thus be excluded from the virtual environment.
Virtual processes: Virtual processes represent the process-specific interaction among the entities that together comprise the virtual system and/or virtual environment. The expression of virtual processes is often achieved through computational modelling of the underlying physical processes existing in physical reality.	As these are dynamic models, the time element associated with the transformation of physical entities (e.g., plastic blocks) through a physical process (e.g., a machine which melts plastic) is crucial. For example, in a DES model, the (virtual) process flows are modelled using networks of queues and servers; the servers can be initialised with distributions that represent the processing times of the physical entities. Thus, in an OR/MS M&S model, the virtual processes are implemented through a combination of model-specific values and the underlying M&S methodology and a simulation engine.	For OR/MS DTs, it is important to consider the granularity of virtual process representation. For a plastic injection moulding factory, a DT that models the physical transformation of raw material (e.g., polymer) from solid to a liquified state and then to the final product, may not be essential (although this may be possible through physics-based modelling).

Communication Channels for Information Exchange: The third component of the VanDerHorn and Manadevan (2021) definition of DT relates to the interconnection between physical reality and its virtual DT representation. The information exchange component is subdivided into three elements, *physical-to-virtual connections*, *virtual-to-physical connections*, and *information fusion* (Table 2). Similar to our approach in Table 1, we assess the OR/MS conventional models and OR/MS DTs with these definitional elements. Our discussion on information fusion is particularly important for the RtS definition introduced in section 3.1.

Table 2 *A comparison of conventional OR/MS simulation and OR/MS DT based on VanDerHorn and Mahadevan (2021) definition of Information Exchange*

Def. elements of info exchange	Conventional OR/MS Simulation of a Physical System	OR/MS DT
Physical-to-virtual connection	Although data can be automatically collected from a physical system and stored in a database, distribution fitting and other forms of analysis will require the intervention of the modeller. As there is a manual element, the frequency of information exchange is minimal. Indeed, numerous OR/MS models are driven using distributions computed from very old data that were never updated.	Data acquisition is mostly automatic; updating virtual representation using measurements derived from the physical system does not usually require complex analysis; the frequency of data updates is in real-time. However, the experimental element of a DT will need to include distributions for faster than real-time simulations. Automation may enable the DT distributions to be recomputed at pre-defined intervals or when new data arrives.
Information fusion	In this paper, we define information fusion as combining historical data with real-time data. Going by this definition, since conventional models only rely on historical data and distributions, there is no scope for information fusion.	Synchronisation of the virtual representation of the physical systems (the digital replica) is usually achieved through real-time data. However, for the experimental element of the DT, the underlying computational model will need to use information fusion (i.e., using historical data with real-time data). This is further explained in the context of RtS in the later sections of the paper.
Virtual-to-physical connection	The objective of the virtual-to-physical connection for information exchange is to draw insights from the virtual system and make appropriate changes to the physical processes to achieve the desired state of the physical system (VanDerHorn and Mahadevan, 2021). A simulation is a decision support system; making changes to the physical system based on experiment results is the implementation stage of an M&S study. However, there is often a time lag due to the need for further considerations (including investments and stakeholder trust); the learnings from a study are often not implemented.	In an OR/MS DT, the virtual-to-physical connection often has mechanisms to control real-time feedback to the physical system based on either the visual replicas in DT (e.g., accumulation of stock taking place in the physical reality) or through faster than real-time experimentation. Interfacing of virtual simulation to physical systems has also been referred to as symbiotic simulation or on-line simulation (Aydt et al., 2009; Onggo et al., 2018). As DTs are primarily used for real-time decision-making, the time lag associated with making changes to the physical processes is minimal (indeed, it may also be automatic, e.g., through actuators which receive control feedback from DTs).

3.1 Defining Real-time Simulation (RtS)

Conventional OR/MS models, in addition to being able to represent "future" systems, are also widely implemented to capture "existing" physical realities. Examples include simulation models of hospitals and factories, distribution hubs and supply chain networks, airports and container ports. Like DTs, such models represent the physical system, the physical environment, and the processes of the physical reality (VanDerHorn and Mahadevan, 2021). However, unlike real-time DT execution, OR/MS simulations are implemented to execute faster than real-time (also referred to as simulated time).

For short-term decision-making, DTs may include OR/MS models for faster than real-time experimentation and optimisation. However, there also exists the opportunity to transition a conventional OR/MS simulation model of a physical system (which uses only historical data) to a DT (which uses real-time data), such that the former model is incrementally developed by replacing the distributions used to drive the model with real-time data feeds, as and when they become available. We refer to these transitional models of conventional OR/MS simulations as *real-time simulations* or *RtS*. To distinguish the conventional models from the hybrid RtS and DTs, we present a conceptualisation based on key aspects of a modelling study, which we refer to as its dimensions. This is presented next.

4 CONCEPTUALISING REAL-TIME SIMULATION AND DIGITAL TWINS

For this discussion, we define a conventional OR/MS simulation as using historical distributions to populate a core computational model. During the experimentation phase, such models are initialised with a warmup period, followed by the results collection until the simulation end time—results from experimentation inform medium to long-term decision-making. Figure 1 maps the conventional OR/MS simulation, depicted as a black circle, along the dimensions of *modelling objective*, *data needs*, *model implementation* and *experimentation*.

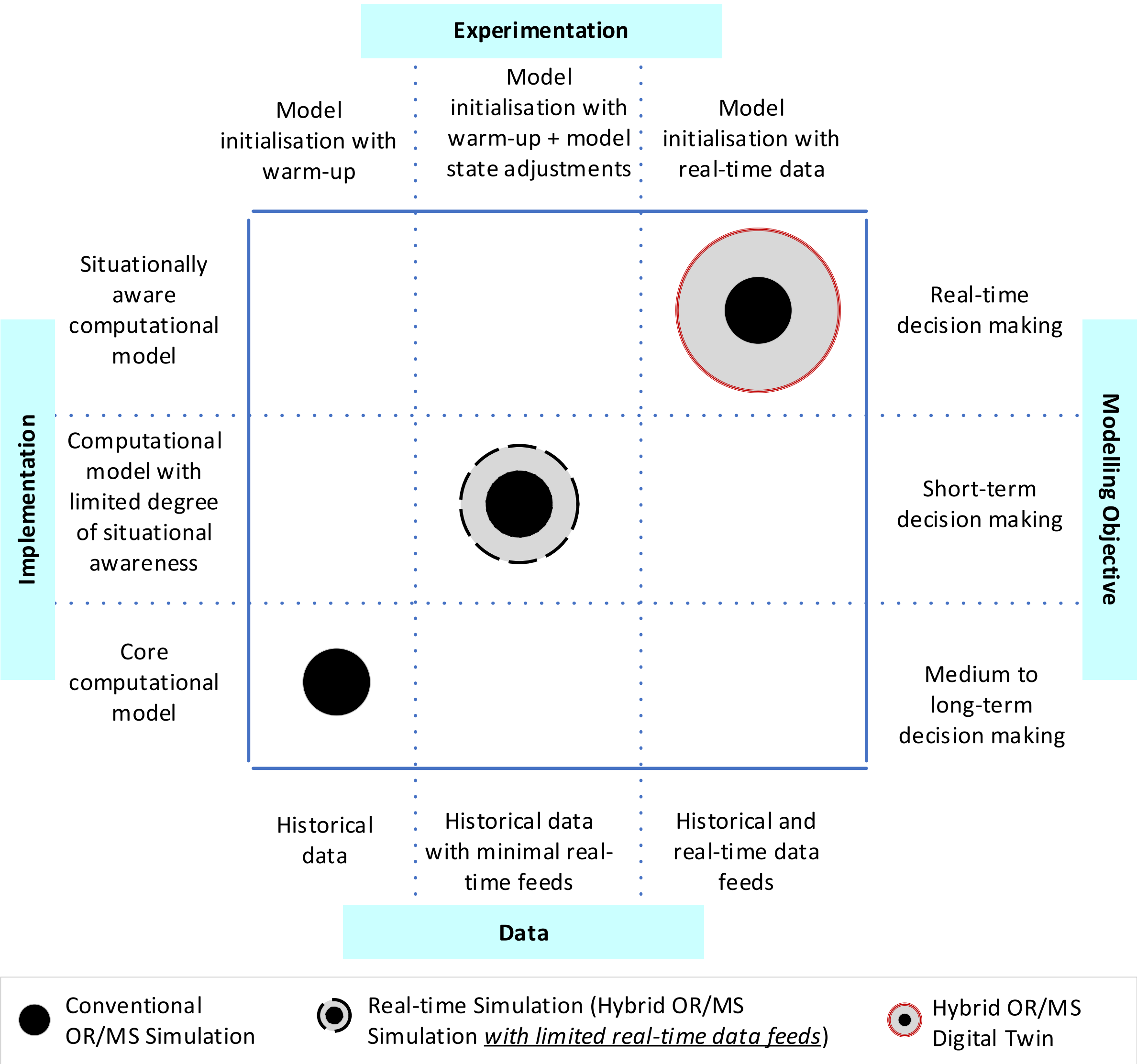

Figure 1 *Conceptualisation of RtS and DT using the dimensions of modelling objective, data requirements, model implementation and experimentation.*

A RtS, illustrated as a concentric circle with a dashed line, has, at its core, the core computational model (represented as the black circle), but with some of the historical distributions complemented with real-time data feeds. The grey outer circle represents real-time data; the dashed line illustrates that only limited real-time data is available to a RtS. Mapping of RtS in the four dimensions shows that such models are mostly used for short-term decision-making (*modelling objective axis*), it is dependent mostly on historical data but with some real-time data (*data axis*); the latter has implications in terms of model initialisation as it now includes the added element of making intrusive changes to the model state after warmup (*experimentation axis*). With the *implementation axis*, we note that RtS have limited situational awareness (this is not surprising considering these models have access to minimal real-time data), and the core remains the computational model— the conventional OR/MS model discussed in the earlier paragraph.

A DT is shown in Figure 1 as a concentric circle similar to RtS but with two differences. (1) Our definition of DT assumes integration with real-time data streams necessary for the virtual representation of entities, processes, and resources. As such, the dashed line used for RtS to illustrate information deficiency is replaced with a continuous red border. (2) Similar to the illustration for RtS, the grey outer circle represents real-time data; however, compared to the former, the latter has a larger diameter. This visually represents that the dependency of DT on real-time data is far more than compared to RtS. However, similar to RtS, the OR/MS DT also includes a computational model for experimentation (represented as a black circle); thus, DTs are equally dependent on distributions computed from historical data (refer to the *data axis* for the DT). Moving on to the *modelling objective axis*, a DT can be especially suited for real-time decision-making, although intuitively, it could also be viable to assist decision support in the short-term, for example, 2-4 hours. What is defined as "short-term" is subjective, and its viability will generally be determined based on the context of the application.

We define DT as a situationally aware computational model (*implementation axis*) that fulfils the following two objectives: (1) The virtual representation of the physical elements of a system as it evolves through real-time. (2) Faster-than-real-time simulation experimentation at specific pre-defined trigger points. (1) is likely to be a critical determinant for (2); for example, in a manufacturing facility, bottlenecks identified through the real-time assessment of key performance indicators (KPIs) could trigger simulation experiments to inform stakeholders of possible options, thereby assisting in real-time decision-making. Compared to DTs, we argue that the primary objective of RtS is (2). The *experimentation axis* notes that a DT will be initialised using real-time data streams, diminishing the need for warmup time and model state adjustments.

5 METHODOLOGICAL AND TECHNICAL INSIGHTS IN DEVELOPING REAL-TIME SIMULATION (RTS)

In Figure 1, the step-wise illustration of conventional simulation (bottom-left), RtS (centre) and DT (top-right) represents the evolution of conventional models to hybrid RtS and DT models. Transitioning from simulations using only historical distributions to fully-fledged DTs may be challenging since the gamut of real-time feeds needed for the DT realisation may not be available. Also, it may be technically challenging to integrate the data feeds with DT (refer to section 2). In such cases, a RtS can effectively use the real-time values available to the modeller by substituting them, in the underlying computational model, for values derived from historical distributions. Indeed, this was the approach taken by the authors while developing a real-time model of an A&E department in AnyLogic™. The A&E RtS uses secondary data from *Symphony* (hospital patient flow system) and real-time data from *NHSquicker* (https://nhsquicker.co.uk/). The remainder of this section provides insights on developing RtS based on the authors' experience. The discussion is structured around the four dimensions of modelling objectives, data needs, implementation, and experimentation.

5.1 Insights on Modelling Objectives for RtS

Organisational decisions are often challenged by shifting or competing goals and uncertain, dynamic environments. The decision-makers' situation awareness – an up-to-date state of knowledge about the current situation - can be influenced by the provision of appropriate real-time information. This can be achieved through descriptive information about the current state of the system, or through predictive information, such as short-term forecasts of system state metrics. Prescriptive information using RtS projects the development of a situation over a short time horizon and can support operational decisions informing system recovery through model experimentation. For the development of RtS models, focusing efforts on technical challenges is essential, however design principles are also required to support the needs of decision-makers who will interface with the model for decision-support (Harper, Mustafee & Pitt, 2022). Design decisions include, for example, intuitive output presentation and visualisations, and should be considered part of the set of modelling objectives from the outset of the RtS study. This generally requires a collaborative approach with the aim of satisfying the needs and requirements of users that cannot be anticipated at the study outset, and to adapt design as users, needs, and environments evolve during the development phases (Barricelli et al., 2019).

5.2 Insights on Data Requirements for RtS

One of the four main components of conceptual modelling is the model *input*; Robinson (2008) defines the inputs as those elements that can be altered to improve the problem situation. As an RtS is a transition model, a mid-point, in the shift from its current state as a conventional OR/MS implementation to the future state of a DT, it uses both historical data and real-time data feeds as inputs. An objective of input data analysis for RtS is, thus, to undertake a technical evaluation of the stakeholder organisation's data acquisition systems (DAS) for their potential to relay data automatically. From our experience, this necessitates broadening the participation from the stakeholder organisation to include database managers and technical team leads. For RtS it is assumed that not all data can be captured or sent in real-time. For these data points, the traditional mechanisms are to be used. Thus, the inputs in a hybrid RtS model will include values extracted from both real-time data and those computed from historical distributions.

5.3 Insights on RtS Implementation

RtS models will have a limited degree of situational awareness as they include minimal real-time data feeds. Even with data received from DAS in real-time (integrated into the RtS models as variable values), the stakeholders may determine the frequency of updates since the DAS will have other business functions to fulfil. Our implementation of A&E RtS uses feeds from patient flow systems (DAS in A&E departments) and includes a backend database trigger fired at a pre-determined frequency; the trigger executes a SQL (Structure Query Language) and sends the information through a Web API. RtS will also require a parsing function to process the incoming data stream and automation that implements a throttling behaviour in terms of model execution, i.e., the RtS is updated as new data comes in; the frequency of the update also determines the degree of situational awareness. Yet another element of implementation is the definition of trigger points which would start the automated execution of experiments. The trigger points are often based on KPIs. The threshold values of the KPIs will continually have to be checked by the RtS when new data is received.

5.4 Insights on RtS Experimentation

In conventional OR/MS modelling, multiple scenarios are developed for experimentation. The scenarios enable the stakeholders to test different strategies for (possible) implementation in the medium to long term. In the case of RtS, the objective is to assist the stakeholders with short-term decision-making. In RtS, experimentation can be executed automatically when the assessment of new data against pre-determined KPIs thresholds indicates a breach. In our experience, it is important to associate specific breaches with pre-developed RtS scenarios that must be *automatically loaded* and executed. There are also several challenges associated with model initialisation. For example, before experimentation, the current simulation time will need to reflect the time associated with the last tranche of data updates; appropriate adjustments to warmup time must be made before experimentation since the current time is continually progressing; real-time values for model components like queues and servers must be injected into the model, which will override the values assumed by RtS after the model warmup.

6 CONCLUSION

The availability of increasing volumes of data presents a challenge to modellers to maximise the value that could be potentially derived from this data. The use of real-time data streams with OR/MS computational models holds the promise of increasing situational awareness and assisting with near real-time decision-making. Implementing such hybrid models requires deploying knowledge from Computer Science/Applied Computing, Information Systems/Databases and OR/M&S. In the literature, the emergence of the Digital Twins (DT) concept has meant that multiple definitions are being used. In this paper, we approach DTs from the standpoint of researchers in OR/MS. We reflect on conventional OR/MS simulation models and their meaning in the new DT landscape. We argue that the computational model must exist in an OR/MS DT to enable faster than real-time experimentation, although we agree that a parallel objective of such DTs is to enable visualisation through virtual replicas of the physical system as it transitions through real-time.

How might the community transition from the conventional OR/MS approach that relies on historical distributions to a fully-fledged OR/MS DT with real-time data sources, the latter realising the dual objective of presenting virtual replicas and also enabling situationally aware real-time experimentation? From our experience in developing RtS, we identified that the transition from conventional models to pure OR/MS DTs might be assisted through the implementation of hybrid models that are driven using historical distribution *but also* include limited real-time data. We define these models as real-time simulations (RtS). Further, we have distinguished RtS from OR/MS DTs in our conceptualisation of the four modelling dimensions: modelling objectives, data requirements, model implementation and experimentation.

RtS implementation is technically challenging as it must fuse real-time data with values generated from distributions to represent, at the start of the experimentation (and after the model warmup), the best possible approximation of the physical system at the current wallclock time. After initialisation, the RtS will rely on distributions to populate the stochastic elements in a model. As more data becomes available, an RtS could potentially include an element of virtual representation, but distributions and model state adjustments will still be necessary for experimentation.

Future work will expand on the methodological and technical insights on RtS implementation we briefly discussed in section 5 of the paper. Articulation of design principles for RtS is an area of future work. Yet another stream of research is empirical work. In a subsequent publication, we will present our RtS of an Urgent Care system in the South West of England, which is integrated with *NHSquicker* (Mustafee and Powell, 2020) and which acts as a data acquisition system.

System failures associated with data acquisition systems would result in the non-availability of real-time data, impacting an RtS. Thus, an avenue for future research is to investigate novel algorithms that provide the best data estimates during such interruptions. Towards this, researchers could investigate using Machine-Learning and AI-based approaches to generate synthetic data for use in RtS and DTs. Similarly, Parallel and Distributed Simulation (PADS) techniques, such as optimistic synchronisation (Fujimoto, 2001), could enable the rollback of computations when real-time feeds are (eventually) restored, which is yet another opportunity for future research.

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