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Front Running Simulation: A Digital Twin Framework for Real-Time Replication, Prediction, and Goal Navigation

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Abstract

Front Running Simulation (FRS) is a digital twin-enabled capability that continuously replicates the current state of physical systems, predicts probable future states, and identifies actions to navigate defined goals while minimizing the expenditure of scarce physical resources. Unlike traditional simulation, which operates offline with predefined initial conditions, FRS is continuously synchronized with reality through Digital Twin Instances (DTIs), allowing forward-looking simulations from the present state. FRS is based on three core activities—replication, prediction, and navigation—supported by data, Models of Reality (MoR), simulation, and information. Data enable replication. Simulations based on MoRs enable prediction through causal and probabilistic methods, and information enables goal-directed action selection. The integration of Digital Twin Aggregates (DTAs) and Artificial Intelligence (AI) introduces Bayesian data-driven prediction that complements physics-based simulations. This hybrid approach combines exploration of possible futures with rapid identification of probable outcomes. As the examples demonstrate, FRS shifts the focus from only adverse event avoidance to goal attainment under constraints, enabling proactive, information-driven decision-making. It provides a unifying Digital Twin FRS framework for Models of Reality, data, simulation, information, and AI to improve operational efficiency and effectiveness in complex systems.

Keywords: front-running simulation; digital twin; models of reality; information

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1. Introduction

Throughout history, humans have had a keen interest in predicting the future. At the very fringes of credibility, we have had shamans and fortune tellers who profess to foretell the future with the entrails of chickens and in the position of stars. In ancient Greece, the Oracle of Delphi was reputed to foretell the future, albeit in ambiguous utterances. Crystal balls and tarot cards became all the rage in the Middle Ages. Humans looked for any method, no matter how implausible, in order to deal with the uncertainty of the future and in hopes of predicting the future so that they could successfully deal with adverse future events that would prevent them from achieving their goals.

So why is it that humans are so interested in having a crystal ball to predict the future? The main reason is that most of human existence, and almost all its progress, is driven by goal seeking while attempting to minimize scarce physical resources. For most of human history, that goal seeking was simply survival.

These attempts at predicting the future were to augment what humans naturally do. Humans constantly attempt to realize their goals by replicating the current state of

reality, predicting the possibilities that can happen, and then taking actions to navigate them (navigate is an especially appropriate word. Unlike replicate and predict, navigate represents not only an effort but an outcome. It is defined in the Cambridge Dictionary as "to *successfully* find a way from one place to another." https://dictionary.cambridge.org/us/dictionary/english/navigate, Accessed on 4 July 2026) from the present into a future that realizes their goals. Humans do this for short-term goals, such as immediate survival, and long-term goals, such as retirement.

For example, our goal as we drive is to arrive at our destination safely, avoiding accidents. To do so, we continually engage in replication, prediction, and navigation with our goal of arriving at our destination safely. When we approach an intersection, we assess the velocity of a vehicle coming perpendicular to us and predict whether the vehicle can cause an accident threat to us in the intersection. We do this on a continuous basis. Based on our continuous predictions that the vehicle is slowing and will stop in time, we simply continue through the intersection.

However, if our predictions based on the vehicle's progression rate are that the vehicle will be unable to stop, we use information that we have about driving to navigate so as to avoid an accident. Based on our mental simulation of the probabilities of what actions will produce what outcomes, we will take such actions as slamming on our brakes to stop before the intersection or accelerating to get through the intersection before the arrival of the oncoming vehicle.

We replicate the current environment, predict what we think will happen, and, using the probabilities of success for different actions, continually navigate to our goal throughout our day. The issue that we have, given all the traffic accidents that actually happen, is that the human brain is extremely limited. This limitation is in replicating the current environment, predicting what is going to occur, and the probability of actions for successful navigation. Humans historically considered themselves fortunate to just achieve their goals. The minimization of physical resources was an unusual bonus.

With the advent of computers, we now have the opportunity to have a crystal ball to foresee the future of achieving our goals and minimizing physical resources. As described above, this requires that we engage in replication, prediction, and navigation. This is the purpose of Front Running Simulation (FRS).

Unlike the usual simulation models, which run unconnected to time in the physical world. FRS is conceptualized to perform like the driving example. FRS is performed on a continual loop replicating the current state, predicting future states, and providing data and information to navigate to goals. The cadence of its loop depends on the rate of change. For the driving examples above, FRS runs constantly. In production facilities, every fifteen (15) minutes most likely would suffice. However, the cadence is driven by need and only limited by available computing capability.

A common misunderstanding arises when a conceptual Kuhnian paradigm is evaluated using criteria more appropriate for domain-specific technical implementations or what Kuhn described as "normal puzzle solving" [1]. Front Running Simulation (FRS) is not proposed as a new optimization algorithm, control methodology, simulation engine, machine learning model, or predictive maintenance technique. Nor is it intended to replace these capabilities. Rather, such methods represent examples of technologies that may be employed within an FRS implementation.

Digital Twin-enabled FRS is instead a conceptual and architectural framework that organizes and integrates capabilities including replication, predictive simulation, probabilistic forecasting, and navigation into a coherent operational paradigm. Its purpose is to shift increasing amounts of exploration, evaluation, and decision-making from the physical

world into the digital realm, where alternative futures can be examined before actions are executed in the physical world.

In the remainder of this paper, I will discuss the capabilities and new 21st century, or, as I have contended, the Third Millennium [2] digital/virtual (this is a continued example of my use of virtual and digital as synonymous, which I will continue to do so in this paper. There actually is no true virtual space. The virtual representation is always instantiated in atom-based physical material. In humans, it is in the carbon-based matter of the brain. In digital computers, it is in the silicon-based matter of digital processor and memory components. "Digital" and "virtual" do share the characteristic that they are both intangible representations, so their interchangeability is warranted) concepts that we are bringing to bear, such as digital twins with Front Running Simulation. FRS will provide us with the data that we need to understand and replicate our environment, simulation for prediction of future events, and information to navigate to our goals. With the computing capability that we now have available or soon will, we will possess the ability to at least probabilistically understand what is occurring, especially adverse events, and prevent or mitigate their effect. This represents a quantum leap from our current capabilities.

2. The Digital Twin Model

The Digital Twin Model is the basis for Front Running Simulation. The commonly accepted Digital Twin Model is shown in Figure 1 [3]. The Digital Twin Model is used across a wide variety of disciplines and industries [4]. It consists of three components: physical objects in the physical environment, digital objects in a digital environment, and a persistent two-way connection between the physical and digital. The persistent two-way connection is the particular feature that FRS relies on. Data is sent from the physical to the digital to provide replication on a real-time basis or a periodic basis depending on the use case. Prediction via simulation is performed on the right-hand digital side, and the resulting information and data are returned to the physical environment so that constantly physically navigating to the desired goal can be accomplished.

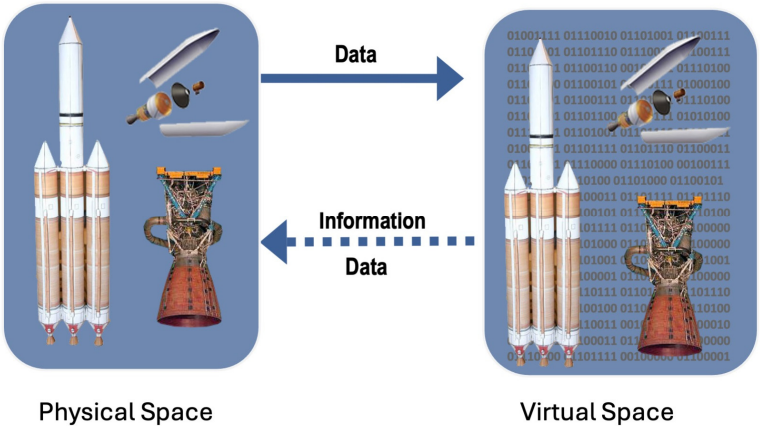


Figure 1. Digital Twin Model.

There are three types of Digital Twins [5]. Of the three types of Digital Twins, Digital Twin Prototype (DTP), Digital Twin Instance (DTI), and Digital Twin Aggregate (DTA), the DTI and the DTA are the most relevant to FRS. DTI is created when its Physical Twin Instance is manufactured. DTI remains tethered to its Physical Twin Instance during its remaining life.

Driven by use cases, the DTI contains the longitudinal data of its Physical Twin counterpart. Examples of the types of data the DTI can collect are: "the system's own identity, the location of a system and/or its components, the change in velocity and

acceleration, state changes, both discrete and continuous, from one state to another, such as off to on, not-triggered to triggered, heat gradients over time, the forces that are acting on the system, such as heat, air pressure, and gravitational forces, and the presence of sound, light, and a wide spectrum of electro-magnetic waves, the presence of other objects and their mass, shape, and relative speed and direction in relationship to our artifact" [6].

Unlike the Physical Twin Instance, its DTI remains available and useful after its Physical Twin Instance is retired from service. The DTI replicates its corresponding Physical Twin, and the DTI prediction is specific to that Physical Twin.

Within the Digital Twin Model, the Digital Twin Aggregate (DTA) represents the population-level instantiation of Digital Twin Instances (DTIs), capturing longitudinal and latitudinal data across many similar assets, processes, or systems over time. Unlike a single DTI, which reflects the state and behavior of an individual entity, the DTA embodies the accumulated experiential history of the entire class, including operational conditions, interventions, and outcomes.

In the context of Front Running Simulation (FRS), the DTA serves as a probabilistic and empirical type that enables Bayesian-informed prediction by leveraging correlations and patterns derived from this population history. This allows FRS not only to simulate causally modeled futures within a specific DTI, but also to augment those simulations with Bayesian statistically grounded likelihoods of outcomes and candidate actions observed across the aggregate. As the scale, diversity, and temporal depth of the DTA increase, the fidelity of these probability estimates improves. This thereby enhances FRS's ability to recommend actions that achieve task goals while minimizing wasted physical resources under time-constrained or information-limited conditions.

Figure 2 represents my current Digital Twin Model, which is a throwback to its original introduction in 2002 [7]. The physical objects in this environment are replicated in the large virtual space on the right-hand side.

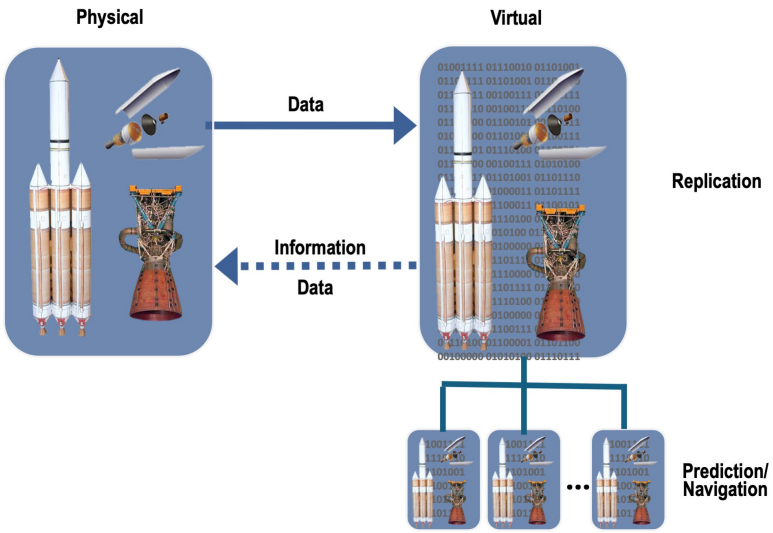


Figure 2. Digital Twin Model 2026.

The forward prediction and navigation are performed in the lower modules that inherit the same initial conditions, which are the replication of their Physical Twin Instance. However, the different simulations will have different assumptions regarding how future events will affect them and will predict different outcomes. Different actions will run against these different scenarios to find the action that will best obtain the goal that is being sought.

While there is only one replication space shown in the model, its state at a set cadence can be captured and saved for future use, analysis, and traceability. That is, unlike its physical counterpart, where once the state changes, the old state, as are all states in the physical world, is lost.

3. Introduction of Front Running Simulation

While FRS is a concept of general applicability, I introduced it as being particularly applicable to production or manufacturing facilities. These facilities are intended to be highly deterministic to be both efficient and effective. Their intent is to plan production to produce specified products using the minimum amount of resources. There is even a common term for this—lean manufacturing. Any deviation from the lean manufacturing plan, such as an equipment malfunction, is considered an adverse event to be avoided or mitigated as quickly as possible. Because of a lack of predictive capability, these adverse events are mostly dealt with on an inefficient reactive basis after the adverse event occurs.

My first description of Front Running Simulation was in a Whitepaper series that I did in 2017. This paper was called "Driving Digital Continuity in Manufacturing" [8]. I continued to refer to FRS in my work over the ensuing years, most recently here [9].

It is instructive to reproduce the original FRS description as a starting point here.

"Instead of simply a factory replication showing what is currently occurring on the factory floor, we would run simulations of the next few seconds, few minutes, and/or few hours. We would utilize the current state of the factory data at any specific point in time and simulate from that point on a continuous basis.

This means that the simulation would run in front of the actual factory, providing a window on what would happen to the factory in the immediate future. Using this front-running simulation, we could provide OverWatch of the factory and step in to adjust or even shut down intelligent equipment if the simulations indicated a potential problem developing.

This would not only allow us to see what actually is occurring on the factory floor at all points in time but also predict problems in the future based on the current and actual states of the factory floor.

Front running would be especially useful during the manufacturing ramp-up of a new product. Production could be simulated forward from each step of the Bill of Process (BoP) utilizing actual information from the steps already performed. When the front-running simulation showed that the future processes were not going to produce the product as desired, the BoP could be adjusted right then and there. This would reduce the number of bad builds and compress the time to move through ramp-up to full quality production. This is just one example of digital continuity between Product Engineering, Industrial Engineering and Manufacturing Operations.

This integration of virtual and physical activities requires complete fidelity and timelessness of digital continuity. Having machines communicate with each other and having humans work alongside robots, i.e., cobotics, requires this kind of digital continuity. IIoT on the factory floor cannot safely exist without this capability."

The main characteristics of the original view of FRS are:

- Goal-seeking replication, prediction, and navigation;
- Continuous Overwatch of factory operations, matching planned operations against predicted operations;
- Continuous replication of the current physical state as the simulation starting condition;
- Continual simulations of predicted future states including adverse events and deviations;
- Continual simulation of predicted future operational outcomes of actions to navigate to goals;

- Temporal horizon and update cadence determined by operational dynamics and use cases.

This was a reasonable first perspective of a new paradigm. Up until then, simulation had been viewed as a planning and exploration tool, untethered from actual reality. Computer simulations were established with user-defined initial conditions and executed to produce outputs based on programmed assumptions. Their usual use was as a planning tool for development activities. Once the simulated entity went into operation, the simulation was put away.

This was primarily because the computing capability to run simulations in real time, let alone faster than real time, simply did not exist. However, by 2017 when I introduced FRS, it could be foreseen by plotting Moore's Law that the computing capability FRS would require was on the near horizon.

3.1. Front Running Simulation in Overwatch Mode

Figure 3 is the current Front Running Simulation Model, as I have been historically presenting it. It is effectively the standard Digital Twin Model presented vertically and advanced over time. This is the FRS Model in what I called Overwatch mode, running on a continual loop whose cadence is dictated by the change in its environment. While it is engaged in monitoring activities as is common in factories, Overwatch is intended to go beyond that. Overwatch is intended to predict future factory states and take action to bring the factory back into steady-state operation to meet its planned goals if deviations or disruptions are predicted.

Consistent with the Digital Twin Model, this figure is divided into two environments. The bottom part is the environment of our physical world with its physical objects. This environment is completely constrained by the laws of our physical universe. Time moves in one direction and has a cadence over which we have no control. The only way to move into the future is to wait for the passage of time. Only one possibility will happen. All other possibilities are collapsed into one actuality.

The upper part of the figure is the virtual environment with Digital Twin Instances (DTIs) that correspond to their physical object counterparts. In this virtual environment, we are constrained only by the Models of Reality that we choose to institute in this environment. We must follow the rules of the physical universe in terms of cause and effect. However, we can unconstrain time, meaning that we can control the speed of time, which allows for prediction.

However, the environment at every time x is dictated by the reality we have captured from the physical world in the form of IoT sensing and the resulting data. To predict the future, we need to replicate and synchronize the physical reality state in the virtual environment. We do that in the same way humans do by sensing the physical world and recreating it in a virtual world.

In FRS at every time x + y, what we want to do is to predict the future states of the physical environment and its DTIs. This is why replication is so important, because if we do not have the same state of reality as it exists in the physical environment, we will not be able to accurately predict what will happen in the future. At every time x, we want to predict what will happen based on the state that we start with and the facts and assumptions that we make about how reality behaves.

Because we may not be perfectly accurate in our understanding of reality, the result will be probabilities of the future states of different things that may occur. While we need to be aware of the potential for deviations, if we have planned our production processes properly and executed according to that plan, we will see a prediction of what we had planned matches what then occurs.

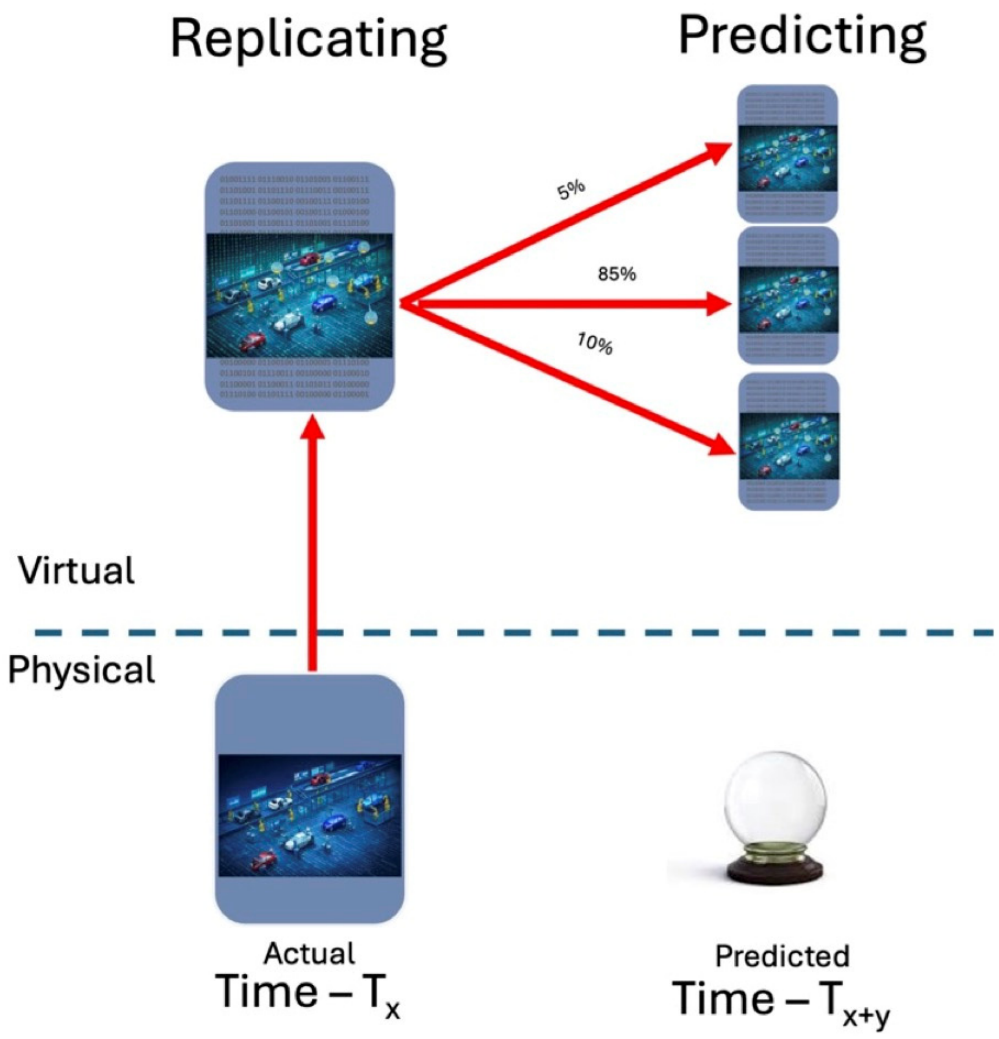


Figure 3. Front Running Simulation (FRS)—replicating and predicting.

Obviously, one thing that FRS must continue to do in Overwatch mode is to look at its predictions and see how well they match what then occurs in reality. This will allow us to modify the facts and assumptions that we have been making or add additional data collection so that our projections will become increasingly more accurate in modeling the actual physical world.

3.2. Front Running Simulation and Goal Deviations

There are a couple of points to make with regard to deviations from our plans that have the potential to prevent us from meeting our production goals. While certainly we would like to predict and prevent these deviations, especially if they are partial or total equipment failures, our primary concern is meeting our goals while using the minimum necessary resources.

If we cannot predict that a deviation is going to occur and one does occur, then our task is to take actions so this does not prevent us from meeting our production goals. In many cases, the cost of preventing this deviation may be far more expensive than letting it occur and taking other actions that prevent this problem from affecting the planned attainment of our goals. We need to remember that our primary focus is not on preventing adverse events or deviations, but on obtaining our goals with a minimization of scarce physical resources.

Figure 4 represents the FRS model in predicting deviations or adverse conditions. Where we have an issue is when we start to see adverse events, actual or predicted, occur

that are not what we have planned for in the production facility. We need to see the probabilities of future events that will occur from that deviation to be detrimental to us in obtaining our goal. At that point in time, we need to look for information actions that have probabilities of getting us back to achieving our goals.

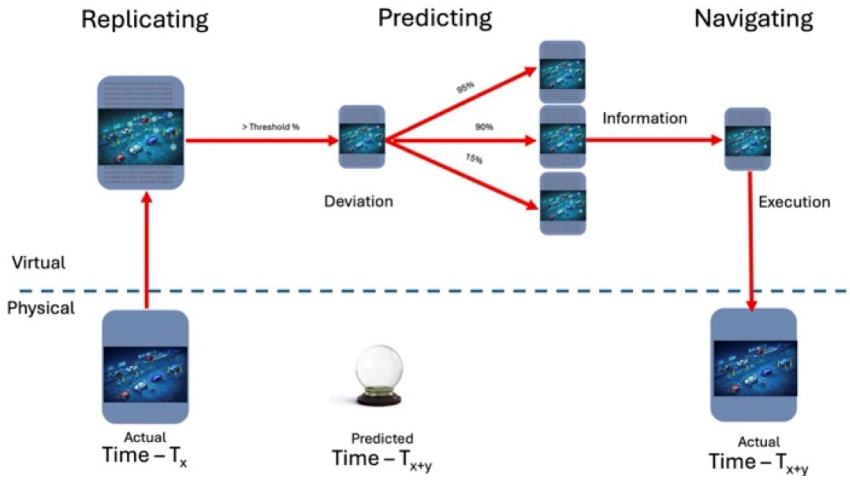


Figure 4. Front Running Simulation (FRS)—replicating, predicting, and navigating.

Most importantly, we will examine which actions maximize the probability of obtaining our goals and, secondarily, attempt to minimize the amount of scarce resources in obtaining those goals. We create or use information to select the action that we determine matches our risk profile. We will then execute those actions so as to appropriately navigate to avoid the deviations, mitigate them, or even negate their effect and thereby obtain our goals.

We do this first in the virtual space where there is almost zero cost if we are mistaken that we have found a solution. When we are confident in our solution in virtual space, we then move to physical space. This requires us to execute the solution successfully, so that our navigation will result in the physical world reproducing the virtual world result.

This is, in essence, what FRS is intended to do: replicate the physical world, predict future events, look for deviations that will prevent us from reaching our goals, and then select actions that will allow us to navigate back to successfully obtaining our goals.

There are two critical elements here. It is one thing to predict the future our crystal ball shows us. However, it is another thing to have the capability to physically execute a solution. An accurate prediction of goal-obtaining actions without the ability to perform those actions successfully to obtain the physical results is useless.

The primary purpose of FRS is to achieve its goals. FRS replicates, predicts future states, and then provides action-oriented information to navigate to those goals. The secondary purpose is to minimize the use of scarce physical resources. Given its primary goal, FRS may recommend information that uses more resources than the minimum if the probability of obtaining its goals with the minimum resources does not meet the risk threshold for success. While avoiding adverse events, such as machine failures, would appear to be highly desirable, FRS will recommend that only if the action for that avoidance is more resource-effective than allowing the adverse event to occur and mitigating it with some other action.

4. FRS Operational Substrate

Front Running Simulation requires an operational substrate to support replication, prediction, and navigation. Figure 5 is a visual representation of their functions. The operational substrate is composed of Models of Reality (MoR), data, simulation models, and

information. These elements do not merely precede FRS as a prerequisite. These elements form the active medium through which replicated reality is continually projected forward, allowing operational goals to be pursued while minimizing the expenditure of scarce physical resources. MoRs and data guide and select, whereas simulation and information guide and interpret. To understand how FRS replicates, predicts, and navigates, we need to specifically understand the function that these operational substrate elements perform.

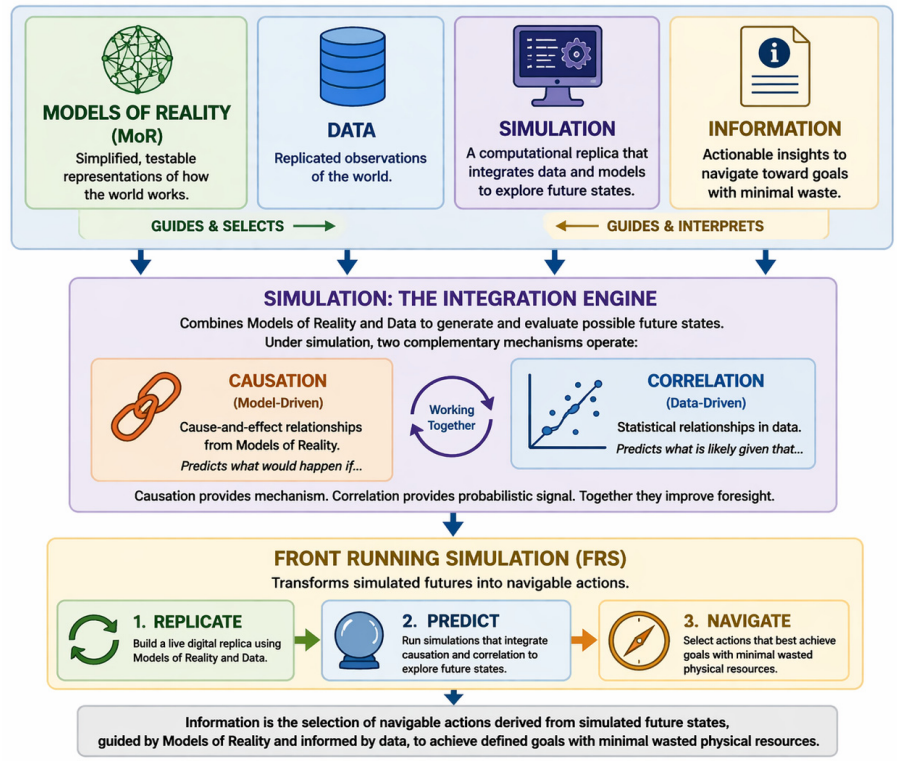


Figure 5. Front Running Simulation (FRS) substrate.

4.1. Models of Reality

Models of Reality are structured representations of how the world operates [10]. Consequently, MoRs are integral to all three elements of replication, prediction, and navigation. We rely on MoRs to produce a regularity that we can rely on [11]. We rely on reality to produce the same results from the same causes. As humans, we develop MoRs naturally. The most basic MoRs are biological and ontological. We develop many of these MoRs soon after birth [12–14]. We develop a sense of space and spatial orientation, object permanence, causality, motion continuance, and a direction of time.

We expand these MoRs by interacting with the physical world. Almost every child learns by experience that something hot will cause pain, no matter how many times they may have been told that before they touched a hot object. Children hopefully learn from both the permanence of objects and their parents not to walk into traffic.

We acquire MoRs that are more formal through education that exists as evidence-based scientific abstractions. We acquire formulae and models in science and engineering that move from general abstractions to precise calculations. We also find MoRs in statistics and correlations where we may not fully understand the cause and effect. However, we understand that this does provide us with probabilistic regularity.

MoRs are the sum total of human intelligence. While this is often thought of as an act of causal reasoning (the philosopher David Hume pointed out that causality is not something we directly observe like color or shape. Causality is something we infer from experience that the future will resemble the past and cannot be logically proven [15].

Hume, D., *Enquiry Concerning Human Understanding*. 1748, London), it is far more than that. MoRs include pattern recognition, heuristic expectations, probabilistic anticipation, contextual interpretation, and action-oriented understanding. There is not much, if any, causal reasoning occurring in the traffic example.

These MoRs provide the structure and theory for why we can predict the future with at a minimum a directional predictive capability and at a maximum with almost absolute certainty. This makes FRS feasible.

4.2. Data

Data is the substrate element that enables replication. Data are facts about the state of reality [16]. To replicate the physical aspects that pertain to our use cases of physical objects and their environment, we need to collect, process, and organize data in the digital realm.

Replication determines the current understanding of the state of the physical world. This is the starting point from which all future actions will progress. Without a full and complete understanding of where we are, we will not be able to predict what the future states will be, nor will we be able to navigate to our goals.

Replication usually involves more than capturing data at a single point in time. Replication implies duplicating something in a way that is understandable and not merely observable. A single data point capture represents a fact about reality at a moment, but in isolation, it is often insufficient to determine meaning or state.

It is only when data are captured longitudinally—across time—that they can be evaluated against our Models of Reality. Through temporal continuity, patterns emerge that allow us to determine whether the observed behavior is consistent with the known structure, physics, or process dynamics. In this sense, replication necessarily involves model-constrained sense-making [17], in which data acquire meaning by fitting within an existing representation of how reality actually behaves.

Until fairly recently, the collection of data was considered a human-mediated process. Humans observed, interpreted, and recorded the data of the physical world. That severely limited the quantity and quality of the data available. Humans lived in a small bubble of potential data that was readily accessible to them. The limited data availability was not a constraint because human brain computing power was also limited.

The Third Millennium brought computer-based capture of data, commonly referred to as IoT, which enabled massive amounts of objective data to be collected, processed, and organized without human mediation. While this expanded the bubble of potentially accessible data by magnitudes [18], this would be useless to humans without concomitant access to computing capability to reduce that data to be useful to humans. Digital Twin FRS provides this capability.

The problem is that the universe presents us with an infinite number of facts about reality. However, data are highly granular, so we only need to collect the data needed for our use cases. We do not need to replicate the entirety of a physical object in data, only the attributes of the object state we require, such as only outer mold lines (OMLs) and not anything internal. We need to use our MoRs to determine what facts we need to determine what is relevant for the predictions we need to make. Selecting the data that is relevant to our needs is often an iterative process.

The characteristics that facts need to have for FRS are that the data are [9]:

- Selected for purpose;
- Contextually relevant;
- Objective;
- Complete;
- Accurate;

- Interoperable.

4.3. Simulation

Simulation is the substrate element that enables prediction. There is a common perspective that it was the development of computers that enabled simulation. While this is true of digital simulation, the simulation itself is as old as human existence, as I have described of a prehistoric man producing simulations of hunting for food with his tribe [19]. Humans of today constantly perform complex simulations similar to FRS, as my driving example in the introduction demonstrates. Simulation is defined as one process that imitates another process [20]. A core aspect of processes is that, by their very nature, processes are time-evolved. By this description, simulation is a foundational aspect of human thinking.

The invention of computers in the last half of the 20th century was a watershed event for simulation. This marked the first time in history that the computing behind time-evolving simulation was performed by something other than the human brain. Because of the limited computing capabilities of early computers, these simulations were relatively simple iterative mathematical calculations, with output being reams of paper with numbers that needed to be deciphered and visualized by humans [21].

Fast forward to today. Computing power has increased by approximately 100 billion times since the mid-1970s (the operations of the first supercomputer, the Illiac IV, reported to me in the late 1970s. Its computing speed was theoretically 25 megaFLOPS. The current fastest supercomputer, the El Capitan, has a speed of 2.8 exaFLOPS). This is a discontinuity scale shift. Computer-based simulations have become highly complex, and their output can be visually photorealistic videos. The modeling of physical objects with their environments closely mirrors the behavior of their real-world counterparts under comparable forces [22,23]. This enables the transition from physical world trial-and-error with substantial waste to goal-directed navigation with minimized wasted scarce physical resources in the virtual world.

Simulations are about modeling and predicting possible future outcomes. There are two approaches that simulation uses: causation and correlation. FRS is intended to be a fusion of these two methods: physics and big data [24]. For causation, there are well-defined and understood inputs. We apply functions to these inputs to produce well-defined outputs that have an acceptable margin of error. We have almost complete confidence that in the physical world, these inputs will always result in these outputs.

For correlations, there are no explicitly defined inputs or governing functions. Instead, we observe multiple variables over time and identify statistical probability distributions [25]. Outputs are not produced by applying known functions, but by extrapolating from historically observed relationships. The behavior is probabilistic rather than deterministic, with confidence expressed as likelihoods rather than fixed margins of error. The strength of the correlations will determine whether we can rely on them for predictions.

The issue with using correlations in FRSs is that these simulations can have multiple variables. Simply using correlations assumes that they are independent, which they may not be. This will produce distorted outcome distributions. The use of Monte Carlo techniques can help in addressing this issue [26,27]. Monte Carlo simulations can incorporate correlated input variables by sampling from joint distributions that preserve the observed statistical relationships.

Because of the DTA, the probabilities are Bayesian in nature. In traditional Monte Carlo methods, probability distributions are assumed, estimated from limited historical data, and are often static over time. FRS Monte Carlo method, with its DTA use, is empirically grounded and continuously updated. Under conditions of relevance, consistency, and

proper modeling, the larger the population and the more experience over time of DTIs collected in the DTA, the more accurate the Bayesian probabilities become. This ensures that the simulated scenarios remain consistent with the empirically observed system behavior, which is critical for FRS.

4.4. Artificial Intelligence-Based Evolution of Front Running Simulation

Since the introduction of FRS, there has been a major technological advancement that enables the evolution of FRS into a much more powerful capability. This technological advancement is Artificial Intelligence (AI). AI has added a new dimension of predictive capability to FRS to augment simulations based on causal and correlative predictive simulations.

Technically, AI is not a simulation because it does not imitate one process by another. AI enables behavioral prediction based on big data and Bayesian inferences. What FRS has now evolved to is an additional capability of longitudinal behavioral accumulated data by the DTA to not simulate but infer probable future outcomes. This does not replace simulation but augments it. DTA AI predictions, which are also Bayesian-based [28], may recommend actions whose causal/correlated mechanisms are not fully understood but whose historical correlations with successful outcomes are statistically supported.

It is risky to rely on this black-box prediction versus white-box simulation. However, in a hybrid form of using both these methods, DTA AI prediction can be triangulated with the simulation. In the best case, this can be for reinforcement of the simulation result, and, in the worst case, to cause further questioning of the simulation results.

Because DTA AI is effectively instantaneous, it may provide necessary action that a simulation may be too slow in providing. While that is risky in a situation where an action is immediately required, DTA AI may be the only way to provide one. This means that the DTA becomes much more powerful. Effectively, DTA AI becomes a prior distribution generator. Simulation explores possible futures, while AI, based on DTA, ranks probable futures based on historical data.

It is noteworthy that DTA-based AI predictions should not replace simulations. A hybrid fusion of simulation and DTA AI prediction greatly enhances FRS's capabilities. FRS becomes the unifying architecture between classical engineering simulations, modern AI systems, and Digital Twin theory. FRS now consists of both how physical systems should perform either causally or probabilistically and how physical systems have actually performed over time. This is a huge leap in strengthening FRS as a predictive capability.

4.5. Information

Information (this section follows my proposed formulation of Information as I = <G, $R_t(D)$, A, P(G | A, $R_t(D)$, MoR), C>, where G is the goal, $R_t(D)$ is the replicated state of reality based on data at current time t, D, A is the action, P(G | A, $R_t(D)$, MoR) is the probability of obtaining the goal, given the action taken based on the current replicated state of reality and the Models of Reality used, and C is the wasted physical resource costs that I will replace) is the substrate element that enables us to navigate to achieve our goals. There is almost no consensus, even among academics, as to what information is [29]. I have long proposed that the relevant perspective is to focus on what information does [30]. With that focus, I have contended that information is a potential replacement for the scarce physical resources of time, energy, and material.

Information is the selection of navigable actions to achieve defined goals with minimal wasted physical resources. These actions are derived from the relevant data representing the current replicated state, guided by Models of Reality and predicted through simulation. Information enables us to determine and perform goal-oriented tasks while minimizing the expenditure of scarce physical resources needed to perform these tasks successfully. The

physical resources we have at our disposal are time, both labor hours and elapsed time, energy, and materials.

Figure 6 displays bars representing the total cost expenditure for performing a hypothetical goal-oriented task under different conditions. The left side represents the performance of the task using trial and error. We can divide that task into two categories of resource usage: the optimum minimum expenditure of scarce physical resources and the remaining scarce physical resource usage that we actually expend in performing the task. This latter category is considered to be wasted resources.

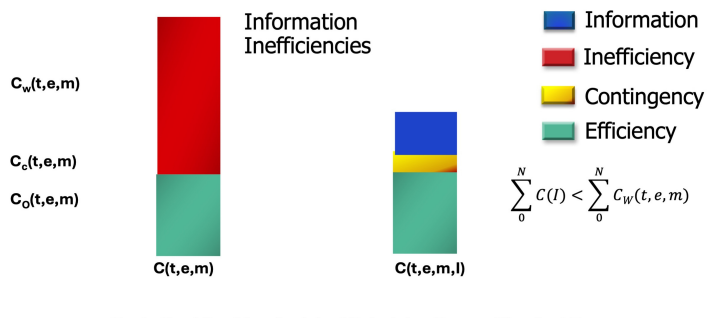


Figure 6. Information as task wasted time, energy, material substitute.

The first category of physical resource usage, which is the lower part of the bar, is the minimum expenditure of physical resources that, if we were omniscient and omnipotent, we would need to perform the physical task. This category is the minimum resources we would utilize to successfully complete the task if we knew the actions that we needed to take and that we could execute those actions perfectly. This category is always subject to constraints of what we will do (moral) and what we can do (physical and legal).

Because we are neither omniscient nor omnipotent, the upper part of the bar is the remainder of the physical resources that we actually use to perform the task. By definition, these are wasted physical resources. Because we are not omnipotent, we may know what we need to do but simply do not have the technical capability to execute.

We are also not omniscient. So more commonly, we do not know what to do. We historically have used trial-and-error to find the actions that work, in which every failed attempt wastes physical resources. This is called the Edisonian method because Edison made 10,000 attempts to discover the correct elements required for the light bulb [31]. We have often determined the information that produced successful actions, only to not capture it or to only keep it as tacit information (this is more commonly called tacit knowledge. As I have described elsewhere, knowledge is a repository in which information and data reside. Knowledge is a metonymic substitution for data and potential information that reside in a knowledge repository) that resided in one individual and often disappeared when the individual died. Tacit information still results in physical resource waste due to its ill-defined, obscure, and intuitive nature [32].

To quantify and consolidate these different types of physical resources, we must employ a cost or payoff function [33]. Here we are using a financial cost function that transforms the physical resources into monetary costs. The entire cost of the task is C(t,e,m). The cost of the optimum usage is Co(t,e,m). The cost of the remaining or wasted resources is Cw(t,e,m).

The right side of Figure 6 shows the role of information. The minimum expenditure of physical resources to perform the task efficiently and effectively does not change. However, information can substitute for or replace the wasted resources, as shown by the upper part of the bar. We said above that if we "knew" the actions we needed to take or not take, that

is what we would do. The use of information is how we know what actions to take and not to take.

However, we are still neither omniscient nor omnipotent. So we most likely need to build in a contingency buffer. Contingency is waste that we accept. The information about the actions that will result in the minimum of physical resource usage may have a lower probability of success than actions that result in slightly higher expenditures. Therefore, we may select the latter actions, which have a higher probability of success. This results in a contingency expenditure of physical resources, represented by the middle bar on the right. The cost of the contingency usage is denoted by Cc(t,e,m).

The issue we have with this information is how to price it. We do not have units of information as we have for physical resources. Despite having no unit of measurement, information has a cost. While we cannot measure these costs in units, we can quantify the costs of hardware, software, and labor to develop information.

The condition under which this substitution of wasted physical resources by information holds true is indicated by the formula $C(I) < \sum Cw(t,e,m)$, where Cw is the cost of the wasted resources in the upper left bar. This formula represents that the replacement of information for wasted resources is beneficial only if the cost of information is less than the cost of wasted resources for all the times the task is performed.

Figure 6 shows information replacing all the wasted resources. This is the ideal. This probably does not happen except in fully automated tasks. However, because the potential for wasting resources is infinite (the data that a perpetual motion machine is not possible still has not stopped the waste of resources trying to invent one. The data that the Earth revolved around the sun and not vice versa was available for hundreds of years. That did not stop the waste of an uncountable number of hours calculating the orbits according to the Ptolemaic theory. The action of the information associated with both these examples, in order to replace wasted resources, is simply "stop". If a task is impossible to accomplish the entire bar for the task is red, i.e., all physical resources are wasted resources), information can and has substituted for task wasted resources.

It is also important to understand that information is a non-rival good [34]. Unlike physical resources, information is a resource that can be used over and over again without diminishing it. It is an asset and not an expense like the wasted physical resources this information replaces. Once created, the cost of information used in a task is the fixed cost of the computing/communication infrastructure. However, for this to be the case, this information needs to be captured, organized, and reused as potential information in a knowledge repository [9].

The idea of using information as a replacement for wasted resources is what enables FRS to navigate in obtaining goals. FRS would be useful if all it did was replicate and predict, allowing humans to attempt to determine what actions to employ. With information created ad hoc or retrieved from a [9] repository, FRS can assess the deviation gap between the current predicted state and the goal to more exhaustively, efficiently, and effectively create and search the solution space to recommend actions to obtain the task goals or send commands to implement actions. The examples below illustrate this.

5. HITL and HOOTL

I have not previously dealt with the topic of Humans-In-The-Loop (HITL) or Human-Out-Of-The-Loop (HOOTL) with respect to Digital Twins. The Digital Twin is equally applicable to both cases. The requirement for a Digital Twin is that data and information come from the digital realm to the physical realm. That data and information may go to a human, so that the human can assess and make decisions as to the actions that need to be taken.

With regard to FRS, HOOTL presents prediction issues. Replication will give us data about what humans did, but we can have accuracy issues with predictions about what humans will do. If we have sufficient DTA history, we may have reasonably good Bayesian-based predictions based on past human behaviors. (This also assumes that humans share the same entity goals. I addressed the issue of humans creating "negative information" to intentionally waste resources at a presentation, The Future of Digital Twinning: Technological Challenges and Implications for National Security, to the U.S. Office of the Director of National Security (ODNI) (https://youtu.be/s2pOoy7X_WY?si=CMtxPtsuojgmq93z), Accessed on 4 July 2026).

Similarly, information in the form of commands may be sent to the Physical Twin Instance itself in order to command the action. It may also be that for autonomous objects that data and information relevant to the specific situation being encountered by the autonomous object will be sent to it, and the autonomous object will make its own determination as to actions that it will take. I have pointed out that Digital Twins can be great value to humans in the loop by helping guard against biases such as confirmation and confidence bias [35].

I have long proposed the idea of what I called cued availability [30], which foreshadowed the ability of AI. Humans not in the loop will usually be required when the time frames for responses exceed the ability of humans, such as the operation of nuclear reactors. However, to understand and respond, the risk of a highly inappropriate response that a human would never perform increases dramatically. FRS will need guardrails to prevent this.

6. Front Running Simulation Examples

Here are two hypothetical but representative examples of FRS in deterministic production facilities. The first is a discrete production automotive factory. The second is a continuous production petroleum refinery. Both have productions that involve a deviation or adverse event during the shift.

6.1. Automotive Discrete Manufacturing Welding Line

An automotive body and white welding line is running a high-volume shift build. It has clearly defined task goals for the day. It has a manufacturing process that details each production process through the product build.

The manufacturing process is designed and validated to meet the task goals. The task goals are:

- Achieve 1040 units by end of shift;
- Maintain acceptable weld quality thresholds;
- Minimize overtime, energy spikes, and downstream rework;
- Avoid unnecessary line stoppages that waste scarce physical resources.

The plant uses FRS that runs every fifteen minutes throughout the day, predicting operational results through the remainder of the shift. FRS uses replicated, real-time state data from all its stations.

At 8:10 am, there is an initial process deviation or glitch. A robotic welding cell begins taking 3.8 s longer per cycle due to the following: an intermittent torch positioning lag, a slight access vibration, and extra confirmation passes on weld seams.

However, the quality remains acceptable, so the line does not stop. FRS notes this deviation and incorporates it into its simulation. Because the deviation is small, the manufacturing process remains within limits for the next few hours in the simulation. However, FRS starts predicting a higher probability of deviation.

By the 10:00 am FRS run, FRS predicts with almost 100% probability that by 1:30 pm, the upstream buffers begin filling. The conveyor dwell time starts to increase. The down-

stream inspection stations are idling intermittently. By late afternoon, the predicted queue surge creates a localized bottleneck.

When this prediction happens, it triggers FRS to generate several information candidate action paths that are evaluated against the probability of not meeting daily production goals by causing additional energy use, labor impact, and the risk of future disruptions. FRS creates four different options.

The first option is to have an immediate robot shutdown to replace the torch assembly and eliminate the delay that is occurring. The second option is to speed up the conveyor belt by 4%. The third option is to micro-rebalance the workload by shifting one minor weld operation to an adjacent robot with available slack, slightly extend the lunch micro-maintenance window by three (3) minutes to recalibrate the axes, and adjusting the buffer logic so upstream robots insert controlled spacing, rather than continuous flow. The fourth option is to accept the backload and add an overtime inspection crew.

FRS evaluates these options. FRS determines that the first option, immediate robot shutdown, does prevent the later bottleneck but will cause a 12 min hard stop. This results in lost production and an energy surge restart.

The second option is to increase the speed of the conveyors by 4%. This offsets the delay but raises the weld heat variance in energy consumption. This then increases the probability of downstream rework.

The third option of micro-rebalancing the workload is that the bottleneck probability drops from 62% down to 8%. The daily build target is still achievable. There is no full stop required.

The fourth option is to allow the bottleneck and remediate later. The goal is still obtainable, but it has the highest labor and energy cost expenditures.

With a human in the loop (HITL), FRS recommends the third option: micro rebalance the workload. The plant manager looks at the four options and concurs with the recommendation for option three.

The result of the workday actually playing out is that by accepting option three, the morning production continued uninterrupted, the lunch micro maintenance recalibrates the robot, and line pacing adjustments prevent queue buildup.

So, at the end of the shift, the daily target is met. There is no overtime required, and the energy usage remains within tolerance. The welding glitch was not avoided, but FRS achieved the goal state with nearly minimum waste.

6.2. Continous Production Oil Refinery Facility

This example is of a crude oil refinery that consists of distillation columns, heat exchangers, compressors, and catalytic cracking units. The refinery has a well-defined continual manufacturing process that has the following task goals:

- Maintain throughput at 92% of maximum capacity;
- Maximize yield of high-value middle distillates;
- Stay within safety and emissions constraints;
- Minimize energy consumption and flaring.

The plant uses FRS that runs every 15 min throughout the day, predicting operational results through the remainder of the shift. FRS uses replicated, real-time state data from all its refinery stations.

At 9:12 am, there is an initial deviation. A subtle disturbance occurs where the feed stock density drifts slightly heavier than forecast. A heat exchanger shows increased fouling resistance, and the column bottom temperature begins inching upward. However, the operators see only a minor deviation. There is nothing that requires immediate intervention. The process remains within safe limits.

However, in its 10:15 run, FRS starts to show a real risk probability for later in the day. In that simulation prediction, the reboiler duty slowly increases to maintain separation, and energy consumption climbs. At around a predicted 2:40 pm, the overhead pressure margins shrink. If this is left unchecked, the operators will need to reduce the throughput or flare gases. Based on this 10:15 FRS run, information candidate action options are developed and evaluated.

The first option is immediate aggressive stabilization. This consists of aggressive increased cooling, sharply adjusting the reflux, and temporarily reducing the feed rate. This option eliminates the deviation quickly but spikes energy consumption and reduces valuable distillate yield.

The second option is to slow throughput reduction. It proposes lowering the feed rate by 5% and maintaining conservative operating margins. This option guarantees safety but misses daily production goals and reduces revenue yield.

The third option is preemptive maintenance shutdown. It consists of bringing the unit down for exchange cleaning immediately. This option does eliminate drift entirely, but it causes massive lost throughput, startup fuel burn, and catalyst stress.

Option four proposes a slightly increased side-draw flow to redistribute the heat load, adjusting the reflux ratio incrementally rather than aggressively, delaying the heat exchanger cleaning until the scheduled maintenance window, and accepting a small temporary rise in bottom temperature. This proposal results in energy consumption remaining within the target envelope, the bottleneck probability dropping from 54% to 11%, and the desired product yields remaining within tolerance.

The refinery operators choose the fourth option, which means that the plant continues operating with a slight deviation. The adjustments redistribute energy rather than eliminating the adverse event or deviation. No flaring occurs later in the day, and the production targets are met with minimal energy use. The deviation was not eliminated. It was navigated to a successful conclusion that met the refinery's operational task goals.

These examples demonstrate that FRS is not necessarily a deviation or adverse event avoidance. It is goal-directed navigation, grounded in data-driven replicated reality that is predicted by simulation. While avoiding predicted anomalies is to be desired wherever possible, the overarching responsibility of FRS is to meet the task goals with information.

7. Scientific and Technical Challenges and Open Research Questions

As with all paradigm shifts, DT FRS creates a new set of scientific and technical challenges that will need addressing. It also opens a wealth of new research opportunities. While this is hardly an exhaustive list, the ones addressed here are:

- Computational Scalability;
- State Representation and Abstraction;
- Model Interoperability;
- Causal and Correlation Prediction;
- Risk quantification and Validation.

7.1. Computational Capability Scalability

As with digital twins in general, the advancement of Front Running Simulation Digital Twins is dependent on computational capabilities (this has always been the case. It took about a decade and a half from my introduction of the Digital Twin Model concept in 2002 to see serious discussion by both industry and academics. The computational capability simply did not exist to realize Digital Twins before then. Computational capability also includes communication technology). That computational capability will be needed to

collect and process the massive amount of data needed on a continuous basis to do accurate replication of the physical world.

Computational capability will also be needed to execute the large number of predictive simulations necessary to predict probable future states of the system and then predict the effect of informational actions to meet goals. These computational requirements increase substantially as the cadence of replication and predictive time frames decrease and the scope of the solution space increases. As AI starts to play more of a role in prediction, its computational requirements will add to this.

Where this computational capability takes place will also play a role here. This required computational capability will be distributed among local computing, edge computing, fog computing, and cloud computing. The determination of where this computing should take place will be dependent on the use cases and will be a research opportunity as to how to decide this. Research is also needed on estimates of the availability of future computing capability to meet different FRS capabilities in model fidelity for replication, prediction, and goal navigation.

Related to computational scalability is the issue of model fidelity as it pertains to computational costs and methods to reduce model computational size, eliminating features not needed for use cases while retaining needed model fidelity. For example, we may not need computationally intensive photorealistic renderings. As systems become more complex, the number of potential navigational actions may become extremely, if not infinitely, large. Efficiently identifying high-value interventions without exhaustively evaluating every option remains an important research area.

7.2. State Representation and Abstraction

I have long contended that the universe constantly presents us with an infinite amount of potential data. Determining what data are needed to present an accurate state of an object in its environment is critical for both replication and prediction. FRS performance depends on the quality of its replicated state. Missing, delayed, biased, noisy, or contradictory data can significantly degrade prediction quality and navigation effectiveness.

Additionally, the data needs to be interoperable across different digital twins in order to build up to a system and even a system-of-systems perspective. There are efforts such as FAIR principles (Findable, Acceptable, Interoperative, and Useable) [36] that try to address this problem, but data selection and data quality still remain a fundamental research problem. The issues and characteristics are extensive. If of interest, I will point to my chapter on the topic of digital twins and data [9].

7.3. Interoperability Across Heterogeneous Systems

As the examples above showed, there are multiple systems that would be involved in FRS. Ideally, we would like to have digital twins from different sources make up those systems and not require that they be monolithically developed. As I have pointed out elsewhere [19], this is a characteristic of a synchronous Digital Twin Metaverse. Digital twins here will have architectural heterogeneity, meaning different data formats, granularity, units of measurement, etc.; this is going to require interoperability between these individual digital twins.

A common solution for interoperability is to produce standards and ontologies. This works in the physical world, but exhaustive standards may not be possible in the digital world. This is because of the much finer granularity of data and information than atoms and molecules. As a result, to address this in the digital world, we have a multitude of standards, which means that we really do not have "a" standard.

These other mechanisms I have identified are platform include defining ad hoc programming conventions, harmonization of programming conventions among software providers, and a platform's own middleware. A promising solution that I have proposed may be to deploy agentic AI. Agentic AIs may be able to explore the solution spaces between different digital twins and provide the necessary mapping and translations. There is substantial opportunity for research in all these areas.

7.4. Causal and Correlative Prediction

Physical systems, environments, and operational contexts change over time. Methods for continuously updating and validating Models of Reality without destabilizing operations remain an important challenge.

It was pointed out above that AI can offer highly accurate predictions without a causal understanding. Research is needed to determine when correlation-based predictions will be sufficient from a technological aspect, a social aspect, and a legal requirement as opposed to when causal models are required.

7.5. Risk Quantification and Validation

The value of FRS depends on the accuracy of its predictions of both what probable outcomes will occur in the future and what actions will change those outcomes to enable our meeting goals and at what risk. We need to understand the probability of assessments to trigger intervention. We are going to need to develop robust methods for estimating, updating, and communicating risk. The more DTA data we collect will enhance Bayesian-based probabilities. Traditional measures such as prediction accuracy may be insufficient, so research is needed on other methods. (This is usually referred to as Uncertainty Quantification (UQ). However, uncertainty is the probability that an event can be 0% to 100%. That is irreducible uncertainty and cannot be quantified. The uncertainty must be reduced to a risk, or it cannot be quantified. This was established by Frank Knight [37].)

Unlike replication, future-state predictions cannot be directly verified until time unfolds. Research into developing rigorous methodologies for validating FRS predictive performance is needed. Also, research into developing resilient systems if true epistemic uncertainty exists, as it may in HITL systems, remains an important scientific challenge.

8. Conclusions

Front Running Simulation (FRS) represents a fundamental advancement in how we approach goal-oriented activity in complex physical systems. Although humans have always engaged in rudimentary forms of replication, prediction, and navigation, FRS elevates this capability to a level of scale, speed, and rigor that was previously unattainable. By continuously synchronizing with the current state of reality and projecting forward into probabilistic future states, FRS provides an operational "crystal ball" grounded not in speculation, but in data, Models of Reality (MoR), simulation, and information.

The key contribution of FRS is not merely improved prediction, but also goal-directed navigation under constraints. Traditional simulation has largely been used for planning and exploration, detached from real-time operations. By contrast, FRS is tethered to reality, continuously resetting its initial conditions to the present state and evaluating future trajectories in the context of achieving defined task goals while minimizing scarce physical resources. This reframes simulation from a passive analytical tool to an active operational capability.

The integration of Digital Twins—particularly the Digital Twin Instance (DTI) and Digital Twin Aggregate (DTA)—provides the structural foundation for FRS. DTIs enable high-fidelity replication of the current state, while DTAs introduce a longitudinal,

population-based learning capability. With the incorporation of AI, especially Bayesian-informed inference derived from DTA data, FRS evolves into a hybrid predictive system. In this hybrid model, causal and Monte Carlo-based correlation simulation explores possible futures, whereas AI ranks probable futures based on observed behavior. This fusion strengthens both predictive accuracy and decision responsiveness, particularly under time-constrained conditions.

Critically, FRS shifts the focus from adverse event and deviation avoidance to goal attainment under resource constraints. As demonstrated in the examples, the optimal course of action is not always the elimination of a deviation. Instead, FRS evaluates whether deviations materially impact the ability to achieve goals and identifies actions that maximize the probability of success with minimal expenditure of time, energy, and materials. This aligns directly with the principle that information serves as a replacement for wasted scarce physical resources.

FRS also introduces important considerations regarding execution. The value of prediction is contingent on its ability to act. Accurate foresight without executable capabilities has no operational benefit. Therefore, FRS must be tightly coupled not only with sensing and simulation but also with the physical and organizational ability to implement selected actions. This reinforces the importance of aligning FRS outputs with real-world constraints, including human decision-making (HITL), autonomous systems (HOOTL), and necessary guardrails to eliminate or at least mitigate inappropriate actions.

Finally, Digital Twin FRS should be understood not as a standalone technology, but as an integrative architecture. It unifies MoR-based simulation, data, information, and now AI principles into a coherent framework for operating in the Third Millennium, an era defined by virtualization, computation, and data-driven decision-making. As computing capabilities continue to expand and data availability increases, FRS will become increasingly precise, adaptive, and indispensable.

In summary, Front Running Simulation transforms how we engage with the future:

- From reactive to proactive;
- From isolated simulation to continuous synchronization with reality;
- From resource-intensive trial-and-error to information-driven efficiency.

FRS enables us to move from a world constrained solely by physical trial and error to one in which we can virtually explore, evaluate, and select actions before committing physical resources, thereby achieving our goals more effectively and efficiently than ever before. In order to fully implement FRS, there are numerous challenges to overcome and numerous opportunities for research. These include computational scalability, state representation and abstraction. model interoperability, causal and correlation prediction, and risk quantification and validation.

In this respect, FRS formalizes at a systems level what humans have always attempted to do: construct representations of reality, anticipate possible futures, and select actions most likely to achieve desired goals. Operating within a digital environment populated by Digital Twins, FRS extends this fundamental capability to levels of scale, scope, fidelity, consistency, and computational capability that dwarf those achievable through unaided human cognition, creating a fundamentally new operational capability for navigating complex systems.

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