



# Analysis of a closed-loop digital twin using discrete event simulation

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## Abstract

Given recent advancements in technology and recognizing the evolution of smart manufacturing, the implementation of digital twins for factories and processes is becoming more common and more useful. Additionally, expansion in connectivity, growth in data storage, and the implementation of the industrial internet of things (IIoT) allow for greater opportunities not only with digital twins but with closed loop analytics. Discrete event simulation (DES) has been used to create digital twins and, in some instances, fitted with live connections to closely monitor factory operations. However, the benefits of a connected digital twin are not easily quantified. Therefore, a test bed demonstration factory was used, which implements smart technologies, to evaluate the effectiveness of a closed-loop digital twin in identifying and reacting to trends in production. This involves a digital twin of a factory process using DES. Although traditional DES is typically modeled using historical data, a DES system was developed which made use of live data to improve predictions. This model had live data updated directly to the DES model without user interaction, creating an adaptive and dynamic model. It was found that this DES with live data typically provided more accurate predictions of future performance and unforeseen near future problems when compared to the predictions of a traditional DES using only historic data, resulting in smarter decisions and implementation of more timely solutions.

**Keywords** Digital twin · Discrete event simulation · Real-time factory analytics · Closed-loop processes · Smart manufacturing

## 1 Introduction

Recent advances in technology, having been integrated into factories, mean that manufacturers across the world have access to a wealth of equipment and process analytical data and information. This wealth of data has resulted in what is known as Industry 4.0 and an era of smart manufacturing. A generic framework for establishing smart manufacturing is as follows: smart design, smart machines, smart monitoring, smart control, and smart scheduling [1]. Smart designs and smart machines mean that information and knowledge can be communicated. This allows for smart monitoring and control which utilizes bi-directional communication to receive data and send signals on a connected network.

Additionally, smart manufacturing entails smart scheduling, which allows for data driven models to make decisions for the factory floor, without a need for user interaction. Smart scheduling utilizes smart control and smart monitoring to respond directly to information from the machines and sensors. The emphasis of the majority of work around smart manufacturing is focused on this idea of smart monitoring and control [2]. In order for monitoring and control to be established a high level of connectivity across the factory must be established. There are numerous, well-documented ways of employing hardware and software to establish enterprise level connectivity [1–4]. A factory that has established enterprise level connectivity allows information to be transferred from equipment on the factory floor to enterprise level databases. This level of ubiquitous connectivity is vital to both monitoring a smart system and eventually controlling it. This type of connectivity forms a loop of bilateral data transfer and decision making, which has also been termed as “closing the loop” [5–7].

Within research on connected digital enterprises, some emphasis has been placed on the digital twin, recognizing

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that this type of visualization in the smart factory can lead to smart decisions [4]. A digital twin is the virtual representation of a physical system, is connected in real time to data changes, and is allowed to make changes to the physical system [8]. A digital twin can be used to observe the current status of the physical system, but also to optimize and predict the future status of the physical system. Digital twins can take different forms such as in the dozens of human-machine interface software available, charts and mathematical models, and even augmented reality. The development of digital twins is not yet fully mature in manufacturing settings, and it is understood that more research is required to further evaluate the benefits of implementing a digit twin [9].

Discrete event simulation (DES) can be used to create full digital twins and digital pieces of a process: for example, DES has been used with data analytics to decrease the number of defects in a production line [10] and to reduce waiting time of items in queue in automotive production [11]. There are dozens of these types of examples of digital representation in manufacturing, demonstrating that DES can be effective in visualizing systems to improve outcomes [12–16]. The focus of this research will be the development of a digital twin through DES modeling of a factory process to analyze a traditional versus connected digital twin's ability to simulate production.

## 2 Background

### 2.1 Traditional discrete event simulation

All processes found in manufacturing can be categorized as either discrete or continuous. Continuous events are things such as a lake filling up with water, the change is continuous, and there are infinite number of states. Discrete events are events in time that can be defined, identified and numbered. However, even continuous processes, such as steel production, can have discrete events including melting, cutting, packaging, and shipping [17]. Thus, DES is used widely in many fields to identify problems and optimize performance.

Smart manufacturing often includes closed loop operations of an integrated part of a system [4]. Although closing the loop has been accomplished in different ways, DES has often been used and may be one of the most effective ways to make predictions and find automated solutions [18]. Traditionally, DES models rely on historical data and trends to simulate production, which then can predict outputs or find optimal solutions [10, 12, 13, 19–21]. In some instances, particularly when high variability is expected, more recent data has in some way been used in addition to longer-term historical data [14–16, 22].

Research has been done on improving factory predictions and estimates through the use of DES. One such experiment was done by creating mathematical models using a technique called data mining and then creating the DES model based on these mathematical algorithms [23]. The results from this research were significant, as they demonstrated that large amounts of data are available and can be effective in the use of DES modeling, specifically as it relates to the ability of DES to identify bottlenecks. Previous to this study, DES was primarily implemented as a Monte Carlo style simulation in which certain input variables would be randomly manipulated to quantify their expected impact on outputs. Better et al. showed that combining data analytics and DES could be more intentional and specific, providing rapid and focused feedback [23].

DES has been used in manufacturing to enable predictive analytics. Different software such as Tecnomatix Plant Simulation [24] and Arena Simulation [10] have been used to build digital models of current manufacturing processes. These digital models not only serve to visualize problems, but also to provide solutions to manufacturing problems. However, these models are limited to processing historical data within the model and lack any specific connection to current factory operations. Thus, they neither utilize real time data to improve their results, nor is it possible to loop results directly back into the system. Once optimized for a certain set of historic data, these models typically have served their purpose and are not of use once significant changes are made in the physical system, which has resulted in the term “throw away models” [14, 25, 26].

### 2.2 Adaptive or flexible DES models

The idea of feeding up-to-date, or live data to a model built with historical assumptions has been explored previously. In a certain water fabrication scenario, recent data that was manually updated, proved to be essential because the process itself is variable in production [27]. This experiment is notable because researchers made a clear comparison of the added benefits of additionally using live data versus using only historical data. Using estimated production parameters, throughput was simulated and followed actual output trends. However, when actual production parameters were used instead of the estimates, the accuracy in prediction was dramatically improved.

DES models have also been connected to databases to allow simple integration of data as it is updated [26]. These types of models allow an enterprise to integrate models with data that is updated and extends the use of DES to adaptive and flexible situations. While these models do not allow for real-time connections to the data sources, they show that more up-to-date data leads to greater accuracy in predictive performance.

### 2.3 Connected DES models

Although adaptive DES models are beneficial and comparatively simpler to implement than traditional DES, a digital twin needs to digitally connect to the physical system. Recognizing the value of connecting to live data, frameworks have been set forward for establishing an adaptive and connected DES model [28]. This has resulted in studies using live data to analyze a system and optimize scheduling in real time [29]. These connected DES models typically tie into databases and live connections in order to identify variable parameters within the factory enterprise. Studies have even been published drawing clear comparisons between models utilizing live data and models reliant on historical data or manual updating of parameters [30]. While these studies are just emerging and are limited in their overall application across a broad range of manufacturing enterprises, they are showing that for their focused studies the use of live data to build a dynamic DES may lead to more accurate predictive capabilities.

Bi-directional communication from digital twin to physical system is essential to closing the loop. Frameworks have been developed aiming to solve this dilemma and solutions have been well-documented [31]. The emphasis on real time connections is based on an understanding that in order for simulation in manufacturing to be effective, we must have valid and clean data inputs [28]. Obtaining clean and timely data is a major problem, and papers have been written that look into automating this process while preserving the data quality and addressing additional data collection problems [32]. Understanding that the quality of data is improving, leads to the question of what improvements in optimization and prediction could one get from applying a closed loop DES model.

These emerging, fully connected DES models are not simple to create, and there is a gap in the research when it comes to quantifying the specific benefits of converting a traditional DES model to a fully connected DES model. From these studies, it is apparent that its feasible to convert a traditional DES model a connected DES model. The difficulty is that there are limited studies on the benefits of connecting these DES to live data. Thus, the question is not whether it is possible to create connected DES models, but rather, what is the value of connecting the DES and does this value justify the connection of more complicated systems. As such, this paper will explore the creation and analysis of a connected and closed-loop DES.

## 3 Methodology

To validate the claim that a connected DES can quickly provide more accurate short-term solutions,

1. A deliberately simplified and modular, lab scale demonstration factory was created that implements smart manufacturing complete with smart designs, smart machines, smart monitoring, smart control, and smart scheduling, thus, enabling the creation of a truly connected digital twin using DES.

Additionally, in order to quantify the benefits of a connected digital twin versus a traditional digital twin,

2. A traditional DES model was created that initially only used the historical data of the demonstration factory and subsequently, was modified to connect to live data in the demonstration factory. A variety of tests were then performed to measure the benefit of a connected DES versus a traditional DES model.

### 3.1 Factory — physical connectivity

To better explore opportunities in smart manufacturing, a demonstration factory was built at Brigham Young University (BYU). This demonstration factory was deliberately simplified to create a test bed for simple integration of the smart factory in a digital enterprise, specifically as it relates to the digital twin. The benefit of having such a system has recently been studied and verified [33]. Although this demonstration factory sorts dice, research findings can be applied to general manufacturing processes seeking to implement smart manufacturing. The demonstration factory delivers six-sided dice on a main conveyor belt where a robot picks up and sorts these dice based off the top face into a tray to complete a full set of dice 1–6. Once assembled, each tray is recycled through the system, rolling the dice and depositing them back onto the conveyor belt. Additional dice that cannot be placed in the current tray, are stored in a buffer area and these dice may be used later to fill tray positions. An image of this demonstration factory can be seen in Fig. 1.

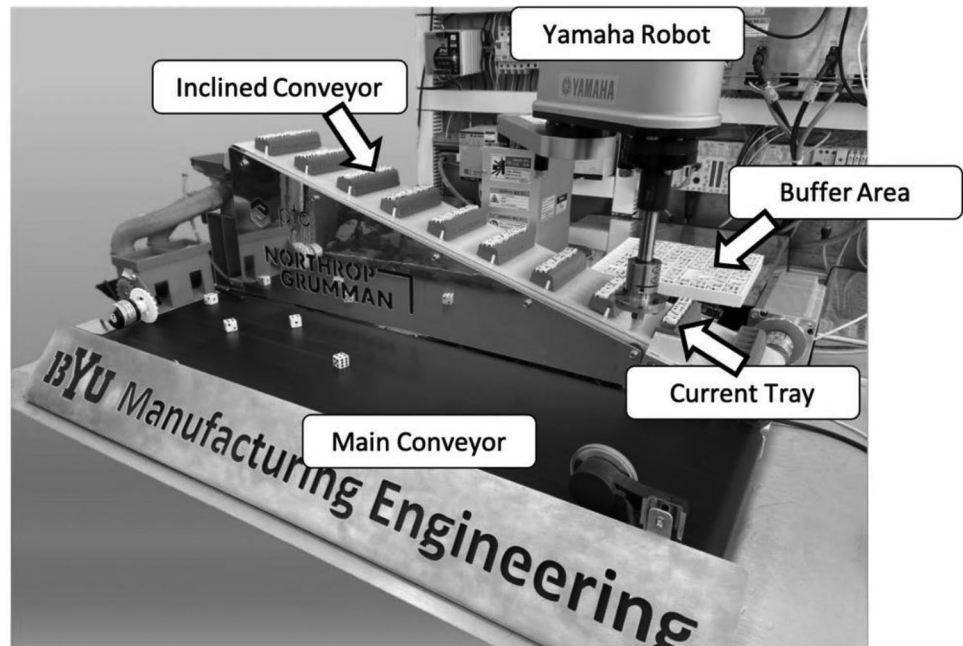
Steps were taken to accurately reflect a real production scenario, and the demonstration factory was fitted with industrial level machines and technology such as an Allen Bradley CompactLogix 5380 PLC, Festo CPX-FB36 and CPX-AB-8-KL-4POL fieldbus, Robot Vision iVY2 RCX340 vision system, Yamaha YK400XG robot and RCX340-4 controller, and additional sensors, motors, etc. The general hardware structure and integration of the test bed can be seen in Fig. 2. The demonstration factory transfers information through Ethernet IP where an Allen Bradley PLC makes decisions and integrates all parts of the system together.

Some factory specific terms are defined in Table 1 as well as corresponding general process terminology.

### 3.2 Enterprise level connection

Following a generally accepted path for implementing smart manufacturing [4], the demonstration factory integrates the

**Fig. 1** The demonstration factory at BYU



ability to monitor, control, and analyze data. The integrated enterprise contains a connection server and enterprise connectivity, which connections are accomplished through PTC Inc. software products, namely Kepware and ThingWorx respectively. The complete digital enterprise of the demonstration factory can be seen in Fig. 3.

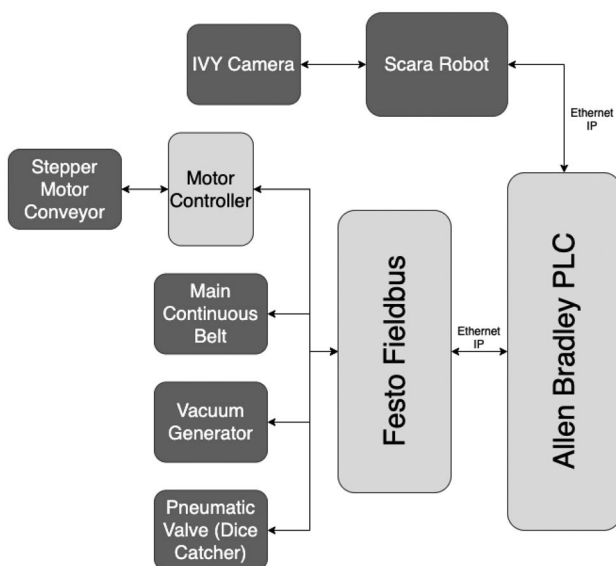
The factory connection connects to the physical devices and allows properties and status of the demonstration factory to be placed on a server, allowing for ubiquitous and bi-directional data transfer. Through industrial connectivity,

the smart factory platform provides a software environment where that data can be evaluated using custom coded algorithms to store, visualize, monitor, and control information. Data is stored in an external PostgreSQL database that functions as the factory enterprise. Ultimately, this industrial level software provides an integrated interface for monitoring, controlling, scheduling, and visualizing. This implementation has led to a digitally integrated enterprise test bed, and an ideal environment to quantify the benefits of the closed-loop digital twin of a smart factory.

### 3.3 Closed loop digital twin

A DES model was created based on the historical and live data of the demonstration factory. The model was verified and validated against multiple runs of the demonstration factory. Specifically, it was confirmed that the digital twin was accurate in modeling the physical state of the demonstration factory at any given moment as well as accurate in replicating the average production volume of the system. The model was created using FlexSim, a simulation software developed by FlexSim Software Products. This software allows for real time connections to servers, databases and even PLCs. The resulting digital twin is a 3D replica, which can be seen in Fig. 4.

To create a genuine digital twin, the simulation connected to live data using 2 different methods. First, for data that required analysis of distributions, information was sent in 5-min intervals. The 5-min interval allowed data to be averaged while still ensuring timely data updates. These packages were stored in the enterprise, see Fig. 5. Secondly, in some instances, 5 min was not enough for the response



**Fig. 2** Hardware structure of the BYU demonstration factory

**Table 1** Terms used in this paper as they relate to manufacturing processes

Term	Description	General process term
Dice Produced	Whenever a dice is picked up and sorted, a dice is produced	Unit production, raw production
Dice position	When the dice is removed from the conveyor the x and y position and rotation of the piece is recorded	Alignment of units, could lead to waste and lost materials
Robot speed	The percentage of the max physical speed at which the Yamaha robot is working	Speed of the line and process, leads to potential bottlenecks
Dice distribution	When the dice were rolled on the conveyor, the distribution of the dice faces was not uniform, for instance, the faces of the dice were more often 4, 5, and 6. This refers to the real distribution	Supplier quality, raw material specs and limits

to be considered live or real time. In such cases, such as when the robot speed was reduced, the DES model was tied directly to the factory connection, which connected directly to the PLC for real-time connectivity of process variables. Regardless of how it was accomplished, in both instances, data was directly connected to the simulation without a need for any human interaction, thereby, completely automating the solutions. Additionally, data could be sent back to the physical system using the same two methods, either in information packets sent through the enterprise or sending signals through the factory connection. Figure 5 shows the complete closed loop system with the DES model, which acts as the digital twin with connection pieces to the enterprise and the factory. When the DES detects a potential problem, it will send a signal through these connections. Signals can be sent through the enterprise for the smart factory to then convert to a display or notification in order to alert the operators. Signals are sent through the factory connection to directly control the factory and stop or modify production.

The specific connections from the physical system to the digital twin can be seen in Table 2. The input parameters are taken from the physical system using the specified data transfer method. These are inputs for the DES model

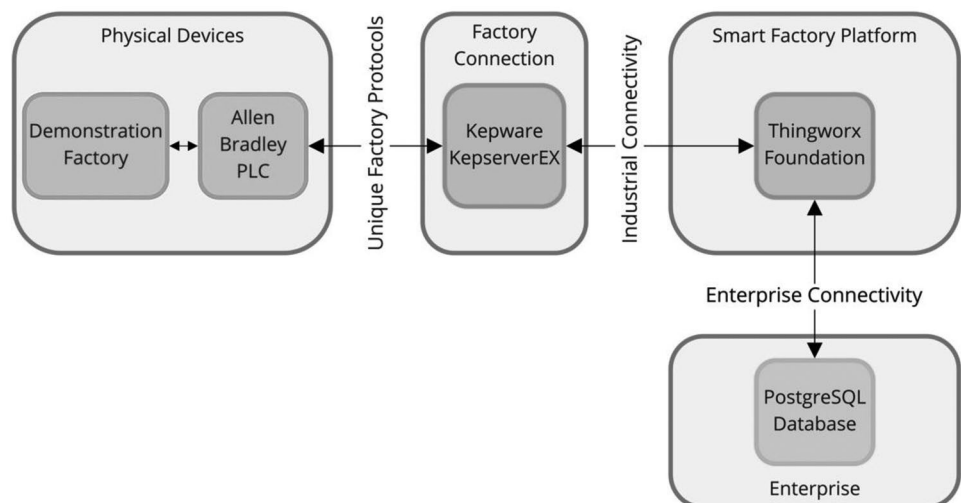
to use in its analysis. Results are then generated from the DES model, and these outputs are sent to the physical system using the specified data transfer method.

The DES follows the same sequence of events as the physical factory. Dice were rolled onto the conveyor belt where the robot would sort them either into a tray or the buffer area. The dice could then be sorted from the buffer to the current tray when needed. The conveyor belt would then cycle and the process would continue. A diagram of this process can be seen in Fig. 6, which also goes into the greater detail of the logic of the DES. This diagram identifies the live data inputs and outputs from Table 2 in dark circles.

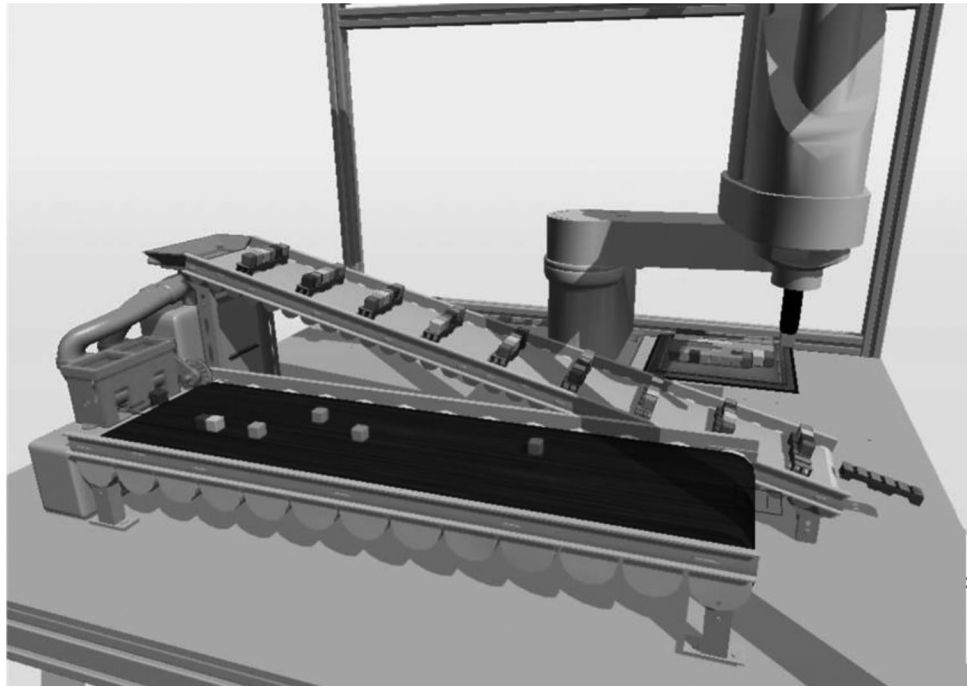
### 3.4 Testing setup

On startup, dice will be placed in the buffer with an equal number of dice 1–6; however, it was noted that dice do not follow this assumed uniform distribution. Dice numbers 4–6 are rolled more often than 1–3. This led to inconsistencies in production, because in the beginning of startup the demonstration factory’s buffer had an equal number of dice it could pick from to fill up trays quickly. As time

**Fig. 3** The software implementation of a digitally integrated enterprise, showing how industrial level connections are used in the smart factory platform. The smart factory contains the ability to monitor, control, aggregate, and visualize data



**Fig. 4** The DES model of the demonstration factory



elapsed, it would eventually run out of the fewer rolled dice and production slowed slightly. It was therefore necessary to first determine the length of time it would take for the system to reach a steady operational state.

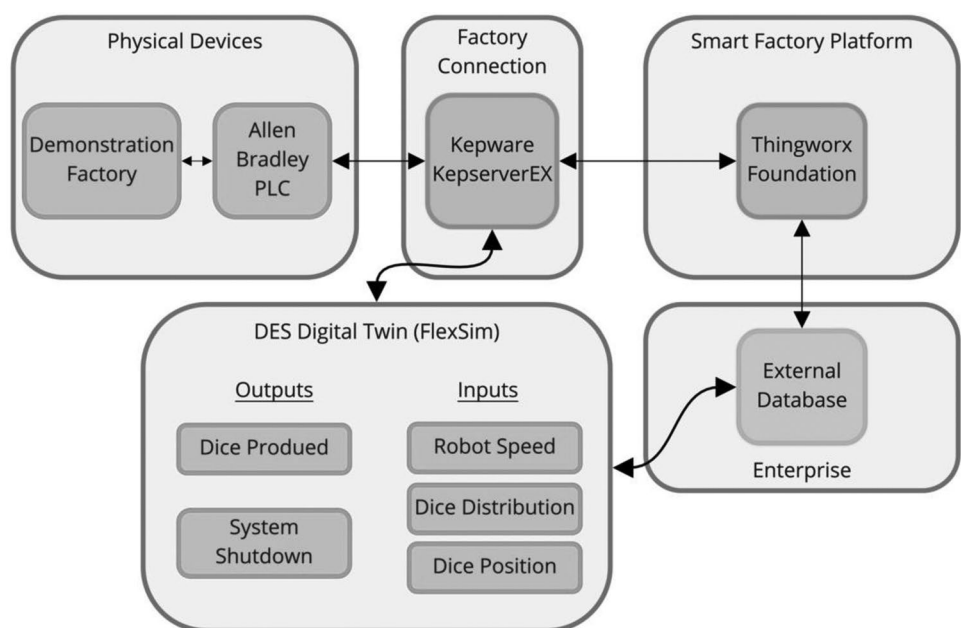
Although there are variations in the number of dice produced every five minutes, in the first 15 to 20 min of production more dice are produced. This is because of the uniform distribution of dice in the buffer, from which the system can pull dice from to fill trays, thus increasing the number of dice produced. After 15 to 20 min, the initial

buffer is depleted, and the number of dice produced is not dependent on the dice manually placed in the buffer. Thus, the warmup period was determined to be 20 min. All tests will be ran after this 20-min period.

### 3.5 Types of tests to run

The demonstration factory was run for several shifts — a shift refers to a 12-h run—and averages were recorded. The averages were used to create historic distributions and a traditional

**Fig. 5** FlexSim closing the loop and creating a digital twin

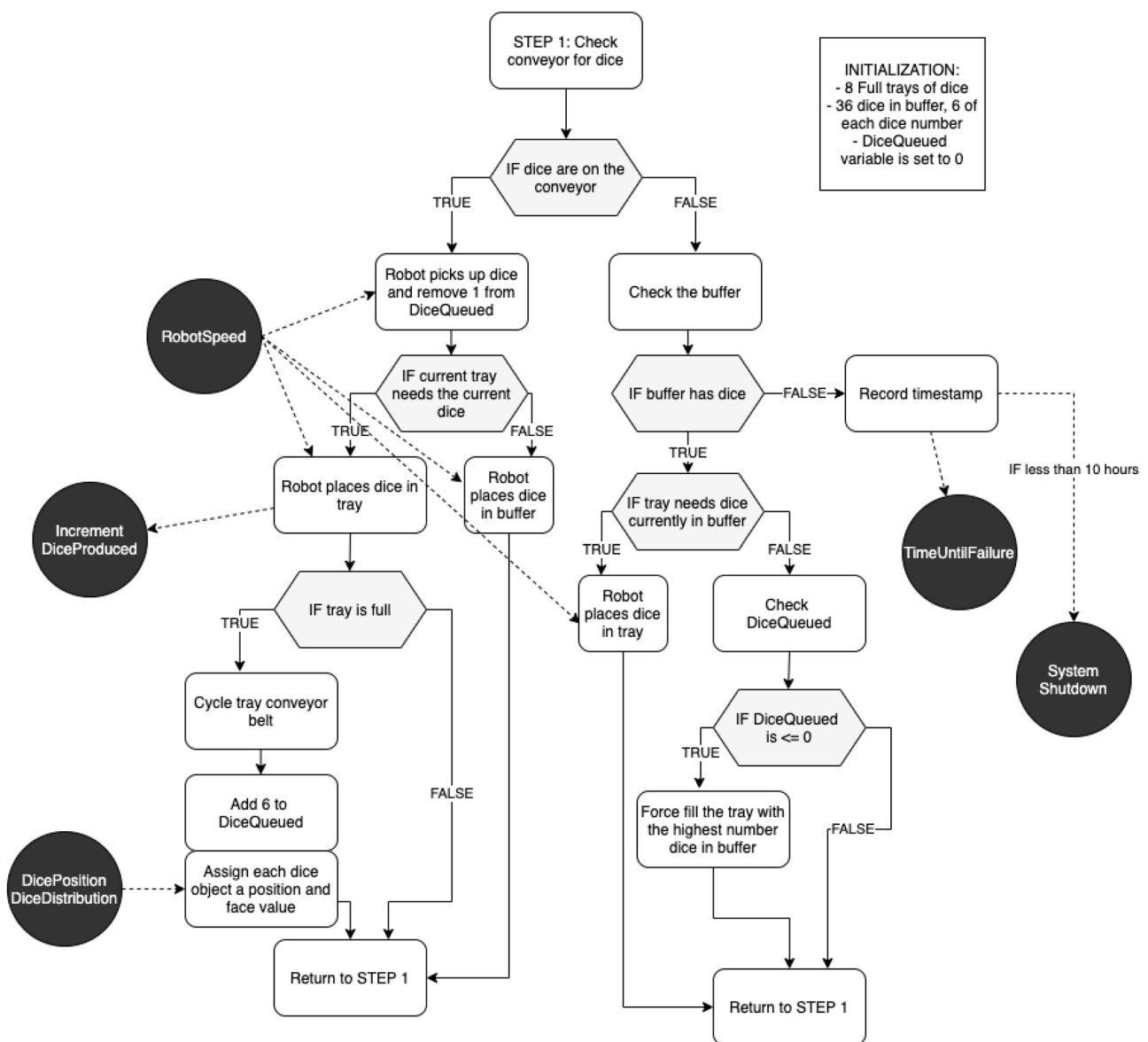


**Table 2** List of parameters and data information

Parameter	Description	DES model I/O	Data transfer method
Dice produced	Counter for how many dice are sorted by the robot	Output	Factory connection
Dice position	The position of the dice on the conveyor belt when picked up	Input	Enterprise
Robot speed	The set percentage of the max speed the robot is operating at	Input	Factory connection
Dice distribution	The distribution of the dice being sorted from the conveyor	Input	Enterprise
Time until failure	A prediction provided by the DES of the estimated time until the demonstration factory drops too many dice off the conveyor	Output	Enterprise
System shutdown	A signal that shut downs the factory based off the time until failure	Output	Factory connection

or base line DES model. Three tests, seen in Table 3, were then performed to evaluate the variety of benefits that may be seen in a connected digital twin. The inputs into each of

these tests is the live data component; all other parameters are held constant and thus historic data can be used to emulate these processes that would otherwise change our production



**Fig. 6** A flow chart of the DES model. Dice queued refers to dice entering onto the conveyor belt and waiting to be picked up by the robot

outputs. These constants are inputs such as motor speeds, light quality, processing times, and other variables. The outputs of these models are predictions that can then be used by operators and managers to make timely decisions and, specifically referring to the third test seen in Table 3, even allow the model to autonomously make decisions and control factory parameters and production.

### 3.5.1 Test 1: throughput and bottlenecks — method

The purpose of this first test was to determine how effective a connected DES model would be in improving the accuracy and precision of predicting throughput when an unexpected failure or modification occurred. Assuming that large amounts of data are available, a factory should know approximately how often their lines shut down or maintenance is performed, even so, a factory may still have unexpected events that are not accounted for in their large historical data sets. For instance, lines may have to be shut down, speeds on conveyors reduced, or workers may be unavailable. By connecting the model to live parameters such as speeds and line shutdowns, the connected DES would be able to make predictions based on these changes without needing additional historical data, and instead, rely on live data. To test this hypothesis, a test was run with variable robot speeds to analyze how a traditional and connected DES would respond.

The connected DES was connected to live robot speeds, and a bottleneck was created by intentionally modifying the robot speed to model a line failure and other random event. The traditional DES model was created using the data during testing, so it had access to the averages, highs and lows of dice produced, but because it was not connected to live data, could not specify robot speeds and thus could not identify when production may be higher or lower than the average. Using Microsoft Excel, we produced 7 randomly generated numbers between 1 and 10. These numbers corresponded to the percent speed the robot would run as described in Table 4. The demonstration factory was then run, modifying the robot speed every 10 min to the new speed specification, thus modeling factory line variation. The number of dice sorted was recorded as dice produced every 5 min, so 2 values were recorded at each speed. The test started for 10 min at full speed (100%) and ended at full speed (100%) for 5 min. Table 4 shows the number of dice produced and the robot speed. The number of dice produced does not have a linear relationship with the robot speed; this is a good example of why a connected model

**Table 4** List of random robot speeds used in testing

Random number	Robot speed %	Dice produced
N/A	100	42, 47
7	70	37, 42
4	40	34, 36
9	90	40, 44
7	70	45, 46
2	20	25, 27
10	100	47, 49
1	10	21, 15
N/A	100	40

can be useful. Multiple variables may affect an output and relationships between variables may not be immediately obvious. The connected DES model was running in the background and was instantaneously adjusting predictions based on the variable speed, thus allowing it to identify trends. The traditional DES model, used as a basis of comparison, was created using this historic data.

### 3.5.2 Test 2: supplier quality — method

Similarly, in test 2 of Table 3, we wanted to quantify how a connected model responds to unexpected changes. Specifically, we were testing if a connected DES model could identify unique trends in a system where no previously recorded data is available. To test this, we introduced material from a new supplier. Similarly, plants may source raw material from different suppliers, and while these suppliers advertise identical specs, they may actually deliver material on opposite ends of their specified limitations, meaning production with that specific material may vary from historical trends. This test looked at evaluating how effective the connected DES model can predict these variations.

The demonstration factory was run using dice with pips, but through observation, we noticed that when we rolled these dice on the conveyor, the distribution of dice faces were not uniform. Additional dice were purchased that had printed numbers instead of pips, and we observed that these dice had a unique distribution as well. Although both sets of dice were advertised as fair and uniformly distributed dice, we found that in fact they had a different distribution. Finding the correct distribution of materials is time consuming and takes large amounts of experimentation.

**Table 3** Tests run and inputs/outputs of the tests

Test number	Process represented	Inputs to model	Outputs from model
1	Throughput and bottlenecks	Robot speed	Dice produced
2	Supplier quality	Dice distribution	Dice produced
3	Process alignment	Dice position	Time until failure



This led to us wondering what the quality of historic data would be when materials with unique distributions are introduced. To test this, we ran the factory with only the numeric dice and recorded the number of dice produced. Then, to represent a new supplier's material, we removed the numeric dice from the system and replaced them with the piped dice. We assumed that we had no historic data on the distribution of either dice and instead used historic distributions to predict dice produced. However, the connected DES model used the distribution of the last 1000 dice sorted as an input for our model based on live data. The distribution was taken from the PostgreSQL database, and the method for this in FlexSim can be seen in Fig. 7.

### 3.5.3 Test 3: process alignments — method

This third test of Table 3 aims at further demonstrating the ability to identify serious errors and problems on the factory floor that would otherwise go unnoticed. One such instance in our demonstration factory is an alignment piece that keeps dice from rolling out of the reach of the robot. If damaged, more dice fall out of reach of the robot, and they will fall off the end of the conveyor belt. The dice are recycled in our system, so if too many dice fall off the conveyor, then the demonstration factory runs out of dice to sort and stops until more dice are delivered. This leads to a buildup of material waste and takes negatively impacts the productivity of the factory.

We have termed this waiting as a system failure, since only an operator can come and resolve the issue. We wanted to eliminate this unnecessary waste of material and time.

Using our historic data to build the traditional DES model, we recognized the average position on the conveyor belt meant that nearly all dice were picked up by the robot. Only 1 in 1000 would be missed. This test was a little bit different in that we did not use live data to “train” the model, instead the model was simply looking for variations from what it was expecting in the historical data. This meant that when a dice was missed the connected DES model could run a prediction on how long the demonstration factory could run before failure. We defined a failure as the demonstration factory running out of dice to process on the conveyor belt. It was assumed that every shift, which runs for 12 h, an operator could restock whatever dice had been lost by being out of position, if the system ran dry before an operator got there then a failure would occur.

To calculate the time until failure, the DES connected to the external database to determine the current percentage of dice missed by the robot. It would then simulate production, running 60 h into the future, and record back in the database the estimated time until failure. If time until failure was less than 20 h, an operator was notified to go restock the system. If time until failure was less than 10 h, the DES system was shut down through the Kepware connection, and an operator was notified to resolve the problem.

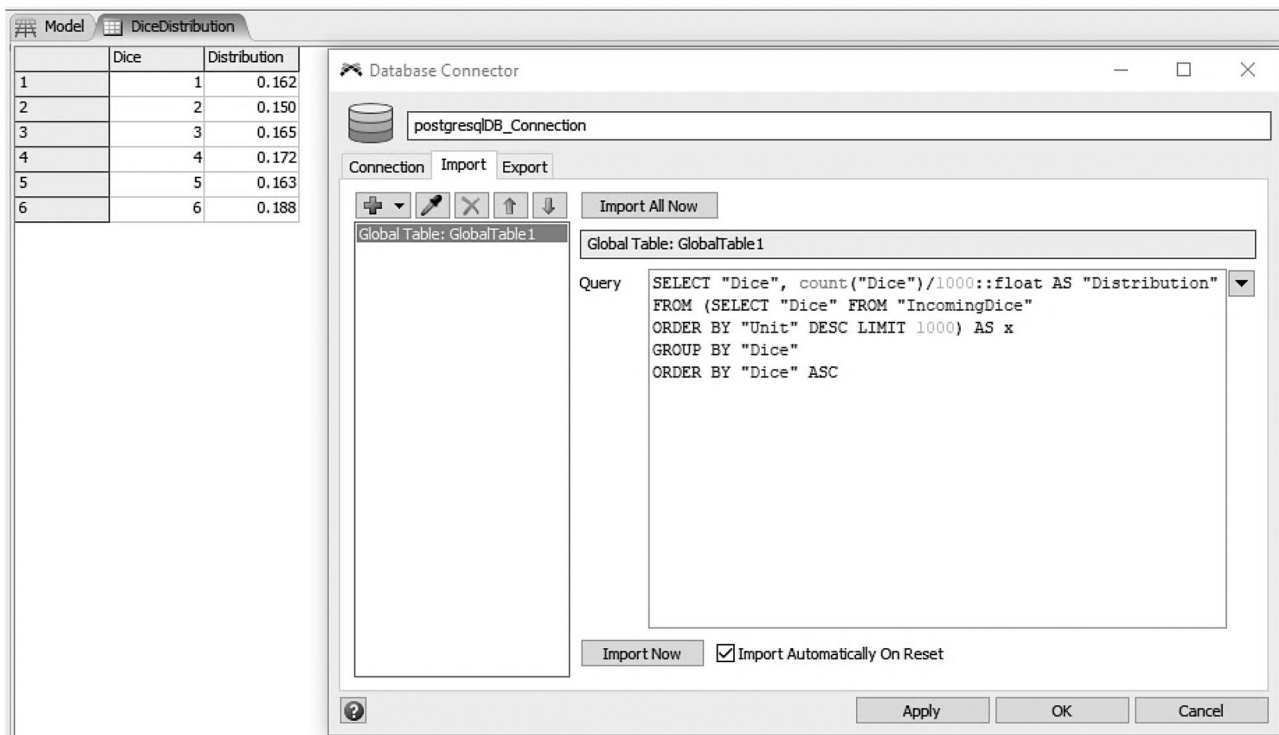


Fig. 7 FlexSim connected model input

## 4 Results and discussions

### 4.1 Test 1: throughput and bottlenecks

After running the test described in 3.5.1, we discovered that long term, the actual number of dice produced in the 85-min period was 637 units. Using the historical data of dice produced, we predicted 629 and using the live data of the robot speed, predicted just 577. The historical model did better because we built the historical model off the number of dice produced from the same data set, effectively overfitting the model, in order to show a best-case scenario for the traditional DES model. However, when looking at specific time intervals, the live data of the connected DES was still much more precise in predicting units produced, because historical data model predicted ranges of dice produced much wider than the live data model. These results can be seen in Fig. 8. The dotted lines refer to the historic DES model and solid lines correspond to the live model. As seen in Fig. 8, the number of dice produced in 5 min had a wide range of values because of the randomness of the dice. The system fills trays one at a time, so at any given tray may wait longer or shorter depending on the dice it is sorting from the conveyor. The stochastic nature of the system also led to differences in the actual number of dice produced and the predicted number of dice produced.

The model with live data was able to predict highs and lows in a much tighter margin. Overall, it could predict greater specificity at a 35.1% improvement. Additionally, the average error for the historic data was 28.3% and only 12.9% for live data, effectively cutting the error in half. These numbers can be seen below in Fig. 9.

With the intent of analyzing the accuracy of the long-term predictions of these models, the experiment was run a second time. A new set of random values was chosen for the robot speed, and 655 dice were produced. While the historical model predicted 646 dice produced, the live model

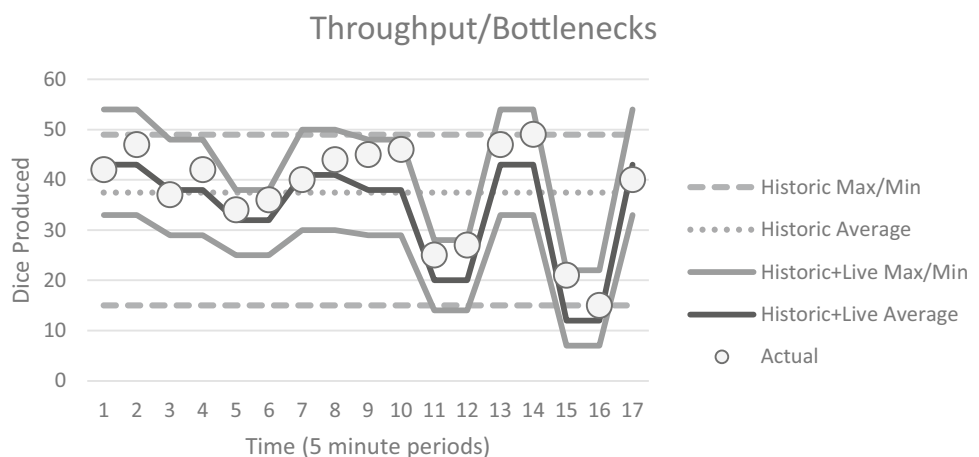
predicted 649 dice produced, showing that comparable long-term results could be achieved from both models. The connected DES and the traditional DES had comparable results because the historical data was intentionally not updated with the most current run. In the first run, the historic model was overfitting its predictions based off the training data, and in this second test that advantage was limited. In this case, both models were within 10 total dice produced when predicting long-term production. All other measurements in this second run closely reflected our findings from the first test.

In summary, we found that both the traditional DES and the connected DES had comparable long-term predictions for average number of dice produced. The benefit seen here is that a live model can maintain accurate long-term predictions while also improving the ability to more precisely make short-term predictions. A traditional DES would be able to find long-term averages, but when a factory experiences disruptions to production then a connected DES would be useful in identifying the potential short-term losses. As shown in Fig. 9, short-term predictions are consistently twice as accurate. Conversely, if small improvements are made that increase speed of production, the connected DES will immediately reflect that change in its short-term predictions. The benefits of live data seen in this test are the improved ability to make short-term predictions.

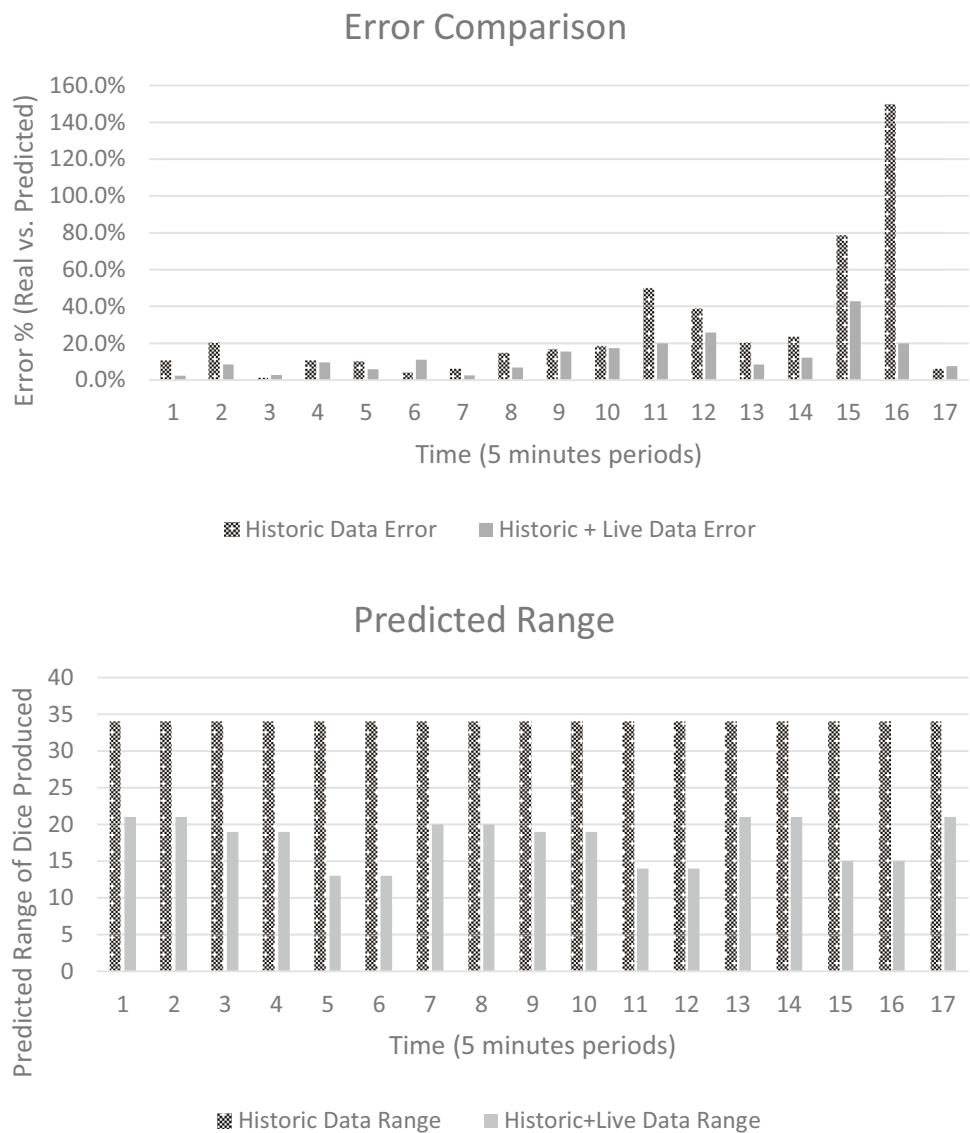
### 4.2 Test 2: supplier quality

Following the methodology outlined in 3.5.2, we ran test 2 of Table 3 and observed, as shown in Fig. 10, that the connected DES model, in this case, benefited our predictions. The historic data model was extremely accurate when predicting using material 1 (the numeric dice). However, when a new material is introduced the prediction for dice produced is unchanged because the historic model uses the large amounts of historic data, but it is untrained on any new

**Fig. 8** Precision of models in predicting dice produced when adjusting the robot speed



**Fig. 9** Error and precision comparison



data until it is taken offline and updated. The connected model, on the other hand, reads in the new distribution and creates an adaptable moving average calculation to account for these slight variations with only some delay.

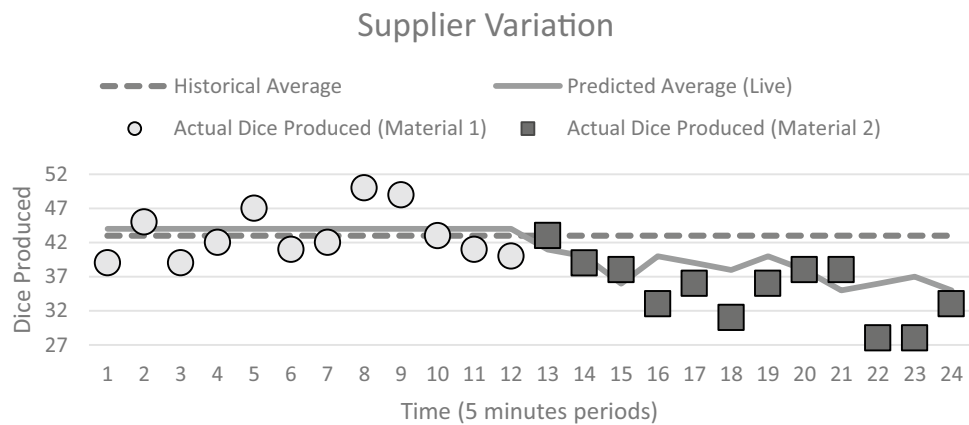
As a manager in this factory, you may not be expecting a significant variation in production due to raw material, and the effects of this change may not be clearly reflected until many parts have been produced. In reality, changes that go undetected by operators may have dramatic effect on the outcome of production. In this case, the actual average of the historic/numeric dice is 43 dice every 5 min. For the new units, the actual average is closer to 35. This may not seem significant and may even go unnoticed by the system, but in a 12-h shift the demonstration factory would be producing 1000 fewer units than expected. The connected DES model does not respond instantly to the change, but in 5 min, it already starts to adjust and between 15 and 45 min can

completely adjust for the distribution of the new material. This has a large impact to industries processing raw materials, because not all suppliers deliver comparable material and traditional predictive analytics requires large amounts of historical data to build an accurate model. It was shown here that a connected model can adapt quickly to change, whereas the traditional model required an offline update and the user needing to be aware of a possible issue.

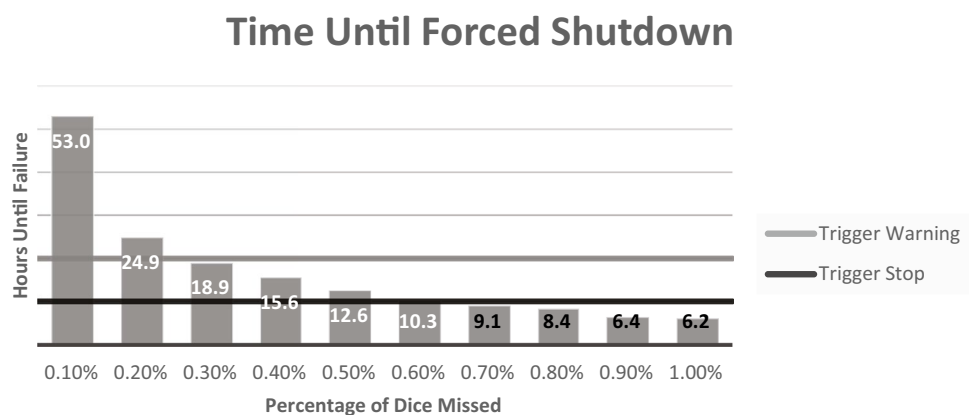
**4.3 Test 3: process alignments**

Initially, we were unaware as to how many dice we could afford to lose off the conveyor belt of our demonstration factory before production was affected. After running the test outlined in 3.5.3, the DES accurately identified when the demonstration factory would fail. The results can be seen in Fig. 11 below. We ran the connected DES, manually

**Fig. 10** Prediction of change in production when new material is introduced



**Fig. 11** Chart of hours until failure when looking at dice missed



feeding it possible distributions of missed dice from 0.1 to 1%, and it recorded in a database how many hours until failure, meaning the system had run out of dice and was stopped waiting. From this report, 0.1% of the dice being missed would lead to a failure after 53 h, giving an operator sufficient time to restock these dice during a shift. The DES estimated that when 0.3% of the dice were being missed the system would shut down in less than 20 h, and an alert was sent to the operator to restock. The DES also estimated that when 0.7% of the dice were missed, the system would completely shut down in under 10 h, and thus, it shut down the physical demonstration factory and alerted an operator to resolve this issue. These results are subject to change and in another scenario — with different speeds or distributions — this time until failure would change, so having a live connection adds significant value. A connected DES can accurately model the current scenario and identify changing targets of how many dice could be missed.

It was shown in this test that a use of live data in the DES model accomplished what is otherwise impossible in traditional DES models. The connected model updated, in real time, distributions that effected the performance of the demonstration factory and was able to use these updated

distributions to accurately adjust future predictions. Furthermore, the digital twin allows for adaptable adjustments based on live data parameters. This test further demonstrated how DES could be used to close the loop. Using a connected DES, we were able to input data from the database and write packets of information back into the database for our other systems to read and access. In this way, the loop was closed, so workers could receive live updates, and in extreme situations, the digital twin even took control and shut down processes. Although there are other methods to closing the loop, many of which are in place in state of the art manufacturing settings, the ability to close the loop using a digital twin allows for integration of emerging technologies into antiquated systems.

## 5 Conclusions and future work

A digital twin was created using DES software that digitally represented our demonstration factory system. This DES model was validated using historical data. Additionally, a second DES model was connected in real time to our demonstration factory process. In addition to using historic data,

this second DES model was updated in real time, without user interaction, and the model itself could control certain factory parameters and alerts to make smart decisions in a factory environment creating a smarter closed-loop digital twin.

Using these DES digital twins, the benefits of using a real time connected DES as opposed to a traditional historical data DES was analyzed and quantified using three tests.

1. The throughput and bottlenecks test aimed at assisting a factories desire to increase throughput by tracking performance. Although the long-term predictions, an hour or more, of these two types of DES models were very similar, the connected model enhanced our ability to predict short term performance, including
  - 35% improvement in the precision of predictions.
  - Twice as accurate in making short-term predictions over 5-min intervals.
2. The supplier quality test quantified the benefits of a connected DES when a change in material or suppliers results in unexpected change in quality and production.
  - Unexpected changes in production were unaccounted for by the historical DES, but the connected DES model immediately began making adjustments in its predictions.
  - Within 15 min of this change in supply, the connected DES alerted operators of potential long-term scenarios.
3. The process alignments test used the connected DES to identify the need for maintenance in the demonstration factory.
  - A distribution of product that was falling off the conveyor was updated live in the connected DES model. This value reflected a maintenance need on the factory floor.
  - The DES model accurately predicted failure and through live connections stopped production and alerted operators, preventing waste.

Ultimately, it was determined that a traditional historical DES makes accurate long-term predictions using historical averages, but a real time connected DES with live connections to the demonstration factory can be used to predict significant changes where correlation between inputs and outputs is not immediately obvious. This benefit was quantified to better show the improved performance of the digital twin. The application of these findings can be generalized across a wide spectrum of manufacturing enterprises and give greater insight when determining if a digital twin is a viable addition to forward thinking smart enterprises.

Future research points to evaluating the speed at which problems may be identified and viable options for automating those responses. In some cases, the tests here were performed using 5-min packages of information. Research could be done aimed at shortening or lengthening that time and observing results to try to achieve more similar results fit to the physical system. Tests were done assuming constant relative variance, additional tests may be performed that aim at quantifying variation under various operating conditions of interest. Additionally, an in-depth comparison between the benefits of DES and predictive analytics may be explored, particularly as it relates to their ability to close the loop on a system.

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**Availability of data and material** The datasets used and material of this study may be made available by the corresponding author upon reasonable request.

## Declarations

**Ethics approval** Not applicable.

**Consent to participate** Not applicable.

**Consent for publication** The authors approve of publication of this manuscript and accompanying images.

**Competing interests** The authors declare no competing interests.

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