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ENGAGING STAKEHOLDERS TO EXTEND THE LIFECYCLE OF HYBRID SIMULATION MODELS

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ABSTRACT

Developing a simulation model of a complex system requires a significant investment of time, expertise and expense. In order to realize the greatest return on such an investment, it is desirable to extend the lifecycle of the simulation model as much as possible. Existing studies typically end after the 'first loop' of the lifecycle, with the computer model suitable for addressing the initial requirements of the stakeholders. We explore extending the modeling lifecycle to a 'second loop' by introducing an existing hybrid simulation model to a new group of stakeholders and further developing it to capture new requirements. With the aid of an example application, we explain how the hybrid model facilitated stakeholder engagement by closely reflecting the real world and how the model lifecycle has been successfully extended to maximize the benefit to Eurostar International Limited.

1 INTRODUCTION

The model development process is often explained as consisting of four steps: i) system description, ii) conceptual model, iii) model design and iv) model coding (Robinson 2013). These steps exist in this particular order because information from one is required to inform the next. However, the process is known to be highly iterative (Willemain 1995; Balci 1994; Robinson 2013) and as a modeler progresses through the simulation lifecycle loop (conceptual modeling, model coding, experimentation and implementation (Robinson 2004) and begins to experiment with the model, he / she may be prompted to repeat some or all of these steps.

In this study, we discuss work conducted in partnership with Eurostar International Limited (EIL). A sophisticated hybrid simulation model (Mustafee et al. 2017; Brailsford 2015) was previously developed by working with key stakeholders from the leadership and management teams of EIL. We wanted to explore engaging a new group of stakeholders as part of a further iteration of the model development process to extend the lifecycle of the existing simulation model. We discuss how this process can incrementally add detail and operational effectiveness to simulation models.

Much literature has examined the 'first loop' of the simulation lifecycle (Robinson 2004), this study contributes to our understanding of the modeling process by demonstrating how the simulation lifecycle loop can be extended by a 'second loop'. Robinson et al. (2014) suggested that the way to progress facilitated modeling is to develop a methodology. We discuss capturing the requirements of a new group of stakeholders and, further, successfully informing the new group through a second loop. This has yet to be considered in the literature. We discuss how an existing hybrid simulation model of EIL's London terminal, situated in St. Pancras International Station, was incrementally extended by soliciting input from a new group of stakeholders in order to help create a new EIL tool for controlling peaks in passenger arrival rate and reducing queues. We contribute to the growing interest in hybrid simulation by providing a case study of a hybrid model used to support industry and discussing how the hybrid approach helped reduce the "*communication gap*" between modeler and stakeholder (Jahangirian et al. 2015).

Prior to this study, a hybrid simulation model was developed with key stakeholders from EILs leadership and management teams. In this study, we discuss engaging new stakeholders via workshops to extend the lifecycle of this simulation. First, we highlight some background literature relevant to this study (Section 2), provide an overview of how EILs London terminal currently operates and explain the proposed new system for managing peaks in passenger arrivals (Section 3). Following this, we briefly explain how the existing simulation model was developed and summarize how, through engaging a new group of stakeholders in a workshop, it was modified to address peak passenger arrivals (Section 4). We then present some simulation results and provide an overview of the workshop findings (Section 5). Finally, we discuss the process by which stakeholders were engaged to extend the simulation lifecycle using a second loop (Section 6) and offer a few concluding remarks (Section 7).

2 BACKGROUND

There is a considerable amount of literature describing the steps undertaken during the lifecycle of a simulation study (Balci 2012; Banks, Carson, Nelson, and Nicol 2010; Hoover and Perry 1989; Law 2007; Nance 1994; Kreutzer 1986; Pidd 1988; Robinson 2004; Sargent 2001). These differ in the level of detail they offer. For example, the description of Kreutzer (1986) contains nine steps while that of Pidd (1988) just three. Regardless, within each, it is possible to recognize a similar process. In this study, we envisage the modeling lifecycle consisting of four stages (for all simulation paradigms) as defined by Robinson (2004): conceptual modeling, model coding, experimentation and implementation (Figure 1a). Further, we follow the model development process discussed in Robinson (2013) (system description, conceptual model, model design, model coding — Figure 1b), which consists of a more detailed model of the first two steps of the lifecycle loop. Here, rather than representing the order of the steps, the solid arrows represent the flow of information required to develop a computer model through what is known to be a highly iterative process (Willemain 1995; Balci 1994; Robinson 2013). The dashed arrow shows that there is a correspondence between the resulting computer model and the real world.

Stakeholder involvement is considered beneficial for the success of simulation studies (Eldabi, Paul, and Young 2007; Fone et al. 2003; Jun, Jacobson, and Swisher 1999; Gunal and Pidd 2005; Lowery et al. 1994; Wilson 1981). Failure to involve stakeholders throughout the simulation study lifecycle can often lead to the findings not being implemented (Brailsford and Vissers 2011; Fone et al. 2003; Young et al. 2009). At the same time, in organizations with many decision makers, involving all relevant stakeholders through all stages may not be feasible.

Relatively recent studies have explored the benefits of involving stakeholders in the modeling process (Kotiadis et al. 2014; Robinson et al. 2014). Tako and Kotiadis (2015) present a framework for involving stakeholders throughout the model lifecycle. However, these studies typically end after the first loop of the lifecycle model, with the computer model that is developed suitable for addressing the initial requirements of stakeholders being the key outcome of the study. Much less work exists exploring the possibility of extending the modeling lifecycle with a second loop (see Figure 1a) to capture changing stakeholder requirements or include new requirements from a new group of stakeholders.

In a summary of causal factors of low stakeholder engagement, Jahangirian et al. (2015) identifies "*difficulty with understanding and working with simulation tools, techniques and models*" as a key issue. Hybrid simulation models, i.e., single conceptual models implemented in software using more than one simulation paradigm (Mustafee et al. 2017; Brailsford 2015; Brailsford et al. 2018), have gained popularity in recent years. Models combining agent-based modeling (ABM) with discrete-event simulation (DES) are particularly appealing in service industry applications (Brailsford 2014) because, as Siebers et al. (2010) notes, ABM is well suited "*when the goal is modeling the behaviors of individuals in a diverse population*". Although it is possible to replicate many of the benefits of ABM using a traditional DES

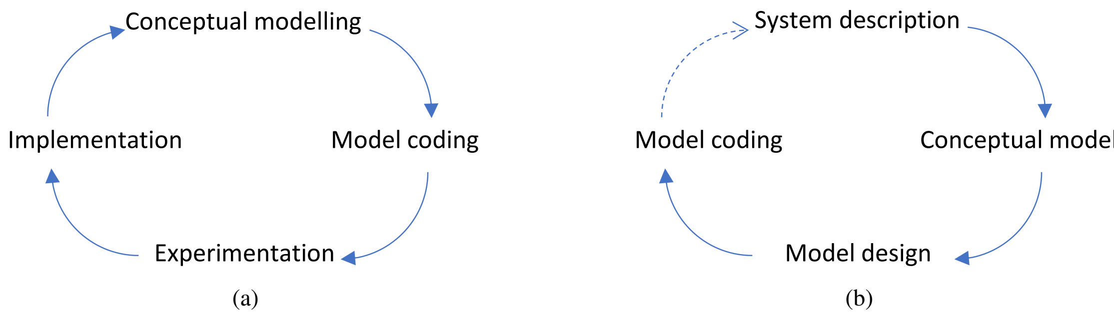


Figure 1: a) The simulation model lifecycle. b) The model development process.

approach (Brailsford 2014), a hybrid approach may help reduce the "*communication gap*" (Jahangirian et al. 2015) between modeler and stakeholder as this allows for the system to be captured in a way that is recognisable to stakeholders.

3 CASE STUDY

EIL is the only high-speed railway company operating international train services between London and continental Europe via the Channel Tunnel. Its core destinations including Paris, Brussels, Lille and Amsterdam. Further, it operates services to Disneyland Paris and runs seasonal trains to the south of France and the French Alps.

As EIL operates an international service, passengers are required (similar to an airport) to pass through security screening and border control before boarding the trains. Due to the growth in demand for EIL services since it first began operating in 1994, the throughput of passengers at these checks has become a bottleneck, sometimes resulting in long queues. EILs passenger throughput at terminals is a limiting factor in terms of the number of tickets that can be sold and the number of services that can be operated. A number of projects are underway within EIL to increase capacity at its terminals and speed up passenger throughput at checkpoints. One such project has been to develop detailed simulation models of each terminal.

All passengers traveling at EIL's London terminal are required to pass through a series of checks (i.e., security / x-ray, UK border control and French border control) before boarding the trains. Figure 2 shows a simplified diagram of the checks all passengers are required to pass through. As shown, passengers proceed through the system from left to right. Every passenger must pass through exactly three of the six checks ($c_1, c_2, c_3, ..., c_6$). Each check has **S** servers with throughput rate **R** drawn from some distribution. Ahead of each check is a queue ($q_1, q_2, q_3, ..., q_6$) with a capacity to hold **N** passengers. Different routes are available for eligible passengers depending on characteristics such as nationality, type of travel documentation and age (e.g., some routes use e-gates, for which require passengers be European citizens over the age of eighteen and traveling with a biometric passport). There are three possible routes in all. All passengers can proceed along route 1, (via c_1, c_2, c_4) but only a subset of those passengers could proceed along route 2 (via c_1, c_3, c_5) and a further subset along route 3 (via c_1, c_3, c_6). Because of the limited queue capacity ahead of each check, it is possible that the queue will back up to a previous check, thereby preventing further throughput. For example, q_4 may reach its capacity n_4 and prevent c_2 from processing any more passengers. This in turn may cause q_2 to reach its capacity n_2, leading to the obstruction of c_1 and, in turn causing route 1 to become completely blocked. Each queue and check operates on a first come first served policy, hence, now passengers held in q_1 who could proceed along routes 2 and 3 are blocked by passengers waiting to pass through route 1. This can lead to situations where q_2 and q_4 are at capacity but q_3, q_5, q_6 are well below capacity or even empty. After the first check there is limited space, hence, $n_2, n_3, ..., n_6$ are finite. There is significant space to extend q_1 if necessary (much more than is typically used), hence, n_1 can be considered infinite. After completing all checks, passengers wait in the departure area (which has a limited capacity) until they are notified of their platform and requested to board the train.

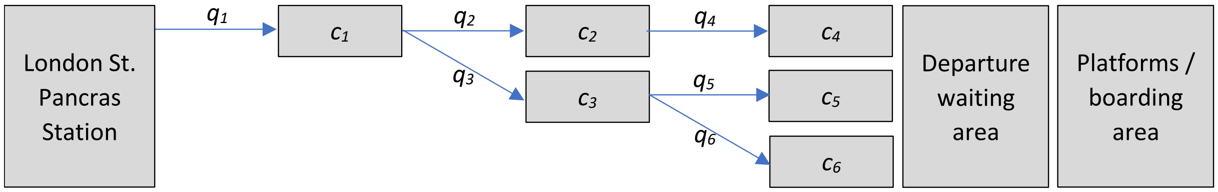


Figure 2: Process flow diagram of the required passenger checks at EIL's London terminal.

If the departure area reaches capacity, throughput through all the checks would be stopped until additional capacity is made available.

Passengers purchase tickets from EIL for a specific service with a set departure time. Until recently, information on tickets and pre-travel information provided by EIL through various channels (e.g., online or via e-mail) informed all passengers to arrive forty-five to sixty minutes before departure. Passengers are also informed that check-in will close thirty minutes before departure. In reality, it is normally closed twenty minutes prior to departure. If a passenger arrives at the checks with less than twenty minutes before departure, his / her ticket will not open the gates at the first check and he / she is either turned away or re-allocated onto a later train. By default, check-in opens ninety minutes before departure, however, that information is not passed to passengers. Terminal Duty Managers (TDMs) can adjust the check-in opening time as they see fit on each day. If a passenger attempts to go through the checks before check-in opens, his / her ticket will be rejected and he / she will be asked to wait. EIL will not allow passengers through the checks before their check-in opens due to limited capacity in the departure area (see Figure 2).

EIL collects a wealth of data relating to passenger movements in its terminals. From analyzing historical data, it is possible to observe that passengers arriving for a train are approximately normally distributed with the arrival rate peaking forty-five minutes before departure. On any given day, there is variation from this distribution (i.e., a margin of error) which is particularly dependant on passenger profile. For example, variation is typically observed to be greater on public holidays when large numbers of families and groups travel compared to work days when high numbers of business and frequent travelers make journeys.

Demand for EIL services varies throughout the year and week. Peak days exist when the number of travelers is significantly higher than average. Similarly, on any given day, EIL services see variation in demand, typically with a morning and a more significant afternoon peak corresponding to the start and end of the working day. EIL's service timetable reflects this variation in demand with more frequent services during the morning and afternoon peaks. At peak times on peak days, it is a challenge to process the high number of passengers through the required checks (Figure 2) fast enough to ensure they all are able to board their train on time. Sometimes, long queues can result and occasionally passengers have missed their train while waiting in queues. Ahead of anticipated peak days, EIL's TDMs will often ask for notifications to be sent to passengers travelling on certain services via SMS (short message service, aka text messaging) requesting them to arrive earlier, either sixty to seventy-five minutes or seventy-five to ninety minutes before departure, in an effort to better manage peaks in passenger arrivals and minimize queues.

As EIL's demand has grown, SMS sends are now regularly request by TDMs. This system incurs a cost to EIL and passenger can receive multiple notifications about the time they should arrive, which can be confusing. Similarly, providing EIL with a mobile phone number is not compulsory, thus, the message will not be received by all travelers (typically around half). Hence, EIL has developed a new tool, known as the Dynamic Arrival Tool (DAT), to replace SMS messages. The DAT is a software tool that allows EIL to modify the arrival time information on a passengers ticket, and similarly the information that passenger will see online and receive via e-mail. Figure 3 illustrates the passengers' movements before joining the queue for the checks in EILs' terminal and how they are impacted by notifications to arrive early.

TDMs, responsible for day-to-day management of EIL's terminals, are typically focused on passenger numbers in the near future and will identify services for which they would like passengers to be notified to arrive early via SMS one to two weeks in advance. In order for the DAT to be effective, services for

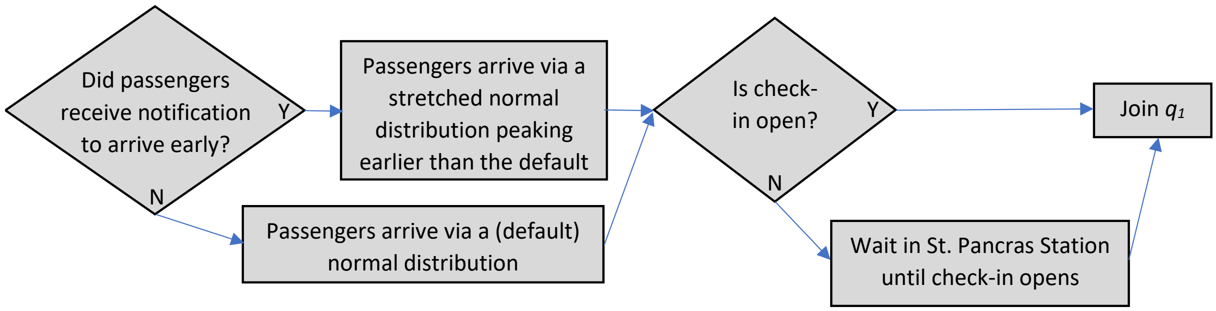


Figure 3: Passenger movements before required EIL checks. When passengers arrive, if the 'check-in' for their service is open they join q_1 (see Figure 2). Otherwise, they wait in the station until check-in opens.

which TDMs would like passengers to arrive early must be identified in advance of them downloading their tickets (the vast majority of EIL ticket sales are online) or purchasing it in one of EIL's terminals. Tickets are typically available for purchase six months in advance of the date of travel, hence, to ensure a notification sent via the DAT reaches all passengers, the information must be adjusted in advance of that. From analysis of EIL's data, the majority of passengers ($> 50\%$) do not download their ticket more than a week in advance of travel. Therefore, if information regarding arrival times were to be adjusted a week in advance, it would reach only half of travelers (comparable to the SMS system).

4 MODELING METHODOLOGY

A simulation model of EIL's London terminal and passenger checks was developed separately from the DAT (in a 'first loop' of the lifecycle) with stakeholders from EIL's leadership and management teams. A hybrid ABM and DES approach was used to develop a model in AnyLogic (AnyLogic. 2019). In the model, agents (passengers) are generated and prescribed a series of traits including age, nationality, type of identification documentation, the frequency of travel with EIL, details of the service they are traveling on, class of ticket and size of the group they are traveling with. All of these parameters impact the route each passenger, or group of passengers, is able to pass through the checks (see Figure 2). The model incorporates EIL's departure timetable and simulates prescribed passenger numbers arriving at the terminal in advance of a scheduled service and proceeding through the checks (a series of discrete processes) after check-in is opened. Passengers interactions with each other and their environment are governed by a social force model (Helbing and Molnár 1995) (a common ABM method used in pedestrian modelling). As the simulation is run, queues can be observed building ahead of the checks.

To initiate a 'second loop' of the lifecycle, a workshop was held with TDMs, representatives of EIL managing the new DAT and representatives of the team that developed the DAT software. The purpose of the workshop was to develop a conceptual model (Robinson 2013) such that the potential impact of the new DAT could be captured and (later offline) incorporated into the existing simulation. TDMs were asked to explain how they currently identify days and specific services for which they notify passengers to arrive early via SMS. They were further asked to explain what they think would be the impact of asking those passengers to arrive early. In the workshop, the TDMs were given a timetable for a specific day including departure times and the number of travelers on each service along with information summarizing passenger profiles. The example timetable they were given was representative of a peak day, with a total number of travelers close to the highest EIL sees on a single day in a typical year. The timetable and summarized passenger profile details, in the format provided, were something very familiar to TDMs. They regularly access information like this as part of the terminal operational planning process for upcoming days. They were asked to identify which services they would like to target with notifications to arrive earlier than the default forty-five to sixty minutes and by how much: sixty to seventy-five minutes or seventy-five to ninety minutes before departure. Lastly, they were asked if and how they would adjust the check-in time.

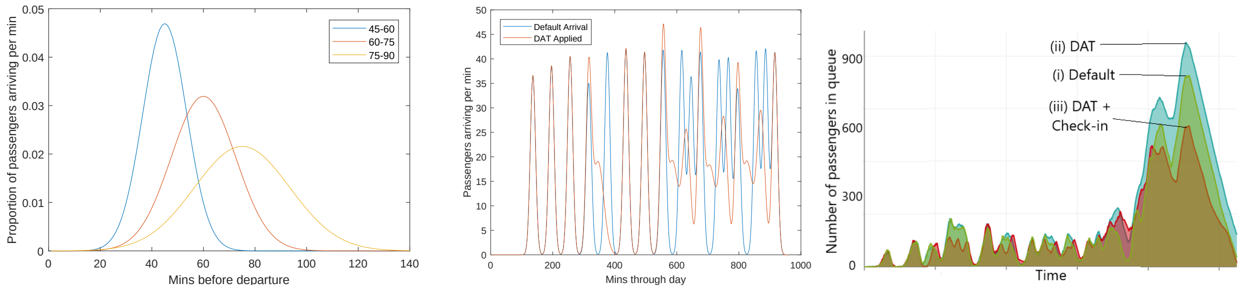
The DAT was not included in the original scope of the simulation model (nor the impact of the existing SMS system). The existing simulation model was presented to the workshop group. The model developer explained the benefits of simulation, how the existing model was currently being used to support EIL and, further, how it could be extended to capture the impact of notifying passengers to arrive early via the SMS or DAT systems. It was explained that the timetables annotated by the TDMs during the workshop, along with the passenger numbers and passenger profile details, provided the input data for the model and would be simulated such that the impact of the early passenger arrival notifications could be tested. After the workshop, necessary model coding adjustments were made. Specifically, changes were made such that the arrival distribution of passengers for any train could be uniquely controlled rather than passengers for each train arriving according to the same distribution. The results that follow (in Section 5 are based on simulations and analysis of the workshop timetables in the modified simulation model. Once simulation results had been computed, a further workshop was organized to feedback results and findings to the stakeholders.

5 WORKSHOP FINDINGS, EXPERIMENTATION AND RESULTS

During the first workshop when asked to explain the impact of the SMS / DAT systems, TDMs said they would reduce the peaks in arrival rate. Looking at a single service in isolation they are correct. Figure 4a illustrates the arrival distribution of passengers ahead of a specific service and the impact of notifying passengers to arrive early via SMS, as explained by the TDMs. Notifications shift the peak and stretch the (approximately) normal distribution of passenger arrivals. This arrival distribution is clearly evident in EIL data. Controlled experiments have previously been conducted within EIL to observe the impact of SMS sends. TDMs anticipate that the impact of the DAT will be comparable to the SMS system. However, from the TDMs explanation, they understood that doing this also reduced arrival peaks over the whole day and subsequently the queue behind the first check (q_1 in Figure 2). Although this seems logical, it is in fact incorrect (see Figure 4b).

In the feedback workshop Figure 4b was explained to the TDMs. This takes the known arrival distribution per service, the day's timetable and passenger numbers and computes the predicted arrival rate of passengers throughout the day. This is computed for all passengers receiving the default arrival information and, hence, arriving via the default arrival distribution (i.e., forty-five to sixty minutes prior to departure). It is also computed for the case where passengers on certain services have been asked to arrive early (i.e., sixty to seventy-five or seventy-five to ninety minutes prior to departure as determined by the TDMs in the workshop) and, hence, arrive via an extended distribution. Note that peaks are either not reduced or the reduction is negligible. In some cases, this action can even increase the peak arrival rate. Typically, due to the congested timetable, peaks are simply shifted. For example, when passengers are asked to arrive early for one service this will shift the arrival peak. Instead of arriving in parallel with passengers for the service that follows, passengers who have been asked to arrive early arrive in parallel with passengers for the service before them and, hence, the arrival peak comes earlier. Therefore, the logic of the TDMs that this will reduce the queue ahead of the checks does not materialize. The simulation results support this.

Further, in the feedback workshop, the TDMs were shown Figure 4c which gives an example of results generated by the simulation model, plotting queue length behind the first check (q_1 in Figure 2) throughout the day. Three scenarios are shown: (i) all passengers arrive via the default arrival distribution with the default check-in opening time, (ii) the arrival distribution is shifted for certain services as a result of the TDMs recommendation to notify passengers to arrive early but check-in opening times are unchanged, (iii) the arrival distribution is shifted as (ii) and check-in opening times are adjusted as appropriate. The results show that asking passengers to arrive earlier without appropriately adjusting the check-in opening time can actually make queues worse (i.e., longer). Asking passengers to arrive earlier and adjusting the check-in opening time has the real potential to reduce queues. The plot shows the significant afternoon peak of the day, corresponding to multiple peaks in passenger arrival rate in quick succession as shown in Figure 4b.



(a) (b) (c)

Figure 4: (a) The arrival distribution when notifying passengers to arrive at different times on any service. (b) Predicted arrival distribution of passengers throughout the day for the workshop timetable (no change in peaks when DAT applied). (c) Simulation results of queue length throughout the day for three scenarios.

Beyond the specific example discussed, the modeler performed a number of other related simulations. For example, the DAT has the potential to reach a greater proportion of passengers on any service than the SMS (see Section 3), which, due to a contact number not being provided by all passengers, only ever reaches approximately 50%. A further ensemble of simulations showed that as the arrival distribution for a service is stretched further and the peak pushed even earlier (see Figure 4a), controlling the check-in time becomes even more important.

The simulation results showed that when adjusting passenger arrival times together with the check-in opening times, the length of the queue behind the first checkpoint could be reduced. Specifically, for passengers traveling on a service notified to arrive early, the check-in needs to be opened late (i.e., less than the default ninety minutes before departure). The logic of the simulation was designed such that passengers who arrive in the station before check-in is open do not immediately join the queue, but wait elsewhere in the station until the check-in is opened. If passengers arrive and the check-in for their service is open, they will automatically join the queue. This logic was agreed with stakeholders involved in the initial model development (the first lifecycle loop) as representative of passenger behavior. Hence, when asking passengers to arrive early and leaving the check-in opening time at the default, passengers join the queue ninety minutes before departure. Asking passengers to arrive early but not opening the check-in has the effect of allowing the initial queue to clear before inviting the next service to join. When the late check-in is opened, a large number of passengers for that service are already in the station and so quickly flood into the queue. When this was explained to TDMs in the feedback workshop, they agreed this was an accurate representation of the system and passenger behaviour and understood why controlling the check-in time was important when adjusting arrival time.

It was clear that at the time of the first workshop TDMs had not appreciated the importance of controlling the check-in time when passengers have been notified to arrive early. When the simulation results were explained in the feedback workshop, TDMs became newly aware of the impact of adjusting the check-in opening time. They agreed with the logic of the simulation model that if passengers were asked to arrive early and the check-in was open, they would join the queue to go through the checks, which could cause problems if passengers for the earlier service had not yet been cleared. For example, they could then explain that when there are two departures in quick succession, they may open the check-in of the second service late to ensure all the passengers for the first departure have passed through the checks before those for the second departure start going through. Once the simulation results had been explained, TDMs commented that in the past, notifying passengers to arrive early often seemed beneficial. However, similarly, they also noted that on some occasions, despite notifying passengers to arrive early, long queues formed and getting passengers through the different checks in time for their service have been problematic. They commented that this lack of coordination between the arrival time and check-in time may play a part in the problem, indicating that they agreed with the simulation findings.

On any day, the TDM on duty that is responsible for setting the check-in times may be different from the TDM who previously asked for notifications to be sent to passengers to arrive early (via the DAT or SMS). The TDM on duty on a given day, might not be aware of the details of the notifications sent to passengers (i.e., which specific services were asked to arrive early) and, therefore, is unlikely to consider this when setting the check-in times. It was therefore suggested by the modeler that it would be helpful if the DAT could output the adjustments made to passenger arrival times each day, such that TDMs could take this into account when setting check-in times. This was acknowledged by the TDMs as a helpful recommendation and something they believed would improve operation of the terminal by reducing passenger queues. They have, as a result, requested the team developing the DAT system to implement this feature.

6 DISCUSSION

Prior to this study, a loop of the simulation lifecycle (Robinson 2004) had already been completed (see Figure 1a) and a sophisticated hybrid simulation model developed. The task presented here was to introduce the model to a new group of stakeholders and perform a second loop of the lifecycle. There were three challenges involved in engaging stakeholders to ensure willingness to act on simulation findings (Brailsford and Vissers 2011; Fone et al. 2003; Young et al. 2009); 1) developing buy-in for the 'second loop', 2) engaging the stakeholders in the model development process to extend the existing simulation model and 3) completing the 'second loop' by validating the model. The following discusses each of these challenges in turn.

6.1 Developing Buy-In for the 'Second Loop'

The first challenge was to create buy-in to engage the new group of stakeholders with the existing model by explaining the benefits of exploring the roll-out of the DAT system via simulation. This was necessary to initiate a second lifecycle loop and, broadly, followed the principals of the Checkland (1999) inquiring / learning cycle (summarized by Figure 5). It was explained to the workshop participants that the real world (i.e., EIL's terminal and passenger movements) is a complex system, consisting of relationships between many sub-systems. A model of that system, based on explicitly stated worldviews (i.e., a perception of what is going on in the real-world), has been developed and is being used to explore the complex system. An investigation, relating to any proposed changes to the layout or operational procedure of the terminal, can be structured to question initial perceptions. Further to the investigation, it is hoped learning points will be generated and actions for further improvement can be suggested, assuming there is acceptable accommodation among stakeholders (i.e., changes to the system that have a positive impact). The inquiry was pitched, in principle, as an ongoing process and best conducted with a wide range of interested parties. It was explained to the stakeholders that their engagement with the project was essential for its success and to ensure its findings were useful. The modeling methodology was explained to be a useful tool to facilitate engagement with key stakeholders in better understanding and improving the complex EIL system. Emphasis was given to the idea that the model is a method for exploring the problem scientifically and an opportunity for learning as opposed to a tool for precisely forecasting queue lengths (Epstein 2008). It was further explained that in a simulation environment, ideas can be tested risk-free, helping to build knowledge and understanding or generate data that may not otherwise be available. From this, new insights can be gained to aid with design choices and operational decisions before implementation and ensure the best possible solution (Robinson 2004).

Sophisticated visualization in AnyLogic (AnyLogic. 2019) helped to convey the purpose of the model and its potential benefits to the non-technical audience. It is a recognized benefit of simulation models that they can provide a powerful means of visualizing and communicating ideas and can be used to help stakeholders come to a consensus when testing different theories (Robinson 2004). The workshop group was happy to accept that modeling and simulation could be used to replicate and understand complex situations that would be essentially impossible to observe, test and analyze with real-world experiments due

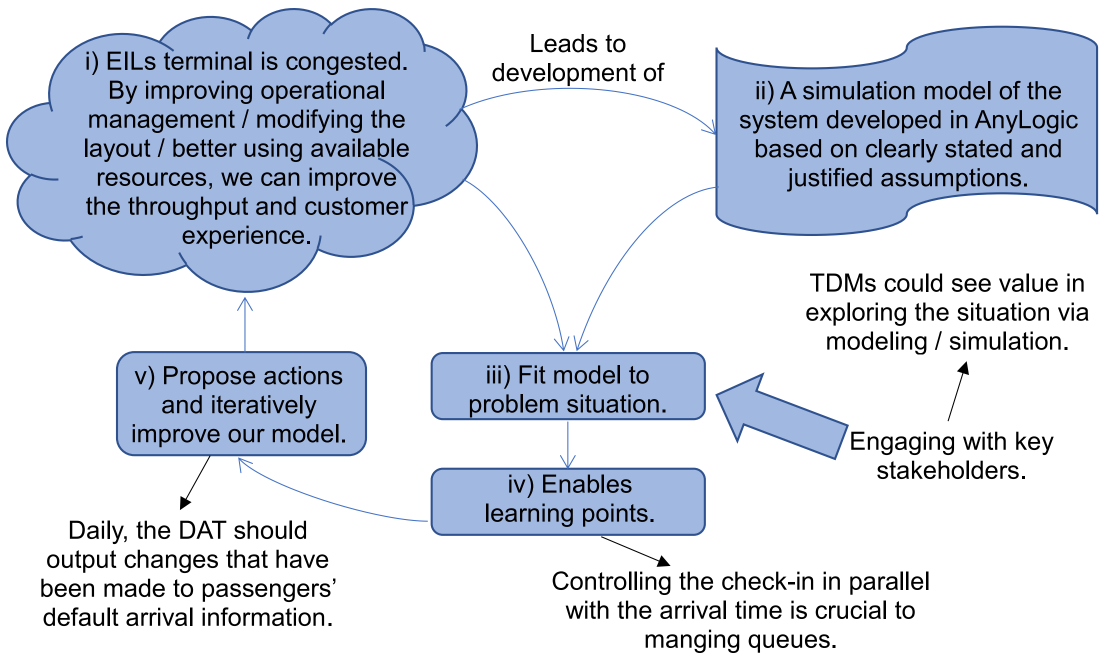


Figure 5: The inquiring / learning cycle of SSM adapted for this study from Checkland (1999).

to the scale of the task and expense involved in adjusting the terminal layout or operating procedure (Maria 1997). They could see the value of the simulation's potential to aid with decision making and understanding (Law 2009). A key finding of the study was that the hybrid approach adopted helped communicate the model design to the stakeholders (Jahangirian et al. 2015). It was explained that ABM captured agent (passenger) characteristics and interactions, while DES captured the process (security / border controls) the agents followed. TDMs could relate to the idea that when the profile of passengers changes, the interaction time with and routes available through the checks are affected. Although this could be captured using a purely DES approach, the ABM approach closely reflects the real world stakeholders are familiar with, thus making it easier for them to engage with. Providing specific examples of how the existing model had already benefited EIL further convinced TDMs of its potential value. It was made clear that building a simulation requires time and expertise (Robinson 2004) and is an iterative process (Willemain 1995; Balci 1994; Robinson 2013). It was openly acknowledged that all models and simulations have limitations that must be recognized with outputs only as good as the model and input data.

6.2 Engaging Stakeholders in the Model Development Process

The second challenge was to involve stakeholders in the model development process (Robinson 2013) — see Figure 1b. Through the first workshop organized, the new group of stakeholders (the TDMs) were involved in a further iteration of the model development process. The DAT and associated passenger characteristics extended the system description of EIL's terminal beyond the scope of the existing model. Facilitated by the modeler, the workshop identified a conceptual model capturing the effects of the DAT, from the perspective of the TDMs, such that the design of the existing computer model could be extended. After the workshop, a new model coding was implemented. In the feedback workshop, the simulation experimentation undertaken and results were explained in depth and any stakeholder questions were answered.

6.3 Completing the 'Second Loop'

Although it is only possible to assess validity after a model has been developed and findings shared, the process of validation should be considered part of the model development process and throughout the lifecycle, not just something to attempt after the model has been completed (Law 2009). An understanding of the inherent assumptions among stakeholders is essential and a key factor for them when judging the validity of the model for the particular investigation at hand. Any erroneous assumption, inappropriate input data, or errors in the model, will all inevitably lead to a loss of accuracy, usefulness and perception of validity among stakeholders. One purpose of engaging stakeholders through workshops is to ensure this understanding exists.

Previous work has noted that a modeler may be required to intervene in creating awareness of the learning that has been achieved (Nisbett and Wilson 1977; Robinson 2004; Rouwette, Vennix, and Felling 2009), which can subsequently help stakeholders develop actions. The modeler explained the problem observed from the simulation to the TDMs (i.e., lack of coordination between arrival and check-in times can lead to longer queues). TDMs agreed that the problem identified through the simulation study may be a key factor causing queues in the station, indicating that they consider the findings valid. Additional simulations undertaken by the modeler, beyond those specifically identified in the first workshop, demonstrated to the TDMs that the problem had been investigated thoroughly and further promoted validity among the group. TDMs requesting implementation of specific actions on the basis of the simulation findings (i.e., asking the DAT development team to include a new feature proposed by the modeler) confirms the validity of the model, completes the second loop of the lifecycle and successfully achieves the objectives of this study.

7 CONCLUSION

There are many reasons to undertake a modeling / simulation study (Epstein 2008). One is to promote a scientific habit of mind. The example we have presented demonstrates how this scientific habit of mind helped EIL maximize the potential gain from the introduction of a new Dynamic Arrival Tool (DAT) to manage peaks in passenger arrival rates. The study contributes by i) demonstrating how an existing simulation was extended via a second loop of the simulation lifecycle with the input of a new group of stakeholders and used to interrogate the operation of the DAT to identify its true source of benefit. Further, identifying and discussing that ii) the hybrid ABM and DES approach used was reflective of the real world (more so than pure DES), which aided stakeholders engagement with the model and helped them to accept simulation findings as valid. This study discusses one incremental change to a vastly complex system consisting of many sub-systems and component parts. Through further applications of simulation and continually applying this scientific habit of mind, our aim is to improve our understanding of the system and continue to incrementally improve its performance for EIL. Due to the time, expertise and expense of modeling complex systems (Robinson 2004), iteratively extending the model in this manner will enable EIL to maximize its return on investment.

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