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The application of a hybrid simulation modelling framework as a decision-making tool for TPM improvement

Abstract

Purpose – Promotes a system dynamics-discrete event simulation hybrid modelling framework; one that is useful for investigating problems comprising multifaceted elements which interact and evolve over time, such as is found in TPM.

Design/methodology/approach – The hybrid modelling framework commences with system observation using field notes which culminate in model conceptualization to structure the problem. Thereafter, a system dynamics-discrete event simulation hybrid model is designed for the system, and simulated to proffer improvement programmes. The hybrid model emphasizes the interactions between key constructs relating to the system, feedback structures and process flow concepts that are the hallmarks of many problems in production. The modelling framework is applied to the TPM operations of a bottling plant where sub-optimal TPM performance was affecting throughput performance.

Findings – Simulation results for the case study show that intangible human factors such as worker motivation do not significantly affect TPM performance. What is most critical is ensuring full compliance to routine and scheduled maintenance tasks and coordinating the latter to align with rate of machine defect creation.

Research implications/limitations – The framework was developed with completeness, generality and reuse in view. It remains to be applied to a wide variety of TPM and non-TPM-related problems.

Practical implications – The developed hybrid model is scalable and can fit into an existing discrete event simulation model of a production system. The case study findings indicate where TPM managers should focus their efforts.

Originality/value – The investigation of TPM using system dynamics-discrete event simulation hybrid modelling is a novelty.

Keywords – TPM practices; System dynamics; Discrete event simulation; Hybrid modelling

Paper type Research paper

1. Introduction

Many problems in production are multifaceted and involve human-related actions/inactions. Udo and Ebiefung (1999) claim that several technical and social changes occur in a system, and where workers are involved, self-interests and management factors are often at play. A maintenance function consists of human and system elements (Shanmugam and Paul Robert, 2015). It includes human errors and reliability (Sheikhalishahi et al., 2016), commitment to continuous improvement initiatives (García Arca and Carlos Prado, 2008; Stimec and Grima, 2018), worker attitude (Ahuja and Khamba, 2008; Binti Aminuddin et al., 2016), maintenance plans and agendas (Basri et al., 2017) and a host of other concepts. Maintenance also covers multiple time horizons (Basri et al., 2017; Seif and Rabbani, 2014). How does one go about investigating a multifaceted phenomenon such as Total Productive Maintenance (TPM), that covers various time horizons? A number of approaches, tools and techniques have been advanced to investigate different concepts relating to TPM. Basri et al. (2017) while reviewing the literature on Preventive Maintenance Planning, highlighted some of these methods such as Artificial Intelligence, Mathematical Formulation, Multi-criteria Decision Analysis, Critical Analysis, and Simulation. Of all these methods, simulation modelling such as System Dynamics (SD), Discrete Event Simulation (DES) and Agent Based Modelling can be used to better understand the complex interactions that exists between different concepts relating to the same system. These methods can also be used to project TPM activities into the future. They are a special class of simulation. There are many ready-made software packages consisting of model building blocks for ease of building the simulation model, and 2D/3D graphical interface for visual effects that can be used to mirror the actual system being investigated. SD and DES are the most commonly used in business and manufacturing and the latter is more prevalent (Jahangirian et al., 2010).

TPM has been well investigated through simulation modelling (Mahfouz et al., 2011; Omogbai and Salonitis, 2016; Thun, 2006; Shahanaghi and Yazdian, 2009; Jambekar, 2000; Duffuaa et al., 2001; Garza-Reyes, 2015; Zuashkiani et al., 2011). SD and TPM has been presented (Jambekar, 2000); so also has DES with TPM being advanced (Duffuaa et al., 2001; Garza-Reyes, 2015). The focus of majority of these studies has been on finding an optimal maintenance plan (Alrabghi and Tiwari, 2015), which rarely considers the behaviours and attitudes of those who will carry out those plans. Whereas, even the best laid plans and strategies can fail if workers are not committed to TPM or if managers do not key into the key principles and enforce their full adherence by those involved. Worker attitude to maintenance is an important element of TPM (Ahuja and Khamba, 2008; Goh and Tay, 1995). Concepts relating to worker attitude and human factors are not easy to model (Shin et al., 2014; Baines et al., 2005), and this may be the reason they are rarely included in a simulation model. But can a simulation model realistically represent the problem situation if the attitudes and motives of those involved in the system are not considered?

Although TPM is not a new concept, the development of novel methods of investigating it continues (Lazakis and Ölçer, 2016; Kumar et al., 2018). The current work is part of an ongoing research effort that is focused on advancing a system dynamics-discrete event simulation (SD-DES) hybrid modelling framework. It is useful for investigating, comprehensively, a complex system with its multifaceted elements that interact and evolve over various time horizons. In the current study, it is used to investigate and take decisions regarding TPM for a bottling line. TPM performance is linked to line throughput, but TPM is investigated on the basis of the maintenance schedule and human factors such as work attitudes and habits.

2. The hybrid modelling framework

SD-DES hybrid modelling is a special case of mixed-method SD and DES, where SD and DES sub-models are built to represent different aspects of the system for example broad/focused problems (Brailsford et al., 2010) as well as non-physical/physical concepts (Alvanchi et al., 2011). In relation to TPM, a broad problem may describe how TPM in general affects manufacturing throughput and company profit, while a focused problem would look into the detail TPM practices. As regards physical and non-physical elements, experience level of maintenance personnel can be considered as non-physical, while number of tasks to accomplish per routine check can be considered as physical. The reasoning behind a hybrid model is that the sub-models, SD and DES, interact, exchanging data, as the hybrid model is run. This sub-model communication mimics the real-life situation where elements as represented by the two modelling paradigms, are influencing each other in a back-and-forth way over time. For example, TPM-related issues such as machine downtime due to breakdown and repair are known to affect manufacturing throughput, meanwhile, pressure to increase manufacturing throughput may lead plant managers to skip scheduled maintenance tasks and machine defect removal in order to reduce machine downtime.

The SD-DES hybrid modelling framework being promoted views the problem through the lenses of systems thinking. Jackson (2003) defines a system as

"a complex whole the functioning of which depends on its parts and the interactions between those parts….. the traditional, scientific method for studying a system is known as reductionism".

TPM as a whole easily fits into this definition. It consists of tasks, resources, decisions, people, information processing, ill-structured problems, and many other parts that work in unison to create a complex and dynamic whole. To comprehensively investigate and model TPM, a systems view is needed, and investigating the relationships between the parts is crucial Jackson (2003). The promoted framework also views the problem as process flow with sequential tasks and activities. Production and manufacturing operations are classic examples of process flow systems. There is a flow of something that is tangible such as parts, activities and information. The choice of both a "systems" thinking and "process flow" view of the problem is deliberate so as to ensure the SD-DES hybrid modelling framework is applicable to diverse problems.

The promoted SD-DES hybrid modelling framework consists of two main parts: the assessment part and the simulation modelling part (see Figure 1). It has been developed by the authors and is currently being validated in a variety of problems and systems, the current case study being one of them. The whole process is an iterative one, whereby the hybrid is developed as the modelling process is progressed. Each part follows a structured sequence of activities, the whole of which makes up the hybrid modelling framework. Frameworks to guide a researcher through the entire SD-DES hybrid modelling process are a rarity (Chahal et al., 2013). We did not come across any framework that guides users on how to undertake preliminary investigation in order to conceptualize the intended hybrid simulation model, nor take one through the detailed modelling process.

The assessment part is what is used to gather preliminary data relating to the system or problem situation. It is during this phase that one begins to visualize how SM would be used in addressing the problem. The assessment is fixated on a specific area. It includes interviews with key participants in the system. In the interviews, use of unstructured questions is advocated because qualitative type of data is collected (Yin, 2014). Qualitative data is a rich source of information when one needs to tap into mental models of participants conversant with a system that is to be modelled (Sterman, 2000).

Interviews on their own are insufficient to fully understand the intricacies of a system (Sterman, 2000). Some responses from participants may be questionable, so observing the system from a neutral perspective is essential. Observation involves walking round and taking copious notes of everything that one sees that would enable an in-depth understanding and modelling of the system. Observations may also include arbitrary time studies.

Figure 1. Key parts of the hybrid modelling framework

Sifting through archival records, where they exist, is also essential. Knowledge about the problem area is a pre-requisite, otherwise one would not know what type of questions to ask or what to look out for. The literature provides invaluable information, it makes sense to read about contemporary issues relating to the problem area prior to undertaking an assessment of the system.

The assessment part would be able to reveal the root cause(s) of the problem, and possibly the type of improvements one needs to consider, based on personal experiences and what others have researched on the topic. However, validation of any proposed improvement remains to be tested either through a reality check or simulation modelling. The latter seems expedient when one considers uncertainty and disruptions to the real system with a trial-and-error approach.

It would be ideal if one could use a standardized and structured instrument for collecting the data, such as the Lean Sensei assessment tool (AME, 2017) or the Rapid Plant Assessment tool (Goodson, 2002) or even modified versions of them. This would help in asking the right questions or searching for the right material, for example. But problems and systems vary such that it is unlikely that one data gathering instrument can be used for multiple problems. If it is used, it would be too rigid (Woolley and Pidd, 1981). In addition, respondents may be unfamiliar with the terms the researcher has used in the instrument. To design an appropriate structured data format is time consuming. The preliminary enquiry is majorly an unstructured one. It is a continued cycle of questions ---> answers ---> reflect ---> questions ---> answers ---> … (Pidd and Woolley, 1980) until the researcher has sufficient information to conceptualize the intended simulation model. It may even be possible that planned questions need to be altered as new information is received.

The second part includes the simulation modelling phase of the hybrid modelling framework. This phase details the modelling process from conceptualization of the hybrid to building and experimenting with the model (Balci, 1998; Sterman, 2000; Robinson, 2004; Chahal et al., 2013; Abduaziz et al., 2015).

The SD-DES hybrid modelling framework is best described through its demonstration in a real-life case study such as one where TPM performance needs to be investigated on the basis of maintenance schedule and human factors such as work attitudes and habits. The SD-DES hybrid modelling framework was considered for the case because:

- The problem involved maintenance scheduling. Scheduling of any kind is often (and best) investigated using DES (Jahangirian et al., 2010)
- The nature of human factors such as work attitude and habits is considered as non-physical or non-tangible, which are best modelled using SD (Sterman, 2000).

- It consists of concepts that are physical (schedules) and non-physical (attitudes and habits) and which are interacting.

3. Assessment phase of the hybrid modelling framework

In line with what has been described in the previous section regarding this phase, an unstructured data gathering task was committed. A researcher needs to be familiar with the key constructs relating to a problem by being a part of the system, studying it, or familiarizing oneself through the literature. Most research undertakings have theoretical underpinnings which can be used to guide one on the type of information to gather and how to go about collecting it. If one were to use previous studies as a yardstick, TPM for example, is majorly about the practices one needs to undertake to ensure that machines are optimally utilized while operating at the highest efficiency levels possible; efficiency can be measured in terms of yield (non-defective products produced) per work shift. Records about machine yield and machine breakdown occurrence can be sifted through. The system can also be observed. In addition, employees who are knowledgeable about the system, for example, machine operators and maintenance personnel, can be interviewed to provide qualitative perspectives regarding TPM.

In the current study, time was spent discretely observing the behaviours of workers- machine operators and maintenance personnel. Machine operators and maintenance personnel were asked TPM-related questions such as breakdown occurrence, machine down time, repair efficiency, machine defect removal and throughput losses. Where documented records were not provided, employees who were familiar with the system were asked to provide credible estimates, for example percentage of machine defects that are not corrected because of unavailability of spare parts. The following field notes summarizes what was gleaned during the three-day assessment of the plant.

Wide variations in throughput were noticeable and majority of these variations were caused by machine unreliability. While machine unreliability was attributed to a variety of causes, the performance of routine checks/maintenance (RCM) as well as scheduled shut down maintenance (SDM) are those that can be managed at the shopfloor level. The focus on shopfloor level management is intentional because a number of decisions taken on the shopfloor can be implemented without recourse to top level management input. In other words, the results of the study can be implemented quickly, thereby allowing a quick turnaround for the hybrid modelling framework. Meanwhile, small (critical) parts of the shopfloor system can be modelled, as being representative of the whole system. This makes the modelling process simpler than modelling an enterprise-wide system, for example.

RCM was done every day for 1 hour, during which time the entire line is shut down. SDM was done every two weeks for eight hours when the entire line is shut down. Sub-optimal performance of both RCM and SDM causes machine defects to accumulate over time, resulting in machine efficiency deterioration and throughput losses. Losses in throughput leads to other types of behaviours such as pressure to skip defect correction if during the maintenance it is found that the defect cannot be repaired on time. When defects are not corrected during RCM or SDM, the efficiency of the machine drops further, thereby worsening the throughput losses. A continuous evolution is occurring and it is this type of dynamics that is the focus of the simulation-based study using the SD-DES hybrid modelling framework.

The plant is well advanced in TPM practices. There are some indicative characteristics that were noticeable. For example, there are signs indicating TPM rules, schedules, policies and the likes. The plant does not miss the daily RCM or bi-weekly SDM. They plan well ahead for each SDM activity. Kaizen teams meet regularly to chart TPM improvements. There is evidence of Good Housekeeping as tools and materials are stored properly in their designated areas. Good Safety measures are in place. All these and more were evident in the plant, to suggest that the organization is advanced in TPM practices.

Based on interviews with key stakeholders in the plant (including machine operators, line managers, maintenance crew and maintenance workers), the following were found:

- The performance of RCM directly affected the performance of SDM. The case of the labelling machine is an example. Defects steadily builds up with every sub-optimal RCM that is done. These defects need to first be repaired (or cleared) during a SDM operation before the maintenance crew can carry out their normal scheduled work. This reduced the effective time the maintenance has to carry out defect repairs and part replacements. The likelihood that a part replacement will be suspended till the next SDM is high in this type of situation.
- While SDM is taken very seriously and well planned, there are instances where replacement parts are not available. In such circumstances, replacements are either not done or they are replaced with make-shift parts. These make-shift parts sometimes do not fit and need to be modified, reducing the effective time that the maintenance have to carry out proper maintenance work. Meanwhile, these make-do parts may not work as effectively as the genuine parts.
- The fulfilment of 100% throughput target drives some types of behaviours relating to the system. For example, anxiety grows the longer machines stay broken down. When production losses have built up over time, the rate of removing machine defects is affected. For example, defective parts may be left un-replaced if it is felt that removing and replacing such parts will extend the time apportioned for RCM or SDM. In fact, line managers who push for consistently high throughput may be soft on those who skimp maintenance in order to minimize machine downtime from routine maintenance.

These case-specific details have not been revealed in any previous study on TPM. However, they support what others have submitted; that human errors and reliability play an important role in TPM (Sharma and Sharma, 2010; Sheikhalishahi et al., 2016; Dhillon and Liu, 2006) and machine operators are as important as maintenance personnel when it comes to TPM (Simões et al., 2011).

4. Simulation modelling phase of the hybrid modelling framework

4.1 Map system using causal loop diagram

Figure 2 is a causal loop diagram CLD in which RCM performance, SDM performance and the key feedback structures connecting RCM and SDM performances with throughput have been mapped.

Figure 2. Causal loop diagram of the key variables and concepts relating to TPM

CLD provides one with a holistic view of the entire system or problem in one single picture. It is also an effective tool in engaging key stakeholders (Dennis et al., 2000; Robinson et al., 2012). It is able to depict, in a condensed manner, the mental model that the investigator as well as the key stakeholders have of the problem. It brings about congruence of opinions.

Identifying the key constructs to map in the CLD is majorly based on one's understanding about the nature of the problem (Sterman, 2000). It is also possible that one can build on what others have developed in situations similar to the studied case. For example, "Pressure to skip defect removal" because of pressures to keep machine running and achieve throughput targets has been considered when modelling non-tangible aspects of TPM, see CLD in Jambekar (2000) and CLD of page 69 in Sterman (2000). Overall Equipment Effectiveness is the key performance indicator for TPM; mean time between failures and throughput are associated with it. Parts availability has been conceptualized in a simulation model by (Duffuaa et al., 2001).

In the conceptual model, three feedback loops (denoted by +) define the systemic behaviours. They cause change and evolution over time in the system. The first feedback loop "R1" is concerned with the performance of SDM. The loop can be traced as follows: The performance of SDM can be measured by the number of machine repairs that are left undone after the SDM has been completed. The lower the SDM performance, the higher the number of repairs left undone. The higher the number of repairs left undone, the higher the MTBF between SDM dates, since the machine is working with more defective parts. The higher the MTBF, the lower the production throughput because the machine breakdowns occur more frequently. When production throughput is low, there is more pressure to meet targets and so there is increased pressure to skip or skim maintenance. The performance of SDM is further reduced. Tracing the start to finish of this loop shows that at the start, performance of SDM was low; at the end, SDM performance is also reduced. In other words, the initial situation is reinforced i.e. start and finish effects are moving in the same direction. This is normally denoted with a positive sign and called a reinforcing loop. In the Figure 2, it is labelled as R1 and given a clockwise direction to indicate the direction of the loop. The second feedback loop, "R2", relates to undone RCM and can be described in the same way as the first feedback loop R1.

The third feedback loop "R3" is concerned with the motivation of each machine operator to undertake an optimal RCM. In the plant, an operator is self-motivated to sustain or improve a clean functioning machine and be lackadaisical where he/she meets the opposite. When RCM has not been properly done by previous operators on the machine, the state of the machine progressively becomes worse in terms of cleanliness and efficiency. Subsequent operators feel that improving the situation will erode their useful operation time and so leave the machine in the same or worse state for the next operator. They also feel that they should not "clean someone else's mess" believing they did not cause it.

When undone RCM accumulates, it increases the work that the maintenance crew have to do when they shut-down for scheduled maintenance. This was witnessed on the labelling machine of the line. The operators on the last shift before the SDM were made to clean the machine that had been covered with glue, littered with broken bottles and had dried-up labels on some machine parts. Although the cleaning was done by the label machine operators, a similar situation was seen at the bottle washing station, but here, the maintenance crew were the ones who had to clean the machine. The time that maintenance crew spend or wait for RCM to be corrected, reduced the time they had for proper preventive maintenance.

The CLD structure was validated by those who were interviewed in the system, when it was presented and explained to them. In addition, some of the constructs such as “Pressure to skip defect removal”, throughput and machine breakdown, have been mapped in CLDs depicting TPM-related case studies (Jambekar, 2000; Thun, 2004; Sterman, 2000).

The CLD depicted in Figure 2 focuses on the short run TPM dynamics that occur between each SDM, and the snowballing effect of it. If for example, one was to look at long-run dynamics such as effect of Training or Worker Experience, the CLD would be mapped differently, just as it would if other constructs (e.g. cost of maintenance) were to be included. The CLD is fit for the purpose of the study.

4.2 Transmit the CLD to a SFD

A stock and flow diagram (SFD) translates the CLD into simulation software terms (Senge et al., 1994). Some parts or variables in the CLD need to be modelled as stocks. These stocks act to accumulate things, physical and non-physical. Stocks accumulate past events and are depleted through current events (Sterman, 2000). Stocks are increased through inflows and decreased through outflows. Denoting a variable that was previously in a CLD as a stock variable in a SFD, is dependent on the system being modelled. The notion is that a stock should represent the state of the system, which could be either something that is tangible or intangible (Sterman, 2000). In the CLD map of the problem situation, two stocks are apparent: undone RCM and undone SDM. They hold the count of undone RCM and undone SDM respectively. The SFD (see Figure 3) was started with these two stocks, while the other components were added piece-by-piece, superimposing and comparing the SFD with the CLD as the SFD is gradually built up in an iterative and inductive manner.

Figure 3. Stock and flow diagram depicting TPM

In the CLD map of Figure 2, a link originates from accumulated undone RCM to undone machine repairs. This link represents the undone RCM that is cleared during the start of the SDM. Hence, a flow rate depletes undone RCM which is added to undone SDM. Typically, undone RCM is given priority before scheduled SDM commences, as was observed in the plant. The stocks and flow rates are the main variables that differentiate the SFD from the CLD (compare Figure 2 and Figure 3). The other variables in the SFD have been extracted from the CLD map of Figure 2.

Although the presented problem fitted one where a SD-DES hybrid model would be ideal, setting apart what needs to be modelled using SD and DES respectively, still needs to be accomplished. Other researchers would at the start of the modelling process delineate the constructs that should be modelled using the different modelling paradigms. For example: strategic and tactical decision making (Abduaziz et al., 2015); enterprise-wide and operational level decision (Rabelo et al., 2005); non-physical and physical concepts in a system (Alvanchi et al., 2011). Although this is one possible approach, the concepts which have been demarcated into SD and DES respectively, can be modelled using a single modelling method. Meanwhile, it is possible to start building a simulation model with one method and realize that another method is needed (Greasley, 2005; Brailsford et al., 2004), for example, to explain in detail some phenomenon that the initial method cannot fully communicate. This is another possible approach to demarcating SD and DES constructs. It may also be that without the inclusion of a second modelling method, the initial model would be too complex to code, such as complex scheduling or job routing rules. This last scenario was the case in the current situation.

There is no doubt that the problem comprises feedback structures so SD modelling is certainly needed. A "systems" view of the problem, as well as a CLD representation guarantees the use of SD modelling. A compelling reason for including a DES remains to be satisfied in the intended simulation model. RCM is an activity that consists of similar routine tasks. RCM tasks are predictable and can even be treated as constants in a SD-only model. On the other hand, SDM tasks are not consistent: they vary from one SDM to another. One SDM may have five main repair tasks, while the next SDM may have seven. Moreover, tasks differ in the required time to complete them such that one SDM task may take one hour while another may take thirty minutes. In addition, SDM as it is in case A, includes some element of RCM that were not done comprehensively. If one were to investigate the scheduling rate and completion rate of SDM tasks in a SD-only model, it would require that a deterministic, top-level approach be taken, i.e. all tasks are treated as having the same length of time. This is because elements in SD (i.e. stocks and flows) which would have been used to model such detailed scheduling tasks, are not formulated to treat entities that pass through them differently.

If one were to model the different tasks and their completion rates in SD, multiple variables representing each type of task would need to be included in the model. This would make the model large and complex. Whereas, a DES model which has building blocks (or elements) that are by default, able to treat entities differently, is better suited for modelling the detailed scheduling SDM tasks for the current case. Meanwhile, modelling the SDM operation in detail is something that is required for the case problem investigation because frequency of SDM is a parameter that would be experimented with in the proposed model.

For the above stated reasons, a SD-DES hybrid modelling framework is proposed, with the notion that the frequency of SDM would be modelled in DES.

4.3 Conceptualize the hybrid

Recalling that the problem is one where the SDM flow process is to be modelled using DES, a discrete event (DE) model is used to represent the SDM part that was in the SFD model. Because the SDM is affected by RCM and their concepts are similar, it made good sense to also include RCM flow process in the intended DE model.

Conceptualizing the hybrid requires reasoning and logic. First is to conceptualize the stand-alone DE model and its components that are to be extracted from the SFD, see Figure 4. In the DE model, only the building blocks sufficient to achieve the study objectives have been included (Robinson, 2015). Adding building blocks into a DE model is software based, since simulation modelling software use different types of building block libraries and programming language, which may increase or decrease the number of building blocks that a modeller has to use. The DE model conceptualized in Figure 4 consists of the following elements:

- Source (or start), which generates the scheduled maintenance (either RCM or SDM), i.e. the rate of RCM or SDM to do.

- Queue, which accumulates the undone maintenance, i.e. the stock that holds the undone RCM or SDM
- Activity, which is the rate at which the RCM or SDM is completed
- Sink (or end) which signifies the end of the RCM or SDM activity.

Figure 4. DE extraction from initial SFD

Thereafter, the SFD is modified to account for the extracted DE variables and elements, otherwise keeping them in the SFD would be a duplication of constructs in the eventual hybrid model. It is possible that after extracting the DE part, the stocks and flow concept that is the hallmark of SD modelling would have been subsumed in the DE model, as in the current model, see Figure 5. It is also possible that all or some may remain. It could even be that some feedback loops have transferred to the DE model. All these are determined by the way the sub models are built and how the eventual hybrid model is to be experimented with.

The process of transiting from the SFD to the hybrid model is an iterative one whereby the hybrid sub models (SD and DES) are modified till the hybrid model itself replicates the initial CLD and SFD concepts, for example compare Figure 5 and Figure 3. Conceptualizing the data exchange operation between variables in the sub models is based on the notion that the hybrid model, Figure 5, was adapted from the SFD concept of Figure 3. It was also conceptualized on the basis that the SD and DES are to be simulated as if they are one whole. By referring to Figure 5, conceptualizing the data exchange is straightforward. Table 1 summarizes the data exchanges between the sub models in the hybrid model.

Figure 5. The conceptualized SD-DES hybrid model.

Table 1. Summary of conceptualized data exchange operation for the hybrid model

4.4 Data to code the sub-models

The simulation model was built using AnyLogic7 simulation modelling software. Coding involves inputting data and model logic. Some or all of the data may have been collected at the preliminary enquiry phase, otherwise additional data needs to be collected. Some data may not be readily available and may require time studies to be undertaken. Where time studies cannot be undertaken for example due to time constraint or costliness of the time study, the researcher can rely on what others have submitted in similar studies (Sterman, 2000), otherwise judgmental estimates from participants familiar with the system can be sought (Oliva and Sterman, 2001), or even a combination of both. On the basis of observed behaviours as well as information provided by key stakeholders in the plant (machine operators, line managers, maintenance workers and maintenance managers) and on how other researchers have approached similar problems, estimates were used to model some of the relationships for variables pertaining to the SD sub model. We describe how some of these relationships were generated.

Firstly, one can start by judgementally estimating data points that best describes the relationship between two variables (see Chapter 14 of Sterman, 2000). It is common in SD modelling, when real-life data or sample data are unavailable. The relationship between accumulated undone RCM and the motivation to do optimal RCM is expected to be non-linear. Motivation is high when SDM has just been completed. The operator feels compelled to ensure the machine remains at the same refurbished close-to-new state. As undone RCM accumulates due to operator attitude and experience, motivation drops faster as operators believe they should not be responsible for rectifying RCM that was not properly done by others. The rate of drop is enhanced as SDM date approaches because the machine operator feels that SDM would clear their outstanding RCM, so he/she reduces the effort to do an optimal RCM. We used our understanding of the system to estimate the boundary values for the effect variable, in our case it is motivation to do optimal RCD. We then estimate that motivation would be 100% when undone RCM is nil, and it would be 85% when SDM is due. This was based on the observed state (cleanliness and frequency of breakdowns as a result of sub-optimal RCM) of the machine after a completed SDM operation and when SDM is due. On the basis of the foregoing, one can estimate other data points (see Table 2) for motivation to do optimal RCM, and thereafter fit the curve to a function (Eq. 1) that best describes it. Notice that motivation is dropping faster as more undone RCM accumulates.

Table 2. Estimated data to model the trend for motivation to do optimal RCM

$$Motivation\ to\ do\ optimal\ RCM = -0.0399 * UndoneRCM^2 - 0.444 * UndoneRCM + 100.6 \quad \text{Equation 1}$$

The relationship between undone SDM or undone RCM on MTBF was also estimated, but this was based on documented records on machine breakdown frequency for the plant. The machine operators in the plant were required to keep detailed records of every breakdown occurrence including the duration and cause. The historical records (numerical data) for machine breakdown were used to estimate the relationship between undone RCM or undone SDM and MTBF. Commonly used distributions for MTBF include Exponential, Poisson and Weibull (Ben-Daya et al., 2009; Hosseini et al., 2000). Past data on MTBF for the plant was fitted to an exponential function (Hopp and Spearman, 1991), from which its relationship between undone RCM and undone SDM could be estimated by the Equations 2 and 3.

$$MTBF = 79.358 * e^{-0.177 * UndoneRCM} \quad \text{Equation 2}$$

$$MTBF = 63.923 * e^{-0.009*UndoneSDM} \qquad \text{Equation 3}$$

Data on breakdowns in the actual plant was used to approximate machine uptime and hence throughput. The X-Y data set consisting breakdowns and throughput for the plant was fitted to a logarithmic equation, from which we derived the relationship between throughput and MTBF for the plant. The relationship is given by Eq. 4.

$$Throughput = 9.8607 * ln(MTBF) + 58.842 \qquad \text{Equation 4}$$

The way a mathematical function was derived for the relationship between undone RCM and motivation to do optimal RCM, a similar approach was used to model the effect of throughput on pressure to skip defect removal. In the case of pressure to skip defect removal, a Table of Functions method of modelling non-linear relationships in a SD model was applied. Generating a Table of Functions model is similar to estimating a non-linear relationship. A Table of Functions is a table/graph specifying the point by point values of an independent variable and the corresponding values for the dependent variable, which can be used to describe their relationship. In the current instance, the independent variable is throughput while the dependent variable is pressure to skip defect removal. The following information was used to build a Table Function that describes the non-linear relationship between throughput and pressure to skip defect removal:

- When throughput is low, pressure to skip defect removal is high. Meanwhile, the minimum recorded operational throughput (when there are no major breakdowns) was about 85%.
- When throughput is high, pressure to skip defect removal is low. Maximum throughput is 100%, although in some rare occasions, throughput exceeds the target.
- Effect of pressure cannot increase indefinitely and would saturate at a maximum level, respectively (Sterman, 2000). Neither will its effect continue to decrease infinitely. It was estimated that maximum saturation point is 15%, considering that anything beyond this would be considered as extreme.
- Rydzak et al. (2006) presented raw simulation results that one can use to describe the effect of throughput on time for maintenance.

Based on the above notions, the non-linear relationship between throughput and pressure to skip defect removal can be conceived as shown in Figure 6. The graph describes an effect that is marginal at the onset of a reduction in throughput, increases rapidly as throughput falls below 95% and slows as throughput drops to 85%. In more specific terms, when throughput is say 90% of the target value, the pressure to skip the removal of any major defect is increased by about 7.5%, because of the likelihood that correcting it may extend the machine downtime, putting further pressure to meet production targets. Meanwhile, when throughput target is consistently being achieved, operators and maintenance managers alike are willing to risk undertaking complex defect repairs that may (or appear to) take longer than necessary. This pressure to skip defect removal is translated to the performance of SDM and RCM (see link in Figure 5). In the simulation model, the point value of the dependent variable is called in the Table of Functions when the point value of the independent variable is attained.

Figure 6. Graph of effect of throughput on maintenance performance.

The way normal RCM performance was intended to be quantified was through the use of a nominal scale. If in the plant, RCM activities are characterized by 100% adherence no matter the motivational situation or throughput pressure, RCM performance is assigned a value of 2. Otherwise it is assigned a value of 1 (which is the current status). This is a logical scaling mechanism for the case: it is either there is compliance or not. A less than optimal compliance is considered as no compliance. This assumption makes sense since when there is full adherence, the effects of throughput and motivation are null. Moreover, it is more subjective to quantify normal performance of RCM using an ordinal scale, for example. With a nominal rating, normal RCM performance is a dimensionless one.

The input data to be coded into the DES sub-model included: frequency of RCM i.e. rate of new RCM to do; duration of each RCM task; frequency of SDM i.e. rate of new SDM to do and schedule of SDM tasks with duration. The company kept records of these data. Using the information summarised in Table 1 as a reference guide, the data exchange between the SD and DES variables is formalised. Undone RCM is the count of items (bin size) in the DES object, UndoneRCM, at each discrete time step. The count is used in the Eq. 2 to update the SD variable, MTBF. The updating of MTBF by UndoneSDM is treated in the same way.

The SD variable, SDM_performance, sends data to the DES variable, SDM_activity (see Table 1). If the normal time that is taken to complete each scheduled SDM task during the SDM operation is set at “x” hour, where “x” is a function of the type of SDM task and its duration attributes, then the updated delay time with a sub-optimal SDM performance and sub-optimal parts availability is given by Eq. 5.

$$Time\ to\ complete\ SDM\ operation = \frac{x}{SDM\_performance} * \frac{1}{Parts\_availability} \quad \text{Equation 5}$$

4.5 Model Verification

The structure of the SD sub-model was consistent with the initial CLD map. The variables and elements that were used to create the model were consistent with logic that describes the real system. The decision rules also captured the behaviour of the key actors (Sterman, 2000). For example, in the real system, any undone RCM that is found at the start of the SDM is done first.

So, in the DES model, RCM tasks were given higher priority than SDM, so that they are concluded first in the SDM_activity element. In addition, the delay setting for SDM_activity was coded to delay RCM and SDM tasks differently, according to their specified times.

Dimensional consistency test was done to ensure that the values and equations are dimensionally correct. Dimensional consistency also helps to verify the correctness of the equation. In addition, the sub models time units and those used in the formulas were checked to confirm there was consistency.

4.6 Validate and experiment with the hybrid simulation model

4.6.1. Model Validation

The objectives of the simulation-based study determine the types of experiments to be conducted with the SD/DES hybrid simulation model. Having prior knowledge about the types of tests that will be conducted with the hybrid model is often needed when conceptualizing the simulation model. Parameters and variables can then be included in the model that would be used to conduct these experiments. For example, it was planned that the hybrid model would be used to test the impact of improving the performance of SDM and RCM. So, in the SFD concept (see Figure 3) two parameter variables namely "Normal RCM performance" and "Normal SDM performance" were configured. In addition, the hybrid model would be used to test the impact of changing the frequency of SDM. To enable this experiment, the DES element, "SDM_to_do" which is the rate/frequency of SDM, was coded in a way that it could be altered to either increase or decrease the frequency of scheduling SDM activities.

The model was configured to simulate the throughput trend over the next one year (365 days). Although the modelling study focuses on the short-run dynamic events between SDMs, one needed to project the trend over a given period. The choice of 365 days coincides with the yearly Turnaround Maintenance where the plant machines are overhauled and brought back to an almost new state, more-or-less restarting another year's dynamic cycle. The animation features in a simulation software enables one to observe the behaviour of the model elements as it is simulated to check whether the model mimics the real situation (Greasley, 2005). The result of running the simulation is shown in the chart of Figure 7, see current as-is graph. The results show high volatility in throughput; currently the bottling line experiences a lot of variability in throughput as a result of machine breakdowns and machine inefficiency. The simulation results predict a downward trend of throughput performance over time, if the status quo is maintained. Line and maintenance managers tend to notice a downward spiral at some point in time and then initiate corrective action such as doing a complete overhaul of the problem machine(s). This ad-hoc corrective maintenance approach is costly and more disruptive than the regular routine and shut down maintenance.

Upon validating the hybrid model the next step is to use it to understand the nature of TPM improvements that should be advanced. In the current modelling framework, a model sensitivity test serves two purposes:

i. The hybrid model is tested for its sensitivity to any estimated input data. In the current study, some data were judgmentally estimated as described in Section 4.4.

ii. The sensitivity of the system to adjustments in each key parameter is examined. The behaviour of the model and the simulation results are used to establish this.

We used these tests to determine the nature of experiments to undertake with the hybrid model.

Figure 7. Simulation results for model validation and sensitivity test.

4.6.2. Experimentation with the hybrid simulation model

Experiment to test sensitivity of the model to estimated input data

The first set of experiments was to establish the sensitivity of the hybrid model to the estimated data that was used in coding it. One of the experiments is reported here. The estimated data (in Table 2) for generating the function to describe motivation to do optimal RCM was altered (see Table 3 information). The rate of drop in motivation was increased by 100 percent mimicking an extreme situation where the motivation drops rapidly and significantly. The function that was generated to fit the data set in Table 3 is given by Eq. 6. This function was used to replace the Eq. 1, for the variable, Motivation to do optimal RCM in the hybrid model.

Table 3. Altered data set to establish the sensitivity of the hybrid model to estimates that were used in generating the function to describe motivation to do optimal RCM

$$Motivation\ to\ do\ optimal\ RCM = 102.05 * e^{-0.025*UndoneRCM} \qquad \text{Equation 6}$$

The hybrid model was run with this alteration. The simulation results for the sensitivity test returned a similar trend to the current as-is graph, see Figure 7. In addition, there was minimal deviation. The implication of this is that the modelled system is not sensitive to significant changes in motivational behaviours towards routine checks and maintenance. In other words, even if motivation is somehow increased or reduced, it has only a marginal impact on throughput.

Experiments to test TPM improvements

The second set of experiments was carried out to observe the model behaviour when values in some key parameters are altered. On the basis of the validated current as-is simulation results which indicates that the system will degenerate over time, the hybrid model is used to show how the system will evolve if some key TPM practices (parts availability, RCM performance and SDM performance) are at their optimal levels. The practical meaning of this experiment is to find out how the system improves when there is full compliance and adherence to TPM practices. In this experiment, parts availability is set at 100%, while normal RCM performance and normal SDM performance are set at 2. The results of these experiments are displayed in

Figure 8. The results for these experiments indicates that amongst the three practices, adhering fully to RCM has the best impact on throughput performance. The simulation results suggest that some practices, when improved on their own may not lead to a noticeable impact, while others may. When such improvements are initiated and there is no noticeable impact, employees are led to believe that it is a waste of time and effort. Employees may resort to old ways of doing things on the premise that the improvement efforts have failed and there is no need to carry on with them. However, a simultaneous improvement in all practices is likely to generate noticeable impact as indicated by the graph that shows the trend when all practices optimal (see Figure 8).

Figure 8. Simulation results for the system, when TPM practices are at their optimal levels

The hybrid simulation model affords one the opportunity to undertake experiments relating to tangible and intangible improvements. An example of an intangible improvement is the type proposed after conducting the previous experiment where all TPM practices are together and fully adhered to. Adherence to TPM practices is similar to behaviours and attitudes which are considered as intangible. In the current study, an intangible improvement was directly modelled and simulated, while the direct impact on system performance was observed. Tangible improvements such as adjusting the SDM schedule (or optimizing it) is what is often advanced when improving TPM performance. The hybrid model was experimented with by reducing the interval between SDMs because it appeared that scheduled defect removals were being delayed too long and were allowed to accumulate. This experiment is akin to finding an optimal time between SDMs, since one way to arrest machine breakdown from defects is to remove the defect before it starts causing frequent machine breakdowns. An ideal experiment for this purpose would first list out the different defects, how frequent they occur and their impact on machine reliability. The defects that occur frequently and those that have significant impact on machine reliability are used to optimize the SDM setting such that line throughput is maximized and machine downtime is minimized. We did not have detailed information about the nature and frequency of each machine defect, so we simply reduced the time lag between SDM by half, from 14 days to 7 days. The result of this experiment is displayed in Figure 9. The simulation results show an improvement over the current status quo and is also compared with the simulation results for full adherence to TPM practices.

The downward trends in the graph of both experiments is due to the accumulation of machine defects: it is slower when SDM interval is shortened. The reversal from downward to sudden upward trend is at the point where all machine defects have been cleared during RCM and SDM. This oscillating trend is one of the fundamental modes of system behaviours see page 114 of Sterman (2000). An oscillating behaviour is more evident with balancing feedback loops and where corrective actions are taken to trigger a reversal in a negative trend. Although there are no balancing feedback loops in the initial concept (see Figure 2), the improvements may have caused one or more balancing loops to occur. This is possible since the improvements are intended to enhance corrective actions. In the case of TPM, corrective actions occur at each RCM and SDM operation. If properly done, the oscillating behaviour (Figure 9) is likely; if not properly done, the downward spiral (see Figure 7) is the case.

Figure 9. Simulation results for the system, when SDM interval is reduced from 14 days to 7 days

If one were to go by an average trend, reducing the interval between SDMs and implementing full compliance to TPM practices both have similar impact on throughput performance, for the modelled system. However, if one were to calculate the accumulated throughput losses over the one-year period, the losses from observing full compliance to TPM practices is about 18% more than those generated for reducing the SDM interval. In other words, reducing the interval between SDMs seems better than implementing full compliance to TPM practices. A combination of both did not show any significant change when compared with reducing the SDM interval. The reason for this may be that reducing the interval between SDMs is in effect increasing the frequency of machine defect removal which is similar to increasing the performance of RCM and SDM related tasks.

Increasing the frequency of SDM will result in more frequent machine shut down for maintenance. It may likely cause an increase in maintenance cost, initially. For example, more lubricants would be used since the maintenance frequency has doubled. In addition, maintenance labour cost per month would go up because maintenance crew are utilized more often. A cost-benefit analysis can be done whereby the estimated gains in throughput (in monetary terms) can be weighed against estimated cost increases.

Altering the plant's maintenance schedule may be something that requires top-management authorisation and extended decision-making, even where the simulation results indicate it is better to do so. What does not require recourse to top-management is the behavioural changes i.e. ensuring that the performance of RCM and SDM are at their optimal levels always, and replacement parts are readily available during SDM operations. Some machine components are expensive to stock and management may not want to tie down capital by stocking these parts. This is where maintenance managers need to be able to predict with accuracy and confidence, when machine components will become defective. But it is not so easy to accurately predict when a defect would occur, unless one has access to reliable historical data about past defects in relation to machine operating conditions such as degradation patterns, working temperature and maintenance history (Riley, 2017). The plant currently collects and updates its records on machine defects. Such information should be used to predict when a machine component will likely become defective, and then plan for just-in-time stocking of the component. So, even if the frequency of SDM cannot be immediately reduced, gains can still be achieved by way of improved TPM compliance.

5. Discussion and conclusions

Based on the simulation results, worker motivation does not significantly affect TPM performance. This may be because only the short run dynamics were modelled in the current case study. On the long run, the situation may change if one considers that low motivation can lead to staff turnover which eventually results in a drop in the effective experience level of workers (Sterman, 2000). If one were to model the long-run dynamics of the same system, say up to 5 years, then the effect of motivation may become significant sometime in the future. To model this, one would need to incorporate other variables such as effect of motivation on rate of turnover, rate of worker replacement, ratio of experienced to new workers and the effect of all these on the performance of TPM, for example. In other words, the hybrid model that was developed for the case would need to be scaled upwards to include additional variables. So, even though the developed hybrid modelling framework is designed to be used as a quick turn-around decision-making tool, it can also be scaled upwards in a situation where one needs to establish long-term evolutionary trends.

In the current case study, during the preliminary enquiry phase, it seemed as if worker motivation to carry out optimal routine checks and maintenance was a major issue. It was something that was observed by the authors. It was mentioned by some of the machine operators. It was included in the stakeholder-validated CLD map that was used to describe the problem situation. But it was eventually found not to be a significant factor after conducting a sensitivity test using the hybrid model. There is something to be learnt from this: the simulation model results can be used to decide what is significant or not. It is sometimes better to include a variable and find out it was insignificant than to exclude it and have the user question the model's accuracy to represent reality; more so where the variable seems to be of great concern to those whose system the model is supposed to represent.

This work promoted a system dynamics-discrete event simulation hybrid modelling framework; one that is useful for investigating problems comprising tangible and intangible elements which interact and evolve over time, such as is found in TPM. In the current study, it was used to model and investigate concepts relating to TPM practices which would have been difficult to model otherwise. These concepts include worker motivation, attitude and compliance level to do optimal maintenance. If they are modelled in a DES-only model, one would need to model them indirectly, for example see Brailsford and Schmidt (2003); Neumann and Medbo (2009). Such indirect modelling in DES do not clearly portray or account for the feedback structures, which are equally important. SD is the natural modelling domain for intangible aspects and their feedback dynamics such as those investigated in the case. But using a SD-only model would fail to capture the intricate flow concept that was eventually modelled using DES. If the flow concept were to be modelled using SD, one would have to make unrealistic assumptions, and it would be programmatically difficult to code.

Maintenance policies have been developed on the basis of other methods such as Multi-criteria Decision Analysis (Emovon et al., 2018) and Condition Based Maintenance (Alaswad and Xiang, 2017). If one were to consider the nature of the problem situation which includes complex dynamic interactions between the problem variables as well as the effect of these interactions on the global system, simulation modelling is advised.

Being able to include all important variables in the model (because of the use of a SD-DES hybrid simulation concept) increases one's confidence that the simulation results are robust enough to guide one in taking the right decisions. In addition, users of the model are less likely to question its reliability where they see all the important aspects relating to their system have been considered. Large complex models need not be built in such situations, since the hybrid model that was built for the case has shown that a small, succinct, simple and efficacious model is possible. This ties in to what is also being promoted with the hybrid modelling framework i.e. to advance a quick turnaround and complete decision-making tool. It enables a quick turnaround because the study is focused on a particular problem, and not problems in the whole system. For example, in the current situation, the work practices relating to routine maintenance and shut down maintenance were the main focus. That is not to say these are the only problems in TPM, but by focusing on one area, the hybrid modelling framework is quick to use and comprehensive in depth regarding the problem it is modelling. If one needs to model a larger whole, the framework can be used to model different parts of the system, for example, Training or Scheduling of Maintenance crew, and then the different hybrid models can be combined. Similarly, the hybrid modelling framework is scalable to model and investigate longer-term concepts such as TPM Employee Turnover. The framework is complete because it guides one from preliminary data gathering, through to building the hybrid sub-models and using the built hybrid model as a decision-making tool.

Those in academia and industry stand to benefit from the current study. The steps in the promoted SD-DES hybrid modelling framework have been designed and explained in a way that makes it easy to reproduce in diverse settings. The concepts that were investigated are typical of any maintenance operation and production setting. DES has been the dominant simulation modelling method in manufacturing (Jahangirian et al., 2010) and models of complete production lines are common. The hybrid model presented in the current study is easily attachable as a sub-model to existing DES models that represent full production lines. This will allow one to visualize how operator attitude and compliance level towards machine care and maintenance, for example, affect the performance of an entire production line.

Frameworks for SD-DES (or DES-SD) hybrid modelling are not new, but our approach is novel in the sense that it comprises two phases. The first phase guides one through the preliminary problem assessment and data gathering stage from where one can conceptualize the intended simulation model. The second phase is the simulation modelling part which commences with a CLD. The CLD is intended to map, in a holistic schematic, all the important constructs relating to the problem. The CLD presupposes that the problem involves complex interactions between constructs, as well as feedback structures that cause the problem to evolve over time. Many problems in real life fit this concept. The notion that the problem also involves a process flow of activities or entities is well suited to almost any kind of production setting. The concept on which the hybrid modelling framework is based is therefore compliant to a variety of production-related problems. To the best of our knowledge, this is one of the few cases where SD-DES hybrid modelling has been applied to improve TPM performance. The diversification of the framework use and upgrade of its functionalities are ongoing.

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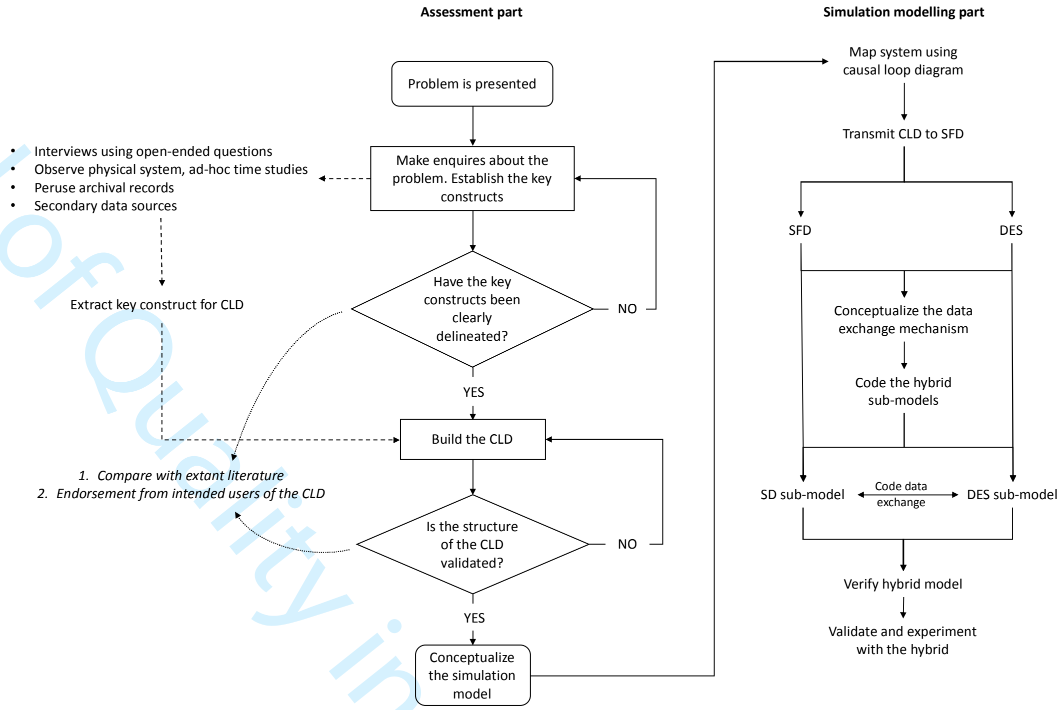

Figure 1. Key parts of the hybrid modelling framework

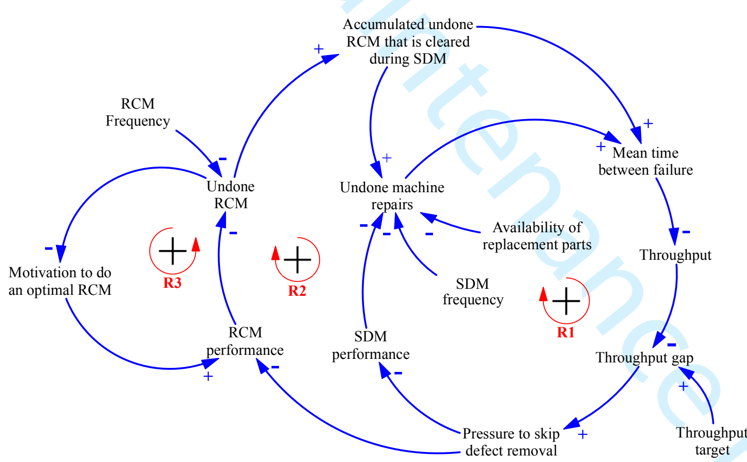

Figure 2. Causal loop diagram of the key variables and concepts relating to TPM

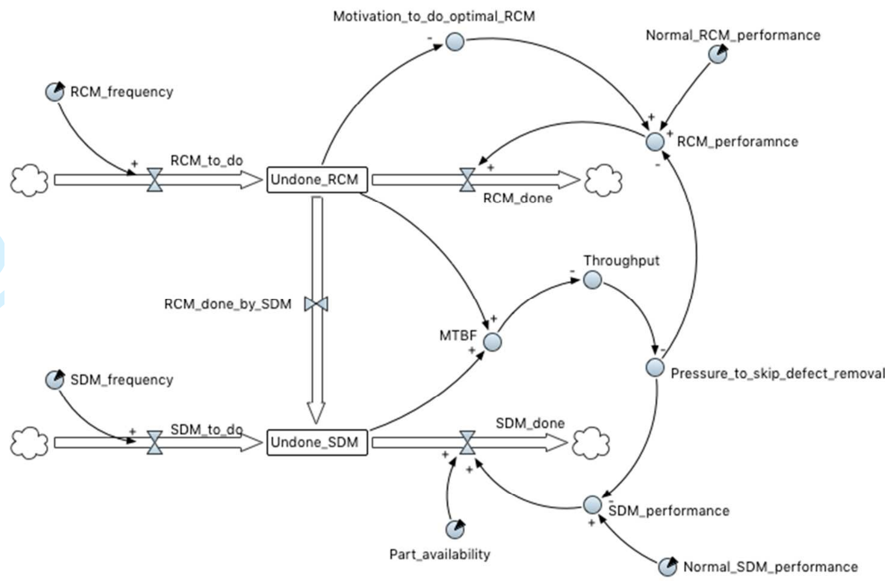

Figure 3. Stock and flow diagram depicting TPM

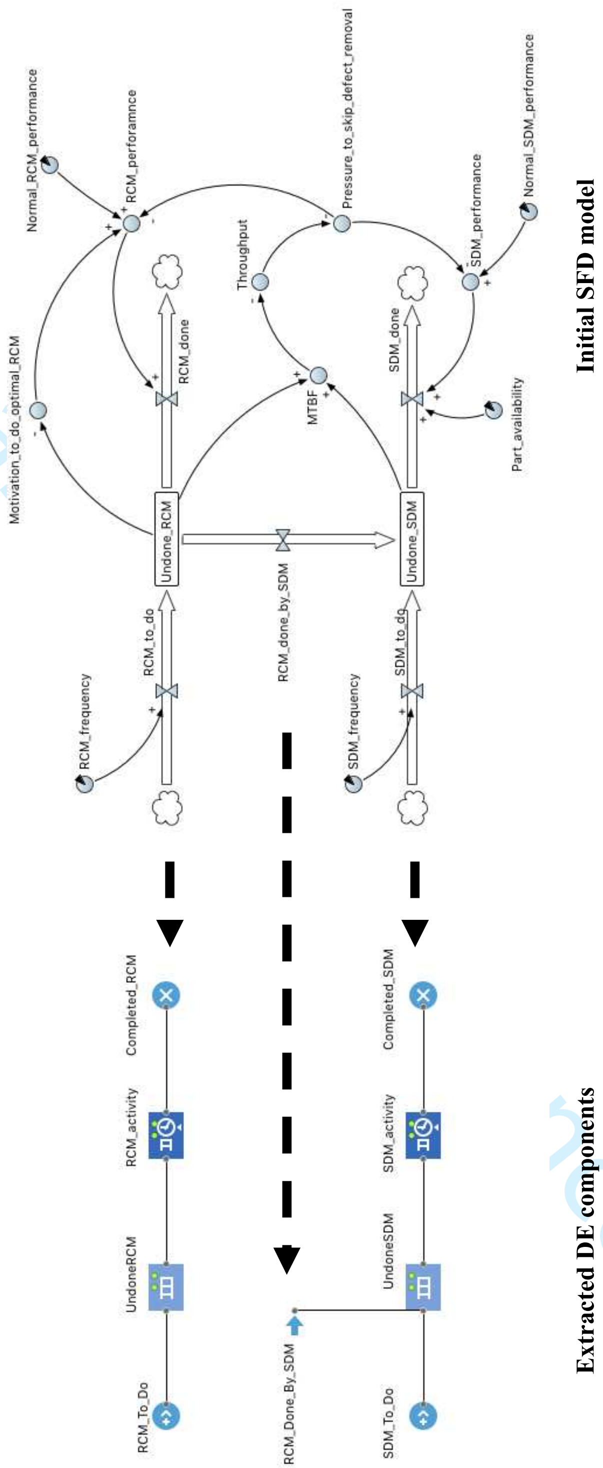

Figure 4. DE extraction from initial SFD

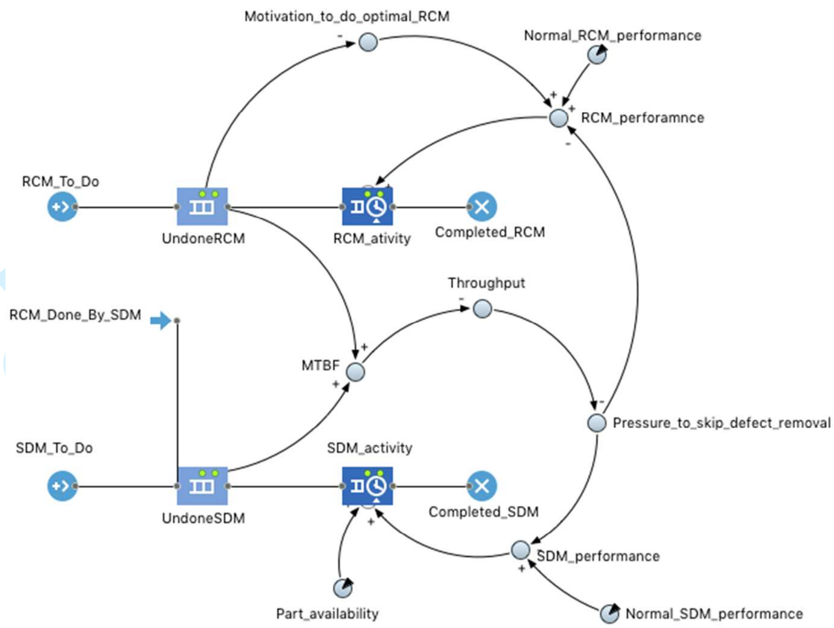

Figure 5. The conceptualized SD-DES hybrid model.

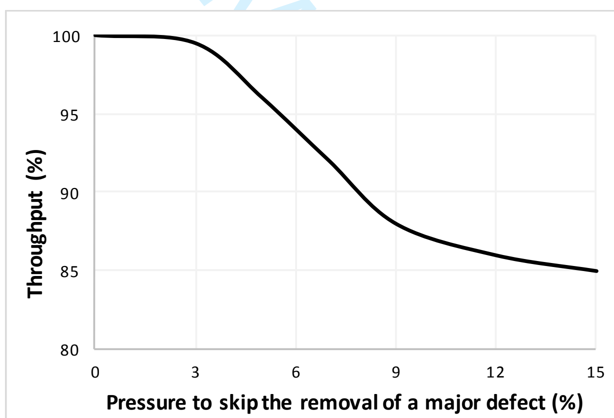

Figure 6. Graph of effect of throughput on maintenance performance.

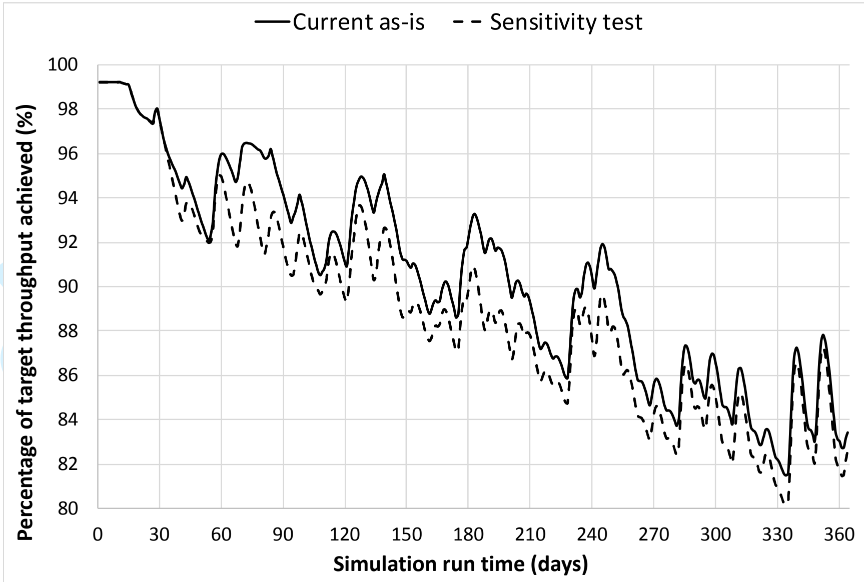

Figure 7. Simulation results for model validation and sensitivity test.

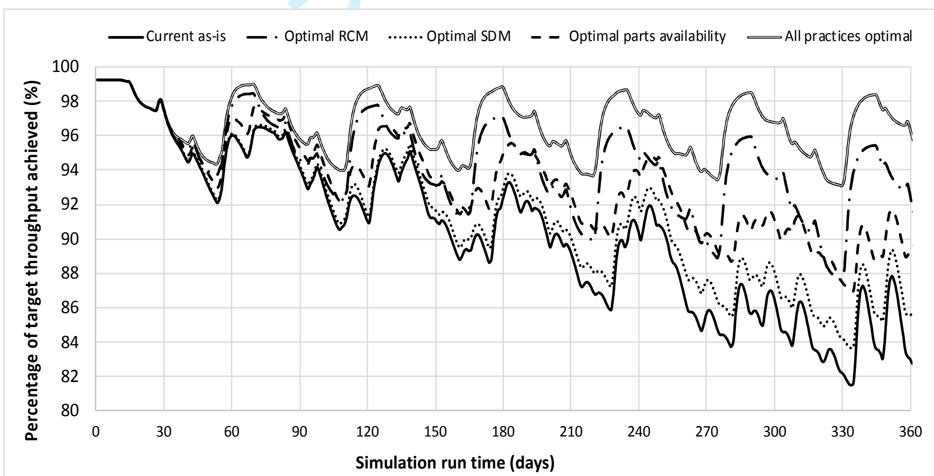

Figure 8. Simulation results for the system, when TPM practices are at their optimal levels

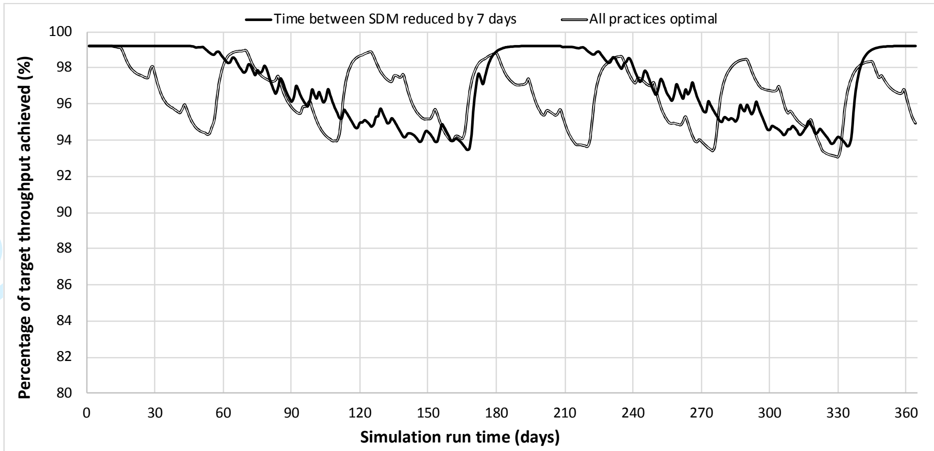

Figure 9. Simulation results for the system, when SDM interval is reduced from 14 days to 7 days

Table 1. Summary of conceptualized data exchange operation for the hybrid model

Sender		**Receiver**	
Variable	**Sub-model**	**Variable**	**Sub-model**
UndoneSDM	DE	MTBF	SFD
UndoneRCM	DE	MTBF	SFD
SDM_ performance	SFD	SDM_activity	DE
RCM_ performance	SFD	RCM_activity	DE

Table 2. Estimated data to model the trend for motivation to do optimal RCM

Undone RCM (percentage)	Motivation to do optimal RCM (percentage)
1	100
3	98
5	95
10	90
15	85

Table 3. Altered data set to establish the sensitivity of the hybrid model to estimates that were used in generating the function to describe motivation to do optimal RCM

Undone RCM (percentage)	Motivation to do optimal RCM (percentage)
1	100
3	94
5	90
10	80
15	70

The application of a hybrid simulation modelling framework as a decision-making tool for TPM improvement

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