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Integrating human factors into discrete event simulation: a proactive approach to simultaneously design for system performance and employees' well being

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The aim of this research is to: (1) Develop an approach to integrating both human fatigue-recovery patterns and human learning into Discrete Event Simulation models of a production system to predict productivity and quality; (2) Validate the predicted fatigue against operators' perceived fatigue; and (3) Demonstrate how this Human Factors-enabled simulation approach can be applied in a case study comparing two manufacturing line designs in the context of electronics assembly. The new approach can predict the accumulation of operator fatigue, fatigue-related quality effects and productivity changes based on system design configurations. In the demonstration comparison, fatigue dosage was 7–33% lower in the proposed system where HF was taken into consideration at the engineering design (ED) stage. In the existing system, the fatigue dose measure correlated with quality deficits with 26% of the variance accounted for – a large portion given the multi-causal nature of production deficits. ED models that do not include human aspects may provide unreliable results in terms of productivity and quality estimates. This research shows that it is possible to design production systems that are more productive while being less hazardous for the system operator.

Keywords: human factors modelling; ergonomics; fatigue; quality; performance

1. Introduction

This paper outlines the development and application of a method to combine Discrete Event Simulation (DES) and Human Factors Modelling (HFM). Effectively applied in the design of operations systems, Human Factors (HF) can improve system performance while reducing health hazards for employees (Goggins, Spielholz, and Nothstein 2008; Neumann and Dul 2010). The potential employee health impact alone from poor HF is significant. In Canada, the manufacturing sector has the highest number of work-related injuries per annum (Industry Canada 2009). Estimates for the cost of work-related ill health rival those of all cancers combined (Leigh 2011), and range from 1.2 up to 6.2% of the GDP in developed nations (Tompa, Culyer, and Dolinschi 2008). Despite the scope of the problem, attention to these issues in the engineering and management literature, where the risk factors for employees in operations are determined (Neumann et al. 2006), remains limited. This paper contributes to alleviating the shortage by developing simulation approaches that can help predict injury risk in early design stages. Bernard (1997) states that 32% of the workplace injuries or illnesses are a result of overexertion or repetitive motion. The application of HFM in the engineering design (ED) stage could therefore potentially mitigate the risk exposure and reduce the number of workplace injuries.

While attention is often focused on direct company costs of injuries, the costs of poor HF can be vastly greater (Rose, Orrenius, and Neumann 2013). Systematic review of available literature has shown system performance aspects co-vary with human effects in 95% of studies that looked at both elements in HF applications (Neumann and Dul 2010). Specifically, productivity, quality, technology implementation and other intangible benefits were observed when HF was applied to production system designs. Production quality, in particular, appears to be affected by poor HF in production (Neumann and Dul 2010). González, Adenso-Diaz, and Torre (2003) have stated that a positive relation exists between improved HF and better product quality. In another case, Yeow and Sen (2006) have shown in the electronics industry that improved HF results in a 'reduction in rejection cost, reduction in rejection rate and improvement in productivity and quality', among other benefits. Therefore, it would be beneficial for an organisation to design their processes with HF in mind, such as the fatigue accumulation HF variable in focus here, as it affects their system yield and costs. Manufacturing companies commonly leave HF efforts to 'retrofitting' production systems late in the development process to address operators' injury problems (Jensen 2002; Dul and Neumann 2009; Neumann and Village 2012). As Miles and Swift (1998) suggest, the effectiveness of changes in design is greater early in the ED process, as it results

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in lower cost, increased ease of change and higher quality. While some authors have tried to shift the HF focus from a reactive response to employee injuries to a proactive response in design (Broberg 1997; Jensen 2002; Neumann, Ekman, and Winkel 2004; Neumann and Village 2012), proactive applications of HF are still uncommon. We propose a methodology to apply HF principles in DES – a tool commonly used by engineering teams in early operations design stages – to allow the application of HF early in ED – before operators are put at risk. This paper will address two HF aspects affecting production systems which can be included into production simulations: fatigue and recovery, which are associated with injury risk, and learning which is associated with improved performance.

1.1 *Discrete event simulation*

DES is an operational research technique that allows the assessment of the efficiency of an existing or proposed system (Jun, Jacobson, and Swisher 1999). It is used to represent a system via a computer program, enabling the testing of ED changes without disruption to the system being modelled (Rossetti 2010). Simulation can be used to solve problems which are too complex or dynamic to be solved by mathematical methods. Using mathematical methods like calculus, probability theory or algebraic methods, there can be only one final solution (Kelton, Sadowski, and Sturrock 2008). DES allows designers to explore ED alternatives at a point in the design process when the ability to make change is easier and more cost-effective than retrofitting an existing system. DES can be widely used in manufacturing and service industries, ranging from the analysis of system design alternatives (Neumann et al. 2006; Neumann and Medbo 2009; Sharda and Akiya 2012) and business modelling (Hlupic and Robinson 1998), to the optimisation of resources (Legato and Mazza 1999; Henrich, Land, and Gaalman 2006; Carlson and Yao 2008) and cost evaluation (Spedding and Sun 1999; Volling and Spengler 2011).

1.2 *Human factors modelling*

HFM is an approach which assesses the mechanical and mental loading that humans are subject to when performing a specific task. It offers designers ‘the promise of an efficient means to simulate a large variety of ergonomics issues early in the design of products and manufacturing workstations’ (Chaffin 2008). With HFM, mechanical loading of the manufacturing line operator, an injury risk factor (National Research Council 2001), can be traced back to the engineers’ decisions made during ED (Love and Barton 1996; Neumann et al. 2006). In terms of HFM, this paper is concerned with how muscular fatigue accumulation, recovery and, separately, learning curves (LCs) affect the production system output and product quality.

1.2.1 *Fatigue and recovery*

One of the ways to quantify muscular fatigue is through Muscular Endurance Time (MET) models. MET is defined as the maximum time that a muscle can sustain a mechanical load during a static exertion (El Ahrache, Imbeau, and Farbos 2006). MVC is the maximum voluntary contraction of a muscle to perform any task, and task workloads assessed in this study are expressed as a percentage of this maximum. Muscular recovery is complementary to muscular fatigue accumulation. Recovery is ‘the need to recuperate from work induced fatigue’ (Swaen et al. 2003). An individual’s recovery need can be calculated as a Rest Allowance (RA), defined here as the ‘time needed for adequate rest following a static exertion, and is generally expressed as a percentage of holding time, i.e. the time during which a static exertion, static posture or a combination of both is maintained without interruption’ (El Ahrache and Imbeau 2009). These models, however, aim at instantaneous fatigue level and there is currently no method of quantifying the fatigue exposure or dose experienced by workers over a full shift.

González, Adenso-Diaz, and Torre (2003) have stated that a positive relation exists between improved HF and better product quality. Yeow and Sen (2003) show that this relation applies to the electronics industry, and improved HF results in ‘reduction in rejection cost, reduction in rejection rate and improvement in productivity and quality’ among other benefits. Discomfort from strained parts of the body, which results in fatigue, has a direct result in quality deficiencies (Eklund 1995). In this study, the relationship and effects of fatigue on the manufacturing line quality and yield were explored to illustrate that fatigue affects the system performance and costs.

1.2.2 *Learning curve*

Researchers have observed that unit production costs tend to fall with cumulative output and experience, and have formed LCs to express this relationship (Nembhard and Uzumeri 2000). Welford (1968) aptly described the impact of learning from experience stating 'It is well known that the initial attainment of reasonable competence at industrial and many other skills is followed by a long period of further improvement during continued exercise of the skill'. In the engineering world, LCs have been modelled to better understand manufacturing costs (Yelle 1979) and for line balancing of new production runs (Dar-El and Rubinovitz 1991). From a HF perspective, LCs allow an understanding of the evolution of task time demands, supporting the management of system ramp-up, for example.

The relationship between task performance time (T_n) and the number of trials follows the power law of practice (De Jong 1957; Welford 1968; Helander 2006). Welford (1968) has proposed that the time taken to perform a repetitive task falls exponentially until it approaches some 'incompressible' minimum as shown in Equation (1).

$$T_n = T_\infty + \frac{T_1 - T_\infty}{n^k} \tag{1}$$

where T_n is the nth cycle time (CT), T_∞ is the incompressible minimum CT – that is the CT that would be taken if the task was repeated for an infinite number of cycles (De Jong 1957) – and T_1 is the time taken by the first cycle. The exponent k expresses the rate at which improvement takes place with practice (De Jong 1957; Welford 1968; Givi, Jaber, and Neumann 2015). While there has been considerable research conducted on LCs (Terwiesch and Bohn 2001; Vits, Gelders, and Pintelon 2006; Jaber 2011, 265), the original equations cited here still stand, and to the authors' knowledge, LCs have not been applied in DES.

1.3 *Research aims: combining DES and HFM*

Human aspects are rarely included in DES and have been seen as the 'missing link' in simulation (Baines et al. 2004). DES models that do not account for natural human variability, for example, may have invalid results (Neumann et al. 2006). Nevertheless, some examples of HFM in DES exist in the literature including HF aspects such as circadian rhythms (Baines and Kay 2002), cumulative spinal loading (Kazmierczak, Neumann, and Winkel 2007), system-level biomechanical loading (Pascual et al. 2008) and work-break autonomy (Neumann and Medbo 2009) in DES models. In a precursor to this study, the accumulation of muscular fatigue was tested in the context of a shaver assembly system (Perez et al. 2014). This line of research will be extended here in an electronics assembly context. This paper extends DES capabilities to account for interactions between the design of the system and the system operators' response to their work. In this study operator workload, and hence injury risk (National Research Council 2001), as well as performance aspects due to fatigue and learning were examined. This creates a more robust modelling procedure including important HF aspects that are typically ignored in conventional DES modelling procedures and industrial design processes (Sobhani, Wahab, and Neumann 2015). Based on the challenge of including HF into production system design, and the relevant HF variable to design introduced briefly here, the aim of this research is:

- First, to develop a methodological approach to integrating both human fatigue-recovery patterns and human learning into DES models of a production system to predict performance in terms of productivity and quality.
- Second, to validate the predicted fatigue against operators perceived fatigue
- Third, to demonstrate how this HF-enabled DES approach can be applied in a case study comparing two manufacturing line designs in the context of electronics assembly: an existing line and a proposed design. We extend this comparison with a cost analysis of the two systems based on the simulation findings.

2. Methodology

2.1 *DES and HFM*

Two manual assembly lines, an existing and a proposed line both assembling the same consumer electronics product, were simulated using Arena 13.5. The existing line was a single piece flow assembly line composed of six assembly stations with one employee per station and a buffer between each station. The existing line was located at the Industry Partner's site. The proposed alternative system was a single-flow assembly line composed of four stations with one employee per station, three automated stations and no buffer between stations. Data were similar for both lines with the same stations or tasks in both the proposed and existing lines. The modelling was divided into two parts: (1) DES, of both lines with in-data obtained from observation and company records, and (2) HFM, which simulated the employees' learning and fatigue responses. A schematic of DES and HFM and their components used is shown in Figure 1; where CT is Cycle Time, PT is Pause Time, FD is Fatigue Dose, LC is Learning Curve and WIP is Work In Progress.

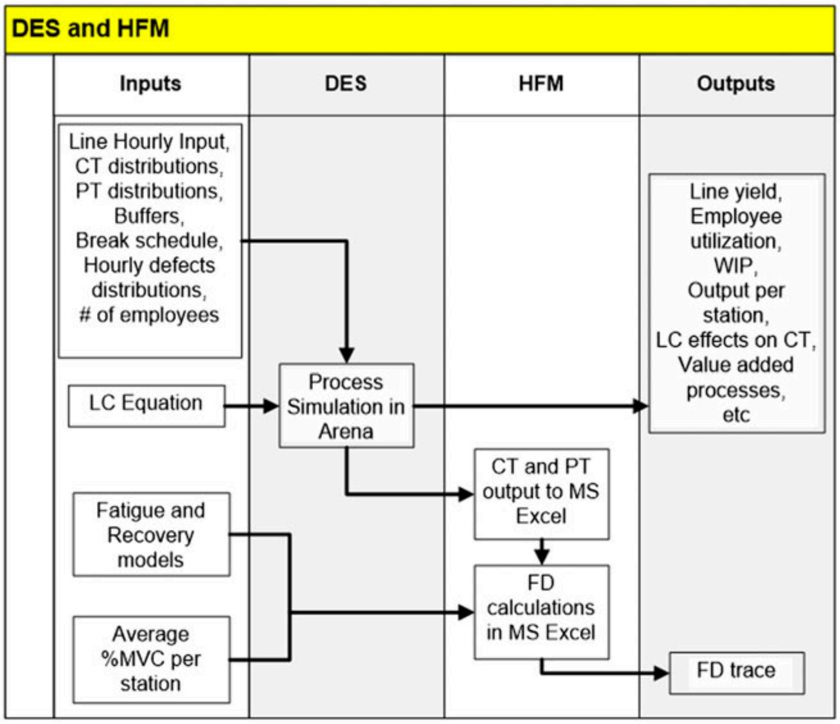

Figure 1. System and HFM logic schematic.

2.2 *Fatigue dose*

The principles of muscular fatigue and recovery were combined to obtain the FD for the employees. The principle of the FD is that it accounts for the fatigue accumulated during the performance of a task and the recovery of fatigue during the following pause. It provides an indicator of the total physiological challenge across the fatigue and recovery phases of the muscular work to the employee's muscles during a shift. The Rose general MET model, shown in Equation (2) (Rose et al. 1992; El Ahrache, Imbeau, and Farbos 2006), was used for fatigue prediction in this paper along with the Rose general RA model (Rose et al. 1992; El Ahrache and Imbeau 2009) for determining recovery needs based on the MET (Equation (3)).

$$\mathrm{MET} = (7.96)e^{-4.16(\%\mathrm{MVC}/100)} \tag{2}$$

$$\mathrm{RA} = 3\mathrm{MET}^{-1.52} \tag{3}$$

The Rose general RA model was chosen as it is not specific to any particular muscle, considers fatigue accumulation below 15% MVC (Rose et al. 1992) and also allowed consistency with the fatigue prediction model. The Rose general RA model also performed best in a comparison conducted in previous research (Perez et al. 2014; Perez and Neumann 2015).

When the employee is provided with enough recovery time, the fatigue level reaches zero (full recovery). Perez et al. (2014) have found problems though when applying static exertion models to dynamic work that has relatively fast recovery times. We side-step this problem here by applying cumulative FD to provide a more comprehensive indicator of the challenge that the work provides to the system operators' musculoskeletal system over the course of a whole shift.

This approach is analogous to Norman et al. (1998) who showed that cumulative loading provides additional injury risk information when compared to instantaneous measures of peak load. Similarly, cumulative fatigue and recovery cycles can capture the dose throughout a working shift and provide a measure of total exposure. To obtain the FD, the area under the fatigue curve, shown in Figure 2, is calculated using the trapezoid formula method (Rahman and Schmeisser 1990).

The calculations for the FD were performed in a Microsoft Excel spreadsheet. The CTs were obtained from the DES model output. The %MVC for each station in the manual assembly line was obtained using the shoulder load prediction

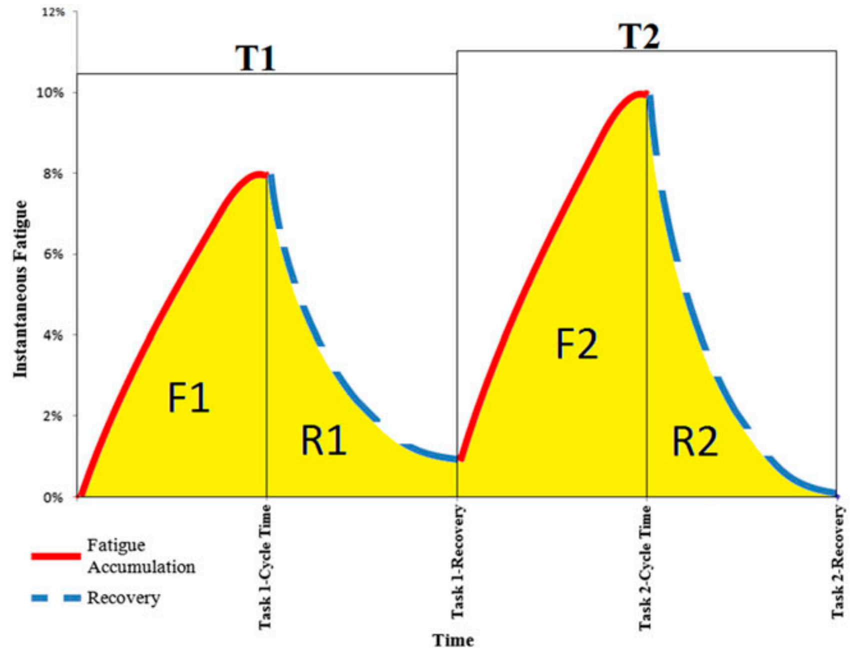

Figure 2. The FD calculation principle.

Table 1. FD calculations sample.

Description	Unit	Column name	Formula
Current Simulation Time	s	A	–
Process Time (CT or PT)	s	B_{CT}, B_{PT}	–
%MVC	%	C	–
MET	s	D	$((7.96)e^{(-4.16C/100)})\ 60$
Fraction of Instantaneous Fatigue	%	E	$(B_{CT}/D)\ 100$
Rest Allowance (RA)	%	F	$(3D^{(-1.52)})\ 100$
Time to Full Recovery (Ri)	s	G	$(F/100)\ B_{CT}$
Recovery Need	s	H	$G\text{-}B_{PT}$
Recovery Received	%	I	$(H/B_{PT})\ 100$
Fatigue level accumulation	%	J	E (1-I/100)
Area under the Curve	% s	K	$\frac{J_{i+1}+J_i}{2}(A_{i+1} - A_i)$

method outlined in Greig et al. (2011). This method calculated individual task shoulder load as %MVC based on the three-dimensional hand location coordinates.

The %MVC for all the tasks in a station was collected for the existing system and then averaged to give a workstation level exposure which was then used to calculate the FD. The FD calculations process is shown in Table 1. To calculate the FD for one task, the integral of the active CT and recovery periods were computed separately and cumulatively summed for each successive cycle.

The area under the curve was calculated using the trapezoid formula (Rahman and Schmeisser 1990). In order to check the validity of the FD estimates, the existing system's operators were administered questionnaires to validate the HFM and more specifically the modelling of FD and LC. Questions were divided into sections regarding fatigue and learning. The questions focusing on fatigue had the operators ($n = 9$) rate their perceived level of 'fatigue (tiredness)' at each hour of the shift, to explore variability within a shift and account for scheduled breaks and disturbances, on a 10-point Borg scale (Borg 1990) for each workstation ($m = 6$) over a full 12-h working shift. The Borg Scale has been widely used for measuring perceived fatigue and discomfort in workplace studies. The Wilcoxon (1945) rank test was performed to understand if the modelled FD and Perceived FD stations ranking was unlikely to occur by chance.

2.2.1 *FD, quality and assembly cost*

To quantify the relationship between FD and quality, the hourly defect rates obtained from the Industry Partner's Quality Data group records and the modelled FD for the existing line were modelled in MS Excel using an exponential fit, which proved to be the best fit. The relationship between quality and modelled FD for the existing line was applied to predict performance in the 'Proposed' line. The quality improvement in the proposed line was used together with the number of units produced, manufacturing costs per unit, lower and upper estimated repair costs per unit and first pass assembly line yield to calculate the monetary benefits of designing a low FD manual assembly line.

2.3 *Learning curve*

The initial CT for each station was provided by the Industry Partner and was considered to be T_1 in the previously mentioned Welford (1968) LC equation (Equation (1)). Line balance planning data were obtained for the four weeks of November 2010 and June 2011. The data showed the CTs per task per station, and the cumulative number of units produced for each month. This was calculated as follows:

$T_{\text{November 2010}} = T_\infty + \left(\frac{T_1 - T_\infty}{n^k}\right)$ and

$T_{\text{June 2011}} = T_\infty + \left(\frac{T_1 - T_\infty}{n^k}\right)$, by rearranging we have:

$$n^{-k}(T_{\text{November 2010}} - T_\infty) = T_1 - T_\infty \text{ and } n^{-k}(T_{\text{June 2011}} - T_\infty) = T_1 - T_\infty;$$

$$n^{-k}(T_{\text{November 2010}} - T_\infty) = n^{-k}(T_{\text{June 2011}} - T_\infty);$$

$$n^{-k}(T_{\text{November 2010}}) - n^{-k}(T_\infty) = n^{-k}(T_{\text{June 2011}}) - n^{-k}(T_\infty);$$

since at T_∞ for the same learning rate, k, the number of units produced, n, would be the same; we have:

$$n^{-k}(T_{\text{November 2010}}) = n^{-k}(T_{\text{June 2011}});$$

The learning rate, k, was found as shown below:

$T_{\text{June 2011}}\ 20{,}000^{-k} = T_{\text{November 2010}}\ 1000^{-k}$ (Jaber and Bonney 2011, 265)

where $T_{\text{June 2011}}$ is the CT in June 2011, $T_{\text{November 2010}}$ is the CT in November 2010 and 1000 and 20,000 are the cumulative number of units produced in November and June, respectively.

Since the operators were not the same in both months, the expression above was solved for the same tasks in the same stations for both months and represents learning at the system level. The average percentage improvement in CTs was used to obtain T_∞, or the lower limit in Welford's (1968) LC equation (Equation (1)). T_1 for each station was provided by the Industry Partner. T_n was calculated for each product that passed through each modelled station. Every time that a unit passed through a station, the value of n was increased by one, and the new CT was calculated based on the learning rate, k. As a validation check, the DES output, as shown in Figure 1, was compared to the production reports and planning data at the Industry Partner, and they were within ±5%. This analysis was done for the existing system only where required data could be obtained; the results were then applied to the simulation of both systems.

2.4 *Analysis*

Conventional DES results analysis was performed on the outputs (Banks 2001). DES output analysis included: (a) Reducing the initialisation bias and finding the point estimator and a confidence interval, (b) Obtaining the minimum number of runs, and (c) Obtaining the run-length for a given number of runs. HFM output analysis included a T-test ($p < 0.05$) to validate the statistical significance of the modelled and existing system's FD. All figures in the following sections, except where otherwise indicated, have been adjusted to protect the Industry Partner's confidentiality. The adjustment preserves the relationship of the results without showing the exact numbers for the two systems.

3. Results

3.1 *System performance results from DES*

Table 2 shows the systems performance results as modelled for the two proposed and existing systems. The existing system's productivity index is benchmarked at 100%. The quality results are predicted based on the fatigue–quality relationship presented below.

3.2 *HF: FD prediction*

Figure 3 shows the average hourly FD per station for both modelled lines in a 12-h work shift. The FD for the proposed line demonstrates a more stable trend compared to the existing line. A two-tailed *T*-test comparing the modelled and existing system showed that the two models were significantly different (*p*-value equal to $1.8 \cdot 10^{-5}$). The average FD was higher and more variable in the existing line ($\mu = 190\%$s, $\sigma = 29$) than in the proposed line ($\mu = 143\%$s, $\sigma = 4$). Similarly, the FD of the existing line had a greater range, 146 to 227%s, compared to the proposed system, 136 to 152%s. The proposed line FD was between 7% (lower boundary) and 33% (upper boundary) less compared to the existing line.

The end of shift Rated Perceived Fatigue obtained by the questionnaire compared to the modelled FD for the existing systems is shown in Figure 4. The prediction of Rated Perceived Fatigue from Modelled FD showed good prediction capability ($R^2 = 0.83$). The Wilcoxon (1945) rank test performed showed that the modelled FD and Perceived FD stations ranking was unlikely to occur by chance. The Wilcoxon statistics obtained were $W_+ = 0$ and $W_- = 21$.

3.3 *FD and quality results*

The relationship between average hourly FD and hourly yield for a 12-h production shift is shown in Figure 5. The existing system's modelled FD and the existing system's line yield data, as obtained from the Industry Partner, had a prediction co-efficient of $R^2 = 0.26$. The cost analysis using these results showed that by considering fatigue-related HF in the manufacturing line, $20,000 could be saved for every 50,000 units produced, or a return on investments of up to 39%. The relationship for the modelled FD and line yield shows that as FD increases, line yield decreases as shown by the slope of the regression line which is −0.017.

3.4 *LC results*

The learning rate, *k*, was found to be 0.483 and T_∞ was calculated to be $0.8885 \times T_1$. Figure 6 shows the LC effects of decreasing the instantaneous CTs for the proposed line for one shift. The LC effects on CT showed that the modelled existing system produced 10.5% more products with LC considered compared to the modelled existing system without the LC effects on CT. Regarding FD, the LC effects on CT showed that the employees in the modelled existing system accumulated a 10.9% greater FD compared to the employees in the modelled existing system without the LC effects on CT.

4. Discussion

Regarding Aim 1 – This research work has developed and validated a modelling approach that can support HF integration at the production system design phase. It is the first time, to the author's knowledge, to apply HF integrated in to DES in two ways: (1) as an output looking at operator workload (Kazmierczak, Neumann, and Winkel 2007; Perez et al. 2014) and (2) as an input, via the LC models to the CTs used within the DES model. DES can also be examined to understand the impact of operational policy to foster autonomy and flow strategy to examine vulnerabilities to worker capability changes or attempts to foster worker autonomy in production (Neumann and Medbo 2009). Such improved simulation capabilities provide the ability to examine interactions between the human operator and the technical and management design choices for the system, creating potential to improve both system performance and minimise the operators' health risks by applying HF in advance of production where costs are lower operators are not yet put at risk. We note that, in this case, the application of DES successfully helped the engineering team identify potential areas of improvement for assembly quality and productivity.

Table 2. System performance results. (* = significant $p < 0.01$ differences).

	Existing system	Proposed system	Difference	DES parameters
Average Human Resources Utilisation	83%	75%	−8%*	Min # of runs: 12. Min Run Length: 720 min.
Productivity index	100%	115%	15%*	95% Confidence Interval. Two tailed *T*-test
Defective units	9.5%	6.1%	−3.3%*	*p*-value: $0.69 \cdot 10^{-5}$

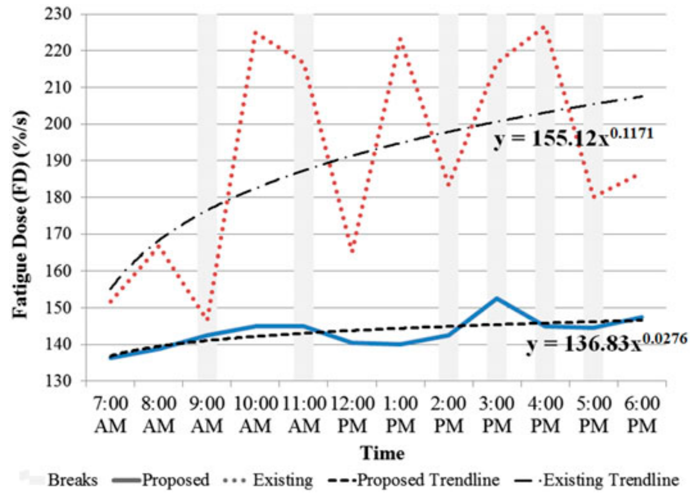

Figure 3. Average hourly FD per operator for the modelled lines over a full shift.

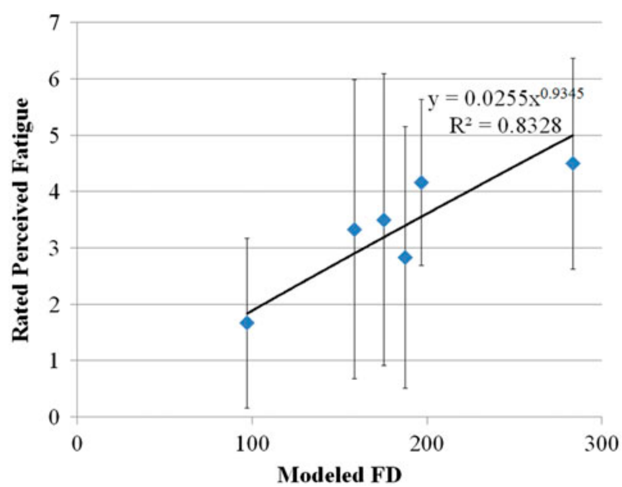

Figure 4. Relationship between rated perceived fatigue and modelled FD for each station (n = 9 per station).

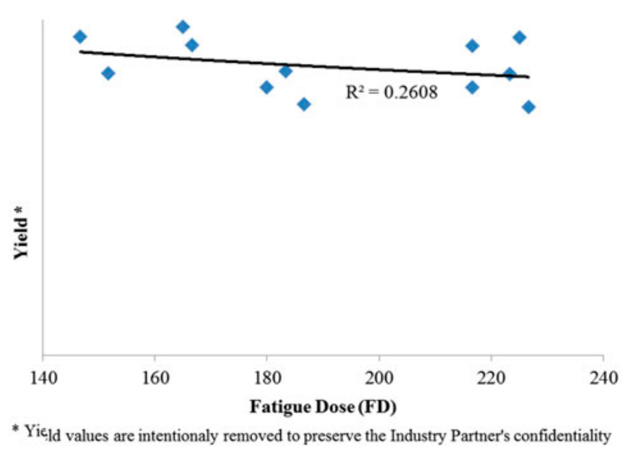

Figure 5. Modelled FD per employee and line yield relationship for a 12-h production working shift.

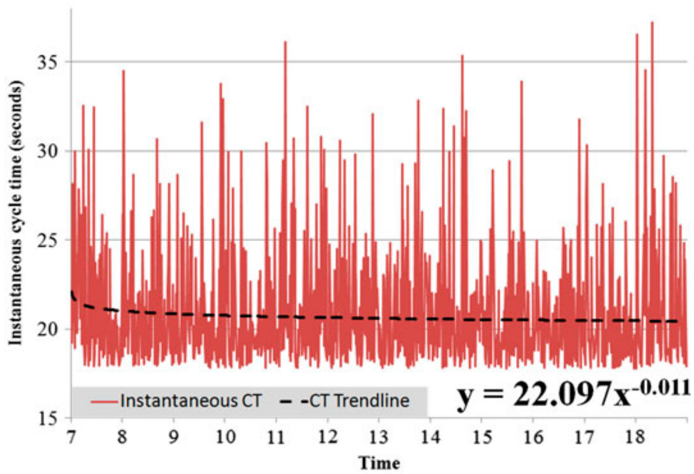

Figure 6. LC effects on instantaneous measured CT for the proposed line. The variability in CTs is a result of the input data to the model.

Knowledge of the relationship existing between FD and line yield (Figure 5) is valuable information for design engineers. In this case, the FD model accounted for 26% of the variance in the defect data. While the quality HF link has been studied previously (Goggins, Spielholz, and Nothstein 2008; Neumann and Dul 2010), there are few tools to help design teams manage this aspect. Targeted changes to reduce FD would result in increased line yield and a reduction of repair costs – both a system and operator well-being benefit. Production line yield has been identified as a critical performance area where HF can help (González, Adenso-Diaz, and Torre 2003). Eklund (1995) has shown statistically significant linkages between quality deficits and HF deficiencies. The sample cost analysis of this study shows that the savings obtained from designing a low FD manufacturing line are notable due to the related tendency for quality defects. Case research in electronics assembly found that production quality savings resulting from improved HF was valued at up to US$956,136 (Yeow and Sen 2006). We note that these substantial savings related to HF do not include injury or compensation costs associated with high workloads (Tompa, Culyer, and Dolinschi 2008), but instead expose what Rose, Orrenius, and Neumann (2013) call the 'hidden costs' associated with poor HF – costs that are difficult to isolate as they are not quantified and are typically aggregated with costs from other causes. While this study focused on physical workload issues, there is potential to expand this line of research with a focus on mental workload, possibly using assessment techniques such as using eye movement tracking (Ahlstroma and Friedman-Berg 2006) or compensatory control measures (Robert and Hockey 1997).

The use of FD as an indicator is novel, although it is analogous to the concept of cumulative tissue loading which has been broadly associated with injury risk (Kumar 1990; Norman et al. 1998). It is also generally consistent with the concept of cumulative trauma disorders (National Research Council 2001). The strong correlation ($R^2 = 0.83$) between workers self-report fatigue and the predictive model indicates the validity of the model in predicting fatigue outcomes. Further work, with larger sample sizes, is needed to refine the relationships and understand the differences in applicability of the different rest and recovery models available (El Ahrache and Imbeau 2009; Perez et al. 2014). Also, further work is needed to develop relationships to further account for the human variability, for example, in fatigue or learning rates which were the same across workers in this simulation study. Humans have considerable within- and between-individual variability in strength and fatigue response which is not incorporated in this model. Although it is typical to design systems with consideration of population averages, or in the case of injury risk factors with a large portion of the population (e.g. 95th percentile) in mind, determining the appropriate approach to handling within- and between-operator variability in HF parameters remains a research issue. Despite this human variability, the simulation model here was able to capture over 25% of the real quality variance – a substantial amount from a managerial perspective. This simplified model approach was also shown to provide valid estimations ($R^2 > 0.80$) of fatigue as reported by the system operators themselves suggesting the approach used here gives good insight into the performance at the employee group level. FD provides insight into the ongoing exposure accumulation of the operator that is not always available from the instantaneous estimations used by Perez et al. (2014). This technique also makes it possible to assess the total demand of production across workstations, similar to the product workload assessment modelling piloted by Pascual et al. (2008). The FD modelling technique could, and should, be used to study long-term effects of fatigue on operators. One challenge here is the choice of what aspect of fatigue to model. In this study, we attended to loading of the shoulder musculature – chosen based on our field observation and discussion with the plant ergonomist as to where the physical demands of the work were of greatest concern. In other contexts, other aspects of fatigue, including mental fatigue, may be of greater concern. The selection and quantification of relevant HF variables, which might include perceptual, cognitive or physical workload aspects, for inclusion in simulation is a non-trivial issue that requires further research (Neumann et al. 2013). Although infrequently addressed in the engineering literature, attention to HF in system design has been associated with improvements in productivity, quality, technology implementation and other 'intangible' benefits like improved communications; furthermore, these benefits are simultaneously linked to lower injury risks for system operators (Neumann and Dul 2010). While a large number of HF variables exist, limited resources mean that it is important to identify those variables known to be of concern in a particular context. Formal tools are currently lacking to support such selection decision-making and expert judgement must be utilised. The approach presented here poses a starting point for further studies related to fatigue processes at work and their effects on system and safety performance. Further research in this area should also emphasise studies of the FD-injury and FD-Quality relationships in a broader range of variables relating to human–system interactions. The current study reveals how important including such variables can be to predict quality-related losses already at the production planning stage, which poses considerable opportunity to improve the lifecycle costs of any production system design.

The LC equation implemented in the DES model affected the simulation of the system. The learning rate, k, obtained was within the ranges of Welford (1968) regarding electronic assembly work. Further work is required to examine the LC impacts of production ramp up in a new manufacturing system. Ramp up is important in determining program profitability; however, it has frequently been dismissed as 'run in' or 'warm up' and treated as an artefact to be ignored in simulation (Neumann and Medbo 2009). While LCs have been applied extensively in operations research (Terwiesch and Bohn 2001; Vits, Gelders, and Pintelon 2006; Jaber 2011, 265), their use in DES remains uncommon and few studies address this issue with empirical data. Since the ramp up time of production is a critical element in the life cycle profitability of the production system (Dhouib, Gharbi, and Landolsi 2009), we propose further work examining how design of the system affects learning rates, and how these rates in turn affect the time to reach full production. Establishing the learning coefficient was difficult. In this study, the data used were at the workstation level which meant that variation between operators was not fully captured and it was assumed that the same operators were at each station during the simulation. Obtaining the CT at $T1$ (the first trial) can be difficult in practice, and better methods for isolating the learning coefficient are needed. Further empirical research in this area is needed regarding the variability of LC across people and workstations as well as the inclusion of mental fatigue in the DES and HFM approach. The latter would complement physical fatigue studied here and provide a more accurate estimation of operator demands in assembly.

The application of the developed method to the two design concepts under consideration revealed that the proposed design would have higher output, reduced operator fatigue and improved quality performance over the old system. This analysis contradicts the view that worker well-being aspects and system performance are in conflict and is consistent with reviews of the applications of HF principles in production contexts (Goggins, Spielholz, and Nothstein 2008; Neumann and Dul 2010). On the contrary, when HF is not included in, for example, Lean-focussed performance improvement efforts, then increases in worker injuries can be expected (Westgaard and Winkel 2011) and the discrete and hidden indirect costs of such injuries will begin to manifest (Rose, Orrenius, and Neumann 2013). The modelling approach proposed here provides system designers with the ability to manage HF that are critical to performance in the early design stages where changes are easy and inexpensive (Miles and Swift 1998; Neumann and Village 2012). A failure to include HF aspects in production planning can, therefore, yield 'Phantom Profits' (Neumann and Dul 2010) in which planned financial gains are compromised by the untracked costs related to human performance variation. Operations management models have been criticised for their failure to attend to human aspects (Boudreau et al. 2003). This research illustrates a general approach to spanning this gap and provides a specific example of how Baines' 'missing link' in DES (Baines et al. 2004) might be included in a practical way. Further research, using both simulation and field observational approaches, is needed to identify the leading HF indicators that are crucial determinants of both operational and safety performance.

5. Conclusions

This project developed and tested a novel approach to combining DES and HFM which can provide predictions of the accumulation of operator fatigue, fatigue-related quality effects and productivity changes based on system design configurations. In the demonstration comparison, fatigue dosage was 7–33% lower in the proposed system where HF was taken into consideration at the ED stage. Furthermore, the FD measure related well with quality deficits with 26% of the variance accounted for – a large portion given the multi-causal nature of production deficits. The LC effects in the modelled existing system showed that 10.5% more products were produced when compared to a modelled existing system without the LC effects. This paper demonstrates a viable and valid approach to incorporating human aspects into system simulations in early design stages. Models that do not include human aspects may provide unreliable results in terms of productivity and quality estimates. The production system comparison here also shows that it is possible to design production systems that are more productive while being less hazardous for the system operator.

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