Improving Human-Robot-Interaction Utilizing Learning and Intelligence, a Human Factors based Approach

Oliff H., Liu Y.*, Kumar M., and Williams M.

***Abstract*—: Several decades of development in the fields of robotics and automation has resulted in human-robot-interaction being commonplace, and the subject of intense study. These interactions are particularly prevalent in manufacturing, where human operators have been employed in a number of robotics and automation tasks. The presence of human operators continues to be a source of uncertainty in such systems, despite the study of human factors, in an attempt to better understand these variations in performance.**

Concurrent developments in intelligent manufacturing present opportunities for adaptability within robotic control. This work examines relevant human factors and develops a framework for integrating the necessary elements of intelligent control and data processing to provide appropriate adaptability to robotic elements, consequently improving collaborative interaction with human colleagues. A neural network-based learning approach is used to predict the influence on human task performance and use these predictions to make informed changes to programmed behaviour, and a methodology developed to further explore the application of learning techniques to this area. The work is supported by an example case-study, in which a simulation model is used to explore the application of the developed system, and its performance in a real-world production scenario. The simulation results reveal that adaptability can be realised with some relatively simple techniques and models if applied in the right manner and that such adaptability is helpful to tackle the issue of performance disparity in manufacturing operations.

NTP: This paper presents research into the application of intelligent methodologies to this problem and builds a framework to describe how this information can be captured, generated and used, within manufacturing production processes. This framework helps identify which areas require further research and serves as a basis for the development of a methodology, by which a control system may enable adaptable behaviour to reduce the impact of human performance variation and improve human-machine-interaction. The paper also presents a simulation-based case study, to support the development and evaluate the presented control system on a representative real-world problem. The methodology makes use of a machine learning approach to identify the complex influence of a number of identified human factors on human performance. This knowledge can be used to adjust the robotic behaviour to match the predicted performance of a number of different operators over a number of scenarios. The adaptability reduces performance disparity, reducing idle times and enabling leaner production through WIP reduction. Future work will focus on expanding the intelligent capabilities of the proposed system to deal with uncertainty and improve decision-making ability.

Index Terms— Intelligent Manufacturing, Human-Machine Interaction, Machine Learning, Human Factors, Neural Networks, Collaborative Robotics.

I. Introduction

Automation has been the focus of advancement within the manufacturing industry for a number of decades, and the use and utilization of robotic operators to perform repetitive assembly tasks is ubiquitous [1]. The role of the human operator persists within these manufacturing processes, however, despite many successful applications some manufacturing tasks still require a level of dexterity or adaptability which robotic operators remain unable to perform. This has resulted in a period of transition whereby these robotic operators frequently perform tasks with human operators as colleagues. The continued presence of human beings in these highly automated systems introduces variation and uncertainty into an otherwise repeatable process; as human beings are subject to the influence of a number of factors which affect their performance in a number of complex and interconnected ways. These Human factors and their influence on performance have been studied for decades and this knowledge is frequently applied from a management perspective. However, limited work exists on how to best leverage intelligence when considering these human factors, and how to apply this knowledge to the study of Human-Machine-Interaction and the domain of autonomous systems.

By studying established concepts within the field of intelligent manufacturing, this work examines the potential of developing robotic systems capable of intelligent data processing to enable adaptable behaviour which can be used to mitigate the effects of the variation in performance of human beings. This increased adaptability is necessary to enable changes in behaviour in response to the actions of others, facilitating collaboration with human colleagues. Consideration of the impact caused by human factors can be used to model the consequent variations in performance, and machine learning can be leveraged to enable the robotic agents to intelligently analyse the observed data, model the relationships between observed human performances, and respond properly to this contextual information.

These human factors are complex, and the natural variation between human beings means that their effects are not consistent across a demographic, and their interactions and combined influence

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H. Oliff is a senior PhD student with the high-value manufacturing group at Cardiff University, Cardiff, UK, CF24 3AA (e-mail: OliffH@cardiff.ac.uk).

Dr. Y. Liu is Raeder of Intelligent Manufacturing and Group Lead for High-value Manufacturing group at Cardiff University, Cardiff, UK, CF24 3AA (e-mail: LiuY81@cardiff.ac.uk).

Dr. M. Kumar is Professor of Service Operations with the Cardiff Business School at Cardiff University, Cardiff, UK, CF10 3EU.

M. Williams is a senior automation engineer with Olympus Surgical Technologies Europe, OSTE, Cardiff, UK.

quickly become an impossible task to model. However, by providing contextual knowledge based on these identified factors, and combining this with intelligent data analysis may potentially be used to predict and adapt in response to changes and variation; with the elimination of variation in performance between operations, enabling processes to achieve a more optimal and agile one-piece-flow, in line with modern application of lean-manufacturing methods [2].

The application of intelligence to robotic systems in such a manner is an area of work that is still in its relative infancy. This work seeks to answer how to capture task performance and the influence of human factors in a suitable manner, and how intelligence can be used to process this information so to improve and enable adaptability in robotic behaviour. In addition, it seeks to develop suitable methods for the contextual understanding of human performance and the factors which may influence it. Section 2 presents a comprehensive review of the current literature, covering a number of relevant areas from which knowledge will be amalgamated. Section 3 outlines the proposed framework which can be used to intelligently process observed data, and use the information obtained to effect an appropriate change in behaviour. Within this framework, we further develop the elements of intelligent processing to assess how such functionality can be achieved. Section 4 illustrates the developed methodology for developing a control system that functions in such a manner, and the simulation model to enable the implementation and on task assessment through the use of a case study. Section 5 presents the key results of both the learning model development, and the simulation evaluation, and these results, the key insights and implications are discussed fully in Section 6.

II. Literature Review

A. Intelligent Manufacturing

Intelligent Manufacturing is a wide-ranging field that is the result of the combination of a multitude of intelligent technologies and methodologies over the past decade, and which exists as a field of study in its own right. Large volumes of work are being done to develop the capabilities of manufacturing systems by utilizing these intelligent concepts to improve existing manufacturing processes and develop novel methodologies, making use of data and informatics [3]. The most notable areas being: Control systems, making use of decentralization, virtualization, reconfiguration, and adaptability [4-6]; Virtual and augmented reality systems, to enable knowledge and skill to be transferred easily between individuals and over distance [7]; and machine learning techniques for intelligent systems [8].

One of the most notable field to have arisen as a result is that of *cyber-physical-systems(CPS)* [9]; which combine digital processing and planning with physical manipulation. such systems on the utilization of data to generate *knowledge* about the process and environment, which can be used to influence the system control. These systems are capable of demonstrating a level of computational intelligence and are capable of autonomous: self-awareness & prediction; [10]; self-configuration [11]; and self-optimization [12]. Combined, these self-x capabilities enable improved adaptability; efficiency; functionality; reliability; safety; and usability [13]; Cyber-Physical Systems are typically defined by their *self-x* capability and the degree to which they are able to generate knowledge from data, which in turn is used to provide different capabilities, with more advanced systems capable of autonomous planning, adaptation, and self-configuration [14, 15]. Current applications demonstrate success in system monitoring and control, but there is little work on applying these principles to improve human-machine-interaction, due in part to the sheer variety of potential applications.

1) Decentralization of Control

More recent advances in computer science have begun to enable advanced systems with a number of intelligent capabilities to be realized. The common factor which enables the emergence of these self-x capabilities is the decentralization of control. Existing control structures are bound by their centralized nature, as centralized control architectures employ a hierarchal structure. As production processes become increasingly complex, hierarchal structures present a number of problems and challenges when faced with enabling intelligent systems to behave in an autonomous and adaptable manner [16, 17]. The distribution of control divides the computational demands, and reduces the overall system complexity, by dividing the control problem down into multiple tasks distributed to a number of agents, which coordinate their actions to achieve the given goal. Recent applications of *intelligence* to these autonomous agents have made use of machine learning (typically a neural network-based approach) to automate each agent's individual control and analytical processes and to control decision-making processes [18].

What is key, is that the agents are autonomous, and able to receive individual sensory input, and are governed by individual beliefs and goals. Individual perceptive ability enables awareness of distinct internal and external environments, which in turn provides embodiment. The goals and beliefs of each agent govern the control of each agent, and internal functions can provide intelligent processing of observed information, to coordinate behaviour with other agents. Embodiment is a term used to describe each agent being aware of only the information that is individually observed or received. This enables different agents with an identical internal control structure, to respond to observed in different ways based on their individual cumulative experiences [19, 20]. Decentralizing control in this way necessitates the consideration of collaborative behaviour, which has itself been a key aim of robotics research for several years. Many examples of robots capable of displaying adaptive collaborative behaviour exist, however, the applications are typically physically oriented, and direct interactions, such as handling of unwieldy components, and for advanced manufacturing tasks. The intelligent agents which form these intelligent systems can be purely virtual, or a logical unit consisting of a combination of hardware and software capable of virtualization akin to elements of a CPS [21]. The structure of these agents further facilitates virtualization and simulation, as the necessary structure closely resembles that of Object-Oriented programming languages. Individual agents can be generated and represented by instances of an object within the model or simulation, each with protected and distinct internal and external structures and functions to facilitate their behaviour. The variation in behaviour that distributed control enables place simulation as a critical tool in developing distributed control systems, as the simulation is a powerful tool enabling the design, evaluation and subsequent optimization of intelligent agent performance on the representative and varied tasks in a repeatable environment [22]. A detailed overview of intelligent agents can be found in [23, 24].

2) *Agent structure & Design*

To enable intelligent processing of sensory data, consideration must be given to how the control system governing the agent should be structured to enable an adaptable and appropriate response. Studies aiming to understand cognitive processes as they occur in humans, and to replicate these *cognitive* processes, have led to the development of a number of *cognitive architectures*, which define the structure of control systems which enable intelligent behaviour. A number of these architectures exist, notable examples including ACT [25], SOAR [26], and C4 [27], but a common feature among many is a modularized structure, with multiple interacting separate elements responsible for different aspects of cognition. These architectures are dated and were conceptualized before the current capabilities of computational systems were fully understood, despite this, the insights with regards to structure and interaction are still valid today. The constituent modules are often structured around a centralized control unit, either a shared space or a module responsible for inter-module communication, which manages the internal *thought processes*. This thought process is then extended by the other *modules* to facilitate necessary behaviours; such as Perception, Learning, Decision-Making, and Memory. The modular structure additionally facilitates the integration of low-level perceptual and motor control systems with higher-level knowledge extraction and decision-making processes [28]. Isolating these areas of processing enables established control techniques for image capture and robotic motion planning to be used for control alongside higher-level processing without interference. This separation is analogous to the distinction between two types of cognitive processing; *Type 1* and *Type 2*. The former fast and intuitive; the latter slower, analytical and contemplative [29]. The relative reliance on each of these two types of cognitive processing is situationally dependent. *Type 1* processing is typical in familiar situations where rapid response time is required, and where a large number of points of observation exist simultaneously. Conversely, situations where *Type 2* processing is dominant, are those where response time is non-critical and focus on the specific relationships between a relatively small number of observations. These situations are typically unfamiliar, and analytical reasoning is used to identify relationships, to form appropriate behaviours [30, 31]. Multiple frameworks exist to implement intelligent computational features to achieve a level of *cognition*, although there are little consensus and a wide variance in their application and capability.

3) *Machine Learning*

Machine learning continues to gain traction and interest as a useful tool in the generation of knowledge from data [32, 33], particularly within the field of manufacturing [34]; as the use of machine learning techniques enables complex, non-linear and temporal relationships to be modelled easily through the use of historical data reserves. Neural networks have been successfully implemented in a number of applications and provide a non-deterministic method of matching a number of input variables to an output, and for approximating relationships between multidimensional data. Their recent successes owing to capacity for analytics and pattern recognition; the ability to be abstracted and manage a large number of data inputs; and their adaptability to suit a wide variety of applications.

Recent developments have resulted in a wide range of network structures. Recurrent networks include consideration of temporal patterns, and are used to process time-series data for pattern recognition; convolutional networks introduce multiple layers of abstractions and have been applied successfully to a number of vision-based learning and recognition tasks; and deep reinforcement learning is used to produce optimal policy generation based on simulation and experience [35-38]. A thorough study of the topic can be found in [39-41]. The utilization of neural networks as a learning model overlaps significantly with the field of cognitive computing a branch of computer science focused on replicating thought processes as they occur in the human brain. Typically, this is through the utilization of combinations of neural networks, to replicate cognitive processes [42, 43]. This has potential implications for the facilitation of collaborative behaviour and the improvement of human-machine-interaction. Recent work on social cognition and social intelligence suggests that providing intelligent robots with social understanding, and human-like cognitive processes and structures, will better enable natural and intuitive behaviour when interacting with humans [44, 45].

4) *Collaborative Robotics*

Collaboration presents several problems for conventional computer architectures which traditionally have centralized and hierarchal structures. Systems based on the principles of distributed control have been proposed to overcome these challenges, as they enable adaptability through a reduction in the system complexity, by dividing complex problems such as task planning, into several smaller problems, which are distributed to a network of multiple *intelligent agents*, which collaborate with one another. The use of decentralized control to provide robotic entities with agency and a level of intelligence can facilitate collaborative interactions as the agents can autonomously adapt their behaviour in response the behaviour of others and coordinate their actions to achieve a common goal [15, 21, 46, 47]. These agents require the capability to autonomously communicate and negotiate with one another in real-time, to align the behaviours of all constituent operators and processes to successfully complete the task [24, 48, 49]. Providing robotic operators with agency presents additional benefits for Human-Machine-Interaction by providing a sense of embodiment, which influences the way agents interact due to the unique nature of each agent's cumulative experience. It enables agents with the same control structure to be more adaptable, and better select appropriate behaviours for multiple situations, as their responses are based on their own experiences. [19, 50]. As the capability of autonomous systems increases, there is the suggestion that autonomous systems should begin to be treated as collaborators, as opposed to tools [51, 52] with appropriate attention given to implementing intelligence in a human-focused manner, with *human* ideals and constraints.

As discussed, the extension of collaborative robotics and intelligent control to human collaboration is well studied in terms of physical tasks. Robotic operators are frequently employed in handling tasks to increase human strength, enabling the handling of large and unwieldy components [53]. These tasks have been improved through coordination of robotic and human operator motion, to facilitate safety in a shared work area through advanced collision detection. Learning methods have also been used for *Direct-Teaching* of robotic operators, combining the flexibility of human with the accuracy and repeatability of their robotic counterparts. This has enabled advanced manufacturing processes such as composite layup and welding fabrication to be automated and to achieve a similar finish and quality to human professionals [54-57]. There are other modes of collaboration which are more passive, whereby knowledge of others, combined with context, can be used to inform behaviour [58, 59]. The knowledge and contextual information can be sampled from the environment, or observed directly, as used in techniques such as gesture control which is increasingly used for robotic control in human-machine-interactions [60]. Comprehensive analysis of the state of the art in computational HMI can be found in [61].

Human operators are a source of disturbance to manufacturing systems and render most optimization techniques ineffective due to variation. No two operators will perform a task the same way, and there are multiple factors which influence human task performance. Knowledge of these factors and their influence on task performance is crucial to informing collaborative decision-making, as it captures the contextual information required to predict their influence. Once this is known, behaviour can be adjusted, facilitating collaborative control of the robotic system elements.

B. Human Factors/Ergonomics

Unlike their robotic counterparts, a multitude of factors exists which may affect human performance. The influence of these factors is typically expressed through the lack of repeatability, accuracy, and a variation in performance ability under different environmental and contextual conditions.

Consequently, Human Operators are often a source of significant disruption to a system. This influence also extends the variation between different human operators, as the aforementioned factors influence behaviour and prevent consistent human performance to varying degrees depending on the individual. A large body of research has been conducted on human-factors from a business management perspective to investigate and model the influence of these factors on human operators in the manufacturing context. Current models use a finite reserve of cognitive *resources*, which are consumed in order to complete cognitive tasks [62]; and the mechanisms by which these *resources* are consumed are influenced by a number of different factors. This section discusses several of these identified human factors and their influence on task performance.

The Type of Task, and how it can be characterized by its demands and nature is perhaps the largest source of human performance variability. The NASA developed 'TLX' framework [63] identifies a number of task types characterized by differing combinations of physical and mental demands. These *task demand characteristics* will influence the way in which a number of factors, such as the task duration, influence the perceived workload; with increased workload perception associated with decreased task performance. [63, 64].

Assembly tasks requiring manual and dexterous manipulation of components are influenced heavily by fatigue, as they require a combination of mental and physical demand. This fatigue will, in turn, influence task performance. Fatigue is a well-studied and complex phenomenon, which is commonly understood to exist in two distinct types: Physical, or motor fatigue, involving fatigue of the muscle; and cognitive, or mental fatigue resulting in the deterioration of cognitive functions [65]. The two types also do not occur independently, and are not entirely distinct, however, and there are known relationships between motor fatigue and increased nervous loading, which is in turn responsible for poorer response times in decision-making tests, and a decrease in motor control and physical function [66]. This relationship implies that dexterity can be detrimentally affected by increased cognitive loading. In addition to the load requirements of the task, the *time-on-task* is another factor which influences the effects of fatigue. Fatigue is a cumulative phenomenon, and repeat demands will have a cumulatively greater effect on task performance [67]; additional factors, including the interstitial period of rest and their duration, further affect the fatiguing mechanism [68].

Using the more traditional definition, fatigue also describes tiredness and the effects of sleep deprivation. Both the immediate and cumulative effects of sleep deprivation on performance have been studied, and both have a significant influence on performance [69, 70]. Human sleep patterns are governed by circadian rhythms which dictate periods of physiological activity and are closely linked to the time of day [71]. A number of patterns in these variations have been identified, termed *chronotypes*, with active periods in these rhythms are linked with increased motivation and task performance. There is a typically a preference for either morning (larks) or night (owls) activity; with corresponding decreases when task performance is measured at a non-preferential time of day [72]. These circadian activity periods can often be influenced by light levels, with higher levels of illumination linked to improved task performance [73] and by satiety, which dictates many of the bodies physiological processes [74, 75] and is, in turn, influenced itself by a number of other factors. Other work has demonstrated the existence of an observable *day-of-the-week* effect, with decreased performance on Mondays, rising through the week to optimal performance on Thursdays [76]. A number of environmental factors, particularly temperature and noise, can all influence task performance if the level is excessive or susceptible to variation, and the impact of which is often to limit the ability to perform tasks concurrently [77, 78].

The last key contributing influence on human task performance, the impact of an individual's emotional state, is perhaps the most abstract. Whilst the influence of emotion on behaviour is generally well understood it is often overlooked from a human management perspective. The most influential emotional state is one of *stress*, the cause, and effects of which are some of the best-studied of these emotional factors [79]. Stress, like fatigue, is cumulative and is consistently found to have a significant and detrimental impact on task performance [80]. There is a close link between stress and frustration, a contributing factor to the perceived task workload [63], as a stressed mental state or a stressful task generate frustration which in turn propagates additional stress. Recent work in the field of social intelligence and cognition aims to use learning techniques to predict emotional states from the observation of actions and behaviours [31, 81], which can be used to identify and account for these emotional states.

C. Summary

The preceding section has examined much of the recent literature within the scope of intelligent manufacturing. What is clear, is that there is substantial opportunity for the increased capability of modern computer systems and computer science techniques to improve manufacturing. Less obvious is how such opportunities can be capitalized upon, and there remains, crucially, no agreed upon methods or systems for achieving the theoretical benefits of intelligent systems. This is due in part to the relative infancy of the field, and the effectively limitless number of applications and their associated problems. Theoretical studies of thought and how autonomy and adaptability can be replicated through the use of computation are abundant in overlapping fields, and many of the insights and methods from both the fields of cognitive computing and multi-agent-systems are valid.

Much of this work is outdated, however, and the capability of modern systems far exceeds those for which these frameworks were designed. A key aim of such systems is to enable adaptability within the robotic elements of manufacturing systems, a goal which great steps have already been taken to achieve. However, despite the ubiquity of human workers and the obvious disruption that is associated with human performance is an area that remains to be addressed. The benefits that adaptation can provide within the manufacturing setting are clear, and consequently, there is justification to apply these methods to the problem of human performance variation and the associated problems this can introduce to these systems.

III. DEVELOPMENT OF RESEARCH FRAMEWORK

The literature review provides numerous insights into how the incorporation of intelligence into manufacturing systems can facilitate adaptable behaviour of robotic operators. Decentralization of manufacturing control systems to individual robotic operators can enable intelligent analysis of their observations. Such analysis can improve collaborative behaviour, through the appropriate selection of action based on the observed state of the process.

By considering a typical manufacturing control process, two independent disciplines can be seen: *Data collection*, concerned with data generation, collection, transfer and storage; and *Robotics*, that accounts for the elements of robotic control, connecting the virtual to the physical, through traditional methods. These disciplines exist separately, but are ever more closely linked, as data-driven robotics systems become more commonplace. In such systems, control systems receive binary signals from sensors (data collection), which are passed to a PLC, triggering the appropriate response logic (robotics). The use of the information generated by this data can be seen in the framework illustrated in Figure 1.

To enable the intelligent processing of this data, the authors propose the following framework, which aims to outline the necessary interactions between these different systems, in a fashion suitable to enable adaptability and collaborative behaviours. The presented framework illustrates the flow of data and information necessary to effectively collect, store, interpret, and act on data generated by a control process. This is primarily achieved by the addition of an intermediary *Cognitive Layer* which contains its own modular elements (illustrated in Figure 2), to implement the necessary data processing steps in an efficient manner. Such processing will enable *intelligent* response to changes in the perceived environment and facilitate agency in the robotic systems.

Within the presented framework, three distinct stages now exist. The first of these encompasses the methods and processes associated with data collection, a vast topic in its own right, with many inherent problems. The available methodology for data collection is application specific, and the framework identifies the critical processes and capabilities that the data collection method must possess. The robotic operators' data controller must minimally have the capacity to gather, store and transfer multiple data instances in a manner that enables compatibility with the computational components.

Data generated within a typical manufacturing process can additionally be defined as being from one of two sources: *Process data*; The data elements directly related to the parameters of the process; and *Environmental data*; any supplementary data which can be used to extract information deemed relevant to the application. Notable consideration must be given to capturing and appropriately recording the relevant data at this stage, which can be generated from a combination of these sources.

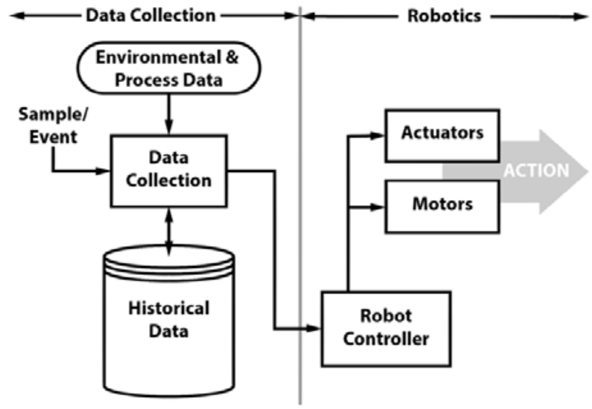

Figure 1. Existing information processing systems illustrated in terms of information flow through the system.

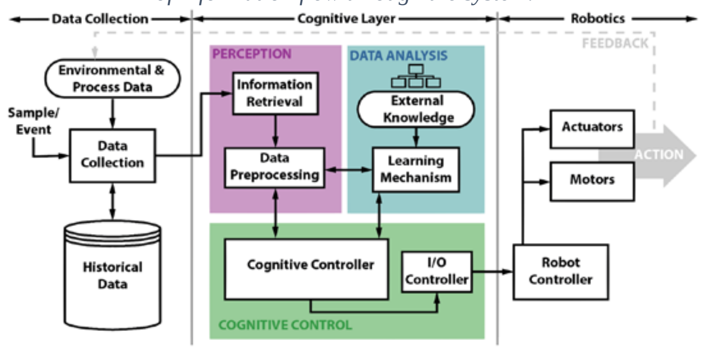

Figure 2. The proposed framework illustrated in terms of information flow through the system. Divided into three functional layers.

Critical to enabling the use of machine learning methods is the capability to store and collate historical data. The historical data reserves must also be available to the controller, and able to be passed through to the cognitive layer for processing.

The intermediary stage is the proposed *cognitive layer* which enables *intelligent* processing of the data. The layer is based on the modular structure seen in existing cognitive architectures. Each of the modules combines a number of functions and processing steps and is responsible for a different area of cognition. Three of these *modules* are proposed initially, covering key areas of processing. The first receives data from the data collection system through an appropriate interface before additional functions perform the necessary pre-processing transformations for the data to be useful to the application. This is analogous to *Perception*, whereby the observed data and the information it contains is affected by the beliefs and aims of the observer. Such processing enables deduction of more useful data instances, for example, establishing a cycle time by looking at the timestamp separation of execution of two different sensor activations.

The analytics module isolates the learning and analytical processing of the cognitive layer. This isolation of these more focused cognitive processes more easily enables the integration with low-level control; the responsibility of the cognitive controller. The learning mechanism here can be used to build a predictive model to associate patterns seen in the observed data with the relevant value. This observed data is supplemented here by additional knowledge, which is not directly observable by the agent. This may include additional contextual information, such as shift patterns or production targets.

The *Perception* and *Analytics* modules are supported by an underlying *Cognitive Controller*, which manages the information flow through the cognitive layer. It manages exchanges of relevant data between the different modules and uses the predictions of the analytics module to dictate the operations and parameters of the robot to exhibit the necessary functionality. The cognitive layer is additionally responsible for passing the relevant command instructions via an appropriate I/O interface to the robotics controller where they can be enacted.

The final stage of the framework isolates those stages concerned with traditional robotics. The control signal generated by the cognitive controller is passed through the I/O interface (to convert the information to the application-specific format) where it is received by the traditional *Robotic Controller*. In many robotics applications, the interface will send instructions to a Programmable Logic Controller (PLC) for execution. The PLC is then responsible for generating the necessary command signal for the motors and actuators to affect the relevant motion of the robot. The operation of the robot results in an *action*, which influences the system, which will affect the recorded environmental and process data, forming a feedback loop. Separating these steps provides a clear distinction between the *digital* and *physical* domains of the system, and isolates the elements of *control planning* (an additional element of cognition identified in existing cognitive architectures) which are necessary to effect the correct motion of the robotic operator. This separation facilitates the division of cognition into higher-level reasoning and preserves necessary elements of *reactive* action. This action can still be enacted by sensors directly connected to the robot controller (i.e. in the case of kill-switches and collision/fault-detection), in addition to reducing the computational load of the processing. Using established techniques and technology from more traditional automation will facilitate implementation and compatibility.

The architecture proposed in this section demonstrates how an intermediary *cognitive layer*, can be utilized within the control systems of robotic elements of the manufacturing process, to provide adaptive functionality, based on knowledge of human factors, and real-time contextual information observed from the environment. The presented case study is intended to demonstrate the potential feasibility of inclusion of knowledge of human factors and to further understanding of how the analysis of generated data may be used to predict and account for the uncertainty caused by human beings and improve production processes through adaptability. Within the framework, knowledge of how the *decision-making* module can process and interpret generated data, to extract this knowledge remains to be established. Preliminary work suggests that machine learning techniques can be used to provide a learned policy to associate observed contextual data which captures the influence of human factors with the appropriate impact on performance.

IV. METHODOLOGY

To investigate the intelligent analysis of the generated data several tasks must first be accomplished. As discussed, the focus of this investigation is how to appropriately generate knowledge from data typically captured from manufacturing processes. The following section outlines the methodology for approaching this work.

To enable exploration, a simulated environment was developed using the AnyLogic simulation platform [82], a Java-Based simulation platform designed for Agent-based, Discrete Event and System Dynamics simulation approaches. This combined functionality, and the ease of integration with external Java Libraries, best suited the applications of this work. The simulation environment was designed to replicate the collaborative interactions between a single Robotic Operator (RO) and a Human Operator (HO), working to achieve the common goal of product assembly as part of a production line. The simulation by design enables exploration of these interactions in a generalized manner. This is achieved by discretizing specific sub-operations into logical 'cells', which enables the methodology to be applied to a non-specific manufacturing operation defined only by its duration or Cycle Time (CT) at each position. The interaction dynamics are then reduced to an upstream and downstream position, which are in turn defined as their own logical combination of sub-operations discretized into a cell. The cells of each operator are separated by some form of transport method for the partially completed products (typically a conveyor), which often doubles as a buffer zone. Design is typically seen in production processes between operations. This formation of the problem in this way is illustrated in Figure 3. Such interaction also bears similarity to fetch-and-deliver type interactions more traditionally studied in the field of human-machine interaction, where one agent must provide the other with an object for them to perform their task.

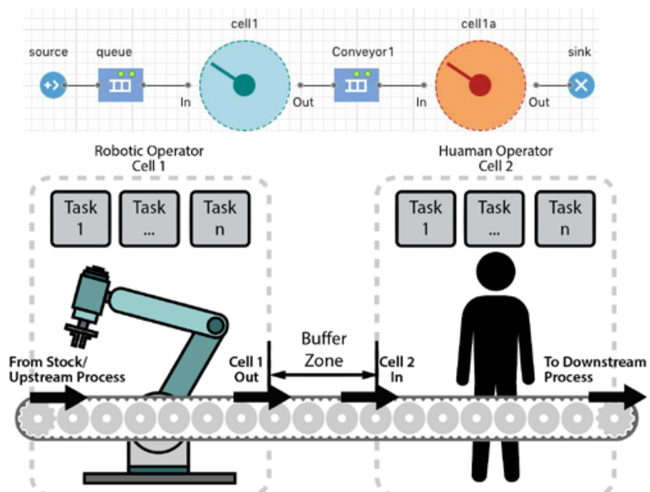

Figure 3. The model developed and the corresponding Anylogic simulation, each cell contains a delay and data capture function.

A. Human Factors Modelling

Whilst the simulation environment primarily functions as a platform to evaluate *on-task* robotic performance, it is also used to generate data for training the learning algorithms. To achieve this, the components of the simulation representing human operators are parameterized to replicate both the variation between different operators and the effects of human factors on their performance. As the number of potential human factors is significant, in this study, a number of human factors relating to fatigue are considered, as this has the most significant influence on human performance across almost all types of task. To achieve this, a number of variables were used to modify the human task performance during simulations runs to represent different aspects of fatigue. The Cycle Time, calculated as the total time duration between products leaving each cell, was selected to represent the task performance within the simulation. This value could be manipulated through the use of the defined variables to represent the effect on task performance.

The *Shift Duration* (SD), was monitored and used to influence the task performance, by increasing the Cycle Time gradually over the duration of the simulation. This decrease in task performance enables the effects of fatigue resulting from time-on-task to be represented. To replicate the effect of the time-of-day and the improved performance seen in afternoon shifts, A *Shift Modifier* was also included and used to influence the set Cycle Time Value. This was incorporated using a variable value set to 1.0 representing no effect or (100%), which can be reduced and multiplied by the set CT value to reduce by the desired percentage. Additionally, a *Weekday Modifier* was included to reproduce the effects that weekday variation has on performance. This was achieved in the same manner as the shift-modifier, with a value which agreed-upon between simulation runs. These values reflect the effect of the identified human factors, but these will influence individuals to a varying degree. To account for this, the relevant parameters used for each operator can be set as required to replicate a variety of influence and susceptibility. These values are arbitrary in the presented case study but will hypothetically enable our learning model to track and account for these influences. The influence of environmental effects was not considered as their impact on performance is comparably negligible if maintained at suitable levels.

B. Dataset Construction

The generated data is collated and used to form a dataset to train the neural network. For all machine learning tasks, initial consideration must be given to the dataset. The dataset generated consists of four input features, the Operator Number (ON), Shift Number (SN), Shift Duration (SD), and Weekday (WD) values forming each data instance with the corresponding cycle time as the label. Consideration of these data points will allow for the prediction of the performance of the HO by the RO based on historical performance. Additionally, patterns in performance that are independent of an individual HO are more easily established by aggregating the performance data for each operator into one singular dataset. To achieve this, a total of fifteen simulation runs were performed using a static behaviour for the robotic operators, as seen in existing automation applications. The data from each of these simulation runs are collated to form a dataset containing a total of approximately 7500 data instances. Each of these simulation runs represents one day of operation, and consists of three shifts, am, midday, and pm, each performed by a different human operator. The operator assigned to each shift was varied to represent the performance of each operator across the full range of working conditions; this was done every 5 simulation runs representing a working week. Generating the dataset in this way enables performance to be analysed and patterns to be resolved over multiple timescales.

C. Simulation Integration

Developing a machine learning model to model the relationships between the observed information and the resulting performance impact is a key aim of this research. A neural network approach was selected to achieve this, due to their wide applicability and use as function approximators, given the complex nature of these relationships. The neural network development was done using the Java-based DeepLearning4j (DL4J)[83] library due to its proven capability and to provide integration with the Java-based simulation platform. This integration enables evaluation in a dynamic task environment. To initially assess the feasibility of the approach, a simplistic *single-layer-perceptron* type network was defined, to perform a multidimensional regression and provide a predicted numerical value for the CT of the human operator when provided with an observed data instance. This value can then be used to inform the speed of movement, or the potential order of operations to reduce the disparity in performances, minimizing the idle times, and consequently improving the fluency of the interaction.

For all machine learning tasks, initial consideration must be given to the dataset. The dataset generated as detailed in the previous section consisted of data instances containing the observed cycle times as labels, and four input features associated with human task performance. The data instance is input to the network, passed through the hidden layers which encode the input/output mappings, and a result is received at the output node in the value for the human cycle time. Standard techniques for data pre-processing to improve accuracy were considered, and the dataset was collected and divided into a training set and an isolated test set and shuffled.

Sigmoid activation functions were chosen to enable the combined input of discrete and continuous data. To do this, each attribute was normalized according to its type. The SD attribute, a continuous value, was normalized over a range of -1 to 1, to prevent saturation of the sigmoid activation functions. Categorical values were encoded with a 'one-hot' normalization, which treats each category as a set of binary input nodes, resulting in 11 total input nodes: 3 values for the ON, and SN attributes, and 5 values for the WD attribute. For the output layer, a RELU activation was chosen, to output a corresponding real value that could be interpreted using the same normalization weights as the training data and used as a prediction based on an input observation. Additionally, dropout with a rate of 1 was added to the hidden layer to help prevent overfitting.

The Java classes which define the Neural Network behaviour can be packaged using Maven to produce a Java Archive file (.jar), which can be included in the AnyLogic model as a Dependency to allow access to both the defined classes, and the larger DL4j library. The simulation was further developed by including these packaged libraries as dependencies and enabling the functionality to obtain a predicted value for the CT based on the observed environment using the trained neural network. Function calls can then be made at runtime to the java class containing the neural network passing information about the current simulation state to the Network through the function parameters to receive in return a predicted value.

D. Performance Metrics

In addition to evaluating the accuracy of the neural network during training, integration of the learning element into the simulation environment was necessary to evaluate the performance when faced with a representative task. This enables a more accurate assessment of the developed model in terms of how well such an approach can be used for real-time adaptive control. Whilst the analytical module is only a small part of the larger framework, developing the functionality to enable intelligent processing and adaptable behaviour is key to realizing the potential of intelligent manufacturing systems. Developing a model which is able to provide accurate predictions based on observation will contribute to further understanding of the suitability of the approach.

Training of the neural network was done using a backpropagation approach to iteratively determine appropriate weights for each node. The use of backpropagation requires multiple passes through the dataset referred to as *epochs*, and the specification of a learning rate, to effectively train the network. Additionally, the number of nodes to include in the hidden layer remained to be determined. A learning rate of 0.01 was selected to mitigate vanishing gradients at the expense of training time; as the output range was relatively small. The Epoch and Number of Hidden Node parameters were evaluated using an exhaustive search approach. The DL4J library provides functionality for evaluation, for the hyperparameter optimization, each evaluation used the isolated test set, and the *Root-Mean-Squared-Error* (RMSE) was selected as the loss function, calculated using Equation.1:

$$RMSE = \sqrt{\left(\sum_{i=1}^{n}(x_i - y_i)^2\right)/n} \qquad (1)$$

This network configuration was then evaluated using a cross-fold validation, percentage split, and the previously isolated test dataset. Expectedly, evaluation of the isolated test set was the poorest, despite the test data being of similar form to the training data.

The predictions made by the module will be used to dictate and inform the larger decision-making processes performed by the respective agent, and consequently must be available in real-time. Within the simulation, these predictions will be used to modulate the RO's speed parameter with respect to the predicted human performance, to match its own cycle time to that of the current HO in the downstream position. As a result, the interstitial buffer zone will remain clear, the number of Workpiece-In-Progress (WIP) will be reduced, and the observed idle time will decrease, indicating improved interaction fluency.

V. CASE STUDY

To evaluate the methodology the simulation model was parameterized to match an example real-world scenario, which involves the assembly of disposable surgical devices. The process takes place in a clean room, and a number of robotic operators constitute the production line. Within the operation, there are several cells where tasks are completed by human operators. Individual manufacturing cells are separated by transport conveyors with a limited number of fixed positions, and consequently a low and definable capacity. The production line has been generally well designed and optimized, but the presence of human operators remains a source of disturbance, due to their variation in their respective cycle time. Baseline measurements were taken of typical cycle and process timings from the production process, which was used to representatively parameterize the simulation model based on an average HO CT of 45 seconds for the observed operation.

In the first instance, the simulation run using static RO behaviour, to act as a control case, and to generate useable performance data in sufficient quantity, based on the identified human factors. Based on a nominal observed cycle time for the specific manufacturing operation of 45 seconds, three HO's were then defined to represent a range of susceptibility to the impact of the identified human factors. This was achieved by adjusting this value using the model parameters. Operator 1 is intended to be an experienced operator, with a faster than nominal CT of 40 seconds. Performance is decreased by 20% however over the shift duration to account for fatigue and the likelihood that the effect is increased due to faster repeat action. Operator 2 is intended to represent an average case, with a nominal base CT of 45 seconds based on process timings taken from the physical production line. No fatigue influence was included. Operator 3 represents a new operator, who is slower in operation, with a CT of 50 seconds, and a reduced fatigue influence of 10%. The influence of the time of day was also considered, and the simulation parameterized accordingly. Operators 1 and 3 were considered *Owls* and are susceptible to decreased morning performance represented by a 10% increase in cycle time during morning shifts, reducing to 0% in the afternoon. In a similar manner, the *weekday modifier* was set to decrease performance by 10% on Monday, and the influence gradually shifts to a 10% performance increase on Thursday, to replicate observed working patterns. Assuming a linear evolution over the shift duration from no fatigue effect to maximum effect, the *fatigue modifier* is calculated by considering the elapsed shift duration vs the total shift duration (7200 seconds) and the percentage increase in cycle time, as per Equation 2. This enables the calculated cycle time for each human operator to be obtained via equation (3):

$$Fatigue\ Modifier = \left(\frac{Elapsed\ SD}{Total\ SD}\right) \times \left(1 + \frac{\%Increase}{100}\right) \qquad (2)$$

$$Calculated\ CT = Nominal\ CT\ \cdot\ WM\ \cdot\ SM\ \cdot\ FM \qquad (3)$$

Where, WM, SM, and FM, are the corresponding weekday, shift and calculated fatigue modifiers respectively. The relevant modifiers used for each of the identified human factors can be seen for each operator in Table.1.

Table 1. Breakdown of the values used to modify the CT for each operator for given states.

Operator Number	**1**	**2**	**3**
Base Cycle Time	40	45	50
Fatigue Modifier (End of shift)	1.2	1.0	1.1
Shift Modifier AM	1.0	1.0	1.0
Shift Modifier Midday	0.95	1.0	0.95
Shift Modifier PM	0.9	1.0	0.9
Weekday Modifier Monday	1.0	1.1	
Weekday Modifier Tuesday	1.0	1.05	
Weekday Modifier Wednesday	1.0	1.0	
Weekday Modifier Thursday	1.0	0.95	
Weekday Modifier Friday	1.0	1.0	

The data is sampled by the robotic operator from the simulation environment to form a data instance each time a product is completed by the HO. This instance contains the identity of the operator currently working, the previous Cycle Time, the elapsed shift duration, the shift number, and the day of the week. These data instances are initially collated into a dataset (as is commonly done by data acquisition systems), as described in section 4.2. This dataset is then subsequently used to train the neural network, allowing the value of a number of hyperparameters to be established. Once the neural network is trained, models of HO performance can be generated by the network, as presented in the methodology.

To evaluate the performance of the control system, the trained network was integrated into the simulation model, and the additional analytical capacity robotic operator's control system used to predict the optimal RO operation speed based on the observed values of the HO. Upon completion of each task, the robotic operator makes an observation of the simulation environment as described above. This instance is then passed to the neural network and a prediction received in real-time. The RO speed is then adjusted to match the returned prediction. These combined processes can be related to the functional elements of the framework presented in Figure.2. The task completion event triggers an observation which is passed by simulation to the agent. This instance is pre-processed as relevant before the internal logic of the agent provides the instance to the neural network, which functions here as the *Data-Analytics* module identified in the framework. The network returns its prediction, and the agent’s logic determines the resultant action. In this implementation, to adjust the speed of the action to adjust its own cycle time to match that predicted for the collaborating HO.

The capacity of the interstitial buffer was limited to 10 products, to replicate the real-world system, although this value is essentially arbitrary. Each human operators’ shift lasts for two hours, and the Shift changes occur for the HO’s at 7200 seconds and 14400 seconds. Upon each shift change, the parameters controlling the human operator within the simulation are updated, without resetting the simulation environment.

Given the great success of neural networks at such function approximation tasks, it is hypothesized that using the generated dataset to train the machine learning model should enable the robotic operator to effectively predict the effect of the human factors on the performance, based on the observed values. As with most machine learning applications, this is likely to require refinement for optimal performance.

If the learning model is able to successfully make these predictions and effect changes in the robotic behaviour in such a manner, it is hypothesized that using these predictions to adjust the operation speed to match that of the human operator will reduce or possibly completely eliminate the time which the robotic operator spends idle awaiting the completion of the human operators’ task. This will facilitate collaborative behaviour, in these kinds of human-machine interactions by reducing the observed idle time of the robotic operator, improving the interaction fluency.

As the developed learning model is still relatively simplistic, it is unlikely the predictions made will be accurate to a degree which will enable perfect one-piece flow, and as such, the continued use of interstitial buffers between operations may eliminate most of the observed idle times from the manufacturing process.

It is also hypothesized that the capacity of these buffers may be greatly reduced from existing levels, as any disparity is likely to be minimised and these buffer zones to remain unfilled. This will additionally reduce the number of workpieces in progress at any given time, without reducing the total throughput of the system.

VI. Results

A. *Neural Network Training*

The neural network was trained using a backpropagation approach to determine suitable node weights, as discussed in the methodology section. The use of backpropagation requires multiple passes through the dataset referred to as epochs, and the specification of a learning rate, to effectively train the network. Additionally, the network configuration, including the number of hidden layers, and the number of nodes in these layers needed to be established. A learning rate of 0.05 was selected to mitigate vanishing gradients at the expense of training time; as the range of the output variable was relatively small. This minimal output range proved to be a problem during early development, as the gradients would often converge and become stuck at local minima. The inclusion of dropout to the hidden layers, (with a 100% certainty rate, to randomly remove one connection at each parameter update) proved to reduce this occurrence and improve the predictive ability greatly. The Epoch and Number of Hidden Node parameters were evaluated using an exhaustive search approach which was repeated for each of the layer configurations, runs were performed for one and two hidden layers to determine whether there is an advantage in increasing the depth of the network. The DL4J library includes a number of evaluation functions. To evaluate the hyperparameters, the Root-Mean-Squared-Error (RMSE) was selected as the loss function, and each evaluation used an isolated test set. The results are presented in Figure 4.

Layers:1	No. Hidden Nodes										
No.Epochs	12	13	14	15	16	17	18	19	20	21	22
5	2.88	2.54	2.79	1.99	2.96	3.82	2.8	2.66	3.33	2.17	2.63
10	2.16	2.38	2.59	1.88	2.59	2.41	2.23	2.1	1.93	1.82	2.03
25	2.69	1.56	2.24	1.62	2.62	2.06	2.26	2.36	1.81	2.05	1.93
50	1.89	2.01	2.21	1.38	2.74	2.77	1.97	2.36	2.27	2.51	2.36
75	1.24	2.69	1.79	1.32	1.93	2.62	1.28	1.33	1.97	1.88	1.67
100	1.40	2.03	1.44	1.17	1.08	1.78	0.95	0.94	1.90	1.01	0.98
200	1.03	1.30	1.03	0.85	0.66	0.98	0.92	0.65	1.53	0.70	0.80
300	0.70	0.92	0.76	0.84	0.68	0.7	0.77	0.62	1.30	0.69	0.90
400	0.70	1.24	0.74	0.79	0.66	0.67	0.78	0.62	1.20	0.71	0.72
500	0.88	0.80	0.72	0.74	0.63	0.64	0.63	0.61	1.07	0.69	0.65
600	0.79	0.77	0.71	0.73	0.61	0.62	0.67	0.6	0.84	0.68	0.63
700	0.68	0.75	0.7	0.66	0.86	0.62	0.65	0.6	0.95	0.67	0.62
800	0.73	1.14	0.69	0.63	0.69	0.61	0.65	0.59	0.94	0.65	0.61
900	0.63	0.74	0.68	0.61	0.66	0.61	0.64	0.59	0.80	0.61	0.61
1000	0.69	0.71	0.66	0.6	0.63	0.61	0.60	0.56	0.77	0.81	0.61

Layers:2	No. Hidden Nodes										
No.Epochs	12	13	14	15	16	17	18	19	20	21	22
5	6.40	4.97	6.66	4.94	4.57	4.97	6.47	5.22	4.61	4.60	4.62
10	3.48	4.97	3.99	4.74	3.70	4.90	6.24	5.17	3.17	3.69	4.58
25	4.48	4.09	4.37	3.70	2.48	2.27	2.69	2.59	2.78	2.51	4.60
50	2.74	2.72	2.64	2.33	3.21	2.97	3.75	2.24	2.75	1.92	3.41
75	4.14	2.30	2.02	2.60	2.87	4.78	3.05	3.32	2.08	3.65	2.06
100	3.75	2.51	0.98	1.81	1.52	1.17	3.31	1.22	2.19	1.15	2.38
200	1.90	1.25	1.05	1.66	1.76	0.80	2.90	1.17	1.32	0.98	0.96
300	1.68	0.90	0.99	1.33	0.70	0.69	1.30	0.78	1.15	0.92	0.73
400	1.39	0.89	1.31	1.57	0.91	0.64	1.16	0.62	1.01	0.82	0.82
500	1.08	0.85	1.15	0.94	0.84	0.61	0.89	0.63	0.94	0.84	0.71
600	1.12	0.75	0.75	0.82	0.79	0.59	0.79	0.70	0.91	0.91	0.60
700	0.72	0.74	1.02	0.73	0.71	0.58	0.71	0.58	0.89	0.62	0.60
800	0.66	0.72	0.97	0.75	0.65	0.59	0.67	0.76	0.88	0.72	0.59
900	0.65	0.71	0.73	0.79	0.72	0.57	0.64	0.68	0.87	0.65	0.56
1000	0.63	0.68	0.73	0.76	0.64	0.58	0.63	0.69	0.85	0.58	0.58

Figure 4. heatmap of RMSE scores, from red (highest) to blue (lowest) for the number of hidden nodes against the number of epochs trained. For a) 1 hidden layer and b) two hidden layers.

From the heatmap, the variations in performance can be visualized, and a number of conclusions drawn. The networks can all be seen to converge within a small number of epochs, as a continuous range of output variables is quickly reduced to the observed range. As the out range is relatively small, a large number of iterations is needed to reduce the error to a level where differentiation between instances is possible. Increasing the number of training epochs may eventually lead to overfitting, although this is unlikely the case in this application as the feature set is relatively small compare to the number of data instances. The heatmaps also show that training past ~500 epochs leads to minimal improvements in accuracy at the expense of considerable training time. The additional hidden layer can be seen to add significant complexity, as the errors are initially higher and converge slower, with a minimal gain in predictive accuracy. The single hidden layer networks can be seen to introduce less error and train more consistently, whilst benefiting from lower training times. As such, a number of potential network configurations can be identified from the heatmap: the 15-hidden-node, 18 hidden-node, and the 22 hidden-node configurations all look viable and result in comparatively low RMSE scores after 500 training epochs. The learning rate of the 15-node configuration is the most stable; with a low initial error that shows progressive improvement as the training progresses in contrast to both the 18 and 22 node configurations, in addition to reducing the network complexity and computation demands. Consequently, the design of a single-layer and 15 hidden-node was selected for use in the simulation, despite the 18 and 22 node configurations lower RMSE scores.

B. Simulation Results

Once the optimal parameters were established, the simulation was again run using the trained network. In the static simulation case, the RO cycle time was fixed at 40 seconds, the result of which is a cumulative idle time of more than 4000 seconds over the total duration of the simulation due to the interstitial buffer being filled, and the RO having to wait for space to become available.

Figure 5a) plots the idle time and workpieces in progress, against time; for the total duration of the simulation run, for the static simulation case. When the RO follows a static behavioural routine, the cumulative idle time can be seen to be influenced by the number of workpieces in progress, as once the buffer zone is fully occupied (10 products in the presented simulation) the RO must wait for space to become available within the buffer, clear before it is able to resume operation. The interstitial period prior to the available buffer space is represented as the plateau before the idle time begins to increase. Figure 5b. plots the buffer contents for the dynamic behaviour case, using the neural network predictions to inform the operator's speed. The buffer contents never exceed 5 units, and there is no resultant idle time observed.

Figure 6 plots the simulated human operator cycle times against the neural network's predictions used to govern the cycle time of the robotic operator. The results are shown for simulation runs over a working week and contains several features. Comparing the predicted values to those observed enables several insights about the performance of the neural network on identifying the influence of each of the human to be observed. The sharp distinctions in the Robotic Operator cycle times in Figure 6 suggest that the neural network is able to successfully identify the performance of the multiple operators, and the proportional increases of both the predictions and observed cycle times suggest that the influence of the task duration is also able to be approximated. Combined, Figures a) through e) illustrate the network predictions for each day of the first working week simulated. Operator 2, in this case, the central set of cycle time measurements, is susceptible to this influence only. By considering the plotted values, the range and predictions can be seen to decrease over the week duration proportionally to the influence of this modifier, suggesting the network is able to distinguish successfully this influence.

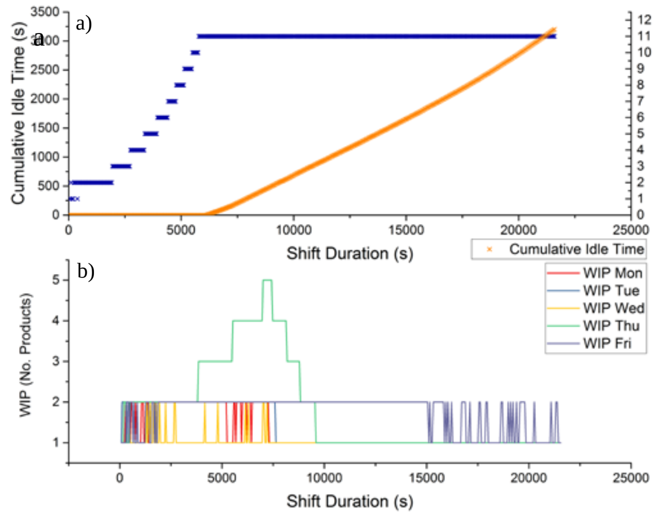

Figure 5. Cumulative idle time and buffer contents against shift duration for static behaviour case; b) Buffer contents against time for dynamic behaviour contents for each weekday.

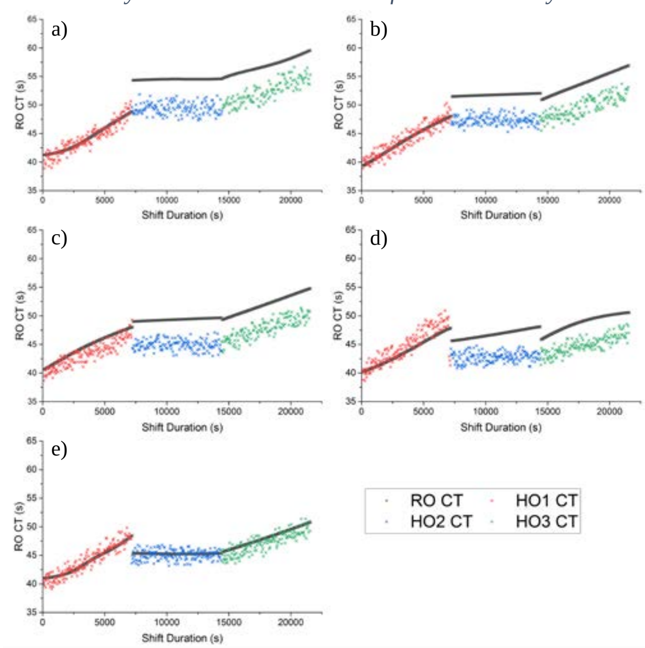

Figure 6. RO CT and HO CT over time for a) Monday, b) Tuesday, c) Wednesday, d) Thursday, e) Friday. Random element seeds are changed between runs, ensuring appropriate variability when the same conditions are imposed.

Figure 7 plots the same values as Figure 6 but highlights how the shift order influences the predictive capability. What can be seen is that the neural network error varies proportionally to the variation introduced by the weekday modifier, for operators 1 and 3 whom it effects, suggesting that the network is able to follow the changes in performance based on time of day preference, as the predictions and errors can be seen to move consistently when comparing am and pm shift performance. Additionally, there appears to be no influence on the networks ability to predict the performance of operator 2 who is not susceptible to the influence of the shift modifier.

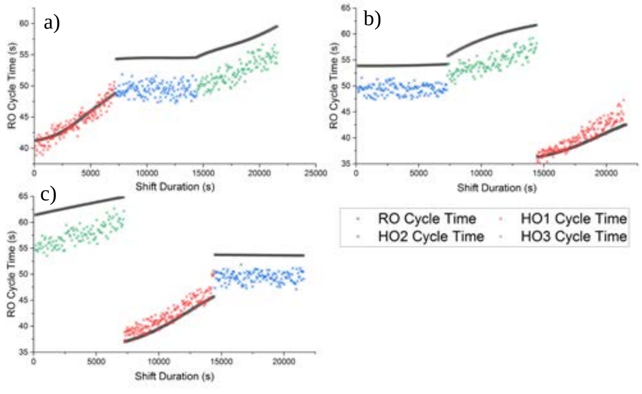

Figure 7. RO CT and HO CT over time for Monday shift of three weeks and corresponding shift orders a) 123, b) 231, and c) 312.

These results suggest that the neural network is able to account for the influence of the human factors which were modelled and that there is likely an unaccounted for factor preventing the network from resolving values more accurate to the performance level of operators 2 and 3. Operator 1 consistently occupies an output range of performance that has limited overlap with the performance of operators 2 and 3. As such, the offset could be a result of the output range having significant overlap, and the contradictory influences of the multiple factors. To determine if the network breadth would lead to increased predictive ability, a 22-node network was configured and trained and used to inform the simulation for a number of similar scenarios. Figure 8 illustrates some of these, and comparison to the 15-node network case suggests that the network structure is not responsible for the loss of accuracy, and in fact, the 22-node performance is subjectively worse for the extreme cases.

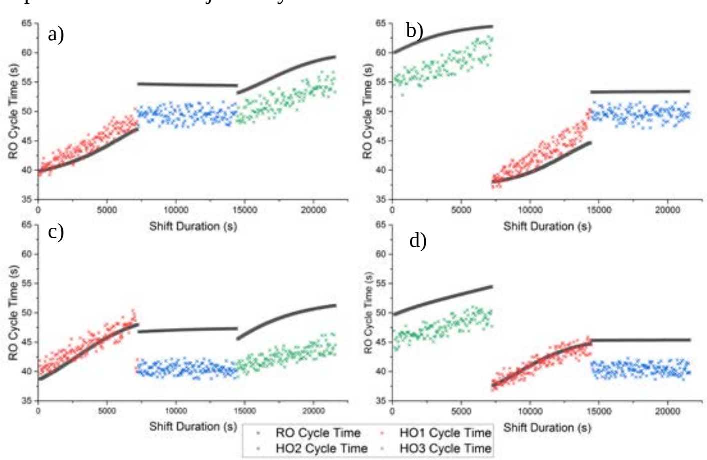

Figure 8. RO CT and HO CT over time for a) Monday 123, b) Monday 312, c) Thursday 123, d) Thursday 312, illustrating the predictions of the 22-hidden-node network. Results are mostly consistent with 15 node network for all scenarios.

Crucially, the neural network is able to reduce the observed disparity and reduce the overall idle time of the system, however, significantly more work is needed to move towards a system capable of perfect one-piece-flow. These trends in predictive capability can be seen to remain consistent across the order of operators and different timescales.

VII. Discussion

What can be seen for the results most clearly is that adaptation of the robotic operator behaviour leads to an overall reduction in the idle time of the robotic operator accumulated over the duration of the three shifts. The reduced idle time can be said to improve the fluency of the interaction, consequently improving the collaborative abilities of the robotic element. The findings demonstrate that systems capable of understanding the variations in the performance of human operators enable behaviours to be adapted, based on the observed actions of the human counterpart. This adaptability has the potential to be usefully leveraged by reducing the disparity in performance. This supports the authors' hypothesis that the integration of intelligent manufacturing concepts can be used to alleviate the uncertainty caused by the human element of these systems; that such an approach is well suited to aiding collaborative task performance; and is achievable with simple, proven methods and available hardware.

The presented methodology may also further understanding of how simulation can be used to explore the efficacy of machine learning algorithms, by enabling functional, application-based testing in a controlled environment. Simulation environments can be designed using powerful tools and established methodologies of discrete event simulation to replicate any number of manufacturing processes. By using the integration methodology detailed, bespoke machine learning solutions can be tested in an isolated and yet detailed and representative environment. Discrete event simulation models are frequently used to inform engineering and business decisions and expanding the capability of these models may allow for novel solutions.

The work highlights the value of pursuing adaptability in robotic control systems and improves knowledge as to how machine learning and principles of intelligent manufacturing should be used to overcome uncertainty within production processes. Reducing disparity in these applications can be seen to reduce the demand for buffer space to manage one-piece-flow like production, and adaptability applied in this fashion may enable improvement to processes where one-piece-flow is currently not able to be implemented, due to buffer or time in system restrictions.

Furthermore, the work also highlights the importance of making use of information from a number of disciplines, specifically, and in contrast to existing Human-Machine-Interaction approaches, how knowledge of the influence human factors on performance can be used to inform adaptable behaviour in robotic operators and enable collaborative behaviours to be enacted in response to observed human behaviours. The authors hope that the presented findings will further exploration of the application of intelligence to human-machine interaction in this way and contributes to knowledge that is required as machines and computers in all aspects become more capable, intelligent, and responsive; and their interactions with humans become more common. Methodologies to ensure that these machines are able to interact and process information in an appropriate manner are essential to developing alongside the technological capability to do so.

From neural network development, additional insights can be revealed. It can be seen that the network structure has a significant impact on the training process and achievable accuracy. This suggests that the network structure is a crucial factor in enabling efficient and effective intelligent data processing and that bespoke structures ad investigation are likely to be required depending on the available dataset, its contents and its structure. Increasing the depth of the neural network could be seen to minimally improve the network accuracy, at the cost of decreasing the stability and performance during training. The networks take longer to converge, and are more susceptible to local phenomena, due to the increased number of constituent nodes.

Whilst the presented neural network can be seen to enable a reduction in performance disparity, there remain sources of inaccuracy. Additional consideration must be given to factors associated with processing real-world data, noise, missing values, and additional randomness associated with Human-Beings as yet unaccounted for improvement to performance and predictive ability could result from re-structuring or division of the dataset. Training of networks on multiple datasets containing information describing individual days, shifts, or the performance associated with each individual operator may influence how the network is able to approximate the influence of human factors.

The application of machine learning techniques is not an exact science, and a certain level of iterative development is necessary to develop networks capable of accurate and reliable prediction. Further work on more advanced network architectures should enable increasingly accurate and capable models to be developed, in line with more demanding learning tasks, and to overcome the challenges associated with real-world data. In addition, multiple networks can be combined to include multiple other factors in the decision-making process. Other intelligent functions, including memory and perception, share the modular nature of analytical thinking. Further work is planned to further investigate how reconcile the strengths of multiple types of network, such as convolutional neural networks, which enable information to be extracted from visual systems, or recurrent networks, which provide the capacity for memory, enabling the network to more accurately determine temporal patterns in the dataset without the need to extrapolate global patterns.

It is important to discuss the fact that whilst the presented case-study is thoroughly explored, a full validation of the proposed framework requires substantially more work and consideration of a number of different applications, a task that is ongoing. This remains one of the crucial challenges in intelligent manufacturing and human-machine-interaction, as no established standards for validation exist. Developing such standards is no small task, as almost all solutions require a bespoke set of components and processes to achieve their own required functionality; additionally, the sheer possibility of variation between human beings and different manufacturing scenarios compounds the difficulty of such a validation task. The next stage of this work will begin training these models and conducting an evaluation using real-world data and developing simulations to further validate this method across a wider range of tasks and scenarios that may potentially be encountered.

VIII. CONCLUSIONS

The aim of the presented research was to further understanding of how to better enable collaborative, intelligent behaviour in human-robot-interaction within the manufacturing context. A crucial element of this is the ability to understand how associated human factors may lead to an unstable and varied performance in human colleagues. The presented solution demonstrates that a simplistic model is able to make appropriate predictions to inform decision-making, which in turn enables adaptable, and autonomous behaviour for working with different human individuals; and to do so in a real-time setting. The work highlights the benefits in terms of collaborative behaviour that the application of intelligence within manufacturing facilitates.

This work represents a portion of a larger and ongoing project on the application of learning to facilitate intelligent behaviour in human-machine-interactions, and further research is planned to investigate these topics.

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