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Industry 4.0 in Labor Intensive Industries, Opportunities and Challenges

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Abstract

Many industries face challenges in industry 4.0's application (I4.0). This paper investigates application of I4.0' technologies in labor-intensive-manufacturing-Systems (LIMS), because many industries require labor-intensive operations. Also, many SMEs perform operations manually due to high automation cost. However, there is no framework for I4.0 application in LIMS. This research used systems-engineering to develop, for the first time, logical architecture of LIMS. A state-based modeling approach was proposed to model architecture. The proposed novel model can simulate interactions between human and I4.0 technologies. This allows assessing impact of I4.0 technologies on LIMS and assuring concurrent optimization of LIMS performance and human-labor's well-being.

Keywords Type your keywords here, separated by semicolons ; Digital Twin, Labor Intensive Manufacturing, Industry 4.0, Cyber Physical Production Systems

1. Introduction

Industry 4.0 (I4.0) promotes digitalization with key enabling technologies including cyber-physical production systems (CPPS), Internet of Things (IoT), Artificial Intelligence (AI), Digital Twin (DT), Computer Vision (CV), and automation [1]. Proper application of I4.0 technologies proved to be effective in improving manufacturing performance. Although application of automation reduced manual labor in some industrial setups, manual operations still play a key role in many manufacturing activities (e.g., maintenance) [2]. Automation requires high investment that can stop many factories, especially SMEs or the ones in developing countries, from implementing it. There are still many factories that are not automated or are fully manual and labor intensive [3]. Application of I4.0 technologies without considering their interactions with humans in LIMS can lead to negative unintended consequences on human [4,5]. Hence, this paper aimed to propose an approach for evaluating the impact of I4.0 technologies in a LIMS to ensure maximizing the benefits to a LIMS and human labour.

2. Problems, Research Gap, and the Scope

Implementation of I4.0 in manufacturing can cause stress (e.g., safety) to human labor and negative impacts on human and operations [6]. Also, higher level human needs (e.g., self-esteem) should not be compromised when applying new technologies. Hence, European Commission introduced Industry 5.0 concept to pay attention to humans in a manufacturing system focusing on interconnection between humans and technology [4, 7-9].Yet, limited research has been done regarding the impacts of I4.0 technologies on human labor [4, 5, 7, 10]. Research has been done on physical and psychological wellbeing of labors [10], without investigating the complexity of interactions between human and technologies [7]. Hence, there is a need to analyses how humans and technology are integrated to assure successful embracing of I4.0 technologies in LIMS [11, 12]. This paper aims to address this gap by proposing an innovative modelling approach that allows assessing the impacts of I4.0 technologies' application on human and LIMS performance.

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3. Labor Intensive Manufacturing Systems

A system is considered labor intensive if the involvement of human operators is considerably higher than machines. This can happen if the nature of operations requires higher human involvement to bring unique capabilities that cannot be replaced by technologies, or it can be replaced but there are barriers such as cost. Some manufacturing operations that require unique human capabilities are machine setup, maintenance, material movements with supervision, production planning [13]. Customised products (apparel, defence projects, jewellery, furniture [3, 9, 14]) need human creativity, while dealing with uncertainty asks human flexibility to dynamically respond to changing needs [7].

High cost or lack of infrastructure is an adaption barrier for many LIMS. For example, in case of IoT technology, even if cost is not a concern, lack of internet-based networks can be a barrier to developing countries[15, 16]. A social challenge for I4.0 application can be obtaining right operators, since new technologies changes work content and requiring skilled Labors. This can lead to fear of job loss or confusion. Application of I4.0 technologies in developing countries may negatively impact industries by leading to losing their competitive advantages and consequently social tensions in labour market [16]. Application of I4.0 technologies has also raised various safety concerns, from dangers posed to human in working with new devices to cyber-attacks and data leakage. Technical challenges can happen due to availability of various technologies that can be applied and various perceptions of what I4.0 means [11]. When implementing CPPS and IoT devices, large volume of data requires storing infrastructure, analysis capability, which combined with human increases the complexity. Legal challenges can vary in different countries. But they can impact adoption to I4.0 due to society/political concerns.

There is limited research that analysed human needs in a LIMS, yet human needs in an industrial setup can be defined as: 1: Safety. 2: Health. 3: Belonging (need for interpersonal relationships), 4: Esteem (need for respect, self-esteem, self-confidence), 5: Self-actualization (reaching full potential) [7, 14]. The first two are the most studied ones, which include ergonomic design of factories. The International Ergonomics Association defines three types of ergonomics: physical (working postures, repetitive movements, material handling, safety, and health), cognitive (mental workload, decision-making, trainings, and human–computer interactions), and organizational (organizational structures, design of working times, processes, communication, cooperative work) [17].

4. Industry 4.0 Application in LIMS

4.1. Systems engineering and System of Systems perspective

Manufacturing systems are complex [18,19]. When applying new technologies in an existing system or designing a new one, interactions among system's elements may cause unseen problems, leading to system performance reduction from what was expected [20]. Thus, to avoid such problems, it is needed to understand the interactions between human and I4.0 technologies in a LIMS. This paper proposes an approach for modelling the LIMS in I4.0 context.

Systems Engineering (SE) discipline focuses on the whole system and the interactions between its elements. Hence, this research uses SE to analyse the interactions that if over-looked might lead to a LIMS underperforming when applying I4.0 technologies as evidenced by literature.

In a novel manner, this research proposes modelling a LIMS in I4.0 context as a System of Systems (SoS) to tackle its complexity when analysing interactions between various elements. SoS is a system whose elements are independent systems but are ordinated to meet an overall purpose. This reference [18] proposed an approach to model the primary processes in a factory, with no inclusion of I4.0 technologies and their interactions with human. This research extends that and proposes how to include human and I4.0 technologies. That work only addressed modelling the primary process flow in production, but this paper includes processes that do not directly contribute to production but support it.

This paper suggests modelling the architecture of a LIMS by defining two categories of processes: transformative and supportive. The first category refers to processes that their functions contribute to transformation of inputs to outputs, such as machining processes. The second one refers to processes that their functions support the first category or are implemented to improve a LIMS performance such as data acquisition for maintenance planning. Processes from both categories can interact with each other. A process can have physical or operational enablers to deliver its functions. The functions performed at LIMS are defined independent of a choosing technology for each function. Interactions between processes is defined by indicating type of interactions among their functions, such as data or physical exchange. This allows defining interactions at functional space of a LIMS. The proposed architecture is a Meta-Architecture, which alternative configurations that include different technology options are instances of Meta-Architecture, shown in Fig. 1.

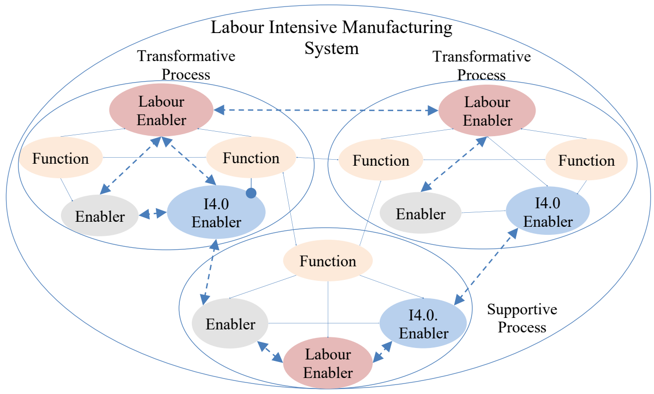

Fig. 1 LIMS SoS architecture

4.2. Industry 4.0 Technologies Integration in a LIMS

Application of I4.0 may require adding supportive processes which expands the scale of a LIMS. Implementing new technologies in transformative processes also increases the system complexity due to forming new interactions between enablers. Here, the consequences of integration of

I4.0 technologies in a LIMS is discussed. However, technical details of each technology can be found in literature.

Robotics: Referring to the proposed architecture, if implementing robotics in a LIMS, the interactions of an operator with a robot can be classified as [7]: coexistence: working independently to deliver separate functions in processes, cooperation: working together in a process or sequential ones in a supportive manner with some levels of independence. collaboration: working together to deliver a function in a process and physically sharing the workspace. The push for mass customization led to more collaborative interactions between robots and human known as cobot, which fixed functions are performed by robots (e.g., moving) while functions that require more cognitive capabilities are performed by human operator (e.g., item placement) [21].

Research suggests strategies of humanetrization of work space to assure human safety or human-cyberfiction to assure operator can work with data (e.g., analysing the data needed for a function [22]). Yet, cost and lack of infrastructure hamper many industries to implement robotics [12].

Computer Vision (CV): this technology aims acquiring/analysing data using cameras and computers. Referring to the proposed architecture, the interactions of an operator with a CV system can be classified as [7]: assurance feedback: operator and CV duplicate the same function. For example, in manual visual inspection, the CV provides extra input as assurance to operator. Thus, the interaction is in the form of analysed data provided to operator which can lead to learning. Sequential interactions: CV performs the function that used to be done by operator (visual inspection) and now the operator can use the CV data to perform another function, such as removing the faulty items from the conveyor. This interaction can lead to fear of job loss or feeling relaxed and not doing a tedious task specially if other functions are assigned to the operators, so no fear of job loss might happen. Concurrent interactions: CV performs certain functions mostly belonging to supportive processes which are introduced as adaption to I4.0, such as machines monitoring for maintenance. Human operator may use the data to perform other functions such as the maintenance or performing a transformative function. In this case, there is not much fear of job loss. If the CV data is provided to operator, it can lead to learning but if the operator does not use the data directly, this can lead to losing interest on adaption to I4.0 and perceiving it as an extra step.

Interactions of operators with CV improves their cognitive capabilities, yet cost, lack of infrastructure, and trust can be barriers for CV’s implementation in LIMS [13].

Augmented Reality and Virtual Reality (AR/VR): this is mostly used to support a process by providing information. There are various AR/VR technologies, such as wearable devices, smart gloves, goggles, and voice-enabled assistants. Referring to the proposed architecture, interactions of a human operator with AR/VR can be classified as: enhancement: AR/VR provides extra data to operator to conduct a transformative processes, such as enhancing the vision of operators in performing an assembly task when they have limited vision to internal components [13]. A result of this interaction will be performing complex tasks more efficiently and operators feeling empowered. Yet, an operator might feel overwhelmed when exposed to too much information or physically uncomfortable in using devices such as wearable gloves. Improvement: AR/VR is mainly used for improving the system and/or human operator performance and well-being (e.g., training operators before conducting transformative processes). The improvement can be in the form of safety or strength offered by those devices such as smart exoskeleton [13]. This interaction type can improve the performance of supportive processes, such as maintenance, by facilitating the access to historical maintenance data. This type of interaction will have positive effect on operator attitude on using such devices.

Overall, the barriers for AR/VR can be the cost, lack of infrastructure, and uncomfortable feeling of human operator and aspects such as ergonomics [23] must be considered.

Additive manufacturing (AM): it facilitates product customization [24]. Referring to the proposed architecture, AM is used in a transformative process, requiring an operator as an enabler to supervise the process (e.g., machine setup). A caused interaction in a LIMS if implementing AM would be the need to learn operating a new machine/procedure. The cost and lack of infrastructure are barriers to adoption to this technology. However, the fear of job loss can be low, since AM is mostly used for processes that are complex and not easily done by an operator.

Data collection/communication and IoT: they play a key role in I4.0 application, while IoT is one of the most used ones. Industrial social networks perform as social media in industry, capturing process data [13]. Referring to the architecture, IoT can be used in transformative and supportive processes. In the former case, IoT can be integrated with equipment used by an operator, such as AR/VR devices, to collect process data, for example for identification of assembly mistakes. The used sensors in transformative processes can improve human-tools interaction efficiency by a precise recognition of human movements to improve safety [13]. In the latter case, environment sensors are used in supportive processes and benefit operators by working environment improvement, for instance, air quality. If data collection does not require operator using extra devices (e.g., wearing uncomfortable gloves), challenge for their application in LIMS is minimum.

Data analytics and Artificial Intelligence: they allow knowledge discovery, with more ML/AI software easily available recently. In LIMS context, the AI/ML is more likely to be used in supportive processes yet can be used in transformative ones too. AI/ML can support an operator on decision makings in transformative processes that need human cognitive capabilities such as, identification of proper disassembly process when each item in the line has a unique shape. Application of AI/ML leads to collaborative intelligence, if AI/ML improves the operators’ strengths, such as improving their problem-solving skills in transformative processes to increase a process’s accuracy [5]. In supportive processes, AI/ML improves the efficiency of LIMS and operators by identifying patterns that leads to unsafe condition for human or optimising the production schedule when availability of human resource is uncertain.

If AI/ML are used to perform the decision-making tasks that used to be done by operators, this can lead to the job loss fear by operator and consequently their negative intervention to prove AI/ML insights were wrong. If operator and AI/ML are working collaboratively, it is needed to assure the AI/ML outputs are clear for the operator to enhance the process productivity. To establish the trust, it is essential to clarify why AI/ML recommends certain actions to human. Ideally, the operator can adjust integration of AI/ML outputs in the decision making component of a process[7].

Digital twin and CPPS: DT has been widely used for different purposes, such as virtual experimentation, performance optimization, monitoring, and control. Referring to the architecture, a DT can be used in both transformative and supporting processes. For example, the collected data from smart goggles can be used by DT for quality prediction. DT can perform production or maintenance planning in supporting processes.

CPPS can be considered as integrative platform of many I4.0 technologies. Referring to the architecture, CPPS can be used in transformative processes, for example to control the machine's movements. In LIMS, the amount of such automated tasks is lower compared to manual operations. CPPS can be used in various supportive processes. For example, IoT collected data can be analysed by AI/ML in a DT of a LIMS to improve human resource planning [25]. DT is an enabling technique for solving fusion of CPPS [26]. This paper uses DT for modelling the proposed architecture, hence more details of DT in a LIMS is explained later.

5. Socio-Technical DT: State -based Modelling

This paper suggests an innovative approach by developing DT of a LIMS with a State-based Modelling formalism (SM). SM demonstrates a system with a set of states, transitional conditions between them, and consequent actions. This paper suggests modelling a LIMS at the highest level of hierarchy as a parent state that includes transformative/supportive processes. The modelled states for processes (called process-states) can include substates to embody their needed enablers (called enabler-states) to deliver their functions. Transitions between process-states and enabler-states can be defined to embody the logic of interactions between processes and enablers.

The resultant DT model has a nested state structure, which the higher levels embody LIMS and processes, while detailed modelling can be defined for enabler-states. A process-state can include several sub states to embody various types of enablers including i4.0 and human. Each enabler-state can be further decomposed to model the disciplinary details, their behaviour, and their interactions with other enabler-states. The enabler-states can model a specific enabler from two perspectives: first, modelling the dynamic behaviour of each enabler in its discipline at the system level to model its interactions with other enablers such as the movement of a human when loading a part on a machine, and second, providing a module for encapsulating its own specific behaviour such as the kinematic of a machine or modelling the cognitive behaviour of a human.

Such structure allows holistic and multidisciplinary modelling of LIMS. The proposed DT can embody different types of processes based on the levels of I4.0 application (transformative and supportive processes) and different types of enablers (human and technical). State models can be simulated, mostly based on discrete event simulation (DES) approach. Manufacturing systems in general operate based on discrete events, hence, DES approach match perfectly to simulate the dynamic interactions between enablers in DT of a LIMS. Interoperation between enablers and process states can be modelled by defining proper variables and parameters. Since the nested state's structure allows encapsulating the modelling details of operators and i4.0 technologies while their interactions can be modelled at a higher system level, the proposed approach allows observing the impact of including a potential i4.0 technology on both operators and overall performance of a LIMS.

5.1. Socio-Technical Digital Twin

This research considers a LIMS as socio-technical system, because it interacts with social aspects of environment and its performance is determined by technical elements and their interaction with human systems. Here, the interaction of a human operator with i4.0 technologies is at the centre of attention, yet the proposed approach can be used to model the human operator interactions with other enablers that are not classified as typical I4.0 technologies.

This research suggests innovative modelling parameters in the proposed DT to assure it will be human focus. Based on the identified interactions between i4.0 technologies and human operator in the previous sections and SE principles, this research defines the following types of interactions between operators and i4.0 technologies as process enablers. This research acknowledges more specific interactions can emerge when including more specific i4.0 technologies.

This research looks at the interactions from three perspectives: function, domain, and timing.

In functional space three types of interactions can exist between an operator and an i4.0 technology to deliver a function: independent co-existence, (IE), independent cooperation (IC), dependent collaboration (DC). In domain space, two types of interactions can be defined: physical (P) and information (I). In timing domain, interactions can be defined as: sequential (S), concurrent (C), and feedback (F).

Theoretically 18 possible combinations of interactions can exist, for example independent co-operation with exchanging information in a sequential manner, or (IC, I, S). However, some might not sound feasible, such as (IE, P, F).

This research suggests defining this Interaction Type parameter, IT_{pi} = (function, domain, timing) for all the process-states in the proposed DT, where 'p' refers to a specific process and 'i' refers to a specific I4.0 technology. This enhances awareness about the existence of interactions that can lead to consequences. Otherwise, the interactions maybe overlooked, and their unintended consequences can negatively impact human or LIMS performance.

This research suggests modelling specific parameters indicating different human needs in DT. The human needs as discussed can include safety, health, belonging, esteem, self-actualization. This research suggests adding the cognitive workload as another need to acknowledge working with I4.0 technologies may require performing some analysis tasks that increase the cognitive workload of an operator.

This research suggests defining a parameter called Interaction Consequence on Human needs, to indicate the level of human needs satisfaction because of interactions.

ICH_{pi}= {[IT_{pi}], [(level of needs' satisfaction)]}={[IT_{pi}], [($Phyisical\ safety_{pi}$, $cognitive\ load_{pi}$ $health_{pi}$, $belonging_{pi}$, esteem_{pi}, $\text{self}-\text{actualization}_{pi}$)]}.

Various qualitative and quantitative approaches can be used to define the level of satisfaction, such as Likert Scale, surveys, and fuzzy logic. For simplicity, this research suggests using the Likert scale with a range of 1-5 to demonstrate "very dissatisfied" to "very satisfied". However, these levels of satisfactions can be presented more accurately. For example, by modelling the human movement in the shared space with a machine, the level of safety satisfaction can be adjusted. Using ML in a maintenance process the level of esteem can be adjusted.

The level of each human need satisfaction at the LIMS level can be assessed in different ways after valuation of all ICH_{pi}. One approach can be calculating the average value of all ICH_{pi}, as shown below, where P is total number of the defined processes in the DT, and I is total number of specific I4.0 technologies in a LIMS. NI refers to the total number of interactions between operators and I4.0 technologies.

$safety_{LIMS}$=$\sum_p^P \sum_i^I safety_{pi}/NI$
$Health_{LIMS}$=$\sum_p^P \sum_i^I health_{pi}/NI$
$Belonging_{LIMS}$=$\sum_p^P \sum_i^I belonging_{pi}/NI$
$Esteem_{LIMS}$=$\sum_p^P \sum_i^I \text{esteem}_{pi}/NI$
$S\text{elf}-\text{actualization}_{LIMS}$=$\sum_p^P \sum_i^I \text{self}-\text{actualization}_{pi}/NI$
$Cognitive\ load_{LIMS}$=$\sum_p^P \sum_i^I cognitive\ load_{pi}/NI$

Theory of constraints assumes the performance of a system is limited to the performance level of its weakest subsystem. This theory can be used to assess the HU-LIMS as given below. ∀ i∈I,p∈P

$safety_{LIMS}$=Min $\{safety_{pi}\}$, $Health_{LIMS}$=Min $\{health_{pi}\}$
$Belonging_{LIMS}$=Min $\{belonging_{pi}\}$
$Esteem_{LIMS}$=Min $\{\text{esteem}_{pi}\}$
$S\text{elf}-\text{actualization}_{LIMS}$=Min$\{\text{self}-\text{actualization}_{pi}\}$
$Cognitive\ load_{LIMS}$= Min$\{ognitive\ load_{pi}\}$

5.2. Human DT and operator 4.0

Some studies proposed human DT (HDT), which is mostly investigated in healthcare domain. HDT models need to be multidisciplinary and embody physiology, psychology, biology, chemistry, and mathematics to demonstrate human qualities such as sensibilities, thoughts, and skills [14, 27].

Ergonomic aspects of interactions between an operator and i4.0 technologies was investigated from physical and cognitive perspectives [17]. The suggested ICH_{pi} embodies ergonomic needs. For example, $safety_{LIMS}$ or $Esteem_{LIMS}$ address physical and cognitive aspects of ergonomics.

The most used approach for HDT development is motion tracking systems, as widely used in entertainment industry. Yet such approaches are not very applicable to LIMS due to their high cost and lack of practicality. Because many sensors are needed to be attached to human body, which causes comfortless and limits the worker movement.

In a LIMS context, modelling the mental workload and operator's cognitive state can be substantially beneficial. With the suggested state-based modelling approach, the HDT can be developed as an enabler-state such that encapsulates the modelling details of various aspects of a human. The enabler-state-HDT can integrate multimodal external cues from human body to assess the impact of workload on physical, cognitive, and psychological states. The idea of state modelling in a HDT has been suggested in other works too [7, 28], but no modelling approach was suggested, specially from the interaction's perspective.

ML/AI can be embodied in a HDT to evaluate/predict the human behaviour using real-time sensor data (e.g., wearable devices or computer vision)[27]. The real data can be used for HDT model calibration and enhancing its fidelity. For example, the correlation between number of quality errors by an operator and the workload can be investigated by ML algorithms and the identified pattern can be embodied in the HDT. Also, HDT can identify unsafe behaviour based on human motions (e.g., collected by optical sensors)[28].

Operator 4.0 concept demonstrates an empowered operator by I4.0 technologies [12]. By using the proposed approach an I4.0 technology will be included in the LIMS only if it satisfies both LIMS performance and human operator well-being improvement, realizing operator 4.0.

6. Discussion: Benefits, Limitations, and Roadmap

The proposed novel socio-technical DT enables achieving adaptive human-centric management of a LIMS. The proposed approach enables simulation of work allocation to human operator when applying an I4.0 technology. This allows scenario analysis and identifying the potential consequences of such work allocation on LIMS performance and human needs. Hence, the proposed approach allows system performance optimization, both LIMS production objectives as well as human operator well-being.

The proposed DT can use historical or real-time data to react to the events in the LIMS and updating the production plan to a new optimal state [7]. For example, in case of workforce absence, the tasks planning can change, or in case of observing a pattern of low quality or injuries a flag can be raised for work content change.

Application of ML/AI in DT allows performance optimization by considering human nature uncertainties. For example, the absence pattern or work quality reduction after a time of high cognitive workload can be identified to adjust production planning and job rotation between operators.

This research acknowledges the modelling limitations. Quantifying impact of a technology on human performance (e.g., cognitive capability) and modelling system emerging behaviour require simplification, and results are subject to uncertainty due to existence of many influencing parameters and lack of well-established models. However, the proposed approach allows to estimate and raise awareness about possible consequences of I4.0 application in a LIMS.

The insights offered by the DT can help decision makers to ensure that the expected benefits of an i4.0 technology will not be offset by rebound effects due to unseen impact of the technology on human operator and their interactions. Also, In the process of selecting between two technologies, they can be compared in a broader perspective; which technology together with the operator can lead to better performance?

It is identified in the literature that factors related to organization strategy, culture, and top management support can play critical for the success of manufacturing system adoption to any new technology [3]. It is agreed that a manufacturer can gain more benefits when applying I4.0, if having sociotechnical approach. This research suggesting involvement of operators in developing the proposed DT. This helps to identify the interactions between operator and a technology and their potential impacts on human operator more realistically. When the workers notice the implementation of the new technology leads to the improvement of their wellbeing in the LIMS, this can facilitate the adaption to the i4.0 technologies [13].

7. Conclusion.

There exists a lack of a modelling approach that embodies the human and technology interactions and consequence of such interaction on operator's well-being in a LIMS in I4.0 context. This paper proposed a novel system of system perspective and used systems engineering principles to propose an innovative logical architecture for a DT that models the LIMS by acknowledging the human role in it. This research suggested developing such as logical architecture with a state-based modelling approach to allow simulation of the DT and observing the impact of any potential technology implemented in a LIMS on operator performance and well-being. The detailed approach of modelling was presented with detail novel modelling parameters including safety, health, belonging, esteem, self-actualization, and cognitive load. The presented work is an starting point such that the decision makers can assess which set of I4.0 technologies can help achieving operational excellence while improving human operator well-being.

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