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Towards Human-Chatbot Interaction: A Virtual Assistant for the Ramp-up Process

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***Abstract*—Nowadays, we are surrounded by virtual assistants in everyday life. But one domain that is assumed to massively benefit from virtual assistants, is manufacturing. In particular, where activities are reliant on human expertise and knowledge, a virtual assistant could help support the human. The vision of this work is inspired by the need for bringing an assembly system more rapidly to an operational state. To achieve this vision, a decision-support framework that aims to better integrate the human operator into the ramp-up activity is proposed. As part of this framework, natural language processing tools are applied to allow the development of a virtual assistant for the ramp-up process. This paper provides an overview of the current work in progress, which is part of a PhD research undertaken at the Intelligent Automation Centre at Loughborough University. It outlines the initial efforts and future steps that have been completed and are planned.**

Keywords—Ramp-up Process, Natural Language Processing, Natural Language Generation, Chatbot, Decision-support, Industry 4.0.

I. Background

Being able to adapt to increasing demand and customisation of products rapidly is crucial for the competitive strengths of manufacturing companies. Thus, manufacturers are required to assemble a new or tweak an existing production system and getting it to full production in a very short time. Despite these two processes bearing similarities, the scope of this research work is on the former. This process of bringing a system from a low level to full volume operation takes place during the so-called production ramp-up [1]. Ramping up a system requires the human operator to perform process and equipment adjustments based on his/her knowledge and expertise as part of an iterative process (**Fig. 1**). Simply put, once the system is in place, it will be tested with certain settings to verify if the required Key Performance Indicators (KPIs), such as functionality, product quality, cycle time, etc., are fulfilled [2]. In the unlikely situation, where this is the case, the ramp-up process is finished. The more common situation is that a change to the physical setup or the process needs to be made. This cycle repeats until the KPIs are ultimately met. As can easily be figured, ramp-up can be a very time-consuming activity [1], as due to the uniqueness of each case it makes it heavily reliant on the expertise and intervention of a human [3] that can vary extremely among different people.

During recent years, the understanding that technology and human require a better interaction to achieve successful production ramp-ups has urged manufacturers to rethink their strategies on mainly relying on the human [4], [5]. As more and more data become available in the manufacturing domain nowadays through an increased level of end-to-end digitisation and automation, also referred to as Industry 4.0, improved monitoring of real-time ramp-up processes can be supported [4]. An important research subject that has been identified through literature, is the improvement of knowledge capture, reuse and communication during the ramp-up to minimise disturbances due to loss of human knowledge. Surprisingly, few researchers have thus far proposed a suitable learning approach and assisting tools (software) for ramp-up [6]. When asked about the function of technology for future ramp-up processes, studies indicate [7] that it will play an important role during ramp-up management, whereas the human will be tasked with problem-solving.

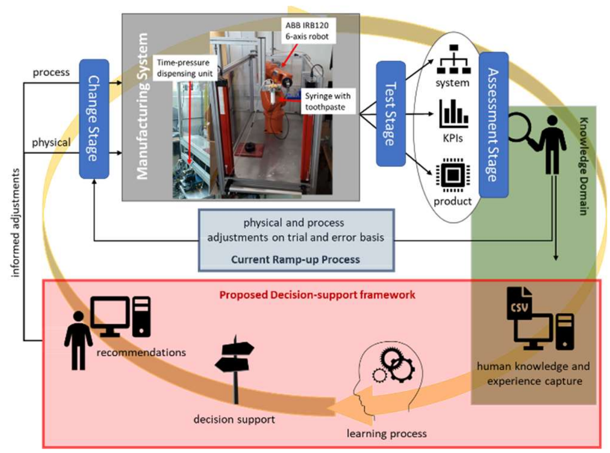

Fig. 1. Overview of the decision-support framework for plug-and-produce assembly systems in contrast to current ramp-up process practice.

The idea presented here is part of an ongoing PhD research work, which mainly aims toreduce the ramp-up effort and ultimately shorten the ramp-up time for plug-and-produce assembly systems. The main objective will be to create a decision-support framework, which will guide a human operator in making adjustments to the equipment and processes of the ramped-up system. One aspect of the proposed decision-support framework includes a module that makes use of Natural Language Processing (NLP) techniques to extract knowledge from captured data and transform it into a meaningful semantic representation. Thus, the hypothesis that is addressed by this work is the following: *"Providing shop-floor operators with a virtual assistant during the ramp-up process will reduce the number of trials required to ramp up a system."* As such, relevant information will be made available in a way that the operator's decision-making for quick system adaptations is supported. This paper presents the idea of a virtual assistant for the operator to provide recommendations in the form of a chatbot.

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II. METHODOLOGY

In order to create a useful decision-support mechanism, formal means of extraction, analysis and interpretation of meaningful data related to human problem-solving are required. For this work, human expertise is captured in natural language during the ramp-up via a developed Graphical User Interface (GUI) as this is a very intuitive way for humans to converse. These data are enriched with data about the system state in terms of process and equipment settings, current and target KPIs. This ultimately allows forming a knowledge base, which contains historical data and information from previous ramp-up scenarios. For this research work, a prototype virtual assistant represented by a chatbot has been developed to provide support to the human in a natural means of communication. A chatbot can be described as a type of conversational or dialogue agent that is able to engage in a natural language conversation with a human, usually through a keyboard. The general information flow between the chatbot and the human can be described as seen in **Fig. 2**.

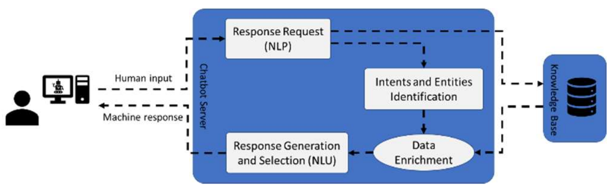

Fig. 2. Simplified Request-Response flow between human and chatbot.

For this research work in progress, a straightforward GUI using Python's Tkinter has been developed to allow the user to engage with the chatbot (**Fig. 3**). Where the human uses the keyboard to type and send a message, the chatbot uses other Python libraries such as NLTK, Keras and TensorFlow to build the conversation. The underlying model that is used here is a Keras's *Sequential* deep learning model [8]. For example, the operator can enquire about certain settings by asking questions related to the individual equipment, such as the nozzle diameter in the given case study explained later. The chatbot reacts to certain identified keywords based on which it chooses is answer.

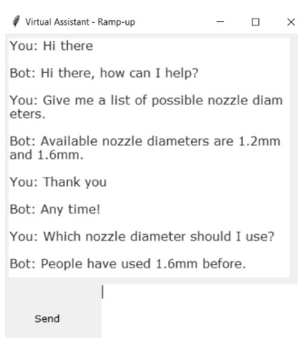

Fig. 3. Current chatbot interface for the virtual ramp-up assistant.

As can be seen, the conversation is currently still very limited and needs enhancements to allow for more detailed questions and answers. One difficulty that was, however, encountered is that many machine learning approaches rely on the availability of sufficient data samples in order to be able to provide meaningful insights about reoccurring patterns. This poses a challenge for the use of these methods during ramp-up as little data are available at that time. Additionally, it has been found that existing chatbot implementations are mostly trained on movie or other reviews. The manufacturing domain as a corpus is not yet sufficiently addressed. As such, data have previously been collected from a manual dispensing experiment to better understand human decision-making for a dispensing-like task which will serve as an input to the proposed chatbot. The data allowed to extract change actions that achieved the necessary KPIs, but also highlighted certain issues that were encountered. By creating a knowledge base with this information and providing it to the user through the chatbot, it is assumed that the trial and error approach conventionally taken in the ramp-up process can be minimised. More information about the data and the experiment itself can be found in [9].

III. CASE STUDY

In order to be able to test the usefulness of the proposed approach in the near future, an industrial use case of a dispensing process has been developed (cf. *Manufacturing System* in **Fig. 1)**. The objective of this experiment is to tune parameters on the setup to obtain products of good quality. There are three product variations and for each participants will have to repeatably create at least one and until you reach the required quality. Good quality is defined by straight and continuous lines, with no excessive dispensing material and close similarity to the given target pictures. The setup's key component is a single 6-axis industrial robot (ABB IRB120), which is connected to an IRC5 controller. Toothpaste, to simulate a dispensing process, is dispensed in a controlled manner through a nozzle that has been mounted to the surrounding frame as the robot will manipulate the metal workpiece. An automated time-pressure dispensing unit (Fisnar JB1113N) is used. If any of the process or equipment parameters are, however, not set fittingly, the desired product quality and performance will not be achieved, and the adjustment step needs to be repeated. More information about the setup can be found in [10]. To validate the underlying hypothesis of this research given in the introduction of this paper, two sets of participants will be asked to perform a ramp-up scenario on the aforementioned glueing workstation. The first group will solely rely on their knowledge and equipment manuals, whereas the second group will in addition have access to the developed chatbot. By comparing the usage and difference in time required to ramp-up the setup to full production state, the usefulness of the proposed virtual assistant for the ramp-up process can be evaluated.

IV. CONCLUSIONS AND FUTURE WORK

This paper is part of an ongoing PhD work looking into reducing the time required to get a system to full production. This stage, also known as ramp-up, is still very human-centric and error-prone. As part of the overall PhD research aim to provide a decision-support framework, one aspect is the development of a virtual assistant for the operator undertaking the ramp-up process. This virtual assistant will be provided in the form of a chatbot, which allows the operator to enquire about certain settings or issues that have previously occurred on similar cases. The chatbot can give recommendations about change actions that can be applied to the system or other useful information. This chatbot is currently under development and its usefulness and, thus, the verification of the introduced hypothesis will be tested on the case study introduced previously. This will be achieved by dividing the participants into two groups, for which one will have access to the chatbot, whereas the other will rely on their sole knowledge and expertise.

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