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Cycle Time Estimation Model for Hybrid Assembly Stations based on Digital Twin

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Abstract. Moving towards factories of the future, Human-Robot Interfaces (HRIs) have come to the foreground. HRIs, offer extended potential in terms of flexibility, time and cost reduction, ergonomics, and the overall company's sustainability. What is needed, is the provision of digital tools that will accelerate HRI integration to the existing manufacturing plants as well as render their complex behavior, predictable. Following this rationale, this paper presents, the design of a prediction model, for robot moves in hybrid assembly stations, based on the robot's Digital Twin and a statistical regression model. In addition to that, respect is given to safety standards as well as to robot capabilities. The resulting model is validated against a simulation software, and further implemented in a pilot case derived from the automotive industry.

Keywords: Intelligent Manufacturing Systems, Production Planning and Control, Statistical Regression, Hybrid Assembly Stations.

1 Introduction

In the Industry 4.0 landscape modern manufacturing plants are constantly evolving. As stated by Chryssolouris in [1], industry is going through an era of market niches. Nowadays, there is an evident need for highly customized products in combination with frugality [2,3]. Thus, what is needed, is that factories, despite the increased complexity of modern manufacturing systems, can achieve high flexibility along with quick responsiveness. Therefore, industrial robotic arms have been integrated in the production plants. The introduction of robotic arms in a manufacturing cell implies increased repeatability, high motion accuracy and heavier weights lifting with ease. However, the human operator must not be neglected in manufacturing systems. More specifically, special human characteristics, such as adaptation, cognition, problem-solving, fast reaction, and improvisation, are human-related skills that in the current situation cannot yet be replaced by robot workers [4]. Consequently, collaborative cells are used in an attempt to extend the capabilities of both robot workers and human technicians [5]. Therefore, production engineers have to reconsider the existing models regarding process planning, so as to take into consideration the collaborative nature of the modern manufacturing cells [6]. In order to do so, simulation software offer increased

capabilities regarding the prediction of the robot workers, at the cost of detailed modelling and design, high computational power and time and increased need for historical production data, which in many cases, especially in SMEs (Small Medium Enterprises), are difficult to acquire [7,8]. However, with the recent technological advances Digital Twins, has enabled engineers to predict the status and constantly monitor a physical system based on their digital counterpart [9,10] Consequently, the need for a quick and robust estimation emerges. Although collaborative cells offer many advantages over conventional manufacturing cells and robot cells, there is another important factor that increases the complexity of HRIs, regarding human operator's safety that in turn affects cycle time and should be one of the initial considerations during the planning stage, when the required information about the layout is limited.

This paper aims to present a methodology for estimating robot cycle time within a hybrid assembly station which by extension will facilitate production engineers during the early design phase of a production line. Notably, for the accomplishment of this goal, a statistical regression model will be used. In addition to that, the existing safety standards, are also taken into consideration, in order to ensure the applicability of the proposed approach in industrial environments. Accordingly, the created model is validated in a real-life industrial scenario from the automotive industry and a laboratory-based machine shop utilizing robotic arms.

2 Problem Formulation and System Architecture

In an attempt to address the above-mentioned literature gaps, the design, and the development of a framework for predicting robot time for task completion is proposed. The basic concept of this framework relies on the creation of a statistical regression model. The outcome of the regression analysis will provide a polynomial equation with automatically calculated weights for each dynamic variable affecting the system's status, i.e. the robotic arm. Therefore, each time the production engineer is either designing a new production line or is making changes to an existing line, the framework and its services can be recalled from a Cloud platform, in order to get a fast and reliable time estimation regarding the processes undertaken by the robotic arm. Then in continuation, the time estimations can be used in the scheduling software used in the company, so that each collaborative working station is assigned with tasks. In order to accomplish this goal, the production engineer uploads to the Cloud platform a json file containing the tasks and the task sequence for the under-examination production plan. The json file is automatically analyzed by the estimator tool, in order to extract the tasks that can be performed by the robotic arm. Then by using the implemented regression model, the time estimations are extracted for each robot task and are saved within the initial json file. Upon completion of the estimation of all the tasks, the json file is returned to the Cloud platform so as to be further processed by the scheduling tool the company uses.

Since the framework is targeted for use in collaborative environments, safety regulations have to be taken into consideration. Therefore, the guidelines provided by ISO/TS 15066 and relevant research works [10-12] have been examined. The above-mentioned ISO is a technical sheet, for specifying safety requirements in collaborative

industrial robot systems. Besides the safety regulations that must be taken into consideration regarding the design of HRIs, the proposed framework is based on the development of a statistical regression model for the robot cycle-time estimation. For the extraction of the regression model, data from the physical robot as well as from the robot's Digital Twin are utilized. The architecture of the framework is presented in Figure 1.

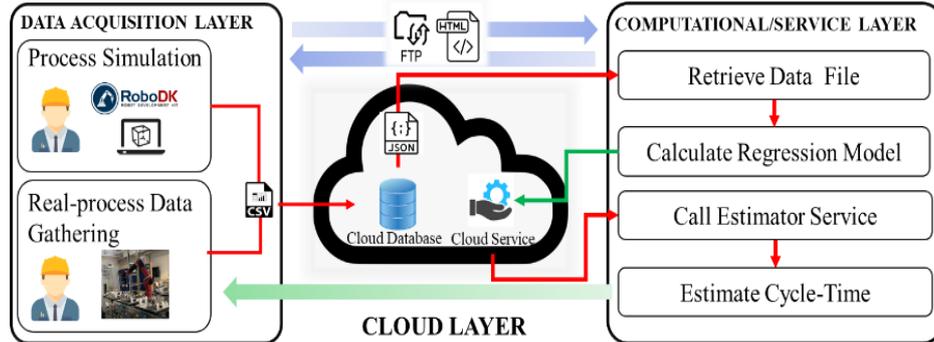


Fig. 1. System architecture for the proposed framework

The data gathered either by the physical robot or the Digital Twin, are uploaded on a Cloud platform. The Cloud platform is responsible for hosting a suitable database where the data are stored and accessed by the end-user application. Besides that, in the Cloud platform, services are also being held, for the data processing.

Statistical regression can be defined as a set of statistical processes for defining the correlation of certain variables affecting a system [13]. Therefore, according to the literature a statistical regression model consists of a dependent variable and one or more independent variables. In this case, the dependent variable is set to be the cycle-time, also denoted as T , for a specific robot motion, whereas the independent variables are the working characteristics of the robotic arm, including its velocity (V), acceleration (A), the distance travelled, in the form of 3D vector (X, Y, Z) and the payload (W) as well. For the extraction of the time prediction equation, an initial dataset has been created, in order to efficiently define and calculate the correlation between the key affecting variables.

In Figure 2b the scatter plot has been generated for the presentation of the obtained values for both the simulation software and the real robot. In addition to that, the yellow line represents the fitment line as produced by the algorithm. Prior to the generation of the regression model, the visualization of the data has been utilized for the selection of the regression model. Therefore, since the data appear to be linearly correlated, a multiple linear regression model has been chosen.

Taking into consideration that robots are used in a repetitive manner, certain tasks were modelled in order to simplify the process planning phase. A typical example of such tasks is the “Pick and Place”. Briefly the robotic arm has to locate a part, grab it from the buffer and position it on the product assembly. In Figure 2a, a representative example of task modelling is presented.

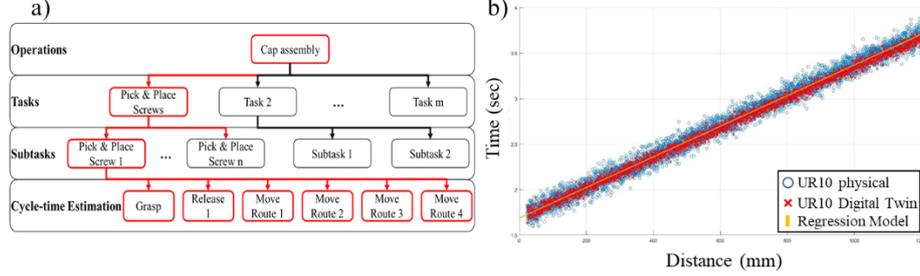


Fig. 2. a) Example of motion modelling; b) Scatter plot of the dataset

3 System Implementation

For the practical implementation, two tasks have been performed. The first task is the development of the suitable infrastructure for supporting the data acquisition and analysis, in order to extract the regression model. For the data acquisition, a simulation module has been developed using Microsoft Visual Studio IDE (Integrated Development Environment), which automatically performs simulations in the RoboDk simulation software [14], with the utilization of the RoboDK API (Application Programming Interface) for .NET in C# environment. The simulation data are exported in a CSV (Comma Separated Values) file. The same module has been applied to the real robot, in order to extract time recordings from the real robot. Therefore, the resulted CSV file contained approximately 10000 values. Then, the regression model, was created by using the Python programming language.

$$T = -3.06869 * 10^{-3} * V + 8.67362 * 10^{-19} * A + 1.70749 * 10^{-3} * X + 1.68041 * 10^{-3} * Y + 1.56752 * 10^{-3} * Z + 1.98345 * 10^{-4} * W + 1.68904 \quad (1)$$

Where, T is the time estimation, V is the velocity of the robotic arm, A is the acceleration, X,Y,Z the distance travelled in each of the axes, and W is the payload.

The second task was focused on the development of a Cloud service, in the form of a desktop application. For the development of the application, a Windows Form Application has been created by using the Microsoft Visual Studio IDE. The application consists of a single Graphical User interface, which is depicted in Figure 3. The developed application is realized as a service, which is available from the Cloud platform. The production engineer loads the process plan from the Cloud platform, which in continuation is automatically analyzed by the tool. and the task sequence is displayed in the GUI. What is more, each task that can be performed by the robotic arm, is interactable so that the user can select it and proceed with the time estimation for the robot. Consequently, upon selection of a task, the engineer has to select robot from the dropdown list. Then each task can be described by a list of motions which are input from the user in the form of total distance travelled and payload carried by the manipulator. As soon as the engineer has finished the input of the robot motions, the task details list is

updated. When the engineer has reached the final configuration, the initial json file for the process plan is updated and the updated version is uploaded to the Cloud platform.

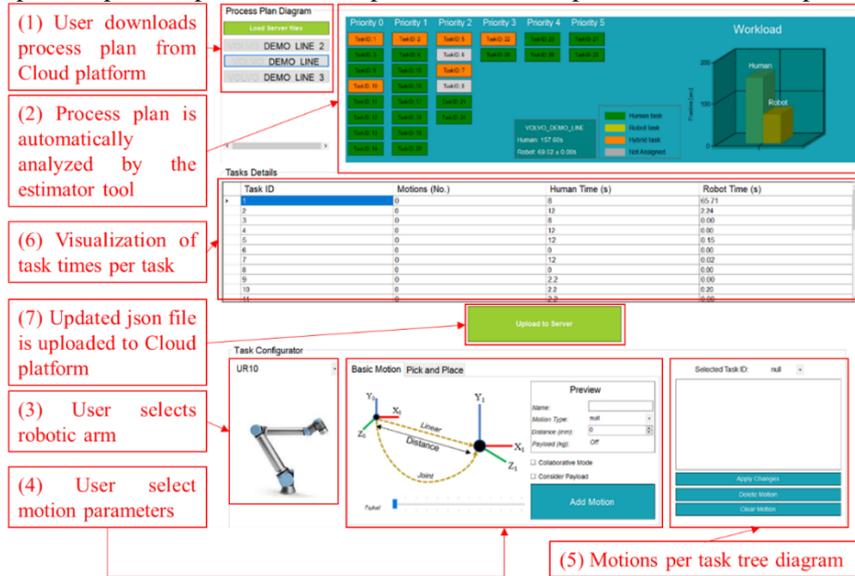


Fig. 3. Estimator's Graphical User Interface

4 Case Study and Results

The applicability of the developed solution has been tested in a use case coming from the automotive industry. Concretely, the validation process took place in a mimic production line, which uses collaborative robotic arms in conjunction with belt conveyers and human technicians for the simulation of the assembly of an automotive gearbox. The collaborative robots and the human technicians are paired so as to form an individual assembly station. The current situation involves fixed automation layout, designed a priori, during the development phase, where the human technicians works independently from the robotic arms. The aim of the pilot case provider is to make the necessary adaptations to the current layout so as to integrate collaborative cells into their actual production line. Therefore, what is needed, is a tool to provide quick and accurate time estimations, in order for the production engineer to conclude on how the tasks have to be assigned/scheduled, so as to achieve greater productivity. Consequently, the current situation suffers from low adaptability, and by extension this affects adversely the production line's flexibility. The lack of suitable digital tools for predicting cycle-time, poses an inhibitor to the pilot case provider, who aim at the integration of hybrid assembly stations in their production line.

Initially, the robotic arm has to pick the component from the buffer and position it on the assembly, which is located at the conveyor belt. Then, the second step involves again the robotic arm for picking and placing six securing screws. Finally, the third step involves only the human technician, who is responsible for screwing the component,

by screwing the six bolts previously placed by the robot. Given the assembly, the tasks that have to be performed as well as the type of collaborative robot to be used, the engineer uses the application, in order to create the sequence of the assembly steps. Through the tool GUI, the engineer first selects the type of the robotic arm, in this case, two robotic arms have been utilized, the UR 10 robot and the SAWYER robot. Then, the engineer creates the list of robot motions. More specifically, one of the most common tasks assigned in collaborative robots is the so called “Pick and Place”. This task comprises of the following sub-tasks. First the robot moves from the home position to the buffer, then the end effector grabs the desired component. Then, the end effector lifts the component and moves it towards the assembly. Finally, the robot places the component to its final position on the assembly. Finally, the time estimations are automatically written in a json file and the json file is uploaded to a Cloud platform which in continuation is used by a scheduling software for the optimization of the production line.

5 Conclusions and Outlook

As far as the added value of the application is concerned, the production engineers have well accepted the application. More specifically after on-site discussions, where the as-is situation has been discussed, they responded that with this tool they were able to get a sufficient time prediction with as low input from the user as possible. Having used the application in order to create a new production plan, the production engineers, could then proceed with designing the process plan in detail, using a dedicated scheduling software. Therefore, from the experimentation on three different scenarios, it has been concluded that the design process has been sped up by 23%, since the production engineers were capable of getting an estimation for the updated process plan. This is backed by the fact that the participating engineers were capable to examine various configurations before proceeding to the detailed design of the production line. In addition to that, it also has been concluded that a 4.5% increase can be achieved in terms of productivity, since better task assignments to the collaborative assembly stations.

The proposed framework has been tested by comparing the predicted values to the actual values, reflecting a 95% accuracy. In the future, the framework will be enhanced so that the prediction model is automatically updated at a regular basis, ensuring high accuracy at each time. Beyond that, the framework will also be improved by the integration of an Artificial Neural Network (ANN), for the cycle-time estimation and task assignment to the hybrid assembly stations, in an intelligent manner, taking into consideration several production parameters, including the balancing of load between the assembly stations.

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