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Dynamic Production Order Allocation for Distributed Additive Manufacturing

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Abstract: Distributed manufacturing systems represent a new paradigm in the industrial context, supported by new technologies provided by industry 4.0. In this paper, a model for dynamic allocation of Production Orders (PO) in the context of distributed additive manufacturing systems is proposed. The scheduling model performs a local optimization of PO allocation considering a production times forecasting model, fed by system state data obtained by means of an IoT platform, and transportation real-time data. A simulation-based experiment was conducted in a test case with real and simulated data collected from an elevator spare parts provider in Brazil. A significant reduction of 77.94% of the Average Waiting Time (AWT) was obtained, allowing for an increased efficiency of the additive manufacturing system, which supports the forthcoming pilot application.

Keywords: Decentralized and distributed control; Job and activity scheduling; Internet-of-Things and Sensing Enterprise.

1. INTRODUCTION

Decision-making in production systems is a complex problem for decision makers, in which industrial production processes present increasingly dynamic and volatile behaviours (Terkaj, et al., 2015; Frazzon, et al., 2018), requiring the development of customized products, implying a high degree of complexity for the control of machines and devices in a distributed, efficient and flexible manner (Avventuroso, et al., 2018). In this context, the increased use of sensors in machines and equipment has enabled the development of approaches based on real-time data, often referred to as “Industry 4.0” (Monostori, et al., 2016) supported by the increasing computing power, focusing on adaptive process control (Terkaj, et al., 2015; Frazzon, et al., 2018).

Technological advances such as Internet of Things (IoT) have increased the availability and volume of data in production systems (Tao, et al., 2018), reducing the cost of collecting and storing large sets of information (Megahed & Jones-Farmer, 2015). Intelligent manufacturing systems integrated to sensors and computational platforms with the intensive use of data modelling and predictive engineering (Kusiak, 2018) allow several opportunities to reconfigure supply chain structures and integrate their operating processes (Fu, et al., 2019). This enables the development of Distributed Manufacturing (DM) systems, combining cyber-physical technologies to create manufacturing networks geographically distributed (Rauch, et al., 2018).

One of the significant technologies in DM is the use of 3D printing, represented by an emblematic shift to on-demand and smaller-scale production, where manufacturing is decentralized, and the final product is manufactured very close to the final customer (Srai, et al., 2016). It is expected that in DM Systems the use of resources will be more efficient, providing better control of the production process, reducing product lifecycle costs and enabling optimal resource loading in response to customer-generated variable-demand tasks (Rauch, et al., 2018). Some recent papers deal with scheduling problems in DM context, such as Fu, et al. (2019) developed a model for integrated scheduling of distributed systems using multi-objective optimization. Lara, et al. (2019) developed an agent-based model for manufacturing network design decisions. Li, et al. (2018) developed an agent-based approach for resource sharing in distributed manufacturing.

In this paper we propose a new conceptual model for dynamic allocation of production orders in DM systems considering data provided by IoT technologies. The proposed scheduling model presents new contributions, focusing on the operational management of distributed manufacturing systems, dealing with the problem of production order allocation considering manufacturing and transportation real-time data. We implemented the proposed approach and tested with real data in a use case to supports a forthcoming pilot application.

2. LITERATURE REVIEW

2.1 Smart Manufacturing and Cyber-Physical Systems

The addition of new technologies and the increase in the number of devices, as well as the extension of visibility outside the industrial environment (*e.g.* supply chain, distributed manufacturing or virtual environment) allowed the emergence of the "Smart Manufacturing" concept, referring to industrial systems with intensive application of information technology, from the factory floor to higher levels, enabling intelligent, efficient and responsive operations (Thoben, et al., 2017).

The development of intelligent industrial systems with cyber-physical integration, commonly called "cyber-physical systems" (Frazzon, et al., 2013; Kusiak, 2018), allows the integration of analytical tools with real time data, becoming a potential field of research involving industrial systems (Heger, et al., 2017; Agostino et al. 2020). This cyber-physical view allows the acquisition of system status data that can be used to support better decisions throughout the production networks, with great potential to change paradigms in relation to the management of processes with a high degree of accuracy and productivity (Monostori, et al., 2016).

Kusiak (2018) proposes that the pillars of smart manufacturing are: (i) materials, focusing on new materials technologies; (ii) manufacturing technology and processes, with emphasis on new additive manufacturing technologies in large-scale production processes (Avventuroso, et al., 2018; Avventuroso, et al., 2017); (iii) resource sharing, focusing on decentralization and digital-physical integration; (iv) data, with emphasis on data-oriented processes (Frazzon, et al., 2018); (v) predictive engineering, with emphasis on anticipation methods to predict the behaviour of industrial variables (Heger, et al., 2017); (vi) sustainability, as an important paradigm for productive systems.

2.2 Distributed manufacturing systems

Distributed manufacturing (DM) systems represent a new paradigm in the industrial context. One of the significant technologies in DM is the use of 3D printing, represented by an emblematic shift to on-demand and smaller-scale production, where manufacturing is decentralized, and the end product is manufactured very close to the end customer (Srai, et al., 2016). This technology simplifies the production process, requiring only the raw material and 3D models of the products as input, as opposed to traditional manufacturing production methods that require configurations and greater numbers of machines and devices to perform tasks (Pour, et al., 2016).

In this context, it is possible to develop DM systems, combining cyber-physical technologies to create geographically distributed manufacturing networks, providing the use of resources more efficiently with better control of the production process and reducing the costs associated with production, storage and transportation, enabling an optimized use of resources in response to variable demand (Rauch, et al., 2018). The development of geographical production structures distributed in facilities with smaller scale of production allows goods to meet local needs and be delivered quickly and at lower cost in a more sustainable way than in traditional globalized mass production (Rauch, et al., 2017). Fig. 1 conceptually illustrates the distribution of manufacturing systems.

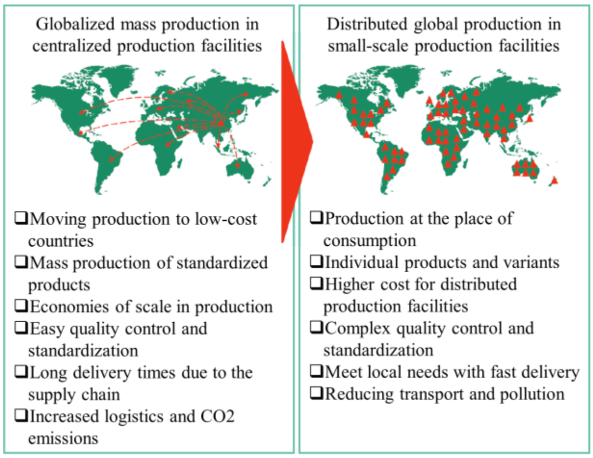

Fig. 1. Mass production and distributed production.

Enablers of DM system development include a range of technologies that are becoming increasingly mature, such as remote sensing and synchronous process analysis methods that can provide better production control and support supply chain integration. More advanced management systems and data analysis that can support decision making by incorporating communication technologies with multiple objects, machines and equipment (Srai, et al., 2016).

2.3 Optimization approaches in distributed additive manufacturing

Some recent research addresses the development and testing of approaches to distributed system optimization. Fu et al. (2019) developed a model for integrated scheduling in distributed manufacturing systems considering multiple flow shops with different numbers of machines. The authors have developed a multi-objective stochastic optimization approach. As results it was indicated satisfactory results compared to other models in the literature. Lara et al. (2019) developed a multi-period model for design and planning of distributed manufacturing systems taking into account trade-offs between investment services and transportation. The model used Mixed-integer nonlinear programming and was tested one hundred case studies in a biomass supply chain. Li et al. (2018) considered a shared scheduling environment in a distributed manufacturing system. The authors developed a multi-agent system in conjunction with two heuristics to solve scheduling problems. The proposed approach was tested in a computational experiment reporting good performance. Li et al. (2017) developed a mathematical model of adaptive optimization for additive manufacturing. The heuristic approach was evaluated in a numerical example reporting satisfactory results. Kucukkoc (2019) developed a similar approach, the author developed a heuristic for scheduling optimization in an additive manufacturing environment in a distributed system.

3. METHODOLOGY

In this section the proposed model to Production Order (PO) allocation is described, along with the considered variables and adopted forecasting models. This section also describes the proposed test case for evaluating the allocation model.

3.1 *Proposed Approach: Dynamic Production Order Allocation*

The proposed model aims to schedule a PO in a distributed manufacturing system, integrating local optimization for each PO, forecasting models for production times and real-time transportation data. The PO allocation includes multiple Production Centres (PC) available in a large territory, as well as multiple ordering points. Thus, the developed model should schedule each PO in order to minimize the response time, taking into consideration:

- **Setup time:** the time required to prepare the machine to accept a PO.
- **Queue time:** estimated waiting time on each production line.
- **Production time:** estimated time to produce a part in a specific production line.
- **Transportation time:** estimated time between the PC and the ordering point.

The objective function should minimize the total response time (*rt*) as:

$$rt = min \sum_{i,j,a,b}^{n} setup_i + q_i + prod_j + transp_{a,b} \qquad (1)$$

Where $setup_i$ is the setup time of the selected i machine; q_i is the queue time of the selected machine; $prod_j$ is the production time of part j in the order; $transportation_{(a,b)}$ is the travel time between production centre a and ordering centre b. The structure of the proposed model is presented in Fig. 2.

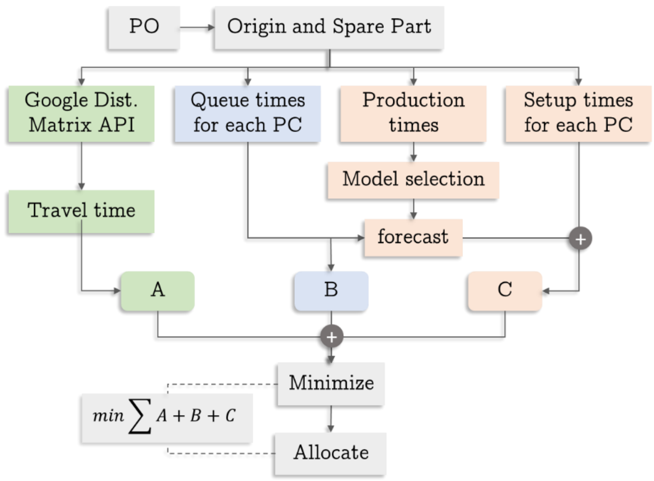

Fig. 2. Proposed approach: Dynamic Production Order Allocation model.

The input will be the ordering point and the spare part to be produced. The output will be the best PC to allocate each PO. Each PO request will perform the scheduling by seeking a local optimization of the total response time. The model will consider three macro variables:

A: Dynamic transportation times from the place of order to each PC available, the data are obtained dynamically through the API of Google Maps, which allows to estimate travel times in real time considering traffic data, type of transport and conditions of roads.

B: Queue times of each production line available in each production centre, data will be captured in real time via the IoT platform considering a distributed and automated system.

C: Historical production data for each type of spare part in each PC with the setup time. The historical data will be treated as time series and used to dynamically and automatically adjust a set of competing forecast models. After adjustment, the best model will be selected using error measurements, and the forecast will be computed considering the current queue time of each production line. Thus, it will be possible to include the stochastic effects observed in the production systems (Heger, et al., 2017) and estimate the production time taking into consideration the estimated moment that the part will be produced in each line. The forecasting horizon is defined as the estimated queue time of each line. Three different forecasting approaches are considered in our model**.**

Autoregressive Integrated Moving Average (ARIMA): a statistical approach characterized by capturing the behaviour of the serial correlation between the values of the time series and making future predictions (Hyndman & Athanasopoulos, 2018). Usually, ARIMA models (p, d, q) are represented by:

$$\phi(B)\Delta^d Z_t = \theta(B)\varepsilon_t \qquad (2)$$

where Z_t represents the modelled time series, B represents the retroactive operator, d represents the order of integration, ϕ is the term that represents the autoregressive parameter of order p, θ represents the parameter of moving average of order q and ε_t represents the sequence of errors, denoted white noise when the average of errors is zero and the variance is constant with homoscedasticity ~ (0, σ2). The best fit model provided by the Akaike Information Criterion (AIC) (Akaike, 1974) is selected for analysis and forecasting.

Exponential Smoothing (ES): mathematical model that aims to adjust a curve appropriate to the historical data of a time series, widely used in many areas, such as business and economics (Montgomery, et al., 2015). The model considers three components: level, trend and seasonality, the additive model is represented by:

$$Z_{t+m} = (L_t + b_t m) + S_{t-s+m} \qquad (3)$$

Where L_t represents the estimated value of the level; b_t represents the trend estimate; $Z_{(t+m)}$ corresponds to the forecast in period $t+m$, m represents how many forward steps it wishes to predict; and S_t is the seasonal time series index.

Autoregressive Neural Networks (NNAR): an artificial intelligence approach for modelling time series, capable of capturing complex and non-linear patterns through training algorithms. The NNAR model is widely used because it allows predictions with univariate models, using the lagged periods of the series itself in the input layer (Hyndman & Athanasopoulos, 2018). The generic model is represented by:

$$Z_t = b_i + \sum_{j=1}^{N} w_{ij} x_j \qquad (4)$$

Where x_j represents the input signals; w_{ij} represents the weights given to each input signal; b_i represents the bias; and

N is the total of input signals in the model. The model uses a non-linear sigmoid and can be considered a generic non-linear autoregressive model.

Considering these models an approach to automatic model selection was proposed, represented by Fig. 3 and described as follows.

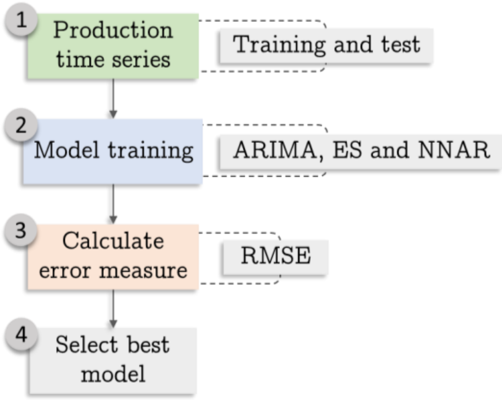

Fig. 3. Procedure to automatic model selection.

1. The historical production time series is divided into two parts: (i) training data, which is used to estimate the parameters of the forecasting models; and (ii) test data is used to evaluate its accuracy of the adjusted model. For this paper, the test data were considered as the last 24 observations from a total of 120 last observations available.

2. For each historical production time series, the three different models considered in this paper are adjusted. The estimation procedure proposed by (Hyndman & Khandakar, 2008) was adopted.

3. Calculate the error measure for each model considering the test data. In this paper Root Mean Squared Error (RMSE) was adopted as a model error measure as suggested by (Chai & Draxler, 2014) and (Hyndman & Athanasopoulos, 2018) when analysing forecasts in the same unit of measurement.

4. Select the best model considering the smallest RMSE error measure.

The proposed model was implemented in R 3.5.2 language, using the libraries 'dplyr' for data manipulation, 'forecast' (Hyndman & Khandakar, 2008) for forecast models and 'googleway' for communication with Google Maps API.

2.2 Test Case: Simulation-based experiment

In order to evaluate the proposed model, a simulation-based experiment was conducted using simulated data combined with real data obtained from a real production system. Data were collected from an additive manufacturing process for elevator spare parts in Brazil. Thus, the experiment was conducted as follows:

- For each simulation-based, an experiment with 1,000 POs was created;
- Five different types of spare parts are considered, where the company provided the average, standard deviation and historical production data;
- The PO were randomly generated, with the mean interval between requests being generated by an exponential distribution (μ = 40) and the quantity of parts per PO by a Poisson distribution (λ = 2) to stress the model to make the allocations;
- The requests were dynamically allocated according to the occurrence of each PO;

6 different ordering points and 4 production centres distributed in the Brazilian territory were defined. The definition of locations took into consideration historical data and previous analyses provided by the company. Fig. 4 shows a map with the approximate locations of the facilities.

Fig. 4. Distributed Manufacturing System.

Two scenarios are proposed for the simulation-based experiment: (i) in the first scenario, the production orders are always allocated considering the closest PC to the ordering point; (ii) in the second scenario, the proposed model was used to perform a local optimization for each PO. In both scenarios the average waiting time (AWT) for each production centre (minutes) was evaluated. In this study, cost aspects will not be taken into consideration.

To define the number of replications, a pre-sampling was performed considering n = 30, which obtained mean = 151.42 minutes and relative standard deviation = 0.23 for the AWT. Assuming α = 0.05, the total of replication was calculated as n = 90 for a percentage error = 0.05. In this way, each scenario was simulated 90 times, being that in each simulation, 1,000 POs were dynamically allocated by considering real-time data and the results estimated by the forecasting models (Hoad, et al., 2010).

3. EXPERIMENTAL RESULTS

To evaluate the AWT in the first scenario, the simulation-based experiment considered the PO allocation in the nearest Production Centre the distance was performed. The results are shown in Fig 5, where higher AWT simulation, average AWT simulation, lower AWT simulation considering all replications performed.

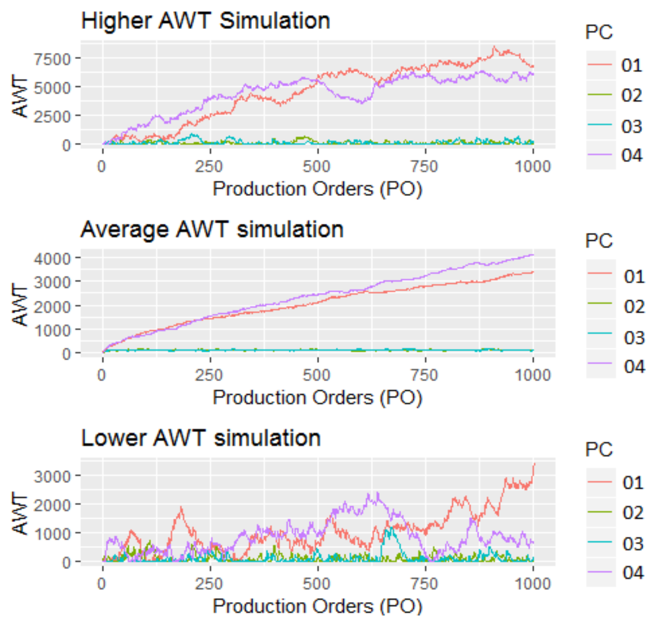

Fig. 5. First Scenario: PO allocation by distance.

For the first scenario, the simulation with the higher queue time obtained AWT of 2,314.7 minutes, average AWT in all simulations of 1,160.8 minutes and the lowest AWT as 506.0 minutes. The relative standard deviation of the 90 simulations was 35.19%.

To evaluate the AWT in the second scenario, the simulation-based experiment considered the allocation using the proposed model, taking into consideration the estimated values of production by the forecasting models, the queue time and the real transportation time provided by Google Maps API, as described previously. As results of the allocation of 1,000 POs, considering 90 replications, the following results were obtained.

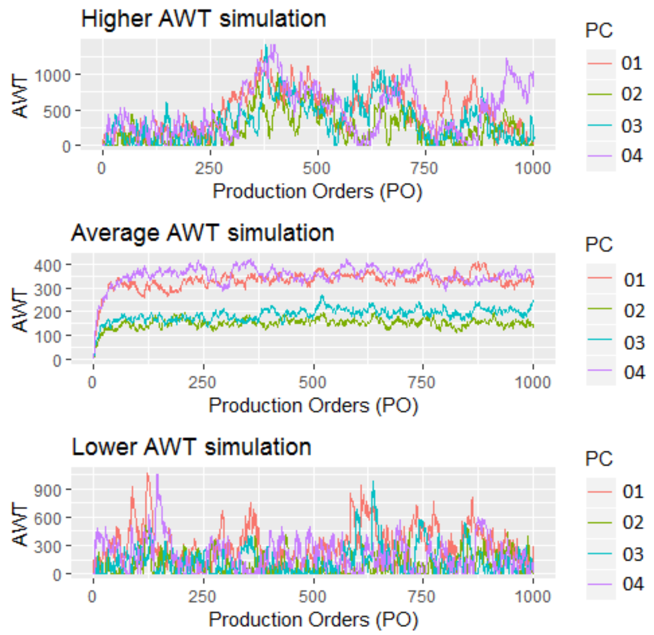

Fig. 6. Second Scenario: Dynamic Model Allocation.

For the second scenario, the simulation with the higher queue time obtained AWT of 380.2 minutes, the average AWT in all simulations of 256.0 and the lowest AWT as 180.9 minutes. The relative standard deviation of the 90 simulations was 15.13%.

By comparing the results of the two scenarios, considering the AWT of each PC, it can be observed that there were significant time gains, mainly for PCs 1 and 4. Fig 7 illustrates the obtained results.

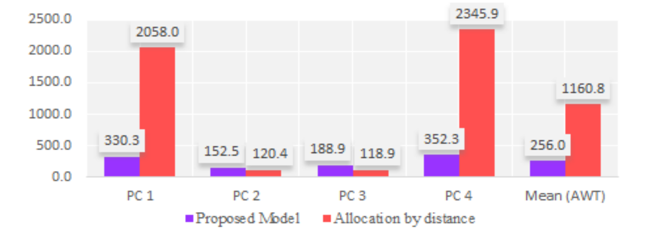

Fig. 7. Second Scenario: Dynamic Model Allocation.

The application of the proposed model for dynamic allocation of POs using real-time queue times, forecasting values of production times, and dynamic transportation data has provided significant efficiency gains in reduction of waiting times for the systems. In PCs 1 and 4, the AWT reductions were 83.95% and 84.98%, respectively; whereas, in PCs 2 and 3, there was no significant AWT reduction. For the average time of all PCs, the AWT reduction was 77.94%, where the AWT reduction was significant according to *t-test* for difference of means ($t = 20.918$ and $\alpha < 0.05$).

Regarding the studies consulted in the literature, the model proposed in this paper presents advances to the current state-of-the-art by incorporating real-time production and transportation data, considering the dynamic changes in the operational conditions of the system. Another important aspect considered in the proposed model is the incorporation of future data through multiple forecasts of production variables, considering stochastic effects observed in the production systems (Heger, et al., 2017). This aspect is described by Kusiak (2018) as a key point in the development of smart manufacturing systems with emphasis on anticipation methods to predict the behaviour of industrial variables. These issues are not found jointly in the studies consulted.

4. CONCLUSION

In this paper, a new model for Dynamic Production Allocation in a Distributed Manufacturing Lines was proposed. The model considered real-time data from queue times, dynamic transportation data, and forecasting values for production times, performing local optimization for each PO. An approach was developed for automatic estimation of forecasting models, taking into account error measures with three different approaches: ARIMA, ES and NNAR.

As main contribution, the proposed model was able to deal with stochastic characteristics of the modelled data in a dynamic environment considering internal and external information. The model was implemented in an open source language and can be easily applied in distributed manufacturing contexts considering real-time data provided by an IoT technology application. In future work will be incorporated reactive scheduling and adaptive capabilities to the model, as well as to evaluate the proposed model in a more complex distributed network considering other competing approaches found in the literature, considering a larger number of PCs and order points, and a larger number of spare parts to support forthcoming pilot application.

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