Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 54-1 (2021) 1126–1131

Effect of lead time prediction accuracy in trust-based resource sharing

Ádám Szaller[a,b]*, Botond Kádár[a]

[a]Centre of Excellence in Production Informatics and Control, Institute for Computer Science and Control, Budapest, Hungary
[b]Department of Manufacturing Science and Engineering, Budapest University of Technology and Economics, Budapest, Hungary

Abstract: Nowadays, challenges are changing production facilities: decentralized production networks are replacing centralized organizations to remain competitive. This paper investigates a resource sharing approach where matching resource offers and requests are made by an intermediate platform. One of the main pillars of collaboration is to keep promises, especially about deadlines: in the presented model, facilities could rate each other based on trustfulness and choose from offers based on this setting. Lead time prediction accuracy has a direct effect on the real processing intervals: if the prediction was accurate, the deadline could be met, which results in good ratings and a higher possibility to win more jobs. In the paper, effect of lead time prediction accuracy is investigated in trust-based resource sharing, and the performance of facilities is compared with agent-based simulation.

Keywords: Co-operative control/manufacturing, Multi-agent simulation, Manufacturing System Engineering

1. INTRODUCTION

Nowadays, globalization, frequent demand changes and tailored customer needs pose serious challenges to manufacturing companies. For example, Build-to-Order companies often have to keep excess capacities to be able to meet the deadlines of fluctuating customer orders. The producer-consumer relationships are also changing, which allows increased cooperation between them (Kaihara et al. 2018). In order to cope with these problems, first multinational companies, then SMEs started shifting from more rigid, centralized organizations towards decentralized production networks (Lanza et al. 2019). The International Electrotechnical Commission proposed *crowdsourced manufacturing* as a possible solution for the abovementioned challenges, which means sharing manufacturing resources with each other via an online platform, with the aim of utilizing them on a more efficient and robust way (International Electrotechnical Commission, 2015).

Resource sharing between manufacturing organizations has been widely investigated by researchers in the past years. For example, Moufid et al. (2017) investigate possible cheatings in resource sharing models by applying a game theory approach. Chida et al. (2019) analyze the stability of request-offer matching in crowdsourcing. Cheng et al. (2019) suggest a platform to integrate additive and subtractive manufacturing resources from organizations with the aim of increasing the resource utilization level and reducing energy consumption.

Manufacturing *lead time* is one of the most important KPIs for companies, who are striving to meet deadlines. In addition, accurate lead time prediction is the key to successful production planning and control (Gyulai et al. 2018). One can find extensive literature in connection with lead time calculation and prediction, however, not in terms of resource sharing. Applying more complex tools for lead time prediction that support quasi-real-time decision making, such as machine learning or data analytics, combined with simulation models, has only started in recent years. These tools can be used to cope with fluctuating reject rates, unexpected tasks and events, etc. (Pfeiffer et al. 2018).

Determining lead times accurately has a strong effect on keeping job deadlines, which is an essential pillar in collaboration. Collaborative resource sharing only works efficiently if companies can count on their partners' promises, such as finishing an undertaken work by the deadline. A useful tool to motivate companies to keep their promises and to penalize unreliable ones is allowing partners to rate each other's performance e.g., based on trustfulnes. Based on Pinyol et al. (2013), computational trust models are mainly used in online commerce and computer technology; however, these approaches could be applied in the manufacturing area, as well.

The authors introduced a trust-based resource sharing model in previous research (Szaller et al. 2020a), where participants share resources with each other *directly*, and can give a rating about each interaction. In another study presented by the authors (Szaller et al. 2020b), a *platform-based* resource sharing approach is introduced, where manufacturing facilities could send resource offers (in case of free capacities) and requests (in case of shortages) to a central platform to match them. Here, choosing between suitable offers is done by taking quality, price and reputation (aggregation of ratings given by other partners) into consideration. Reputation is calculated based on the accuracy of keeping deadlines in both abovementioned models, this way one can distinguish between reliable and non-reliable partners. In this paper, the platform-based resource sharing model is extended, and the effect of lead time prediction accuracy is tested using agent-based

10.1016/j.ifacol.2021.08.132

simulation. The authors investigate how the performance of collaborating partners change if they could predict lead times of their jobs with different accuracy.

Based on Suri (1998), resource utilization has a strong effect on lead times, which also depends on variability. Higher resource utilization level causes longer and less predictable lead times, as working on different jobs in parallel increases the complexity of production planning. In order to investigate this effect, the authors perform experiments to examine the effect of decreasing prediction accuracy when operating under a higher load.

It is important to highlight that in this paper, the authors do not focus on different lead time prediction methods (as one could find useful methods in the literature, for example, in the papers referenced in connection with lead time prediction). The aim is to show the difference between cases 1) when lead time is more accurately determined and partners could rely on each other to a greater extent, and 2) when lead time prediction is not accurate, and failures in keeping deadlines may require changing existing production plans. In addition, these two cases are investigated in terms of crowdsourced manufacturing, where resource sharing is made by a central platform. The novelty of the research presented here is the consideration of lead time prediction accuracy in collaborative resource sharing, which is unique in the literature. The paper is organized as follows. In Section 2, the resource sharing model is described in detail, and possible effects of lead time prediction inaccuracy are mentioned. In Section 4, experiments with agent-based simulation are performed to investigate the effect of prediction accuracy. At the end of the paper, conclusions are drawn, and some interesting future research directions are mentioned.

2. MODEL DESCRIPTION

For easier understanding, some concepts have to be clarified in connection with the platform-based resource sharing model. A *facility* is a participant of the model, it can communicate with other facilities and with the platform and make decisions (for example, choose from different resource offers). A facility can also create production plans for the future taking the incoming orders into account, for example, by applying a simulation model about its own system. When having resource shortages or free resources, it can communicate with the platform about these, considering an internal safety margin. The authors do not distinguish between resource offeror and requester facilities: the denomination depends on the role in the specific interaction.

Facilities, which are sharing resources with each other, form a *federation* (collaboration is only possible between federation members). However, this is an open society: entering and exiting is allowed anytime. As mentioned in the introduction, crowdsourcing is based on an online platform, called *Federation Centre (FC)* here, which role is to

- receive and match resource offers and requests,
- manage contracting in case of a match,
- calculate and update reputation values and ensure their public availability, and
- manage entries and exits.

Facilities receive customer orders regularly from outside the federation. At this stage of research, one order represents one *job*, which is determined by its resource requirements: type (e.g., drilling machine), intensity (e.g., 5 pieces), earliest start time and due date. To fulfil a job, its *resource load* has to be provided, which is calculated by multiplying its resource intensity with the difference between its due date and earliest start time. This means,

- a facility can complete a job if the required resource intensity is available in its production constantly during the time interval, determined by the earliest start time and due date, and
- with higher resource intensity, a job could be finished in less time.

When receiving a customer order from outside the federation, a facility checks if it has the appropriate and sufficient resources to complete it by taking its future plans (already undertaken jobs and offered capacities) into consideration. If it can perform the job using its own resources, the facility extends its production plan with the new job and starts working on it at its earliest start time. If the facility does not have the appropriate resource type or the required intensity, it sends a *request* to the FC containing the resource requirements of the job. The facilities check their future plans regularly, and in case of having unused resources, they send *offers* to the FC, containing information about the specific resource intensity and interval (similarly as in case of requests).

When the FC receives a request, it checks its offer database and tries to find offer(s) that are satisfying the requirements of the request. A request can be fulfilled with only one offer, or a combination of different offers (sent even by different facilities), also. In case of a *match*, the FC sends all the suitable offer combinations to the requester facility, which can choose from them with taking the offeror's reputation, price and quality aspects into consideration. These aspects are weighted relative to each other, based on the preferences of the specific facility. After choosing the best offer(s), a contract is created between the requester and the offeror facilities. Signing a contract means that the offeror facility promises to: (1) complete (do not cancel) the job, (2) complete it by the deadline, (3) complete it in the expected quality. To measure the extent to which the expectations have been met, requesting facilities are rating the offering ones after each interaction, and these ratings are aggregated and summarized by the FC. An *interaction* is rated based on (1).

$$rating_i^{m,n} = \left(100 - \frac{L_i \cdot 100}{t_d - t_e}\right) \cdot \alpha \cdot \mu \qquad (1)$$

Here, $rating_i^{m,n}$ means the trust rating given by $facility_m$ to $facility_n$ in connection with job_i. L_i is the lateness with finishing the job, t_e is the earliest start time and the t_d is the due date (we suppose that $L_i < t_d - t_e$). μ is a subjective rating about the quality of the completed work, and the role of penalty factor α is to sanction lateness to a greater extent: if $L_i \leq 0$, then α will be equal to 1, if $L_i \geq 0$, then α will be a constant model parameter between 0 and 1. Lower α means higher penalty for exceeding the due date. Based on (1), if a job is finished on time and in the expected quality, the trust value will be equal to 100. Ratings given by requesting facilities are summarized by the FC: each facility in the federation has a value called *reputation,* which means the summarized rating, updated after each interaction the facility takes part as an offeror. This value is public for each federation member and used to choose between matching resource offers. A flattened exponential smoothing function is applied to give older feedbacks smaller weights than more recent ratings – this function combines the advantages of the quickly decreasing exponential function and the slowly decreasing linear one.

It is important to highlight that the goal of the FC is not to select the best offers, but to provide some good alternatives with pre-filtering the appropriate ones. The FC can also provide offers from facilities that were previously unknown to the requester. A more detailed description of the model can be found in Szaller et al. (2020b).

Reputation ratings are calculated based on the lateness in finishing jobs, which is closely related to lead time prediction: if a facility can predict the completion time of an undertaken job more accurately, it is more likely to be able to meet the deadline. Thus, it gets higher reputation ratings and has a higher possibility to win more jobs. In the model, real job processing times are determined by normal distributions in order to simulate lead time prediction inaccuracy and generate a difference between expected (promised) and real job completion times. For example, if the expected processing time (i.e., the difference between due date and earliest start time) is 20 model time units, then the mean of the distribution will be 20 model time units. The deviation of the distribution is one of the parameters for the experiments, where effects of prediction accuracy is investigated (see Section 3). In this case, when the expected (or promised) processing time is equal to the mean of the distribution, the facility is called *reliable*.

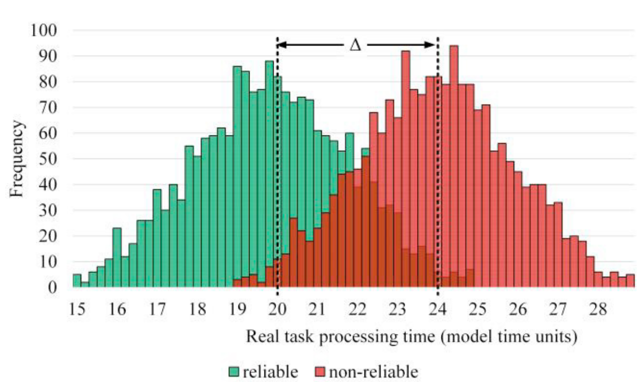

Fig. 1. Generating real processing times for jobs in case of reliable and non-reliable facilities.

The abovementioned case is visualized in Fig. 1 with green colour. In the model, *non-reliable* facilities could exist, also: the distribution from which real processing times are generated for these facilities is shifted with Δ. This parameter is the extent of the agent's non-reliability, given in the percentage of expected processing time. For example, in the case shown in Fig. 1, Δ = 20%, as the difference between the mean of the original and the shifted distribution is 4. In the model, these two parameters – deviation and Δ – determine that how accurate is the lead time prediction in case of a specific facility.

Accuracy of lead time prediction could influence the production plans of the participants as described below. One can distinguish between two types of jobs that are performed by a facility:

- customer orders coming from outside the federation are completed using its own resources, and
- an offer sent to the FC is accepted by another facility.

In both cases, the facility estimates the lead time of the specific job and inserts it into its production plan. If the real finish of a job is delayed compared to the estimated date, it can overlap with:

- already offered resources that were sent to the FC earlier: these have to be cancelled to finish the job, or
- already undertaken jobs that could only be started later and may be finished with additional delay (causing reputation loss, also).

When performing jobs in connection with accepted offers, a decrease in reputation is also a problem since it affects other federation members' decisions in the future (choosing from resource offers). Finishing a job earlier than promised does not cause reputation loss, but in this case, the facility will most probably have idle resources for the remaining time interval, as there is a little chance to find a suitable resource request at the last moment.

3. PROBLEM STATEMENT AND EXPERIMENTAL SCENARIO

To investigate the effect of lead time prediction accuracy on the federation performance, experiments with agent-based simulation were performed using AnyLogic simulation software. The facilities were modeled with agents who are receiving customer orders from outside the federation regularly. In the simulation model, facilities perform different functions when a specific event occurs. E.g., when one of the offers (sent previously to the FC) is accepted and a contract is made, an event is scheduled that will decrease the amount of available resources of the facility at the start time of the offer. The FC – which is modeled with another agent type – also performs pre-defined functions when receiving a message, e.g., a request or offer. It has a database where not matched offers and requests are stored until matching or the end of their validity. The input of the model is a database containing the parameters of facilities: name, location, resource parameters (unit price, quality, amount), Δ, etc. Other, general input parameters for the model that are set in case of all experiments are summarized in Table 1. Some of them are determined by using a truncated normal distribution – in these cases, the sigma values are also included in the table. The lower and upper bounds of the distributions are calculated by adding/subtracting 0.5*sigma to/from the mean of the distribution. For example, in case of incoming order length, orders were generated from a distribution with 20 days mean, 5 days sigma, lower bound 17.5 days and upper bound 22.5 days. For the constant parameters, sigma is 0.

In the experiments, 20 different resource types were initiated: one facility had 10 to 20 types of them with the intensity 8 to 12. To reduce the administrative costs of contracting and the computational load of the FC (providing all possible offer combinations), matching is only possible between exactly one request and a maximum of three offers. Facilities sent offers to the FC about their free resources with a look-ahead for the next 40 model time units. In all cases, the experiments were run for 500 model time units: based on observations, the investigated KPIs do not change after this time in an unexpected way. Since some of the parameters are normally distributed, 10 experiments were performed for each parameter set, and the average of the values is presented in the diagrams.

Table 1. Input parameters for the experiments

Parameter	Mean	Sigma	Unit
Initial reputation for facilities	80	0	-
Planning horizon	40	8	day
Incoming order length	20	5	day
Incoming order arrival rate	1.5	0	1/day
Incoming order resource intensity	8	2.7	-
Max. number of combined offers	3	0	-
Simulation time	500	0	day

The performance of the federation could be measured by comparing the participants' ability to find more reliable partners to work with. Outsourcing jobs to more reliable partners results in less delay in job completion times: *average service level* is used to highlight this setting. This KPI is calculated by measuring percentage lateness is in case of all completed jobs, subtracting it from 100%, and recording the average of these values after each simulation run. To compare the performance of reliable and non-reliable agents, visualizing their *reputation* values as a KPI is a feasible way, as reliable agents are expected to have higher values, thus a higher chance to win more jobs.

4. EXPERIMENTS

4.1 Effect of lead time prediction accuracy on service level and resource utilization

As mentioned, real processing intervals are determined by normal distributions in the model, in order to consider lead time prediction inaccuracy. In the first experiment, the effects of changing the deviation of the distribution (from 0% to 50% of the expected value) and the Δ value (from 0% to 50 % of the expected value) were investigated. These two parameters determine the lead time prediction accuracy of a specific facility. In this experiment, each facility had the same deviation and Δ parameters but different equipment types. Completing jobs later than promised results in lower reputation values, which directly affects the agent's performance, as decision-making between offers is made based on reputation. It is important to highlight that finishing a job earlier than promised does not cause higher ratings than completing it right on time. Thus, the agents get only the advantage of being able to offer resources again earlier in case of earlier finish. Similarly, the maximum service level is 100% in case of each job. This asymmetry could be recognized in real ratings, also: no matter how outstandingly someone performs, there is always a maximum for the rating could be given. The results of the experiment can be seen in Fig. 2. The simulation was run for 500 model time units, but the results are visualized by neglecting the first 30 time units (run-up phase).

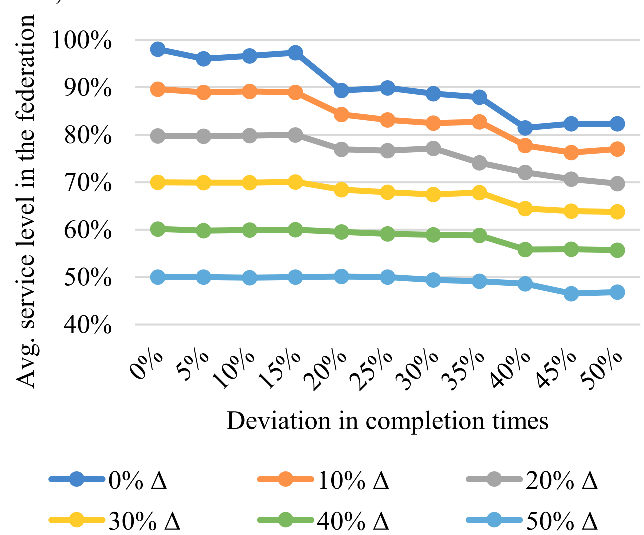

Fig. 2. Effect of deviation in completion times and Δ on average service level.

Based on the results, the following statements could be made. As one could expect, the higher the Δ value, the smaller the average service level is in the federation. When increasing the deviation in the real completion times (leaving the expected value unchanged), the service level decreases. The extent of decrease depends on Δ: smaller Δ causes a higher decrease. Therefore, in case of agents that are less likely to be late (more reliable agents, smaller Δ), the deviation of their lead time prediction has a higher effect on service level than in case of non-reliable agents (higher Δ).

As one can see in Fig. 3, average resource utilization increases close to linearly in the federation when increasing Δ, based on the same experiments that were shown in Fig. 2. This KPI is determined by sampling resource utilization of the federation members in every model time unit. The average of these values after each simulation run was calculated and visualized in Fig. 3. The average resource utilization grows because finishing jobs requires more time as Δ increases. This means facilities have fewer unused resources, but the efficiency of using them decreases – since the number of incoming orders is approximately the same in the experiments (as shown in Table 1).

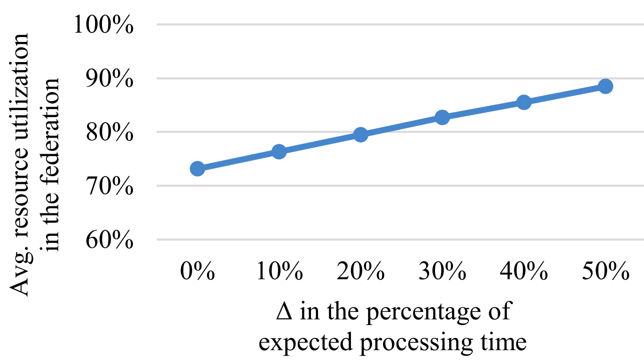

Fig. 3. Effect of Δ on average resource utilization

4.2 *Taking resource load into consideration in lead time accuracy*

As mentioned in the introduction, resource utilization is an important factor that influences the accuracy of lead time prediction. In this experiment, facilities with higher resource utilization can predict manufacturing lead times less accurately, in order to simulate more realistic scenarios.

To visualize the results in a more transparent way, 10 facilities are forming the federation in this experiment. Out of them, 4 are reliable (Δ = 0%) and 6 are non-reliable (Δ = 30%). The deviation of real processing times is determined by dividing the actual resource utilization level of a facility by 2. This means if a facility starts working on a job, and in that time point its resource utilization level is, e.g., 80%, the real processing time of the specific job will be determined by a truncated normal distribution with deviation equals to 40% of the expected processing time (in case of reliable agents). Of course, the mean of the distribution will be shifted with 30% of the expected processing time in case of non-reliable agents.

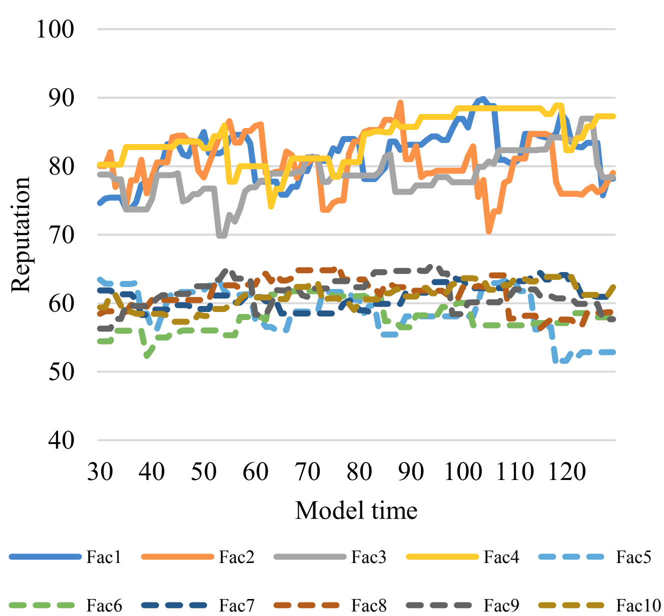

Fig. 4. Change in reputation in the original scenario.

In this experiment, the change in reputation values is visualized in case of the original scenario (10% deviation in real processing times for all agents, Fig. 4) and in case of taking resource utilization level into consideration in the abovementioned way (Fig. 5). In the figures, reliable agents are marked with solid lines, non-reliable ones are shown with dashed lines. The results are visualized between model time unit 30 and 130 (100 model time units), in order to exclude the run-up phase, similarly as in the previous experiment. In this case, it was unnecessary to run the simulation for a longer time, as the main findings are the same after this time interval. Based on Fig. 4 one can see that neglecting the resource load of facilities results in a clear separation of reliable and non-reliable facilities. In general, reliable facilities are between reputation levels 75 and 85, while non-reliable ones are between 55 and 65.

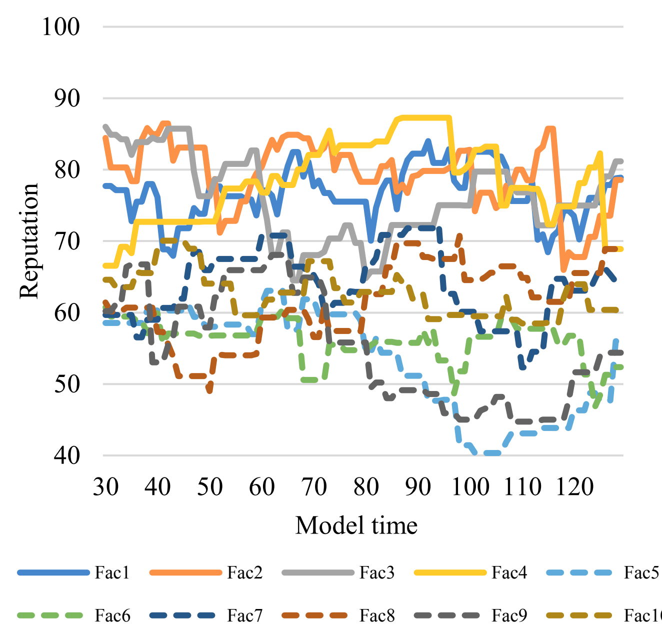

Fig. 5. Change in reputation when taking resource load into consideration in lead time prediction accuracy.

In Fig. 5, one can see that the difference is not that clear between reliable and non-reliable facilities when taking resource load into consideration in determining lead time prediction accuracy. In general, reliable agents are reaching a higher reputation level, but non-reliable ones have sometimes similar values. Another observation is that the reputation values are fluctuating to a greater extent in case of non-reliable agents, compared to the previous case. When neglecting resource load, the values are in a zone with width 10. In contrast, in this case they are changing between 40 and 70. The fluctuation is a little higher for the reliable agents, also. This can be explained with the changing deviation of the processing intervals: when reaching a high reputation level, the facility will win lots of jobs, which will cause high load on its production system and lead time prediction inaccuracy as well. This way, load is balanced between participants who are members of the resource-sharing federation.

CONCLUSIONS

In the paper, the effect of lead time prediction accuracy was investigated in a crowdsourced manufacturing model, where resource offers and requests created by manufacturing facilities are matched by a central platform. In the model, the reputation of resource sharing participants is also taken into consideration: these ratings are based on the extent of keeping promised deadlines (which depends on the accuracy of predicting lead times) and used in choosing from resource offers sent by different facilities. Agent-based simulation experiments have shown that deviation in lead time prediction could strongly affect the average service level in the resource sharing federation: higher deviation causes worse performance. The decrease in performance also depends on the reliability of facilities: if they are more likely to finish jobs in time, increasing the deviation of lead times results in a relatively higher performance decrease. It was also shown that increasing average resource utilization does not mean that the facilities are performing better; they are only working on jobs for a longer time (due to using their resources less efficiently). The effect of taking the resource load of facilities into consideration in lead time prediction accuracy was also investigated: facilities with higher load could predict lead times with lower accuracy. This way, reliable and non-reliable facilities could be balanced in terms of reputation values.

In future works, the model is planned to be extended by a multi-criteria decision-making mechanism in order to create a more complex and realistic decision-making mechanism for the facilities. Another interesting research direction is taking into consideration orders containing independent jobs that may require different types of resources: in this case, the delay with finishing one job could affect starting the next one and require changing already fixed production plans.

ACKNOWLEDGEMENT

This work has been supported by the National Research, Development and Innovation Office, grant no. SNN 129178 and by the European Commission through the H2020 project EPIC (https://www.centre-epic.eu/) under grant No. 739592.

REFERENCES

Cheng Qian, Yingfeng Zhang, Yang Liu, Zhe Wang. (2019). A Cloud Service Platform Integrating Additive and Subtractive Manufacturing with High Resource Efficiency. *Journal of Cleaner Production*, 241: 118379

Chida, T., Kaihara, T., Fujii, N., Kokuryo, D. (2019). Stability Analysis on Resource Matching in Crowdsourced Manufacturing. *Procedia CIRP*, 81: 405-410.

Gyulai, D., Pfeiffer, A., Nick, G., Gallina, V., Sihn, W., Monostori, L. (2018). Lead time prediction in a flow-shop environment with analytical and machine learning approaches. IFAC-PapersOnline, 51 (11), 1029-1034.

International Electrotechnical Commission. (2015). Factory of the Future: IEC Whitepaper, 20-23.

Lanza, G., Ferdows, K., Kara, S., Mourtzis, D., Schuh, G., Váncza, J., Wang, L., Wiendahl H.-P. (2019). Global Production Networks: Design and Operation, *CIRP Annals*, 68 (2): 823–841.

Moufid, M. E., Roy, D., Hennequin, S., Cortade, T. (2017). Game Theory Model of a Production Resource Sharing Problem: Study of possible cheatings. *IFAC-PapersOnline*, 50 (1), 10532-10537.

Pfeiffer, A., Gyulai, D., Szaller, Á., Monostori, L. (2018). Production log data analysis for reject rate prediction and workload estimation. *Proceedings of the 2018 Winter Simulation Conference,* 3364-3374.

Pinyol, I., Sabater, J. (2013). Computational Trust and Reputation Models for Open Multi-agent Systems: A Review. *Artificial Intelligence Review*, 40: 1–25.

Suri, R. (1998). Quick response manufacturing: a companywide approach to reducing lead times, Portland: Productivity Press.

Szaller, Á., Egri, P., Kádár, B. (2020a). Trust-based Resource Sharing in Distributed Manufacturing. *International Journal of Computer Integrated Manufacturing*, 33 (1), 1-21.

Szaller, Á., Pedone, G., Egri, P., Szalóki, Á., Nick, G. (2020b). A Mutualistic Framework for Sustainable Capacity Sharing in Manufacturing. *Procedia CIRP*, 93, 938-943.