Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 112 (2022) 68–72

www.elsevier.com/locate/procedia

14th CIRP Conference on Intelligent Computation in Manufacturing Engineering, Gulf of Naples, Italy

Economic efficiency of automated manufacturing systems design

Daria Leiber[a]*, Gunther Reinhart[b]

[a] Technical University of Munich, Department of Mechanical Engineering, Institute for Machine Tools and Industrial Management, Boltzmannstr. 15, 85748 Garching, Germany

* Corresponding author. Tel.: +49-(0)89-289-15507; fax: +49-(0)89-289-15555. *E-mail address:* daria.leiber@iwb.tum.de

Abstract

Systems for the automated planning and design of manufacturing systems have been widely studied and are a promising answer to current challenges arising from shorter product life cycles, high labor costs, and increasingly complex production resources. However, implementing these systems entails substantial investment, and their profitability depends on various factors. One of the major difficulties in implementing automated planning systems in an industrial context has been establishing a suitable database of resource models. This article presents an evaluation method to compare the economic efficiency of manual and automated planning, including resource modeling. It also explores different application scenarios to determine under which preconditions automated planning is advantageous and where the limits of their application lie.

Keywords: Economic efficiency, manufacturing systems design, decision support system

Nomenclature

APS	automated planning system
ALB	assembly line balancing
NPV	net present value
NPC	net present cost
n	index of a usage period
N	number of usage periods
c_n	cost in period n
r	interest rate per period
c_{sw}	cost for software licenses
c_{hw}	cost for hardware
c_{orga}	organizational cost for introducing an APS
$c_{modeling}$	cost for modeling resources
c_{hr}	hourly rate of a skilled worker
R	number of resources in the database
r	index of a resource
b	learning rate
t_i	time for executing task i
t_c	time for executing task after learning is completed
i	index for performing a task
c_{labor}	labor costs
$c_{maintenance}$	cost for maintaining the APS
$c_{subscription}$	cost for software subscription
P	number of planning scenarios performed
p	index of a planning scenario
t_p	time for one planning scenario
d_{auto}	degree of automation

1. Introduction

Manufacturing systems need to be designed and redesigned with increasing frequency to address the challenges posed by individualized production and increasingly shorter product cycles [1]. Planning a manufacturing system entails selecting, configuring, and layout planning of the resources needed for production and assembly [2]. Classical methods for manufacturing systems planning are presented by [3, 4] and [5]. They describe various planning steps to design, implement, and finally put into operation a suitable manufacturing system for assembling a new product. The tasks involved can be summarized into the following planning stages: requirements analysis, structural planning, layout planning, realization, and

10.1016/j.procir.2022.09.040

operation. The use of digital tools and automated planning systems (APS) for designing manufacturing systems are promising approaches to minimize the planning efforts [6, 7].

1.1. Related works

Numerous methods, algorithms, and systems have been developed and presented to support the various planning decisions needed to arrive at a functioning manufacturing system. Some aim to look at the whole planning process [8, 9], while others look at specific planning decisions in depth.

One planning aspect that has been intensely studied is assigning different tasks to the stations of a line, commonly referred to as assembly line balancing (ALB)[10, 11]. The fundamental ALB problem does not consider resources, but multiple authors have included resource selection into their ALB optimization models [12–15]. Another planning decision that has been addressed thoroughly is the positioning of production resources, especially industrial robots [16–18]. [19] integrate ALB and resource positioning into one optimization problem to consider interdependencies.

However, these planning algorithms usually rely on digital models of the product, the process, and the used resources [20–22]. Despite efforts to standardize data formats [23, 24] and to implement generally accepted databases, interoperability between different software systems remains a challenge [25]. Therefore, implementing the necessary models still falls on the prospective user of an APS and constitutes one of the major hindrances for using APSs in practice.

1.2. Structure of the paper

To address these concerns and give a guideline on evaluating the benefits and drawbacks of using an APS, we develop an evaluation method that relies on a detailed cost model of deploying an APS compared to manual planning.

In section 2, we develop a cost model to evaluate the economic efficiency of using an APS instead of a manual planning process. Section 3 presents multiple analyses of possible scenarios for the deployment of automated manufacturing systems planning. Finally, section 4 sums up the findings and gives an outlook to further research.

2. Evaluation method and cost model

For any industrial company, the primary objective is economic success. Therefore, any decision is viewed through the lens of profitability. In this section, we will explore different factors influencing the profitability of using an automated planning system and present a method to support the decision of a company whether to use such a system.

For the assessment of investment opportunities, multiple evaluation methods exist and are used in practice. The net present value (NPV) of an investment represents all the expected cash flows discounted to today. It is widely used to decide whether an investment should be made or to choose among different courses of action [26].

To assess the economic efficiency of using an APS, the NPV can be simplified to net present cost (NPC) since the two available options – manual planning and automated planning – differ in terms of their associated costs, but positive cashflows are independent of the used planning method and can be neglected for the decision. Equation (1) shows how the NPC is calculated.

$$NPC = c_0 + \sum_{n=1}^{N} \frac{c_n}{(1+r)^n} \tag{1}$$

The usage of an automated planning system is profitable if ΔNPC, see equation (2), is negative, meaning that deploying the automated system results in reduced costs compared to manual planning.

$$\Delta NPC = NPC_{automated} - NPC_{manual} \tag{2}$$

In the following sections, we identify different relevant costs that have to be considered when calculating the NPC of an APS and the alternative manual planning method.

2.1. Invest

For the NPC of the manual planning alternative, no initial investment must be considered because it represents the status quo, so all of the necessary prerequisites are already in place.

The investment $c_{0,automated}$ of the automated system comprises all costs associated with its implementation, see equation (3).

$$c_{0,automated} = c_{sw} + c_{hw} + c_{orga} + c_{modelling} \tag{3}$$

The most obvious costs are c_{sw} for necessary software licenses and c_{hw} the related hardware. Besides that, the investment also includes organizational efforts c_{orga}, such as training for the prospective users or the adaptation and installation of the software.

Another significant factor of the implementation effort is the integration of the expert knowledge that the company possesses into the planning system. Most of the planning systems presented in the literature provide a structure for the modeling of products, processes, and resources but leave it to the user to populate the databases with actual instances as a basis for the planning process. The product and the process need to be explicitly modeled for each planning scenario, but configuring production resources is part of the introduction effort. It is represented by $c_{modelling}$, see equation (4).

$$c_{modeling} = c_{hr} \sum_{r=1}^{R} t_{modeling,r} \tag{4}$$

The time $t_{modeling,r}$ required for modeling one resource depends on the level of the user's experience. This correlation is modeled in learning curves (LC) and was first described by [27]. LCs have been applied and adapted to many different tasks [28]. Several studies have shown that LCs are not only applicable to manual tasks but also cognitive tasks like software installation [29], information technology usage [30], and computer-aided design (CAD) [31].

The learning curve is traditionally represented by a log-linear model that can be amended with a constant that represents the time needed for a task after the learning process is completed, see equation (5).

$$t_i = t_c + (t_1 - t_c)[i^{b+1} - (i-1)^{b+1}] \quad \text{with } (-1 < b < 0) \tag{5}$$

In this model, t_i, the time for the i^{th} iteration of a task, is calculated as a function of the first execution's time, the learning rate b and the target time t_c after the learning process is completed. The value of b lies between -1 and 0 and denotes the learning speed, with values close to -1 representing fast familiarization to the task. Fig. 1 shows exemplary learning curves for different values of b.

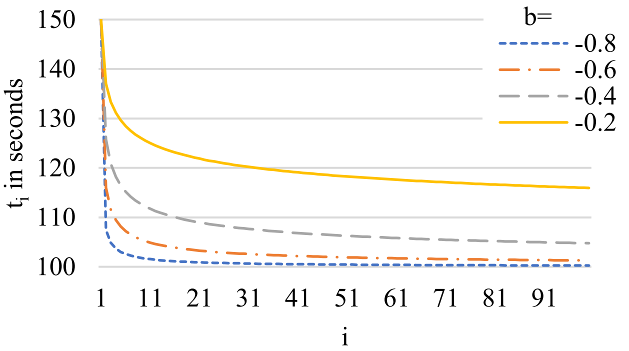

Fig. 1. Learning curve for different b values with t_c=100, t_1=150.

The time $t_{modeling,r}$ in equation (4) can be calculated by applying equation (5) to consider the learning effect in the case of modeling resources.

2.2. Ongoing expenses

Besides the initial investment, both the manual planning and the automated planning system generate ongoing expenses over the considered time of their usage.

$$c_n = c_{labor} + c_{maintenance} + c_{subscription} \tag{6}$$

Arguably the most critical cost factor in both alternatives are labor costs for the engineers conducting the planning or using the APS. The labor costs associated with manually planning $c_{labor,manual}$, see equation (7), are the baseline of the considerations.

$$c_{labor,manual} = c_{hr} \sum_{p=1}^{P} t_p \tag{7}$$

They are defined as the hourly rate of a skilled worker multiplied by the sum of all the planning scenarios conducted in the considered time period. However, the number of planning scenarios in itself has no bearing on labor costs, and the sum of time spent on planning can also be estimated in other ways (e. g. based on the number of employees and their job profiles).

If an APS is used, the manual effort and the number of hours spent on planning decreases for the same output, see equation (8).

$$c_{labour,automated} = (1 - d_{auto}) c_{labor,manual} \quad \text{with } (0 < d_{auto} < 1) \tag{8}$$

However, even with an automated planning system, the manual effort and the labor costs do not go to zero, and the degree of automation d_{auto} plays a central role in the profitability of an APS.

The first reason for this is that the APS requires input by a user, for example, to specify the process to be performed and the requirements of the planning case. Secondly, the quality of the planning results has to meet the same standards independent from the used planning method. Many times, the automatically generated drafts will still need manual fine-tuning. In fact, today's APSs are really planning support tools that make suggestions to the user who is ultimately in charge of the planning decisions.

The other ongoing costs again are only relevant if an APS is introduced. The maintenance costs $c_{maintenance}$ include all efforts related to maintaining the necessary infrastructure of the APS like databases and software installations. Lastly, software license costs $c_{subscription}$ can not only be part of the initial investment but also of the running costs if a subscription license model is employed.

3. Analysis of different scenarios

Based on the cost model developed in section 2, this section explores how changes in different factors influence the profitability of APSs and under which circumstances the deployment of such systems is a promising endeavor.

3.1. Study 1 – Labor costs

Labor costs are one of the main factors driving decisions for and against automation, not only in the planning domain but in manufacturing in general. Therefore, we looked at the impact different hourly rates have on the profitability of using an APS. Fig. 2 shows the NPC for manual planning and three scenarios for APSs with a different number of resources to be modeled in relation to the hourly rate. Table 1 gives the other assumed parameters for the scenarios. The total planning time t_p was estimated by assuming one person with a 40-hour workweek, working 47 weeks a year and spending 75% of their time planning.

The slope of the NPC for using an APS depends on the number of resources to be modeled and the associated labor costs. Under the assumed conditions, using an APS instead of manual planning would be profitable with 200 modeled resources for an hourly rate of 17€ or above, with 600 modeled resources for an hourly rate of 19€ or above, and with 1000 modeled resources of 21€ or above. For an hourly rate of 50€, which is realistic for a western European country like Germany, using an APS under the assumed conditions would provide a NPC advantage between 64 and 84 thousand euros, depending on the number of resources to be modeled.

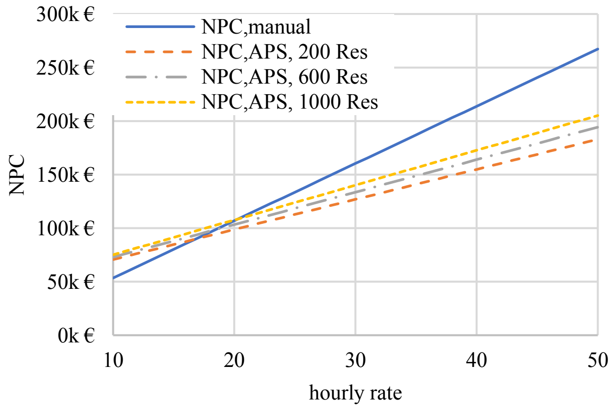

Fig. 2. NPC depending on the hourly rate for manual planning as well as planning with APS with different numbers of resources in the database.

Table 1. Parameters for study 1.

$t_p = 1410h$	$c_{sw} = 20\ 000€$	$t_{1,modelling} = 3h$	$d_{auto} = 50\%$
$r = 10\%$	$c_{hw} = 10\ 000€$	$t_{c,modelling} = 0.5h$	$c_{maintenance} = 2\ 000€$
$N = 5$ years	$c_{orga} = 5000€$	$b_{res} = 0.5$	$c_{subscription} = 0€$

3.2. Study 2 – Planning time

Besides labor costs, other important factors for the profitability of an APS are the amount of planning that takes place and the degree of automation that can be realized.

Fig. 3 shows the NPC for manual planning and three scenarios for APSs with different degrees of automation in relation to the yearly planning time t_p. Table 2 gives the other assumed parameters for the scenarios.

The slope of the NPC is highly influenced by the degree of automation reached with the APS. Therefore, for higher degrees of automation, fewer planning hours are needed to make the APS profitable. In our example, using an APS instead of manual planning would be advantageous for a planning volume of more than 1600 hours per year with a degree of automation of 20%, for a planning volume of more than 640 hours with a degree of automation of 50%, for a planning volume of more than 400 hours with a degree of automation of 80%. After the break-even point compared to manual planning is reached, the cost savings realized by using the APS also increase much faster with a high degree of automation.

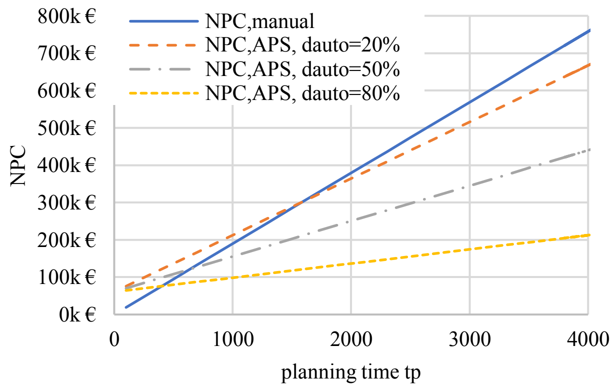

Fig. 3. NPC depending on the planning time per year for manual planning as well as planning with APS with different degrees of automation.

Table 2. Parameters for study 2.

$c_{hr} = 50€$	$c_{sw} = 20\ 000€$	$t_{1,modelling} = 3h$	600 resources
$r = 10\%$	$c_{hw} = 10\ 000€$	$t_{c,modelling} = 0.5h$	$c_{maintenance} = 2\ 000€$
$N = 5$ years	$c_{orga} = 5000€$	$b_{res} = 0.5$	$c_{subscription} = 0€$

4. Conclusion and outlook

In this paper, we gave an overview of the current state of the art in automated manufacturing systems design. We then presented a method to evaluate the economic efficiency of an APS, based on its NCP compared to the NPC of a manual planning process. The developed cost model considers a variety of cost factors. Besides typically considered costs like software licenses or hardware investments, it also includes the effort necessary to integrate expert knowledge (mainly in the form of resource models) into the APS. It is done by considering the time for modeling the resources in the cost model. The learning effect that takes place when a substantial number of resources are modeled is also considered. We then studied multiple deployment scenarios for an APS based on the established cost model and presented the results.

The presented methodology and cost model can be used to determine whether the implementation of an APS is advantageous in a given context. Moreover, the conducted analyses of exemplary scenarios provide the following conclusions:

- It could be demonstrated that the modeling of resources to deploy an APS requires significant effort and can hinder the implementation of APSs in an industrial context.
- In our fictitious scenarios, we illuminated the effect of the hourly rate for a skilled worker, the number of modeled resources, the degree of automation, and the planning time per year on the economic efficiency of an APS. It could be shown that even for moderate hourly rates around 20€, the usage of an APS can be advantageous. From the evaluation, it was also clear that the degree of automation substantially impacts profitability. Even though just a very conservative degree of automation (in our example, 20%) can be profitable, a higher degree of automation leads to significantly higher cost savings.

- We were also able to map out the limits of a profitable use of APSs. If only a low amount of planning hours occurs in a company in a year, using an APS might not be the best choice. The same is true for situations where the hourly rate of a skilled worker is very low.

Based on these conclusions, we see the need for further action and research in the following areas:

- The automatic generation of resource models for APSs is a promising endeavor for enabling the practical usage of APSs. Having methods and tools to automatically derive resource models for the database of an APS from existing data would significantly lower the initial effort necessary for implementing an APS.
- A higher degree of automation has an outsized effect on profitability. Therefore, improving the degree of automation and moving from a support tool to actual autonomous planning is a worthwhile endeavor.

Finally, the limits of our study have to be acknowledged: We focused purely on the economic effects of employing an APS. However, the usage of such a system also entails consequences that might not directly translate into euros. Reservations by planning engineers might decrease the effectiveness of an APS. Ensuring the acceptance of such systems by their users is, therefore, an important aspect as well.

Besides the monetary advantage of reducing labor costs, decreasing the need for skilled labor might also be beneficial if there is a shortage of skilled workers. Another positive effect is the uncoupling of the planning results' quality from the planning engineers' skill. Using an APS also might lead to an increase in the quality of the planned manufacturing systems because the system relies on objective criteria and not subjective assessment.

Acknowledgements

This research is developed with the support of the German-French Academy for the Industry of the Future of Institut Mines-Télécom (IMT) and Technical University of Munich (TUM), supported by the Federal Ministry of Education and Research (BMBF) and the Free State of Bavaria as well as the French alliance for the industry of the future.

References

[1] Abele, E., Reinhart, G., 2011. *Zukunft der Produktion: Herausforderungen, Forschungsfelder, Chancen*. Carl Hanser Verlag, München.
[2] Eversheim, W., 2002. *Organisation in der Produktionstechnik 3: Arbeitsvorbereitung,* 4th edn. Springer Berlin Heidelberg, Berlin, Heidelberg.
[3] Bullinger, H.-J., Ammer, D., Editors, 1986. *Systematische Montageplanung: Handbuch für die Praxis*. Hanser.
[4] Lotter, B., 1992. *Wirtschaftliche Montage: Ein Handbuch für Elektrogerätebau und Feinwerktechnik,* 2nd edn. VDI-Verl., Düsseldorf.
[5] Konold, P., Reger, H., 2003. *Praxis der Montagetechnik: Produktdesign, Planung, Systemgestaltung,* 2nd edn. Vieweg+Teubner Verlag, Wiesbaden.
[6] Michniewicz, J., Leiber, D., Riedl, F., Erdogan, H. *et al.*, 2017. Automatisierte digitale Anlagenplanung: Methode für die automatisierte Planung von Montageanlagen auf Basis digitaler Produktdaten *107*, p. 582.
[7] Keddis, N., Kainz, G., Zoitl, A., 2014. Capability-based planning and scheduling for adaptable manufacturing systems, in *19th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), 2014*, IEEE, p. 1.
[8] Feldmann, C., 1997. *Eine Methode für die integrierte rechnergestützte Montageplanung*. Springer Berlin Heidelberg, Berlin, Heidelberg.
[9] Leiber, D., Hammerstingl, V., Weiß, F., Reinhart, G., 2019. Automated design of multi-station assembly lines *79*, p. 137.
[10] Becker, C., Scholl, A., 2006. A survey on problems and methods in generalized assembly line balancing *168*, p. 694.
[11] Boysen, N., Fliedner, M., Scholl, A., 2007. A classification of assembly line balancing problems *183*, p. 674.
[12] Alakaş, H.M., Pınarbaşı, M., Yüzükırmızı, M., 2020. Constraint programming model for resource-constrained assembly line balancing problem *24*, p. 5367.
[13] Pereira, J., 2018. Modelling and solving a cost-oriented resource-constrained multi-model assembly line balancing problem *56*, p. 3994.
[14] Oesterle, J., Amodeo, L., Yalaoui, F., 2017. A comparative study of Multi-Objective Algorithms for the Assembly Line Balancing and Equipment Selection Problem under consideration of Product Design Alternatives *30*, 1021-1046.
[15] Leiber, D., Vuong, A.-T., Reinhart, G., 2021. Alternative Subgraphs Assembly Line Balancing Problem with Resource Selection and Parallel Stations.
[16] Papakostas, N., Pintzos, G., Matsas, M., Chryssolouris, G., 2014. Knowledge-enabled Design of Cooperating Robots Assembly Cells *23*, p. 165.
[17] Lim, Z.Y., Ponnambalam, S.G., Izui, K., 2016. Nature inspired algorithms to optimize robot workcell layouts *49*, p. 570.
[18] Pellegrinelli, S., Pedrocchi, N., Tosatti, L.M., Fischer, A. *et al.*, 2017. Multi-robot spot-welding cells for car-body assembly: Design and motion planning *44*, p. 97.
[19] Leiber, D., Reinhart, G., 2020. A bi-level optimisation approach for assembly line design using a nested genetic algorithm *57*, p. 1.
[20] Pfrommer, J., Schleipen, M., Beyerer, J., 2013. PPRS: Production skills and their relation to product, process, and resource, in *Proceedings of 2013 IEEE 18th International Conferenceon Emerging Technologies & Factory Automation*, IEEE, p. 1.
[21] Kathrein, L., Meixner, K., Winkler, D., Luder, A. *et al.*, 2019. Efficient Production System Resource Exploration Considering Product/ion Requirements, in *Proceedings, 2019 24th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, IEEE, p. 665.
[22] Järvenpää, E., 2012. *Capability-based Adaptation of Production Systems in a Changing Environment*, Tampere.
[23] DIN Deutsches Institut für Normung e. V. Datenaustauschformat für Planungsdaten industrieller Automatisierungssysteme - Automation markup language - Teil 1: Architektur und allgemeine Festlegungen (IEC 62714-1:2018); Deutsche Fassung EN IEC 62714-1:2018, Berlin. Beuth Verlag GmbH, 2019(62714-1).
[24] DIN Deutsches Institut für Normung e. V. Darstellung von Aufgaben der Prozessleittechnik - Fließbilder und Datenaustausch zwischen EDV-Werkzeugen zur Fließbilderstellung und CAE-Systemen (IEC 62424:2016); Deutsche Fassung EN 62424:2016, Berlin. Beuth Verlag GmbH, 2017(62424).
[25] Weidemann, D., Drath, R., 2010. Einleitung, in *Datenaustausch in der Anlagenplanung mit AutomationML: Integration von CAEX, PLCopen XML und COLLADA*, Springer-Verlag Berlin Heidelberg, Berlin, Heidelberg, p. 1.
[26] Berk, J.B., DeMarzo, P.M., 2020. *Corporate finance*. Pearson; ProQuest EbookCentral, Harlow England, London, Ann Arbor.
[27] Wright, T.P., 1936. Factors Affecting the Cost of Airplanes *3*, p. 122.
[28] Anzanello, M.J., Fogliatto, F.S., 2011. Learning curve models and applications: Literature review and research directions *41*, p. 573.
[29] Saraswat, S.P., Gorgone, J.T., 1990. Organizational learning curve in software installation: An empirical investigation *19*, p. 53.
[30] Robey, D., Boudreau, M.-C., Rose, G.M., 2000. Information technology and organizational learning: a review and assessment of research *10*, p. 125.
[31] Hamade, R.F., 2011. Learning Curves for CAD Competence Building of Novice Trainees, in *Learning curves: Theory, models, and applications*, CRC Press, Boca Raton, FL.