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Procedure for the configuration of learning factories: Application in industry and comparison

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Abstract

During the design of learning factories, the configuration of the technical system plays an important role. The selection of factory elements for learning factories usually takes place based on intuition. Intuitive selection has the disadvantage that the best possible selection is only achieved by chance. In this paper, a method is presented that is based on solving an optimisation problem, which ensures the best possible selection of factory elements considering a target function with restrictions like the budget or the usable area. For this purpose, four steps are distinguished: First, requirements for the technical configuration are derived from the primary goals of the learning factory (step I). Then, factory areas and configuration alternatives containing a combination of factory elements are derived from the products and processes (step II). The utility values of the potential configuration alternatives are determined based on an evaluation method (step III). Subsequently, the best possible combination of configuration alternatives is determined algorithmically by solving an optimisation problem (step IV). This procedure extends the design approach of Abele et al. (2019). It is applied to a learning factory for a company in the mobility industry to evaluate its superiority to an intuitive approach.

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Keywords: learning factory design, design approach, optimisation, decision making

1. Introduction

Learning factories are characterised by the versatile opportunities for competence development in realistic and safe learning environments as well as for applied research in production [1]. To design learning factories, additional aspects are necessary compared to conventional factory planning [2], which are addressed in various design approaches [3]. One of necessary aspects is the selection of the best possible combination of factory elements. Existing design procedures do not describe a systematic and objective selection of factory elements, which are selected intuitively [3]. Furthermore, there is no evaluation of the added value for the use of systematic methods.

This publication proposes and evaluates an optimisation model for the configuration of learning factories, which is derived in Chapter 2. To solve the optimisation problem, a procedure is necessary, that is presented in Chapter 3. This procedure is applied to configure a learning factory for an industrial company. The use case is described in Chapter 4 and different options for analysing possible configurations based on the presented procedure are shown. Chapter 5 provides a comparison of the intuitive approach with the new procedure presented in this publication. Conclusions are summarised in Chapter 6.

2. Optimisation model for the configuration of learning factories

The goal in configuring learning factories is to select the best possible factory elements, e. g. machines or assembly stations with the highest utility in relation to defined targets and requirements. At the same time resources

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are usually limited, e. g. the factory area or the budget [4]. Here, an optimisation problem is underlying, which can be modelled as follows: The learning factory is divided into *i* factory areas. Each factory area *i* contains a certain number of factory elements, which are grouped into configuration alternatives *j*, see Fig. 1. The configuration of learning factories requires a decision regarding each factory area *i*. For example, for a sawing factory area, there could be a total of three configuration alternatives containing one or many sawing machines to choose from. To model this, the configuration alternatives within a factory area should be mutually exclusive. Each configuration alternative has a certain utility u_{ij}, which can be determined, for example, based on specified criteria by the simple additive weightage method, that is used for the evaluation of factory elements for learning factories [5]. In most cases, the configuration alternatives with the highest utility u_{ij} cannot be selected for each factory area, because the area of the learning factory C_{Area} or the available budget C_{Budget} (or other ressources C_k) are limited. The best possible combination of factory elements therefore consists of the configuration alternatives that, on the one hand, meet all resource constraints (such as area or budget) and, on the other hand, generate the highest utility.

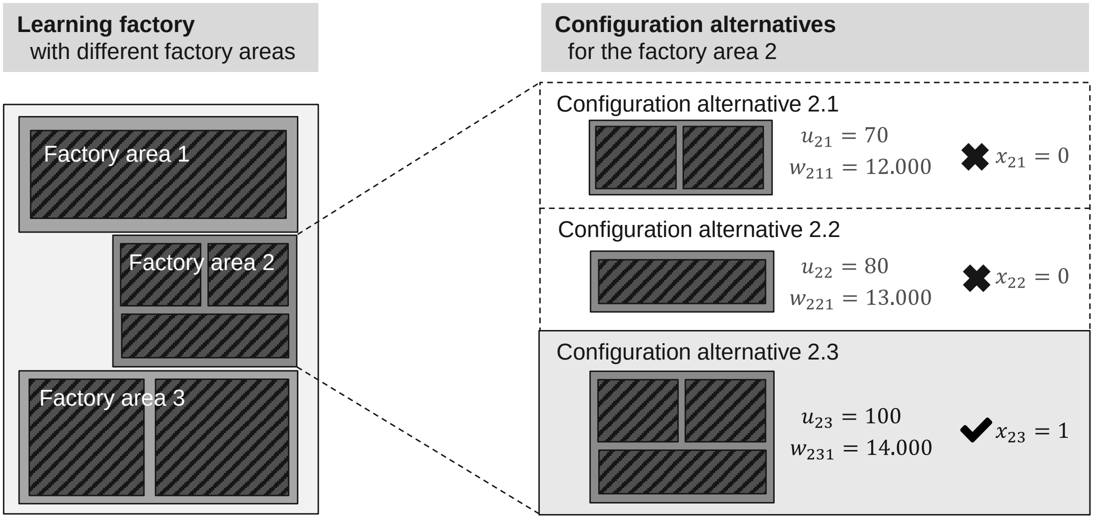

Fig. 1. Configuration alternatives for factory areas in learning factories.

To model optimisation problems, decision variables, a target function, and constraints must be specified. The decision variables describe which configuration alternative is selected. Binary variables for each configuration alternative x_{ij} are used for the given optimisation model. Here, x_{ij}=1 if in the factory area *i* the configuration alternative j is selected; otherwise x_{ij}=0. The target function *U* is composed of the sum of all utility values u_{ij} over all selected configuration alternatives in each factory area. Since only one configuration alternative is to be selected per factory area, the sum of all decision variables x_{ij} must be 1 in each factory area. The constrained resources can be modelled in such a way that the sum of all resource consumptions w_{ijk} by the configuration alternatives must not exceed a certain capacity C_k for the resource *k* (e. g. the budget). Furthermore, the actual measurements are relevant for the factory layout – not only the factory area as a number. Therefore, additional constraints must be considered, that include the length and width of each factory element [6].

$$U = \sum_{j=1}^{J} \sum_{i=1}^{I} u_{ij} x_{ij} \rightarrow max$$

$$\sum_{j=1}^{J} \sum_{i=1}^{I} w_{ijk} x_{ij} \leq C_k$$

$$\sum_{j=1}^{J} x_{ij} = 1$$

$$x_{ij} \in \{0; 1\}$$

When looking at the formulated optimisation model, it is noticeable that it is a multidimensional multiple-choice knapsack problem (MMKP) [7], to which further constraints of the two-dimensional packing problem are added. The configurations with the highest utility that meet all restrictions are optimal.

3. Procedure to configure learning factories

To use the deducted optimisation model for the configuration of learning factories, a systematic procedure is required. This procedure is based on the design approach of [1,8] that is frequently applied [3]. The goal of the procedure is to find the optimal configuration based on the described optimisation model. The developed procedure is divided into four steps, see Fig. 2.

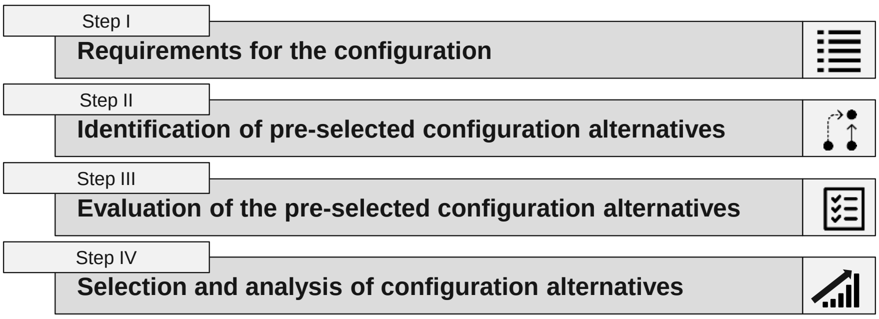

Fig. 2. Procedure for the configuration of learning factories.

In **step I**, requirements for the configuration of the learning factory are identified. In the case of learning factories with the primary purpose of training, the requirements originate from the intended competencies (learning targets) as well as the organisational framework conditions. Here, the morphology of learning factories can be used [9, 10]. Furthermore, a certain budget (or a budget range) for the configuration and the dimensions of an existing or planned factory should be defined. For the next steps, these requirements must also be structured into the areas of product, configuration alternative, factory area or the entire learning factory. For each requirement, it must be determined whether it is a mandatory or optional. Mandatory requirements are used for the pre-selection of products, factory areas and configuration alternatives in step II, while the optional requirements determine the utility value of each configuration alternative in step III.

In **step II**, as a prerequisite the manufactured product or the provided service to be provided by the learning factory must be clarified [11]. Necessary process steps can then be derived from the product or service. Direct production processes and indirect support processes are assigned to the possible areas of the learning factory. Subsequently possible factory elements must be researched that meet all associated mandatory requirements. The collected factory elements for each factory area are grouped into configuration alternatives with different resource consumptions.

In **step III**, the pre-selected configuration alternatives are evaluated. For this purpose, evaluation criteria are derived from the optional requirements of step I. These must be operationalised with measurable variables in such a way that an objective evaluation is possible. Exemplary evaluation criteria and further details on the evaluation procedure can be found in Kreß & Metternich (2021) [5]: e. g. for the primary purpose of training, the interaction capability of the factory elements should be considered in relation to the intended competencies. Afterwards, the evaluation criteria must be weighted (e. g. with a pairwise comparison of all evaluation criteria) and all configuration alternatives are to be evaluated based on the operationalised evaluation criteria.

In **step IV**, the learning factory is configured, so that one configuration alternative is selected per factory area. For this purpose, the developed algorithms for the optimisation model are applied, e. g. with the USBB algorithm of Kreß & Metternich (2021) to solve the MMKP exactly [12]. In addition, different configuration scenarios (with variations regarding the budget or the final dimensions of the learning factory) can be analysed. To cope with uncertainties of the evaluation criteria, the weights can be systematically varied. With the help of the developed configuration system, the learning factory planner always obtains the best possible solution with the highest overall utility value U [13]. In this step, a prototypic factory layout is also designed. This can be determined, using the next-fit or best-fit method. The next-fit method generates layouts that represent simple material flows in the value stream. For this purpose, the factory elements are sorted according to their material flow and placed in the learning factory. [14]. In the best-fit method, the factory elements are sorted in descending order of size and placed in the learning factory [15]. Layouts of the best-fit method show a better use of the area without taking the material flow relationship into account. Furthermore, layouts can be generated algorithm-based on an additional optimisation problem with the objective of improving the material flow between the factory areas, see Kreß et al. (2021) [16].

4. Application and analysis

The presented procedure based on the optimisation model for the learning factory configuration was developed and applied in a project with a German railroad infrastructure company. First, a mobile learning system was developed to introduce competency-based learning [17]. In a next step, the learning factory was developed and the steps I to IV were carried out.

Step I: The objective of the planned learning factory is to enable blue collar workers (as the target group) to perform their processes with confidence and to strengthen interdisciplinary processes and exchanges between different departments. Therefore, the primary goal is training. This resulted in 55 different intended competencies for the future learning factory based on the competency transformation [18]. For each competence, the requirements for the configuration were derived and systematised in factory levels as described in Chapter 3.

Step II: The primary focus of the learning factory is not a physical product, but a service: the maintenance and inspection of the rail system. Therefore, it is considered a leaning factory in the broader sense. To illustrate this service, 13 factory areas are needed, such as factory areas for the switch, the overhead line, and an adjacent track. In addition, various configuration alternatives were derived for each factory area, from simulated, technically simplified to very realistic variants resulting in 40 different configuration alternatives. The total number of possible configurations results from the sum product of the number of configuration alternatives per factory area. In total, 995,328 ($=4^6 \cdot 3^4 \cdot 2^1$) combinations are possible for the configuration.

Step III: Each configuration alternative was evaluated using the operationalized evaluation criteria from Kreß & Metternich (2021) [5]. In this case, the most important evaluation criteria are the interaction capability (variable: number of interactions), actuality (variable: year of market launch) and the integration of errors and waste (variable: number of errors and waste).

Step IV: Furthermore, possible configurations were calculated based on the optimisation model. Three measurement scenarios and three budget variants were used for this purpose, see Fig. 3 (left); this results in nine different configuration scenarios. The utility values are given relatively in relation to the overall best solution and cost data is scaled linearly for confidentiality reasons. Fig. 3 (left) shows that the highest possible utility values of the medium measurements and medium budget variants differ by only 0.6% compared to the high measurement and budget variants. The restrictions (budget C_{Budget} and measurements C_{Area}) that limit the configuration are marked in yellow. To analyse this aspect deeper, the budget constraint C_{Budget} is varied, and utility-cost curves are generated for the three measurement variants of the learning factory (depicted in different colours), see Fig. 3 (right). Each point on the utility-cost-curve displays one configuration. The curves show that the large measurement (in blue) variant has a slightly higher utility compared to the medium measurement variant (in red) – but only if the budget is very high, otherwise they share the same configurations. In the further course of the project, the medium measurement and medium budget scenario is preferred (marked with a red rectangle) because a high overall utility value can be achieved with far less resource investment. In case of planning changes, new optimal configurations can be determined in the shortest possible time by using the configuration system – in this use case only a few seconds or minutes.

Budget C_{Budget} [monetary units]		Measurements of the learning factory C_{Area} [m²]: *High* 50 m x 30 m		*Moderate* 42 m x 25 m		*Low* 30 m x 20 m	
High 1,000,000		U	**100.00 %**	U	**99.61 %**	U	**89.52 %**
		Σw_{Costs}	887,608.35	Σw_{Costs}	885,583.35	Σw_{Costs}	664,520.85
		$\frac{\Sigma w_{Area}}{C_{Area}}$	0.451	$\frac{\Sigma w_{Area}}{C_{Area}}$	0.586	$\frac{\Sigma w_{Area}}{C_{Area}}$	0.682
Moderate 300,000		U	**99.44 %**	U	**99.44 %**	U	**89.37 %**
		Σw_{Costs}	288,358.35	Σw_{Costs}	288,358.35	Σw_{Costs}	67,295.85
		$\frac{\Sigma w_{Area}}{C_{Area}}$	0.390	$\frac{\Sigma w_{Area}}{C_{Area}}$	0.274	$\frac{\Sigma w_{Area}}{C_{Area}}$	0.631
Low 75,000		U	**89.66%**	U	**89.66 %**	U	**89.63 %**
		Σw_{Costs}	67,108.35	Σw_{Costs}	67,108.35	Σw_{Costs}	67,295.85
		$\frac{\Sigma w_{Area}}{C_{Area}}$	0.326	$\frac{\Sigma w_{Area}}{C_{Area}}$	0.466	$\frac{\Sigma w_{Area}}{C_{Area}}$	0.631

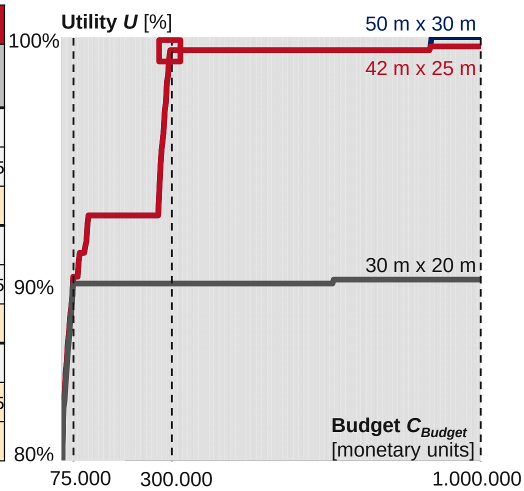

Fig. 3. Analysis of different configuration scenarios.

5. Comparison with the intuitive approach

The procedure for configuring learning factories presented here was compared with the intuitive approach for selecting factory elements. The four project members of the learning factory project described in Section 4 had the task of intuitively selecting configuration alternatives for a total of nine different scenarios (see Fig. 3) considering their learning factory. This results in n=36 configurations with the intuitive approach. The optimal solutions in each configuration scenario were not yet known to the project members at this point. It should also be mentioned that the project members evaluated the configuration alternatives before and thus knew the advantages and disadvantages of each configuration alternative. For the comparison of the two approaches, it is important that only feasible configurations (formulas in Section 2) are considered. This is because infeasible configurations may have higher overall utilities U than the optimum, for example, because they use more area or budget than available. If infeasible configurations were selected, there was a corresponding note in the survey tool and the project members had to readjust their selection.

The respective normalised utility values $u_{normalised}$ are calculated to evaluate the result with a range between 0 and 1. For this purpose, the achieved overall utilities of the intuitive selection $U_{intuitive}$ (minus the minimum possible utility U_{min} of all possible configurations) are divided by the optimal utilities $U_{optimal}$ of the respective configuration scenario (also minus the minimum possible utility U_{min}):

$$u_{normalised} = \frac{U_{intuitiv} - U_{min}}{U_{optimal} - U_{min}}$$

The average of the normalised utility values $u_{normalised}$ for the nine different configuration scenarios are shown in Table 1 (left). On average, the intuitive configurations achieve 77.13% of the optimal solution (22.87 percentage points lower; standard deviation σ = 15.12 percentage points). With a smaller budget, the deviation from the optimal result becomes larger. For very restrictive capacities, the intuitive approach achieves less than 62% of the optimal solution (more than 38 percentage points lower). In addition, a one-sample t-test [19] was performed to test the null hypothesis of whether the normalised utility values $u_{normalised}$ of the intuitive approach are higher than the optimal utility values. With a t-statistic of 9.21, the p-value is $1 \cdot 10^{-10}$. The null hypothesis can therefore be rejected: The normalised utility values $u_{normalised}$ of the intuitive approach are thus statistically smaller than the optimal utility values with a high level of significance. For comparison, the procedure based on the optimisation model reaches 100% in every case, because the optimal solution is found each time.

Intuitively, other configuration alternatives are selected than the optimum. This can be quantified by the relative number of decisions that deviate from the optimal solution for each factory area. It can also be shown that, the average number of deviating decisions is 40.83% (standard deviation σ = 19.18%), see Table 1 (right). This increases up to 67,50% with smaller capacity limits C_k. Again, a one-sample t-test was performed to show that the relative number of deviating decisions is significantly greater than zero ($t=12.77$; $p=1 \cdot 10^{-15}$). To measure objectivity, the interrater reliability is used that is measured by the correlation coefficient of the project members [20]. For this purpose, the decision variables x_{ij} of the intuitive approach were used and the correlation between two project members was determined in each case. Its average is at 41.90% and can thus be assumed to be moderate to low [20].

Normalized utility values

		Measurements C_{Area}			
		High	Moderate	Low	
Budget C_{Budget}	High	83.50%	85.20%	92.05%	86.91%
	Moderate	71.22%	69.52%	88.67%	76.47%
	Low	70.04%	72.47%	61.48%	68.00%
		74.92%	75.73%	80.73%	**77.13%**

Deviating decisions for each factory area

		Measurements C_{Area}			
		High	Moderate	Low	
Budget C_{Budget}	High	15.00%	22.50%	37.50%	25.00%
	Moderate	25.00%	47.50%	45.00%	39.17%
	Low	52.50%	55.00%	67.50%	58.33%
		30.83%	41.67%	50.00%	**40.83%**

Table 1. Normalised utility values of the intuitive approach (left) and deviating decisions for each factory area (right).

In the intuitive approach, different project members choose different configurations. This indicates that the intuitive approach is highly subjective while the optimal procedure is independent of personal decisions. In addition, it has been shown that with the procedure based on the optimisation model, multiple options for analysing the configuration exist, which facilitates decision-making (e. g. with the utility-cost curve).

To check the robustness of the optimisation model for configuration, a sensitivity analysis [21] was conducted on the weightings of the 13 evaluation criteria. The weighting of an evaluation criterion was varied (positively and negatively) until the configuration of the learning factory changed for the first time. On average, the weighting must be reduced by 79.24 % - or - increased by 525.55 % until the configuration changes for the first time. Especially when the individual weighting values are increased, the value range, which is normalised to 1 to 10, is exceeded. Therefore, the optimisation model is very robust in the case of individual errors in the weighting.

6. Conclusion

In this publication, a procedure based on an optimisation model for configuring learning factories is introduced and evaluated. The configuration of a learning factory is determined by the selected and evaluated configuration alternatives in each factory area. The sum of all utility values is taken into account, considering restrictions such as budget or floor space. Based on the optimisation model, a procedure is derived that is divided into four steps: requirements for the configuration, the identification of pre-selected configuration alternatives, the evaluation of the pre-selected configuration alternatives, and the selection and analysis of the configuration alternatives. Compared to the intuitive approach, significantly higher utility values could be achieved with simultaneously higher objectivity, which was measured by the interrater reliability.

The results illustrate that the configuration of learning factories is a complex task for humans. The probability of determining the best possible configuration is highly improbable without the application of an optimisation model, since there are too many possible combinations for the configuration. The importance is also evident given the high cost of the technical infrastructure, especially since the configuration determines the capabilities of the learning factory in long term. Thus, the results of this publication suggest for the development of future learning factories not to rely on intuition, but to make sound decisions based on the presented procedure.

In addition, the presented method could be used to determine the best possible combination of factory elements in conventional factories. Up to now, only evaluation methods, such as utility analysis, have been used for factory planning [2, 22]. However, the considered restrictions, such as the budget or the factory dimensions, are also present in conventional factories. The method presented in this publication can therefore be adapted for conventional factories to achieve better factory configurations.

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