INTERNATIONAL DESIGN CONFERENCE – DESIGN 2022
https://doi.org/10.1017/pds.2022.27

Framework for FAMD-Based Identification of RCPSP-Constraints for Improved Project Scheduling

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Abstract

Product development in today’s manufacturing companies is characterized by multiple development projects under intense time constraints. This means that the success of projects impacts the company's success significantly. However, industrial practices show that many projects fail to meet their time targets. This paper presents a methodology to systematically improve project schedule adherence of development projects by combining exploratory data analysis of historic project data with project scheduling optimizations to enhance the project schedules and enable more successful projects.

Keywords: project management, big data analysis, product development, performance indicators

1. Introduction

Today's manufacturing companies are confronted with a VUCA (volatility, uncertainty, complexity and ambiguity) environment with frequently changing conditions, high innovation speed and global competitive pressure (Schuh *et al.*, 2021). Even established companies are often unable to respond adequately to these challenges. As an example for consequences, between 2000 and 2015 52% of Fortune 500 companies have dropped out of the index, a cross-industry list of US-companies with the highest revenue (Kroker, 2016). Companies are under high pressure to ensure their continued existence in a changing environment. As a result, the pressure to innovate under intense time constraints increases. These factors have a particular impact on product development, where adherence to project plans is a key determinant of meeting strategic milestones in front of competitors. In addition, approximately 70% of a product's costs over the course of its lifecycle are defined during product development (Feldhusen and Grote, 2013). In this context, product development is characterized by project work, the share of which exceeds 50% in many companies (DIN:69909-1:2013-03). A Hays® study shows that the share of project work in the 225 companies from the manufacturing, development, finance and IT sector has increased by about 60% in recent years (Müncheberg, 2015). The success of projects has a significant impact on the success of the company. However, a Project Management Institute study looking into industrial practices shows that about 12% of investments in projects are wasted due to poor project performance. In addition, many projects miss their time (45%) and budget targets (38%) (Project Management Institute, 2021). Against the background of these challenges, the objective must be to ensure the best possible use of the invested resources and to minimize waste due to poor project performance. To ensure that projects can be carried out successfully, project scheduling must be enabled to consider data based insights of previous projects regarding major impact factors on schedule adherence. This poses challenges to project managers, since there are numerous impact factors on the project performance that need to be assessed both on their own and in combination. As the PwC's Global Data and Analytics survey from 2016 covering multiple industries shows, even well trained people with a lot of experience are not able

to consider more than a few impact factors at the same time when making decision (PwC, 2016). Therefore, data analysis can successfully support many project activities currently based on experiences in order to become less dependent on intuition and to identify patterns yet more precisely. Therefore, the framework presented in this paper combines project scheduling through RCPSP with exploratory data analysis (EDA) to propose a methodology that allows companies to systematically learn from their own past projects in order to improve project scheduling. It examines which combinations of factors led to success for different types of projects in order to transfer them to similar new projects and generate successful project schedules.
The remainder of the paper is structured as follows. After the introduction, section 2 continues with a description of the relevant terminology. Section 3 analyses related research and derives the research deficit that will be addressed by the proposed methodology. Section 4 presents the methodology of this paper, starting with a short overview, followed by a detailed description of the four steps of the methodology. The last section gives a critical reflection and draws a conclusion

2. Theoretical background

2.1. Project Management

Project management, as described by Phillips (2003), generally concerns itself with controlling resources available to a project in order to achieve all project goals under given constraints. Project scheduling more specifically targets the issue of scheduling the different resources needed and available for the project. This step is crucial, as it allows for companies to plan ahead and allocate all available resources as effective as possible (Pawiński and Sapiecha, 2012).
The ability to quantify project resources, as well as project performance, is typically introduced via pre-defined factors, which can be used both to describe and to evaluate the project (Mainul Islam and Faniran, 2005; Denton, 1997; Pinto and Prescott, 1990).
Factors that are used to quantify project resources and project performance, as categorised by Chan *et al.* (2004) can be subdivided into external factors and internal factors. As the external factors cannot be influenced by definition, the focus of this paper lies on the internal factors.

2.2. Project scheduling

In practice, projects can hardly be planned independently. The broader context of parallel processes which are also dependent on the available resources has to be considered (Demeulemeester and Herroelen, 2002). As stated by Demeulemeester and Herroelen, this leads to another management challenge, namely deciding the resource allocation from one resource pool across different parallel projects. This area of resource management is referred to as project scheduling and a variety of project scheduling problems are subject to past and current research (Neumann, 2003; Haroune *et al.*, 2021)
The project scheduling problem most relevant to the approach presented in this paper is called "Resource Constraint Project Scheduling Problem" (RCPSP). It describes the problem of having limited resources for multiple projects while each projects duration is subject to minimization (Cavalcante *et al.*, 2013; Artigues, 2010). Additionally, the notion of utilizing multi skill resources in order to resolve project scheduling problems more efficiently has been discussed in (Snauwaert and Vanhoucke, 2021).

2.3. Exploratory data analysis

The rise of the amount of data is ubiquitous and data on potential project impact factors are no exception (Reinsel et al., 2018). As a result, the assessment whether a given impact factor is relevant has become an increasingly data-centric challenge. The framework presented in this paper uses EDA in the form of factor identification to identify relevant impact factors and impact factor combinations. An approach to achieve this objective and which is able to handle mixed data of the type which are encountered in project metadata is factor analysis of mixed data (FAMD) (Escofier, 1979; Saporta, 1990; Pagès, 2004). FAMD, as implemented by (Khan et al., 2010), is a combination of principle component analysis (PCA) and multiple correspondence analysis (MCA). Both PCA and MCA are correlation-driven methods to identify most relevant subspaces in datasets. The difference between the two is the accepted type of data: While PCA

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handles continuous data, MCA does an equivalent analysis on categorical data (Greenacre, 1991). As the analysis in this paper is concerned with mixed data, meaning both continuous and categorical, neither of the two approaches suffices on its own. FAMD is a numeric optimization approach to combine both PCA and MCA in order to allow the analysis of such mixed data.

3. Related Research

The framework presented in this paper aims to combine the EDA, identifying relevant impact factors, with project scheduling to improve resource management based on the insights from the EDA step. In the following, current approaches in these fields are presented and the research deficit explained in order to derive the need for further research.

3.1. Current research in project scheduling

It has become more and more challenging to manage projects in the above-mentioned VUCA-environment, whereby project objectives or project constraints may change dynamically during the life of a project. Human resources are identified to be the most challenging resources in terms of predictability (Wysocki, 2014). Therefore, the focus in this paper is the resource management and the improvement of scheduling projects with resource constraints. In scientific literature, numerous studies exist that deal with the improvement of resource planning by mathematical optimization problems in order to reduce manual effort and to be able to cope with increasingly complex multi-project environments (Habibi *et al.*, 2018). The challenges of resolving these optimizations have been addressed in the context of RCPSP. In the RCPSP, a number of projects i with j activities having duration d_{ij} is considered. There are precedence relationships between activities so that the completion of an activity requires the completion of a group of defined activities P_{ij}. Resources are renewable and are available at full capacity in each period. In total, there are k types of renewable resources, of which a constant quantity R_k exists at the beginning of each period. To perform an activity, r_{ijk} units of resource k must be provided. The RCPSP aims for the minimization of the project duration by changing the allocation of resources to the project activities. The overall problem is highly variable in its possible characteristics of constraints (Habibi *et al.*, 2018; Riesener *et al.*, 2021). One approach presented by Hosseinian et al. (2019) introduces the idea of multi-skills. The authors associate the human resource with different competencies and also incorporate the idea of learning behaviour of the resources. The approach discussed by Haroune et al. (2021) presents a multi-project and multi-skill concept for resolving the RCPSP. The goal is to derive schedules for project managers in a setting of various projects per manager and a shared and limited resource pool of teams with limited capacities and various skills. The authors introduce activities within different tasks associated with different sets of skills and formulate the optimization problem of matching the needed skills of the activities with the skills of the different teams under consideration of limited capacity. As a target function, the overall effectiveness of the project portfolio is identified. This target function is maximized in solving the stated optimization problem. This multi-skill approach is extended through the work of Snauwaert and Vanhoucke (2021) by introducing multiple competencies of different levels for human resources. The authors identified a research deficit in additionally taking into account different levels of skill. The introduction of skill levels allows for a new and more detailed representation of the resource pool. This additional information is used to maximize efficiency levels within a given project. The impact of different multi-skilled resources is then analysed in computational experiments. The approaches presented represent a large number of scientific research on RCPSP. They were chosen because they show the trend to consider more constraints and characteristics of human resources. The trend towards more constraints, such as the skills of the resources, aims to improve the quality and accuracy of the project schedules. These models however, are often based on an excessive degree of abstraction of the real systems. As a result, the transfer of the theoretically ideal project schedule into practice cannot be done. By including more constraints and especially by building these constraints upon empirical observations from historical project data an improvement of applicability and precision is expected.

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3.2. Exploratory data analysis in project management

The framework presented by Solak *et al.* (2010) presents observations on impact factors and their influence on project success. The authors aim to optimize project portfolio management in the context of development projects by analysing the maximization problem of project return under uncertainties and resource limitations over the planning period. Furthermore, a decision process is provided as a guide for maximizing project success while allocating specifically development projects. Instead of focussing on EDA to discover relevant factors, Solak *et al.* first give an in depth description of the project portfolio optimization problem and then use this description to build a stochastic programming model to support the decision making process of allocating resources to the development projects within the portfolio.

An approach to identifying relevant factors by using EDA is presented by Yazici (2020). The author investigate the impact of corporate sustainability capability (CSC) and project management maturity based capability on project success. For this analysis, a set of questionnaires was filled out by various managers across the industry and then analysed using general linear models (GLMs) and analysis of variance (ANOVA) to discover causal relationships among the factors. As a result, the approach is presented as a framework for statistical testing of the relevance of indicators. Given that this approach exclusively focusses on the discovery of new relationships, a development environment for using the discovered information to increase project success is not presented.

Tönnes (2021) presents a similar approach to the one presented in this paper, applying it to the optimization of machinery and plant engineering. The author presents a strategy of building a multidimensional information model of products in machinery and plant engineering in order to identify company needs. A variety of EDA models are then used to determine the relevance of a set of indicators and to optimize the configuration of industrial plants based on the information model.

It can be summarized that EDA is increasingly used in the context of project management in engineering, yet the transfer of identified factors to project scheduling is so far not methodically supported.

The different approaches in section 3.1 share the fact, that the constraints for the project scheduling are defined in advance, rather than being determined from previous projects. Accordingly, the identified research deficit is that no approach exists that uses historic project data to improve the project scheduling by identifying impact factors that have great influence on the project schedule adherence. The approach presented in this paper combines the potentials from EDA to identify relevant impact factors on project schedule adherence and the potentials from optimizations in project scheduling to create a feasible project schedule. Relevant impact factors are identified from historic project data in the EDA step. These insights can then be applied to the project scheduling step to generate successful project schedules. Together, these insights are combined into a project scheduling framework allowing companies to learn from previous projects and improve the quality of project scheduling.

4. Proposed Framework

4.1. Framework overview

Considering the state of research and industry challenges, a need for a systematic way to improve project scheduling and schedule adherence in more and more complex multi-project environments becomes apparent. To address this need, a new framework is proposed and visualized in figure 1. It supports project managers and project management offices to improve project schedules by learning form historic project data. By following the conclusions from section 3.1, this paper will add further constraints to the widely used RCPSP in order to improve the quality of project schedules. The added constraints are determined by analysing historic project data and identifying relevant impact factors for schedule adherence. These impact factors are then implemented as flexible constraints. Flexible constraints are "constraint in which satisfaction is a matter of degree and can be partially relaxed if necessary so as to ensure the feasibility of a problem" (Dubois and Prade, 2008). In the context of this paper, the relaxation of these constraints comes at a price: if a flexible constraint target value cannot be achieved the project performance is influenced negatively. The extent of this penalty factor is quantified by aid of FAMD analysis in historic project data. The optimization algorithm has the task to make the trade-off decision between a higher efficiency within single projects by meeting the flexible constraints and an improved project schedule on multi-project level,

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where a deviation from the target value of a flexible constraint may lead to a significantly better project schedule in total. By following this new framework, a higher quality of project schedules can be provided and project schedules can be carried out more successfully. As each company's experiences and its background are different, company specific historic project data provides a way of taking into account the constraints specific to the applicant of the methodology.
The proposed framework consists of three steps, which are presented in the next section. In the first step, the search field of the data analysis in historical project data is narrowed down. The second step identifies within the search scope relevant impact factors on the project schedule adherence. These impact factors are then implemented into a RCPSP as flexible constraints in the third step.

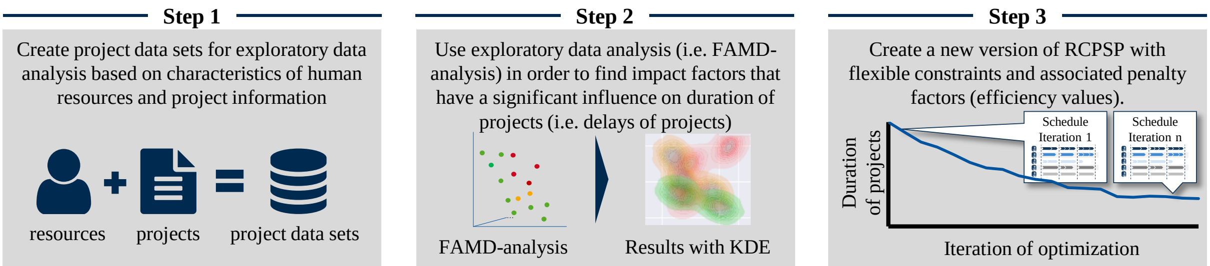

Figure 1. Overview of the methodology

4.2. Step 1 - Defining a project data set

Laying the base for the discoverable insights, the first step sets the scope of the analysis. The result of the step is the input database for the subsequent analysis. In principle, any factor such as project time, number of development sites or age span of team members, which could have a possible impact on a project's performance, can be part of the analysis. The goal of the first step of this framework is to narrow the search field for impact factors on project performance. As mentioned in the introduction in section 1, this paper focuses on projects in the context of product development. In product development, human resources are the most important resource. Thus, the framework focuses entirely on human resources. Accordingly, all impact factors that are to be determined by aid of data analysis are also related to this. The analysis is designed to then determine, what combinations of impact factors are present for historic projects that turned out to be successful. Furthermore, it only makes sense to examine impact factors that can be influenced by the allocation of resources. For example, the age difference within a project team can be actively influenced by a different team composition, which makes the factor age difference in the project team suitable for the analysis. A counterexample would be the core working hours, this factor is the same for all employees in product development and cannot be influenced by allocating a different resource to a project team. As this example shows, it is the characteristics of the human resources that are relevant for data analysis. Historic project data usually indicates which resource was involved in the projects, but the description of this resource by its characteristics is not included in the project datasets. Therefore, the next passage will briefly discuss how the relevant characteristics of human resources can be captured and how they can be used for data analysis.
While some characteristics are directly ascertainable, such as length of company affiliation, area of expertise, native language or age, another important characteristic are competencies, which are more difficult to consider. As pointed out in section 3.1 however, other researchers have stressed the skills of employees as a relevant constraint for deriving realistic project schedules as well. Therefore, this paper examines how employee skills can be defined in the context of the new flexible constraints for the RCPSP. In order to do so, first it is necessary to define the relevant competencies in the context of the company applying the methodology following Riesener *et al.* (2021). Then the relevant competencies are operationalized by assigning different proficiency levels to each competency. Each proficiency level contains respective knowledge elements and skills an employee must possess in order to possess this competency at the corresponding proficiency level. In this way, the competencies of human resources can be objectively assessed. By assigning a proficiency level of each relevant competency to each resource, the competencies of a resource can be considered as an additional characteristic of a human resource in the data analysis. The characteristics are used in the data analysis to evaluate projects by converting them into

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variables at project level. An example of this would be the average length of company affiliation of the members of the project team, the maximum level of proficiency that the project team has in a specific competency or the number of members on the project team who have a certain competency (proficiency level > 0). It is also crucial that all factors allow for a single value to be assigned to a given project. This means, that while the workforce in Full-Time-Equivalent (FTE), as a factor potentially changing during the project is unsuitable for the analysis, FTE_{start}, $FTE_{average\ over\ project\ runtime}$ and FTE_{max} are all suitable factors. The data in question can be collected within companies from an ever increasing variety of project management tools and enterprise resource planning tools. Following the outlined procedure leads to a potentially large number of prospective factors which may be considered in the data analysis. As Fayyad *et al.* (1996) point out, discovering knowledge in data necessarily requires the identification of plausible data set. The reason for this is the danger of random correlation between factors that have no real-world relationship. To address this, a plausibility check through a weighted sum model is employed. The criteria aim to check the plausibility of a given factor being relevant to the adherence of the project to the schedule. While further research may indicate a need for adjustment, we suggest the following criteria:

a) Direct Impact on project resources in terms of budget, equipment or know-how (e.g. budget cuts)
b) Direct social impact on project team (emotional impact) (e.g. pay increase or lockdown)
c) Direct impact on stakeholders (e.g. change of management level to report to)

After the set of impact factors is defined, the last input that has to be determined for each project is the measurement of how successful the historic project has been. For the purpose of this paper, the determination of how successful a development project was correlates with how well the planned project duration was met. This value is the time efficiency of the project:

$$\text{Time efficiency} = \frac{\text{duration}_{\text{planned}}}{\text{duration}_{\text{as-is}}}$$

Figure 2 provides an example for the aggregation of human resource characteristics into a project data set suitable for the analysis.

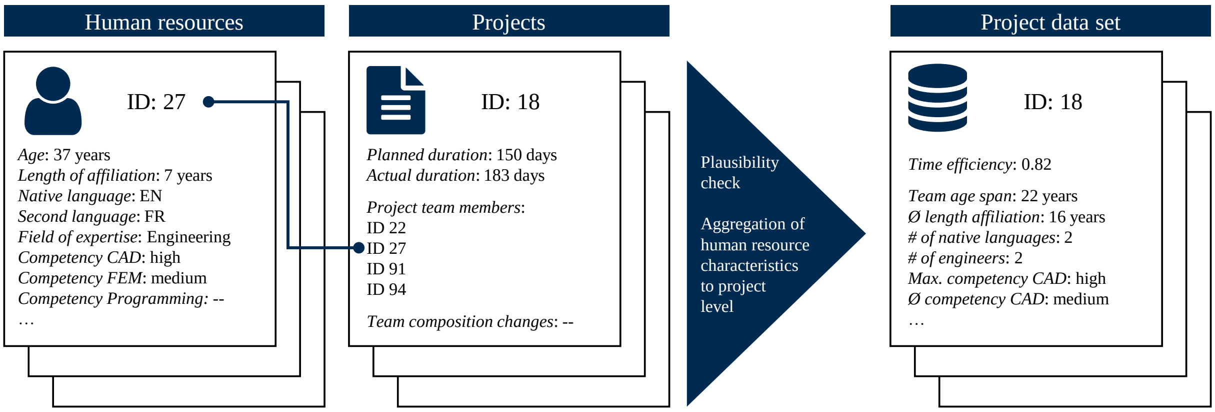

Figure 2. Aggregation of information about human resources and projects into project data set

The result of the first step is the input dataset used in the subsequent analysis. It contains a data set for each project consisting of the time efficiency value as well as various project impact factors. This data set is analysed in step 2 with FAMD.

4.3. Step 2 - Exploratory data analysis

EDA aims at gaining insights from data. This is crucial for the task at hand and the focus of step 2 of the proposed methodology. The objective is to gain a better understanding of what factor combinations impact time efficiency in projects. There are no prior hypotheses made regarding beneficial factors or combinations of factors, besides the plausibility verification in step 1 to prevent misleading statistical correlation. The result of step 2 are relevant impact factors and transparency regarding what combination of factors benefit or harm project schedule adherence.

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The data aggregated in step 1 is analysed using FAMD as presented by Pagès (2004) and implemented by Khan *et al.* (2010). FAMD has been chosen for this purpose, as it can handle both continuous and categorical data and thereby address the characteristics of datasets from historic projects. FAMD returns eigenvectors, each representing a combination of the variables of the dataset that can explain the variance of the dataset, and returns the eigenvectors' eigenvalues, indicating how relevant the eigenvector is overall for explaining the variance of the dataset. Within an eigenvector, the values indicate the relevance of each variable of the dataset to the eigenvector. By determining the elbow of the curve of sorted eigenvalues, relevant eigenvectors can be identified. By determining the elbow of the curve of sorted values within relevant eigenvectors, variables of low relevance can be omitted, which is how the dataset is narrowed down to the relevant factors. The combination of remaining relevant variables within the reduced relevant eigenvectors are used as flexible constraints. It is important to note that no new dimensions are calculated, as would usually happen with FAMD, PCA or MCA, as these new dimensions would carry tangible meaning in the real world. To identify flexible constraints, only the n-dimensional combinations of impact factors with a high relevance according to FAMD are considered going forward.
The translation of factor combinations to flexible constraints is carried out by placing historic projects in the subspace of relevant impact factors, plotting the degree to which the projects adhered to their respective schedules as defined in step 1. Using kernel density estimation (KDE), it is possible to then estimate time efficiency for a given combination of impact factor values, e.g. project core team size being 7 and the age span of team members being 16, as shown in figure 3.
It is to be noted that due to the conceptual stage of the framework, the examples are not industrial use-cases but rather artificial sample datasets for demonstration purposes.

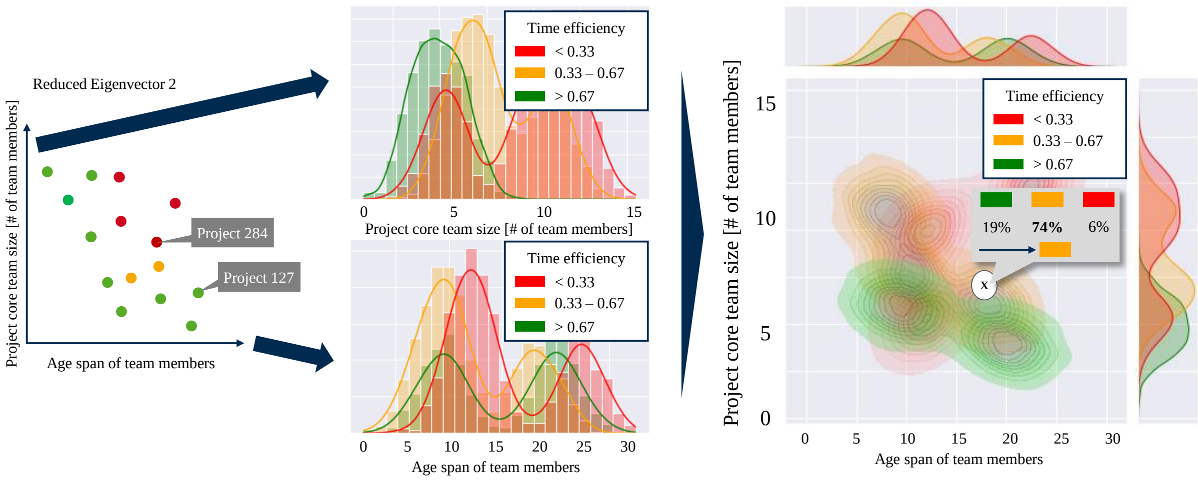

Figure 3. Interpretation of FAMD-analysis results with KDE

4.4. Step 3 - Definition of project design parameters

The third step is to transfer the results from the data analysis into flexible constraints for the RCPSP. The goal is to improve the planning quality of the project schedules. In the RCPSP, project schedules are optimized by changing resource allocations until project completion of all projects is as fast as possible. By introducing more constraints, the problem becomes more complex, but it also represents reality more accurately. Flexible constraints based on historic project data have the potential to improve project schedules and especially to create more realistic project schedules. In order to implement a flexible constraint based on the kernel density estimation from the previous step it is necessary to create a mathematical constraint, a matrix of penalty factors and to include the penalty factor in the project activity duration. The mathematical constraint serves to limit the spectrum in which the value of the respective impact factor lies within the range that can be covered by the analysis of historical project data. Since the impact factors cannot be considered separately from each other, but can only provide insightful findings in their combination (see section 4.3), the influence of

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these impact factors on project performance must also be mapped through the combination of factors. For this purpose, n-dimensional matrices are required, following the n-dimensional spaces of the FAMD analysis, which outputs n relevant impact factors that are in interrelation with each other (see section 4.3). In these matrices, a penalty factor in the form of a KDE-based efficiency value is assigned to each value combination of the impact factors involved (see figure 4). The penalty factors are then used to adjust the project activity durations accordingly. In every iteration of the optimization the following procedure takes place:

1. Define a resource allocation in order to allocate all project activities to suitable resources
2. Calculate values for the impact factors for every project (e.g. Δage_1 → the age span of team members allocated to activities from project *1*)
3. Look up penalty factors in penalty factors matrices
4. Calculate actual project activity duration with the following formula shown in figure 4
5. Schedules activities with adjusted durations for the earliest possible completion of all projects
6. Compare results of this iteration with previous iterations
7. Start again from 1.) with next iteration

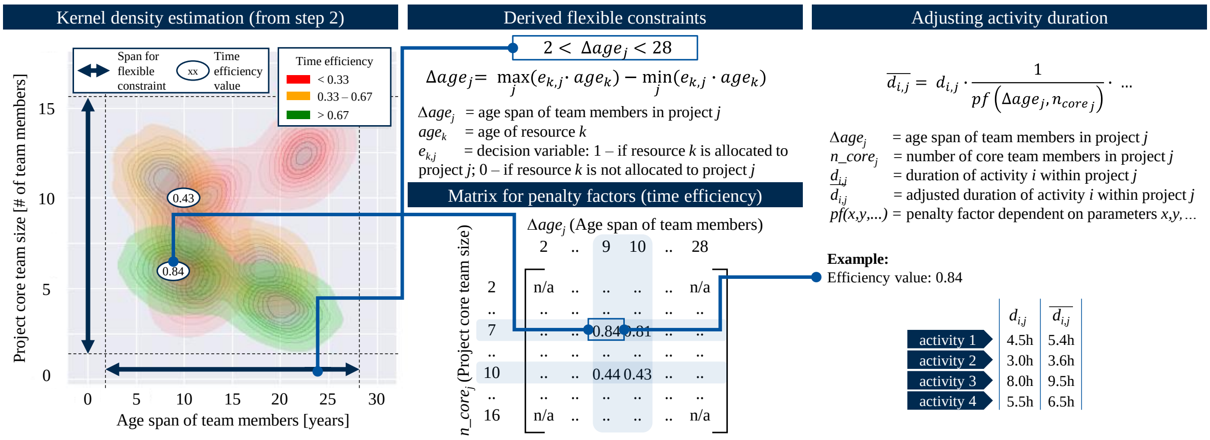

Figure 4. Derivation of flexible constraints and penalty factors (efficiency value)

Based on the described extension of the RCPSP, the optimization algorithm is then able to support the trade-off decision of choosing between a project team that fits the project well (= high efficiency value) but may have limitations on availability against a project team that may have a lower efficiency but better availability. Availability in this context describes how much of the workforce of a resource is still available and not utilized by other projects. An example for this trade-off decision is shown in figure 5.

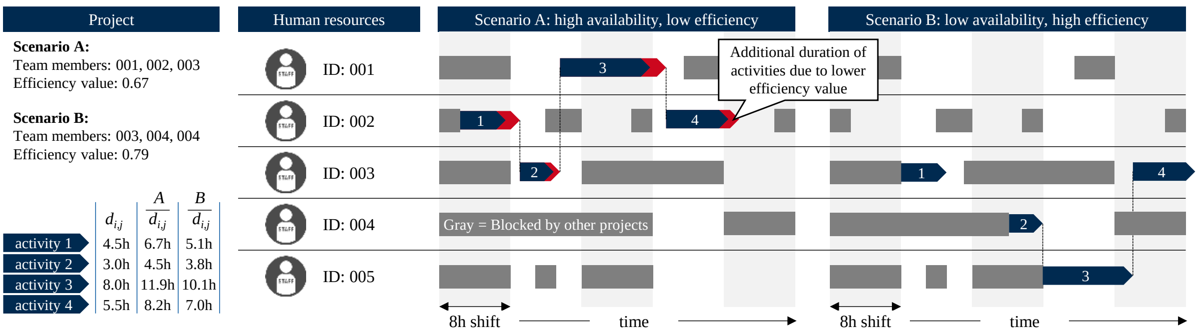

Figure 5. Example for a trade-off decision between availability and efficiency

The example shows a small project containing four activities and two scenarios for the resource allocation. These scenarios are iterations within the optimization and are just two exemplary scenarios out of many possible scenarios. In scenario A resources 001, 002 and 003 are assigned to the project. The resources characteristics lead to an efficiency value of 0.67, which is calculated, based on the

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analysis of historic project data (see section 4.3 and figure 4). In the shown example, it is better to use available resources instead of resources that lead to a higher efficiency value. This very simple example represents one out of many trade-off decisions the optimization algorithm has to make in a multi-project environment. By considering the efficiency value, which is derived from historic project data, the result of the project scheduling optimization is expected to deliver schedules that are less error-prone than project schedules from RCPSP already existing in literature.

5. Conclusion

The paper presents a framework combining FAMD and RCPSP to improve the quality of RCPSP results through the introduction of flexible constraints. Flexible constraints consider relevant factors of past projects through a penalty factor on the time efficiency. The objective is to lay the foundation for future research elaborating a user-friendly implementation to support project managers without having to engage in detail with EDA.

The framework consists of three steps. In step 1, the impact factors for different types of projects are described and a methodology to verify a plausible impact is presented. In step 2, FAMD is used to identify relevant impact factors. The relevant impact factors are translated to flexible constraints in step 3. By using KDE it is possible to derive matrices of penalty factors on time efficiency. These penalty factors are then used to adjust project performance according to the fit of the project team for the project.

The framework is at a conceptual stage. The data presented is sample data and industrial validation of the approach is pending. The applicability is subject to limitations regarding both data quality and data availability. No literature source has been identified specifying the required amount of data for FAMD, though sample implementations suggest a minimum of 10^2 projects with better results to be expected as the sample size increases. All results depend on accurate data for the target value, time efficiency, and the impact factors. The sensitivity towards low data quality is to be determined. Another aspect to be discussed is the focus on schedule adherence omitting potential cost ramifications. Future research is to be conducted regarding cost impacts of this approach.

Acknowledgement

The authors would like to thank the German Research Foundation DFG for the kind support within the Cluster of Excellence "Internet of Production" - Project-ID: 390621612.

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