An Integrated Framework for Dynamic Resource Allocation in Multi-project Environment

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Abstract

This paper proposes an integrated machine learning (ML) framework for dynamic resource allocation in a multi-project environment. The framework utilizes machine learning algorithms to predict future resource demands and identify potential resource shortages. The proposed framework considers various factors such as project priorities, resource availability, and project deadlines to optimize resource allocation decisions. The framework is designed to continuously learn from past resource allocation decisions and improve future resource allocation strategies. The effectiveness of the proposed framework is evaluated through a case study in a real-world multi-project environment. The results show that the framework can significantly improve resource utilization and project completion times while reducing resource waste and cost. Overall, the proposed framework provides a practical solution for dynamic resource allocation in complex multi-project environments.

Keywords: Machine Learning; Resource Allocation; Multi-project Environment; Deep Learning

1. Introduction

A multi-project environment refers to a scenario where an organization is simultaneously managing multiple projects. In such an environment, resources such as personnel, equipment, and funds need to be allocated efficiently across multiple projects to ensure timely completion and optimal resource utilization. Multi-project environments can pose several challenges, such as resource conflicts, competing project priorities, and uncertainty in project timelines and demands. Effective management of resources in such an environment requires a dynamic and flexible approach that can adapt to changing project requirements and priorities. Various approaches can be used to manage resources in a multi-project environment, including traditional project management techniques and advanced data-driven approaches such as machine learning. Effective resource management can lead to improved project outcomes, reduced project costs, and increased organizational efficiency.

Dynamic resource allocation in a multi-project environment refers to the process of allocating resources in real-time based on the current and anticipated resource needs of each project. It involves continually monitoring resource utilization and adjusting resource allocation strategies to ensure optimal resource utilization and timely project completion. Dynamic resource allocation is critical in a multi-project environment because resource demands can change rapidly, and there may be competing priorities for resources. Effective dynamic resource allocation requires a comprehensive understanding of project requirements, resource availability, and project interdependencies.

Machine learning algorithms can be used to develop models that can predict future resource demands and identify potential resource shortages. These models can help project managers make informed decisions regarding resource

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allocation, such as when to allocate additional resources to a project or when to reassign resources from one project to another. Effective dynamic resource allocation can improve project outcomes, reduce project costs, and increase organizational efficiency. It requires a collaborative approach among project managers, resource managers, and team members to ensure that resources are allocated optimally across multiple projects.

To this end, this work contributes to the body of knowledge by proposing a comprehensive framework for dynamic resource allocation in a multi-project environment. Our framework integrates several key factors, including project priority, resource availability, and budget constraints, and offers a systematic approach to optimize resource allocation in real-time. We provide a detailed explanation of the various components of the framework, including the mathematical models used to calculate resource allocation and the algorithms employed to optimize project timelines. We also present a case study that demonstrates the effectiveness of the proposed framework in a real-world multi-project environment.

The remainder of this work is planned as follows. Section 2 discusses and analyzes the literature. Section 3 presents the methodology of the proposed system for resource allocation In a multi-Project environment. The experimental part and results are discussed in section 4. Section 5 provides a summary conclusion of this study.

2. Related Studies

The literature contains many attempts to highlight the importance of efficient resource allocation in multi-project environments explaining the challenges faced by organizations in managing resources across multiple projects, including resource conflicts, competing project priorities, and uncertainty in project timelines and demands. For example, in [5], the authors compared two resource allocation strategies, planning, and execution, in multi-project environments and conducted a simulation study to evaluate the performance of the two strategies in terms of project completion time, resource utilization, and project success rate. They found that the execution strategy performed better than the planning strategy in terms of project completion time and resource utilization, while the planning strategy performed better in terms of project success rate. In [6], the authors presented a comprehensive framework for project portfolio selection which integrated financial, strategic, and operational factors in project portfolio selection. It consisted of four stages: (1) project screening, (2) project classification, (3) project selection, and (4) project prioritization. They argued that this approach enables organizations to align their project portfolios with their strategic goals and maximize their return on investment. In [7], the authors presented a model-based hybrid system for human resource allocation in multi-project management., which considered various factors such as project priorities, project deadlines, project dependencies, and resource availability to allocate human resources efficiently. They also developed a hybrid system that combines the mathematical model with a genetic algorithm to optimize resource allocation. The system was tested using a real-world case study, and the results show that the proposed system can effectively allocate human resources to multiple projects, reduce project delays, and increase resource utilization. In [8], the authors explored the impact of resource allocation under uncertainty on organizational conflict in a multi-project matrix environment. They conducted a case study to investigate how uncertainty in project demands, resource availability, and project priorities affects resource allocation decisions and leads to organizational conflict. They found that conflicting project demands, ambiguous priorities, and insufficient resources were the main sources of conflict in the matrix environment. They suggested that the utilization of decision-making tools, such as multi-criteria decision analysis and portfolio management, can help mitigate conflicts and improve resource allocation decisions in such environments. In [9], the authors presented a multi-objective mathematical model that can be used to optimize resource allocation, project scheduling, and project selection in a multi-project environment. The model considers various sources of uncertainty, such as project duration, resource availability, and project risks, and provides decision-makers with a set of trade-off solutions that balance conflicting objectives. They demonstrated the effectiveness of their approach using a real-world case study and showed that the hierarchical approach can improve project performance, reduce resource conflicts, and enhance decision-making. In [10], the authors explored the resource allocation syndrome as a key challenge in multi-project management by studying that the limited availability of resources and the conflicting demands of multiple projects create a syndrome that requires careful management. They

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presented a conceptual framework that explains the causes and effects of the resource allocation syndrome and highlights the importance of effective resource allocation strategies.

In [11], the authors presented a case study on project scheduling with dynamic resource allocation in a multi-project environment based on the Bogotá Electricity Distributor, which integrated a methodology that combines critical chain project management (CCPM) and dynamic resource allocation (DRA) to schedule and allocate resources across multiple projects. Their methodology takes into account the interdependencies between projects, the availability of resources, and the variability of project duration to optimize project scheduling and resource allocation. In [12], the authors proposed a conceptual framework for allocating project managers to multiple projects in a multi-project environment, in which an effective project manager-to-project (PM2P) allocation was essential for successful project management in a multi-project environment and provided a systematic approach for making allocation decisions. In [13], the authors presented a conceptual framework that aimed to address this issue by considering the competencies of project team members and aligning them with project tasks. They included a competency matrix that maps project tasks to required competencies, a competency database that stores information on project team members' competencies, and a competency-based resource allocation tool that matches project tasks with project team members based on their competencies. They demonstrated the effectiveness of their approach using a case study of a software development company and showed that competency-based resource allocation can improve project performance, increase team member motivation, and enhance project outcomes.

In [14], the authors proposed a resource management process framework for dynamic new product development (NPD) portfolios by debating that resource management is a critical aspect of NPD portfolio management, and traditional resource management methods are often inadequate in dynamic NPD environments. Their framework tried to address this issue by providing a structured approach for managing resources in dynamic NPD portfolios. The framework includes four phases: (1) portfolio planning, (2) resource capacity planning, (3) resource allocation planning, and (4) resource utilization monitoring. They demonstrated the effectiveness of their approach using a case study of a telecommunications company and showed that the framework can improve resource utilization, reduce resource conflicts, and enhance portfolio performance. In [15], the authors presented an integrated framework for cross-project knowledge transfer in project-based organizations (PBOs), in which they argued that effective knowledge transfer is critical for PBOs to improve their performance and gain a competitive advantage. The proposed framework incorporates both horizontal and vertical knowledge transfer mechanisms to facilitate the exchange of knowledge across projects and organizational levels. The horizontal mechanism includes knowledge transfer among projects at the same level, while the vertical mechanism focuses on knowledge transfer between different levels of the organization. The framework also identifies key factors that influence the success of knowledge transfer in PBOs, such as the project structure, project manager's role, and organizational culture.

3. Methodological Design

This section provides a detailed explanation of the procedures and techniques used to develop the proposed framework. We outline the steps taken to collect and analyze data, as well as the mathematical models and algorithms used to optimize resource allocation. The methodology is designed to ensure the accuracy and validity of the results presented in the paper, as well as to enable the replication of the study in future research. We also provide a critical evaluation of the strengths and limitations of the proposed methodology, highlighting the areas where further research is needed.

The design of our model uses Convolutional Long Short-Term Memory (ConvLSTM) networks as a type of recurrent network that is capable of processing spatial as well as temporal data. It combines the convolutional layers with the LSTM cells of an RNN. The convolutional layers process the spatial features, while the LSTM cells capture the temporal dependencies. To apply ConvLSTM for dynamic resource allocation, we can represent each project as a sequence of feature vectors, where each vector contains information about the project's requirements and resource usage over time. The sequence can be fed into the ConvLSTM network, which will learn to predict the resource requirements for each project at any given time.

$$i_t = \sigma(W_{xi} * x_t + W_{hi} * h_{t-1} + W_{ci} * c_{t-1} + b_i) \quad (1)$$
$$f_t = \sigma\left(W_{xf} * x_t + W_{hf} * h_{t-1} + W_{cf} * c_{t-1} + b_f\right) \quad (2)$$

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$$c_t = f_t c_{t-1} + i_t \tanh(W_{xc} * x_t + W_{hc} * h_{t-1} + b_c) \quad (3)$$
$$o_t = \sigma(W_{xo} * x_t + W_{ho} * h_{t-1} + W_{co} * c_t + b_o) \quad (4)$$
$$h_t = o_t \tanh(c_t) \quad (5)$$

When our model is constructed, the input and output samples are used to estimate the learning parameters, which include a matrix of weights and bias vectors. The term "model learning" is used to describe this procedure. When the point estimate is used, the learned model has determinate parameters from the viewpoint of probabilistic theory. The odds distribution still might be derived by the use of Bayesian estimation. To implement Bayesian estimate, Bayesian deep learning takes advantage of variational inference.

Let's think our model has a set of parameters W, which is trained using a set of M examples, e.g., $S = \{(x_1, y_1), (x_2, y_2), \cdots, (x_M, y_M)$. To learn our model parameters, we use the Bayes formula as follows:

$$p(W|S) = \frac{p(S|W)p(W)}{p(S)} = \frac{p(S|W)p(W)}{\int_W p(S|W)p(W)\mathrm{d}W} \quad (6)$$

$$\begin{aligned} \mathrm{D_{KL}}(q(\theta)||p(\theta|S)) &= \int_W q(W)\log\frac{q(W)}{p(W|S)}\mathrm{d}W \\ &= \int_\Theta q(W)\log\frac{q(\theta)\int_W p(S|W)p(W)dW}{p(S|W)p(W)}dW \\ &= \int_\Theta q(W)p(S)\,\mathrm{d}W - \int_\Theta q(W)\log\frac{p(S|W)p(\theta)}{q(W)}\mathrm{d}W \end{aligned} \quad (7)$$

Reducing KL differences, or more simply optimizing the second component in the left asymptote of, is the goal of variational inference:

$$q^*(W) = \underset{q(W)}{\mathrm{argmin}}\mathrm{DKL}(q(W)||p(W|S)) = \underset{q(W)}{\mathrm{argmax}}\int_W q(W)\log\frac{p(S|W)p(W)}{q(W)}\mathrm{d}W, \quad (8)$$

Assuming the $q(W)$ follows an integrated Gaussian distribution and that every value of W_i in the matrix W also follows a distinctive Gaussian distribution, we can transform the variational problem into an optimisation problem, as follows:

$$q(W) = N(W, \mu, \sigma^2) = \prod_i^{n_{W_i}} N(W_i, \mu_i, \sigma_i^2), \quad (9)$$

4. Experimental Analysis

The tenth of October is commemorated annually as World Mental Health Day. The goal of this day is to get people talking about mental health and rallying to help those who need it all over the world. One of the leading causes of ill health and impairment around the globe is mental illness, which affects an estimated 450 million people. It's challenging to keep one's mind in shape these days, what with the global pandemic scenario. To this end, we experiment the proposed model with Kaggle employee dataset in which the Burn Rate for the working employee depends on the contemporary pandemic condition. The main attributes constituting the dataset are Employee ID, Date of Joining, Gender, Company Type, WFH Setup Available, Designation, Resource Allocation, Mental Fatigue Score, Burn Rate. summary statistics of the dataset are given in Table 1.

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Table 1: Descriptive statistics of the training datasets for resource allocations.

	Date of Joining	is_male	is_service	wfh_available	Designation	Resource Allocation	Mental Fatigue Score	Burn Rate
count	22578.000	22578.000	22578.000	22578.000	22578.000	21212.000	20633.000	21626.000
mean	0.507	0.476	0.652	0.540	2.179	4.481	12.550	0.452
std	0.286	0.499	0.476	0.498	1.135	2.047	5.540	0.198
min	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000
25%	0.278	0.000	0.000	0.000	1.000	3.000	8.847	0.310
50%	0.496	0.000	1.000	1.000	2.000	4.000	12.625	0.450
75%	0.755	1.000	1.000	1.000	3.000	6.000	16.447	0.590
max	1.000	1.000	1.000	1.000	5.000	10.000	26.827	1.000

A correlation map can be a useful tool for analyzing dynamic resource allocation in a multi-project environment. As shown in Figure 1, this type of map displays the correlations between various factors, allowing managers to identify patterns and relationships that may impact the success of their projects. By analyzing the data presented on the correlation map, managers can make informed decisions about how to allocate resources effectively, minimize project delays, and maximize their team's productivity. This approach can help organizations to optimize their resource allocation strategies and improve their overall project management processes. It is notable how the variables Designation, Resource Allocation (hours per day), and Mental Fatigue Score directly impact the Burn Rate, being directly proportional, or a strong positive correlation. One hypothesis is that the higher the seniority, the higher the risk of burnout. We can observe that this variable is directly linked to the level of mental fatigue reported by employees, as well as to the allocated hours. Another hypothesis that can be raised is that many hours per day are directly linked to burnout. In addition to the number of hours, it is directly linked to the mental fatigue score provided by employees. It is also important to highlight the WFH Setup Available variable, where an inversely proportional correlation can be observed, where employees with home office available tend to have a lower Burn Rate, while those who do not have it tend to have a higher Burn Rate. We can also observe that employees with a home office available scored lower on mental fatigue, as well as those who do not have a home office available, have a higher mental fatigue score. Lastly, the type of company does not have a direct correlation with burnout, which may lead to the understanding that it is independent of the company's type. Figure 1 demonstrates the relationship between the fatigue score and burn rate.

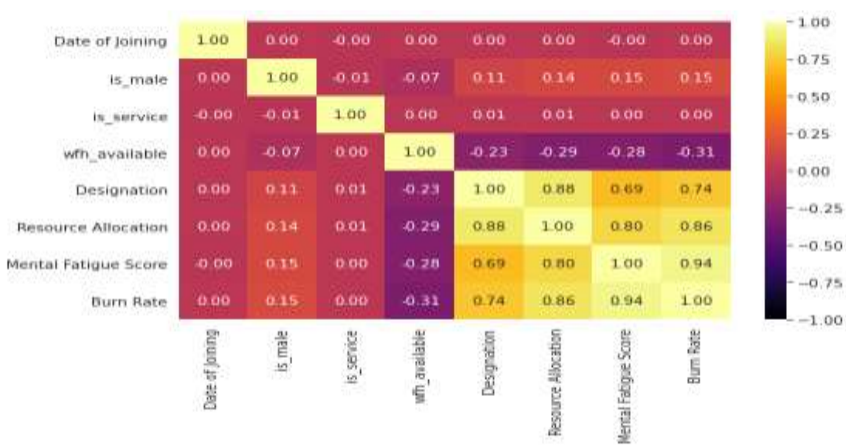

Figure 1: Illustration of correlation map on the training set of the employee data.

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A comparative analysis of ML methods for dynamic resource allocation can help identify the strengths and weaknesses of different approaches and provide insights into which methods may be most suitable for specific project requirements. Table 2 provides quantitative results of comparisons between the proposed model and competing ML for resource allocation.

Table 2: quantitative results of comparisons of competing ML methods for resource allocation.

Model	Mean Absolute Error	Mean Squared Error	Root Mean Squared Error	R2 Score
AdaBoost Regressor	0.063771951	0.033646841	0.133891644	0.891068608
Decision Tree	0.062370203	0.036246447	0.118013061	0.950558714
Gradient Boost Regressor	0.064544287	0.040542439	0.080139329	0.937618096
Lasso Regression	0.094919997	0.077523465	0.073746251	0.918359844
Linear Regression	0.061105408	0.044175073	0.111224837	0.923819285
Random Forest Regressor	0.099770231	0.055579841	0.09661282	0.90058666
Ridge Regression	0.064602961	0.043647347	0.131667717	0.874492386
Support Vector Machines - SVR	0.093889459	0.058524689	0.133438365	0.899996431
XGBoost Regressor	0.179912447	0.073577837	0.229887634	0.039265552
Proposed	0.079112152	0.038355377	0.094268817	0.006510085

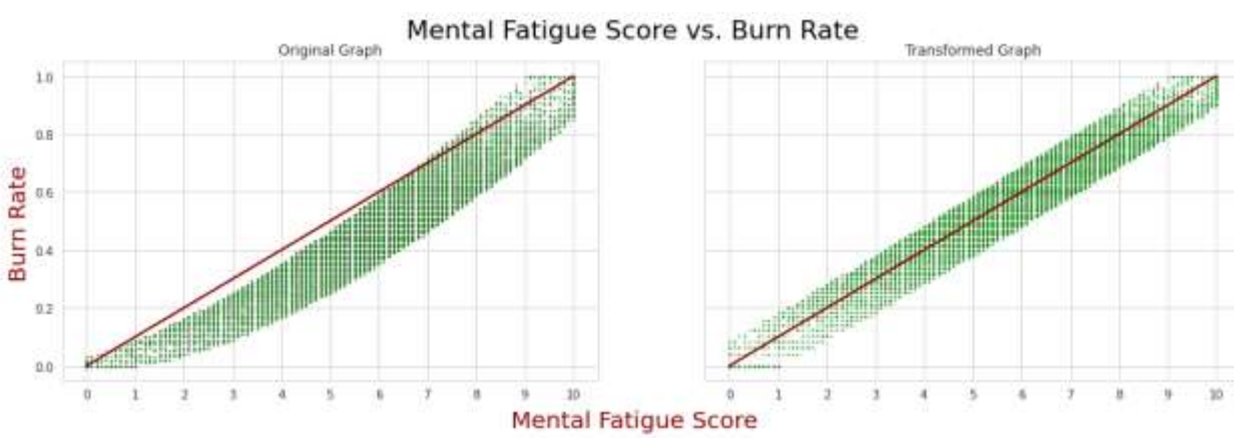

Figure 2: Illustration of the relation between metal fatigue score and burn rate.

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5. Conclusions

The dynamic resource allocation problem in a multi-project environment is complex and requires a sophisticated solution that can adapt to changing project requirements and resource availability. An integrated machine learning (ML) framework that combines different ML techniques such as Convolutional Long Short-Term Memory (ConvLSTM) networks, and predictive analytics can provide a robust and flexible solution to this problem. ConvLSTM networks can capture spatial and temporal dependencies in project data to accurately predict resource requirements, while reinforcement learning can optimize resource allocation strategies to improve project efficiency. Predictive analytics can provide insights into future resource demands and help to proactively allocate resources. This integrated ML framework for dynamic resource allocation can lead to more efficient use of resources, improved project performance, and better overall business outcomes. However, successful implementation requires careful consideration of factors such as data quality, model accuracy, and algorithm complexity. With proper planning and execution, this framework has the potential to revolutionize resource allocation in multi-project environments.

References

[1] Szalay, Imre, Ádám Kovács, and Zoltán Sebestyén. "Integrated framework for project management office evaluation." Procedia engineering 196 (2017): 578-584.
[2] Repenning, Nelson P. "A dynamic model of resource allocation in multi-project research and development systems." System Dynamics Review: The Journal of the System Dynamics Society 16.3 (2000): 173-212.
[3] Hagan, George, Denise Bower, and Nigel Smith. "Managing complex projects in multi-project environments." C. a. L. Egbu, ECW (Chair), Symposium conducted at the meeting of the 27th Annual ARCOM Conference, Bristol, UK. 2011.
[4] Pakgohar, A. (2014). Hierarchical Multi-Project Planning and Supply Chain Management: an Integrated Framework.
[5] Ben-Zvi, T., & Lechler, T. G. (2011, July). Resource allocation in multi-project environments: Planning vs. execution strategies. In 2011 Proceedings of PICMET'11: Technology Management in the Energy Smart World (PICMET) (pp. 1-7). IEEE.
[6] Archer, N. P., & Ghasemzadeh, F. (1999). An integrated framework for project portfolio selection. International Journal of Project Management, 17(4), 207-216.
[7] KHATUN, Mst Taskia, and Kazuo HIEKATA. "A Model-Based Hybrid System for Human Resource Allocation in Multi-Project Management." (2022).
[8] Laslo, Zohar, and Albert I. Goldberg. "Resource allocation under uncertainty in a multi-project matrix environment: Is organizational conflict inevitable?." International journal of project management 26.8 (2008): 773-788..
[9] Hans, Erwin W., et al. "A hierarchical approach to multi-project planning under uncertainty." Omega 35.5 (2007): 563-577.
[10] Engwall, Mats, and Anna Jerbrant. "The resource allocation syndrome: the prime challenge of multi-project management?." International journal of project management 21.6 (2003): 403-409.
[11] Rueda-Velasco, Feizar Javier, Carlos Efraín Cubaque, and Juan Martin Ibañez Latorre. "Project Scheduling with Dynamic Resource Allocation in a Multi-project Environment. Case: Bogotá Electricity Distributor." Applied Computer Sciences in Engineering: 4th Workshop on Engineering Applications, WEA 2017, Cartagena, Colombia, September 27-29, 2017, Proceedings 4. Springer International Publishing, 2017.
[12] Seboni, Lone, and Apollo Tutesigensi. "Development and verification of a conceptual framework for project manager-to-project (PM2P) allocations in multi-project environments." Proceedings of PICMET'14 Conference: Portland International Center for Management of Engineering and Technology; Infrastructure and Service Integration. IEEE, 2014.
[13] Riesener, Michael, et al. "Concept for competency-based resource allocation in multi-project environments." Proceedings of The 4th International Conference on Management, Economics and Finance, 10.-12.09. 2021, Zurich, Switzerland. 2021.

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[14] Abrantes, Rui, and José Figueiredo. "Resource management process framework for dynamic NPD portfolios." International Journal of Project Management 33.6 (2015): 1274-1288.
[15] Zhou, Qianwen, et al. "Integrated framework of horizontal and vertical cross-project knowledge transfer mechanism within project-based organizations." Journal of Management in Engineering 36.5 (2020): 04020062.
[16] Li, Feifei, Zhe Xu, and Haitao Li. "A multi-agent based cooperative approach to decentralized multi-project scheduling and resource allocation." Computers & Industrial Engineering 151 (2021): 106961.
[17] Melchiors, Philipp, et al. "Dynamic order acceptance and capacity planning in a stochastic multi-project environment with a bottleneck resource." International Journal of Production Research 56.1-2 (2018): 459-475.
[18] Lee, Bengee, and James Miller. "Multi-project management in software engineering using simulation modelling." Software Quality Journal 12 (2004): 59-82.
[19] Krüger, Doreen, and Armin Scholl. "A heuristic solution framework for the resource constrained (multi-) project scheduling problem with sequence-dependent transfer times." European Journal of Operational Research 197.2 (2009): 492-508.
[20] He, Naihui, David Z. Zhang, and Baris Yuce. "Integrated multi-project planning and scheduling-a multiagent approach." European Journal of Operational Research 302.2 (2022): 688-699.

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