A HYBRID MODEL FOR EXPLAINABLE UNIVERSITY TIMETABLE OPTIMIZATION USING MACHINE LEARNING AND EXPERT KNOWLEDGE

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Abstract: Creating a university timetable is a complex multi-criteria problem that requires the processing of heterogeneous data, expert rules, resource constraints, and user preferences. This article proposes a hybrid knowledge-based decision-support model for explainable optimization of university timetables by integrating machine learning, expert knowledge, and mechanisms for explainable artificial intelligence. The model uses historical data, expert rules, and satisfaction metrics to evaluate and select the most appropriate timetable variant. A multi-criteria objective function has been developed that combines student and lecturer satisfaction, expert evaluation, and a predicted score from a machine learning model. An explainable artificial intelligence component for interpreting the results is included, as well as a closed-loop self-learning mechanism. The proposed approach lays the foundation for a transparent and adaptive information technology framework for decision-makers in optimizing timetables.

Key words: expert knowledge, explainable artificial intelligence, machine learning, multi-criteria optimization, university timetabling.

1. INTRODUCTION

Timetabling is an important organizational task in higher education institutions, as it affects the efficient use of resources, the workload of lecturers and students, and the quality of the educational process. In practice, this task requires consideration of numerous interrelated factors, such as curricula, lecturers' availability, classroom availability, technical equipment, and the individual preferences of those involved in the educational process [1].

Despite the development of specialized software products, the final choice of a timetable variant often remains dependent on the expert judgment of administrative staff and decision-makers. The reason is that some of the constraints and preferences are informal or context-dependent in nature and are difficult to represent fully through formal mathematical models [1].

In recent years, advances in artificial intelligence (AI) and machine learning (ML) have led to the application of various approaches for the automated solution of university timetabling and related scheduling problems, including genetic algorithms, search methods in constrained spaces, ML models, and hybrid optimization techniques [2-6]. Regardless of the results achieved, some of these approaches rely primarily on historical data or formally defined constraints and do not sufficiently account for the expert knowledge accumulated within the specific university environment.

For this reason, this study proposes a hybrid knowledge-based decision-support model for timetable optimization that integrates ML, expert knowledge, and explainable artificial intelligence (XAI) mechanisms into a unified information technology framework. The model uses historical data to predict the quality of different timetable variants, takes into account predefined expert rules, and provides explanations of the selected variant and the degree to which the criteria are met.

The objective of this work is to develop a hybrid model for timetable optimization based on the integration of ML, expert knowledge, and XAI, which supports the generation, evaluation, and selection of higher-quality timetable variants. The scientific contribution lies in combining a predicted score from an ML model, an expert assessment, and an XAI mechanism into a unified multi-criteria framework for evaluating and selecting university timetable variants. In this sense, the proposed model is positioned within the field of intelligent systems and knowledge-based technologies, as it combines data-driven prediction, formalized expert knowledge, and transparent decision support.

2. THEORETICAL FRAMEWORK AND RELATED RESEARCH

University timetable optimization is a multi-criteria combinatorial problem in which numerous hard and soft constraints must be satisfied simultaneously. Hard constraints relate to lecturers' availability, classrooms, time slots, and academic disciplines, while soft constraints reflect qualitative characteristics such as workload balance, minimization of free slots, and consideration of the preferences of participants in the educational process [1].

Various approaches to solving this problem have been proposed in the literature. Evolutionary and meta-heuristic algorithms, including genetic algorithms, are widely used; they allow for the exploration of large spaces of possible solutions and the finding of good approximate solutions in a relatively short time [2-4]. Optimization-based methods are also used in practical scheduling problems with multiple objectives and resource constraints [5]. Another important class of methods is constraint-based modeling, in which the rules are formally specified, and the algorithm searches for a feasible solution that satisfies the predefined conditions [6]. Matheuristic and multiobjective metaheuristic approaches have also been applied to multi-level and multi-criteria university timetabling [7, 8].

In recent years, approaches based on AI and ML have become increasingly important. They allow the use of historical data to identify patterns and predict the quality of various timetable variants [2]. However, a large portion of existing models rely primarily on available data or formally defined constraints and do not sufficiently

account for the expert knowledge accumulated within the specific university environment.

Another significant problem is the limited interpretability of automatically generated solutions. Even when an algorithm proposes a timetable variant with a high objective function value, there is often a lack of information regarding which factors led to this choice and why that timetable variant was preferred over the others. This hinders both expert verification and the acceptance of the results by decision-makers.

Explainable artificial intelligence methods are particularly relevant in decision-support systems where the final result must be verified and accepted by human experts. Local Interpretable Model-agnostic Explanations (LIME) explain individual predictions by approximating the behavior of a complex model in the local neighborhood of a specific instance, while SHapley Additive exPlanations (SHAP) estimate the contribution of each input feature to the model prediction. These methods are suitable for the proposed hybrid model because they allow the influence of timetable-related features, such as workload balance, conflicts, classroom utilization, and satisfaction indicators, to be interpreted in a form understandable to decision-makers [9, 10].

Consequently, there is a need for a model that simultaneously utilizes historical data, incorporates expert knowledge, and provides an explanation of the obtained results. This research gap forms the basis of the proposed hybrid model for timetable optimization, which combines ML, expert rules, and XAI into a unified framework for evaluating and selecting timetable variants.

3. HYBRID MODEL FOR TIMETABLE OPTIMIZATION

The main idea behind the proposed hybrid model is to combine the advantages of ML and expert knowledge into a unified system that supports the process of timetable construction and optimization. Unlike traditional methods, which rely solely on mathematical models or historical data, the aim here is to combine the accumulated practical experience of experts with the capabilities of modern algorithms for analysis and forecasting. The proposed hybrid model consists of five main components:

- Data Management Module;
- Machine Learning Module;
- Expert Knowledge Base;
- XAI Module;
- Decision Support Module.

The interaction between the individual components is shown in Figure 1, with the sequence of their operation comprising data collection and processing, training the ML model, evaluating the generated timetable variants, applying expert rules, explaining the results using XAI, and assisting in the selection of the most appropriate timetable variant.

The data management module collects and processes the information necessary for constructing timetables, including data on lecturers, student groups, courses, classrooms, time slots, and additional organizational constraints. Historical timetables are used as the basis for training the ML model.

The ML module analyzes the accumulated data and identifies relationships between the characteristics of the timetables and their subsequent evaluation. On this basis, the

system predicts the quality of newly generated timetable variants and assists in selecting the most suitable one.

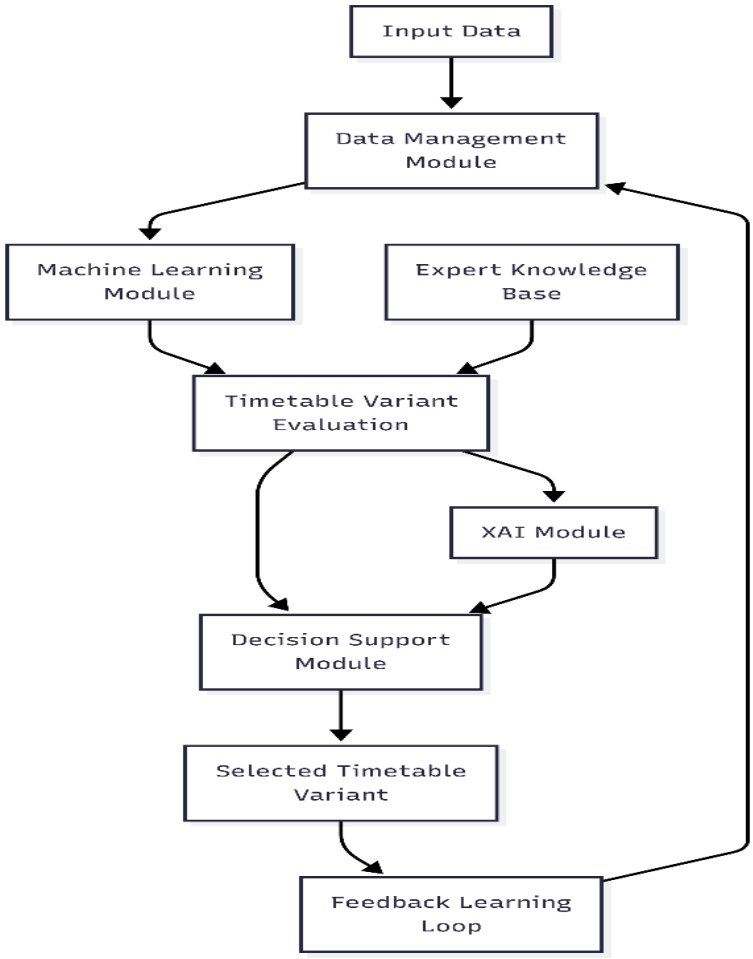


Figure 1. Architecture of the proposed hybrid model for timetable optimization

The expert knowledge base contains rules and constraints formulated by the specialists involved in the planning process. These include both regulatory requirements and practical rules related, for example, to limiting consecutive class periods, avoiding long free periods, and the preferred scheduling of certain subjects.

After valid timetable variants are generated, each timetable variant is evaluated based on the prediction generated by the ML model and the degree to which it satisfies the expert rules. The resulting evaluations are used to select the most suitable timetable variant, with the XAI module providing an explanation of the results. An important feature of the hybrid model is that the ML component does not replace the experts but rather supports them by combining the adaptability of learning algorithms with the reliability of expert knowledge. The selected timetable variant can be used as a source of new data in subsequent planning cycles.

4. MATHEMATICAL MODEL FOR EVALUATING TIMETABLE VARIANTS

One of the key stages in timetable optimization is the evaluation of the generated variants. To this end, a multi-criteria objective function is proposed, which takes into account the interests of the main participants in the teaching process, the results of the ML model, and the expert knowledge accumulated in the process of managing teaching activities.

4.1. Multi-Criteria Objective Function

Let *r* denote an arbitrary timetable variant. The present study extends the authors' previous mathematical model for timetable optimization, which was based on maximizing the satisfaction of students and lecturers with the generated timetable [11]. The basic objective function is given by (1):

$$F(r) = \sum_{j=1}^{l} y_s PS_j + \sum_{j=1}^{k} y_p PP_j \rightarrow \max \quad (1)$$

where:

F(r) – value of the basic objective function for timetable variant r;
PS_j – priority score of the j-th student requirement;
PP_j – priority score of the j-th lecturer requirement;
y_s – weighting coefficient reflecting the priorities of students;
y_p – weighting coefficient reflecting the priorities of lecturers;
l – number of student requirements;
k – number of lecturer requirements.

In the present study, this function is extended by incorporating an evaluation based on expert knowledge and a predicted score from an ML model. The extended objective function is defined in (2):

$$F(r) = \alpha S(r) + \beta P(r) + \lambda K(r) + \delta M(r) \rightarrow \max \quad (2)$$

where:

S(r) – student satisfaction,
P(r) – lecturer satisfaction,
K(r) – assessment based on expert knowledge,
M(r) – predicted score from the ML model,
α, β, λ and δ – weighting coefficients.

In this way, the extended objective function ensures that the satisfaction of the key participants in the educational process, accumulated expert experience, expert rules and data from the actual operation of the system are all taken into account simultaneously.

To ensure the correct aggregation of the individual components within the overall objective function, the weighting coefficients are normalized, such that their sum must equal one, as specified in (3):

$$\alpha + \beta + \lambda + \delta = 1 \quad (3)$$

4.2. Components of the Evaluation Model

1) Student satisfaction

This is calculated using (4):

$$S(r) = \sum_{j=1}^{l} y_s PS_j \tag{4}$$

where $S(r)$ denotes student satisfaction for timetable variant r, and PS_j, y_s, and l are defined as in Equation (1).

2) Lecturer satisfaction

Calculated using (5):

$$P(r) = \sum_{j=1}^{k} y_p PP_j \tag{5}$$

where $P(r)$ denotes lecturer satisfaction for timetable variant r, and PP_j, y_p, and k are defined as in Equation (1).

3) Expert knowledge assessment

Expert knowledge comprises a set of rules and criteria formulated by the specialists involved in the process of drawing up the timetable. These rules reflect both the regulatory requirements of the higher education institution and the practical experience gained from previous academic years. Equation (6) is used to assess the extent to which a given timetable variant meets the expert requirements:

$$K(r) = \frac{\sum_{t=1}^{n} w_t R_t}{\sum_{t=1}^{n} w_t} \tag{6}$$

where:

$K(r)$ – overall expert assessment of the timetable r,
R_t – degree of fulfilment of the t-th expert rule,
w_t – weighting coefficient determining the importance of the relevant rule,
n – number of expert rules.

The value of the indicator R_t is normalized to the range from 0 to 1 as follows:

$R_t = 1$ the rule is fully satisfied,
$0 < R_t < 1$ the rule is partially fulfilled,
$R_t = 0$ the rule has not been fulfilled.

The weighting coefficient w_t allows different rules to have varying influences on the final assessment. In this way, more important constraints are given a greater weight.

The indicators have been selected following consultation with experts in the organization of the educational process and cover key aspects related to timetable quality. These may include the even distribution of the workload across student groups, the compactness of the timetable, the minimization of gaps between classes, consideration of lecturers' timetables, the effective use of teaching rooms, the

availability of suitable time slots for specific subjects, as well as the number of detected scheduling conflicts and the need for subsequent adjustments.

The weighting coefficients assigned to these indicators reflect their relative importance in the overall assessment. They are calculated by aggregating the assessed priorities of the relevant stakeholders and normalizing the resulting values so that they can be used consistently in the evaluation model.

This provides a more objective basis for data collection and for forming expert assessments that reflect the actual priorities of those involved in the timetable construction process. The resulting assessments can be used both in forming the expert evaluation and as input features when training the ML model.

An anonymous questionnaire is proposed for collecting assessments of the relevant indicators and their ranking by importance from experts, lecturers, students, and other stakeholders. The target group for the survey is not selected at random but consists of individuals with a thorough knowledge of the subject area. The methodology for evaluating the indicators and determining the corresponding weighting coefficients is based on the authors' previous work [12].

The resulting weighting coefficients are not used only to calculate overall satisfaction. In the proposed hybrid model, they are also used as input features when training the ML model, which enables the algorithm to take into account the actual preferences of those involved in the teaching process.

The advantage of this approach is that it allows new rules to be added easily without altering the rest of the model. Furthermore, experts can dynamically adjust the weighting coefficients depending on the specifics of a particular academic year, degree program or faculty. In this way, the expert knowledge base becomes an active component of the system, complementing the results of the ML model and enhancing the practical applicability of the generated timetable variants.

4) Predicted score from the ML model

The ML module generates an assessment based on an analysis of archived data from previous academic years. After training, the ML model assigns a predicted score to each timetable variant. The predicted score of the ML model, $M(r)$, is defined within the interval [0, 1], which is consistent with the normalized ranges of the other components in Equation (2). A value closer to 1 indicates a timetable variant with higher predicted quality, whereas a value closer to 0 indicates lower predicted quality.

The predicted score from the ML model is expressed by (7):

$$M(r) \in [0,1] \tag{7}$$

which reflects the expected quality of the timetable variant according to the patterns identified in the historical data.

The final selection of the timetable variant is made by maximizing the objective function $F(r) \rightarrow \max$. In this way, the system is not based solely on historical data or predefined rules, but combines information from various sources, which allows for more balanced and practically applicable solutions.

4.3. Closed-loop self-learning

The proposed hybrid model incorporates a closed-loop self-learning mechanism (Feedback Learning Loop), through which the system can be refined based on data from the actual use of the timetable. After each timetable has been used, the collected data are used to update the archive, further train the model, and improve prediction accuracy:

- actual student satisfaction;
- actual lecturer satisfaction;
- corrections made by decision-makers;
- the number of changes that have occurred during the semester.

These data are added to the archive and used in subsequent training of the model. In this way, the model can be gradually refined after each academic year.

5. MACHINE LEARNING AND EXPLAINABLE AI COMPONENTS

5.1. Machine learning component

The proposed ML component supports the optimization of the timetable by analyzing archived data and predicting the quality of newly generated timetable variants. Unlike traditional approaches, in which criteria are predefined by experts, here the model extracts patterns from previous timetables and uses them to evaluate new timetable variants.

Each archived timetable variant serves as a source of information regarding the distribution of classes, conflicts that arose, subsequent adjustments, student and lecturer satisfaction, and the evaluation by decision-makers. The accumulation of such data enables the development of a model capable of predicting the quality of future timetable variants even before their final approval.

5.2. Preparation of training data

Before training, all archived timetables undergo preprocessing, which includes removing incomplete or incorrect records, standardizing the designations for courses, lecturers, and class groups, normalizing numerical characteristics, and forming a unified training dataset.

Each record in the dataset describes a single timetable variant through quantitative and qualitative characteristics, which subsequently serve as input data for the ML algorithms.

5.3. Selection of Input Features

The quality of any ML model depends largely on the correct selection of input characteristics. This study uses indicators that describe both the structure of the timetable variant and its qualitative characteristics.

Key input characteristics may include structural, resource-related, and qualitative indicators, such as the number of lecturers, student groups, courses, and classrooms, average daily workload, free time slots in the timetable, conflicts that have arisen, classroom utilization rates, the distribution of lectures and lab sessions, time slots reserved for faculty council and academic council meetings, student and lecturer satisfaction, and evaluations based on expert rules. The use of such a set of

characteristics allows the model to account for both the quantitative and qualitative aspects of timetable variants.

5.4. Definition of the Target Variable

The target variable used for training the ML model is derived from the normalized quality assessment of a timetable variant, as defined in Equation (2). Since the main components of the assessment have already been introduced in the previous subsection, they are not repeated here.

In the training dataset, each timetable variant is associated with an overall quality score within the interval [0, 1]. A value closer to 1 indicates a higher-quality timetable variant, while a value closer to 0 indicates a lower-quality one. The task of the ML model is to learn the relationship between the input features and this quality score, so that it can predict the expected quality of newly generated timetable variants.

5.5. Choice of the Machine Learning Algorithm

To build the predictive component of the proposed model, ML algorithms suitable for tabular data and for assessing the importance of input features are considered. In the initial implementation, ensemble learning methods such as Random Forest and XGBoost are appropriate candidates because they can model nonlinear relationships between timetable characteristics and the resulting quality assessment.

The comparison of alternative algorithms should be based on prediction accuracy, robustness, interpretability, and training time. This makes it possible to select the algorithm that provides the best balance between predictive performance and practical applicability in the specific university environment.

5.6. Training and validation

In the intended implementation, model training is performed on historical data from previous academic years. The dataset should be split into training and test sets, and k-fold cross-validation can be used to evaluate the models' generalization ability.

The quality of predictions can be assessed using standard metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2). MAE measures the model's average absolute error, RMSE places greater weight on larger deviations between predicted and actual values, and R^2 indicates what proportion of the variation in the target variable is explained by the model. Comparing these metrics allows for the selection of an algorithm with the best balance between accuracy, robustness, and the ability to generalize to new data. Since the predicted score $M(r)$ is normalized to the interval [0, 1], the MAE and RMSE values can be used directly to compare different ML models.

5.7. Interaction with expert knowledge

A key feature of the hybrid model is that the results of the ML model are not used in isolation when selecting the optimal timetable variant. The predicted score $M(r)$ represents only one component of the overall objective function.

Upon completion of the training, each new timetable variant is assigned a predicted score, which is subsequently combined with the assessment derived from the expert

knowledge base. In this way, the final choice is not determined solely by the statistical relationships in the historical data but also takes into account the accumulated practical experience of the specialists involved in organizing the teaching process.

Thus, the hybrid model combines the advantages of ML and expert assessment, reducing the likelihood that the model will propose solutions that are mathematically optimal but practically inapplicable in the specific university environment.

5.8. Explainable artificial intelligence component

One of the main shortcomings of modern ML models is the limited interpretability of the obtained results. In most cases, the algorithm proposes a timetable variant without specifying which factors had the strongest influence on the predicted score. This hinders expert verification and reduces decision-makers' trust in the automatically generated timetable variants.

In the proposed model, methods such as SHapley Additive exPlanations (SHAP) [10] and Local Interpretable Model-agnostic Explanations (LIME) [9] can be used to implement the XAI component. After the predicted score is calculated by the ML model, the XAI module analyzes the influence of individual input features and provides an explanation for the resulting prediction. The explanations can be presented as a textual description, a graphical visualization, or a ranking of the factors according to their significance. In the context of timetable optimization, XAI makes it possible to identify the factors that are most important for selecting a specific timetable variant, such as student and lecturer satisfaction, classroom utilization, the number of conflicts, or the availability of suitable time slots. The resulting explanations can also be used to refine the expert knowledge base by formalizing relationships that have a consistent influence on timetable quality as new expert rules.

In this way, the XAI component increases the transparency of the hybrid model and facilitates the acceptance of the results by decision-makers, while leaving the final decision to the experts.

6. DISCUSSION

The proposed hybrid model combines ML, expert knowledge, and XAI mechanisms into a unified process for evaluating and selecting timetable variants. Its main advantage is the integration of heterogeneous information sources – historical data, expert rules, satisfaction indicators, and predicted scores from the ML model. This allows for a more balanced evaluation of timetable variants and reduces the risk of the selection being based solely on formal constraints or solely on statistical dependencies in the data.

Another significant advantage is the ability to increase transparency in decision-making. By using XAI techniques such as SHAP and LIME, the system can provide an explanation for the selection of a specific timetable variant, showing which characteristics had the strongest influence on the predicted score. This facilitates expert review, increases the trust of decision-makers, and supports the acceptance of automatically generated timetable variants.

The model is also adaptive, as it incorporates a closed-loop self-learning cycle. Data from the actual use of the timetable can be added to the archive and used for subsequent

training of the model. In this way, the system can gradually adapt to changes in curricula, organizational requirements, and the preferences of participants in the educational process.

Despite these advantages, the proposed model also has some limitations. Its quality depends on the availability, completeness, and reliability of the archived data. In the case of incomplete or contradictory data, the predictive ability of the ML model may be limited. An additional challenge is the formalization of expert knowledge, as some of it is informal or context dependent. Subsequent empirical validation using real university data is also necessary to assess the effectiveness, robustness, and practical applicability of the proposed approach.

7. CONCLUSION AND FUTURE RESEARCH

This study proposes a hybrid model for university timetable optimization that integrates ML, expert knowledge, and XAI into a unified framework for evaluating and selecting timetable variants. The model combines historical data, expert rules, satisfaction indicators, and a predicted score from an ML model, thereby providing a basis for more transparent and well-reasoned support for decision-makers.

The main contribution of this research lies in the development of a multi-criteria approach in which the predicted score from the ML model is not used in isolation but is combined with expert assessment and an explainability mechanism. The inclusion of an XAI component allows the model's results to be interpreted and justified, which is particularly important for decision-support systems in a university setting.

Future research will focus on the empirical validation of the proposed model using real-world data from a university setting. A comparative analysis of different ML algorithms is planned, as well as an evaluation of the model's practical effectiveness using metrics such as the number of conflicts, subsequent adjustments, workload distribution, classroom utilization, and student and lecturer satisfaction.

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