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Automated fair team formation in STEAM activities using Satisfiability Modulo Theories (SMT)

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Abstract. One of the problems that schools or organizers of STEAM (Science, Technology, Engineering, Arts, and Mathematics) camps face to is the balanced distribution of students according to gender, skills, and academic background in a fair manner. In this study, we used a Satisfiability Modulo Theories (SMT) approach to solve the problem of fair team formation. Our implementation of the approach uses the Z3 SMT solver. In our preliminary experiments, we successfully generated fair and balanced teams from 50 students across different scenarios. Using SMT in educational settings saves time and effort for school administrators and organizers of STEAM events, and it also provides an efficient and effective solution to distribute students equitably across teams.

Keywords: Automated Team Formation, Fairness, STEAM Education, Satisfiability Modulo Theories (SMT)

1. Introduction

STEM (Science, Technology, Engineering, and Mathematics) and its extension STEAM (which incorporates the Arts) have become essential educational frameworks for preparing students to address real-world challenges through interdisciplinary thinking and collaborative problem-solving [1]. STEAM is widely recognized as a modern and effective approach to teaching that deepens subject under-

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standing. Developed countries have increasingly adopted STEAM in their national strategies. According to recent rankings, Canada leads in STEM graduate output, followed by Russia, Japan, South Korea, the United States, Ireland, the United Kingdom, Australia, Finland, and Luxembourg [1]. These programs often rely on collaborative, team-based projects, making fair and effective team formation a key requirement.

Despite the global rise of STEM and STEAM education, there remains a significant lack of structured data, digital tools, and research in some regions, including Iraq. Although many Iraqi schools have started organizing STEM-style camps and student activities, the process of forming student teams is typically done manually by teachers. This method is often time-consuming, subjective, and prone to imbalances in gender representation, skill levels, and academic backgrounds. To bridge this gap, we propose a novel approach using Satisfiability Modulo Theories (SMT), implemented through the Z3 solver developed by Microsoft Research [16]. Our model encodes fairness constraints – such as skills, gender balance, and background diversity – and efficiently solves them using Z3 to generate well-balanced student teams [14].

In this study, we report on developing and experimenting with our SMT-based tool on a dataset of 50 students. Most of the cases, the tool successfully generates 10 diverse and balanced teams in a very short time frame. This demonstrates the efficiency, scalability, and fairness of our approach, which can be readily integrated into STEAM-based education environments.

The rest of this paper is organized as follows. Section 2 reviews related work. Section 3 describes the dataset and team formation constraints. Section 4 provides details on how the model is encoded into SMT. Section 5 presents the implementation of our approach and reports on experimental results. Section 6 provides a discussion and concludes the paper with future directions.

2. Related work

Team formation has been studied in various fields such as education, human resources, and project management [12]. Traditional approaches often rely on manual selection or random assignment, which may lead to unfair or unbalanced teams and might be time consuming [2, 4].

In recent years, researchers have explored some approaches for team formation using optimization, machine learning, and constraint programming. For example, some studies use genetic algorithms [7, 13] or clustering techniques to group students based on skills or personality traits [11]. While these methods can improve team balance, they often require tuning and may not enforce hard constraints like gender or background diversity.

Satisfiability Modulo Theories (SMT) has emerged as a powerful tool for solving constraint-based problems in scheduling, verification, testing [5] and education [8]. For instance, an SMT-based scheduling system was successfully designed and tested using real university data to solve course timetabling problems with the Z3 solver, demonstrating its practical utility in academic environments [15]. Z3, a state-of-the-art SMT solver developed by Microsoft Research, is capable of handling complex logical and arithmetic rules efficiently [14].

Some researchers have used SMT for course timetabling, project group allocation, and fair scheduling [3], but its application in STEAM team formation remains limited.

Our work builds on this foundation by applying SMT to form fair and diverse student teams. Unlike earlier methods, our model guarantees constraint satisfaction for team size, skill levels, gender balance, and background diversity. To the best of our knowledge, this is one of the first applications of SMT in fair team assignment for STEAM education settings.

3. Dataset and constraints

Due to the absence of publicly accessible datasets concerning team formation in STEAM-focused activities, especially within Iraqi school environments, a synthetic dataset [9, 10] was created to reflect realistic student characteristics. This dataset includes representative features such as gender, educational background, and skill levels across key STEAM disciplines. It was thoughtfully constructed to capture diversity and ensure that all constraints were feasible. To verify its effectiveness, the dataset was tested using our SMT-based team formation model, which confirmed that the generated teams met all specified requirements.

3.1. Dataset description

Our dataset contains information on students who participated in the program. Each student record is stored in JSON format, as shown in Table 1.

Table 1. Dataset attributes.

ID	Unique numeric identifier
Name	Student's first name (anonymized)
Gender	Female (F), Male (M)
Background	Arts, Engineering, Science
Skills	Rated from 1 (lowest) to 5 (highest): • Programming (technical ability) • Design (visual creativity) • Math (quantitative skills) • Creativity (original thinking) • Science (theoretical knowledge)

The dataset consists of 50 records. For example, a student may have a Programming score of 4 and a Design score of 2. These skill scores help measure each student's strength in different areas. This dataset allows us to create teams that are diverse in gender, background, and skill levels. By analyzing this information, we can use a solver to build balanced teams that meet specific fairness goals.

3.2. Fairness constraints

To make sure teams are fair, we defined a set of constraints that the solver must follow. These constraints help to create balanced and diverse teams. The fairness constraints are as follows, where the scalars might differ in different scenarios, see Section 5.2.

- **Team Size:** Each team must have exactly 5 students.
- **Minimum Skill Totals:**
  - Programming ≥ 10
  - Design ≥ 10
  - Math ≥ 8
  - Creativity ≥ 6
  - Science ≥ 8

  These totals are the sum of individual student scores in each team. For example, if five students each have a Programming score of 2, the total will be 10.
- **Gender Balance:** Each team must include at least 2 males and at least 2 females.
- **Academic Background Diversity:** Each team must include at least one student from each of the 3 backgrounds (Arts, Engineering, Science).

These constraints ensure that every team has a mix of students with different strengths and experiences. They help promote equal opportunities and diverse collaboration in STEAM activities.

4. Problem encoding into SMT

Satisfiability Modulo Theories (SMT) is an approach used to solve problems that involve both logic and arithmetic constraints [6, 14]. In our model, we used Boolean constraints and linear integer arithmetic constraints to create fair and diverse teams based on student data. We introduce the following parameters, including the decision variable $x_{s,t}$:

- S: set of students
- T: set of teams
- K: set of skills
- B: set of backgrounds
- min_skill_k: minimum required total for skill $k \in K$ in a team, where $min\_skill_k \in \mathbb{N}$

- min_bg: minimum number of backgrounds in a team, where $min\_bg \in \mathbb{N}$
- min_gen: minimum number of students of the same gender in a team, where $min\_gen \in \mathbb{N}$
- $skill_{s,k}$: score of student $s \in S$ in skill $k \in K$, where $skill_{s,k} \in \{1, 2, 3, 4, 5\}$
- gen_s: gender of student $s \in S$, where $gen_s \in \{0, 1\}$
- $bg_{s,b}$: student $s \in S$ has background $b \in B$, where $bg_{s,b} \in \{0, 1\}$
- $x_{s,t}$: binary decision variable, where

$$x_{s,t} = \begin{cases} 1, & \text{if student } s \in S \text{ is in team } t \in T, \\ 0, & \text{otherwise.} \end{cases}$$

Using these parameters, we encode the following fairness constraints:

- Each student must be assigned to exactly one team:

$$\forall s \in S. \sum_{t \in T} x_{s,t} = 1.$$

This constraint can be further translated to the Boolean constraint

$$\forall s \in S. \left(\bigvee_{t \in T} x_{s,t} \right) \wedge \bigwedge_{\substack{t_1, t_2 \in T \\ t_1 \neq t_2}} (\neg x_{s,t_1} \vee \neg x_{s,t_2}).$$

- Each team must contain exactly five students:

$$\forall t \in T. \sum_{s \in S} x_{s,t} = 5.$$

- Each team must meet minimum skill totals in each skill:

$$\forall t \in T\ \forall k \in K. \sum_{s \in S} skill_{s,k} \cdot x_{s,t} \geq min\_skill_k.$$

- Each team must include at least min_gen males and females, respectively:

$$\forall t \in T. \sum_{s \in S} gen_s \cdot x_{s,t} \geq min\_gen.$$
$$\forall t \in T. \sum_{s \in S} (1 - gen_s) \cdot x_{s,t} \geq min\_gen.$$

- Each team must include students from at least *min_bg* different academic backgrounds. To express this, we first need to introduce new binary variables $bg_{t,b}$ to express if a team t has at least one student with background b.

$$\forall t \in T,\ \forall b \in B.\ bg_{t,b} \ \Leftrightarrow \bigvee_{s \in S} (bg_{s,b} \wedge x_{s,t}).$$

Then, the original constraint can be easily expressed as

$$\forall t \in T.\ \sum_{b \in B} bg_{t,b} \geq min\_bg.$$

Note that the above constraints are universally quantified. In our tool, we intend to only apply quantifier-free logics, therefore all universal quantifiers get expanded, due to a relatively small domain.

5. Experimental results

5.1. System architecture

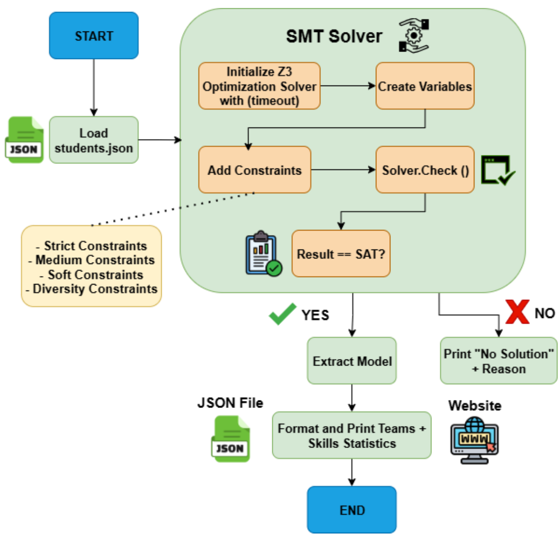

Figure 1. System architecture showing the main modules of our team formation tool.

We integrated and incorporated our SMT model in a tool that we developed in Python using the Z3 SMT solver. The architecture follows a modular structure:

- **Input Module:** Loads the student dataset from a JSON file.

- **Constraint Module:** Defines all SMT variables and constraints (e.g., skills, gender, background).
- **Solver Module:** Uses the Z3 engine to compute valid team assignments based on all constraints.
- **Output Module:** Displays or saves the team assignments.

Figure 1 shows an overview of the system workflow.

We built a web application to display the results generated by the SMT solver. The platform provides summary statistics and allows students to see which team they have been assigned to, as shown in Appendix A.

5.2. Setup

We tested our team formation model using a synthetic dataset containing 50 student records. All experiments were conducted on a machine equipped with an Intel Core i5 processor and 8GB of RAM.

To evaluate the impact of varying fairness and diversity constraints, we designed four distinct scenarios. The details of each scenario's constraints and logic are provided below. As Section 5.3 reports on it, the solver successfully generated fair and diverse team assignments in all feasible cases, except in Scenario 2, where no feasible solution was found. These results demonstrate the model's efficiency and responsiveness to different constraint settings.

Scenario 1: Skill Thresholds, Gender Balance, and Background Diversity

This scenario enforces constraints across skills, gender, and academic backgrounds. Each team must consist of exactly five students and satisfy all the constraints under those settings:

- **Minimum Skill Totals:**
  - $min\_Programming = 10$
  - $min\_Design = 10$
  - $min\_Math = 8$
  - $min\_Creativity = 6$
  - $min\_Science = 8$
- **Gender Diversity:** At least 1 females and 1 males: $min\_gen = 1$
- **Background Diversity:** At least two backgrounds per team: $min\_bg = 2$

Scenario 2: Stricter Skill Thresholds with Gender and Background Diversity

Scenario 2 maintains the same diversity constraints as Scenario 1 but applies significantly higher skill requirements. Each team must consist of exactly five students and satisfy all the constraints under those settings:

- **Minimum Skill Totals:**
  - $min\_Programming = 16$
  - $min\_Design = 16$
  - $min\_Math = 14$
  - $min\_Creativity = 12$
  - $min\_Science = 15$
- **Gender Diversity:** At least 1 females and 1 males: $min\_gen = 1$
- **Background Diversity:** At least two backgrounds per team: $min\_bg = 2$

Scenario 3: Skill Thresholds and Background Diversity (No Gender Constraint)

Scenario 3 maintains the same skill requirements as Scenario 1 and enforces background diversity, but it removes the gender constraints. The aim is to evaluate whether relaxing gender requirements affects the feasibility and composition of the resulting teams. Each team must consist of exactly five students and satisfy the constraints under those settings:

- **Minimum Skill Totals:**
  - $min\_Programming = 10$
  - $min\_Design = 10$
  - $min\_Math = 8$
  - $min\_Creativity = 6$
  - $min\_Science = 8$
- **Background Diversity:** At least two backgrounds per team: $min\_bg = 2$

By removing the gender constraint, this scenario allows us to test the flexibility of the model when only academic and skill-based diversity are prioritized.

Scenario 4: Full Diversity with Skill Thresholds

Scenario 4 enforces all fairness dimensions by combining skill thresholds, gender diversity, and academic background diversity. The constraints are equivalent to those in Scenario 1, but this scenario is designed to explicitly test the model's ability to enforce full diversity in a uniform and rigorous manner. Each team must consist of exactly five students and satisfy all the constraints under those settings:

- **Minimum Skill Totals:**
  - $min\_Programming = 10$
  - $min\_Design = 10$
  - $min\_Math = 8$
  - $min\_Creativity = 6$
  - $min\_Science = 8$
- **Gender Diversity:** At least 2 females and 2 males: $min\_gen = 2$
- **Background Diversity:** All the backgrounds in each team: $min\_bg = 3$

5.3. Performance

We evaluated our tool's performance across the four scenarios on the dataset of 50 students. Each scenario was tested in terms of feasibility (whether a valid team assignment could be found under the given constraints) and solver runtime. The results are summarized in Table 2.

Table 2. Performance of team formation in different scenarios.

Scenario	Feasible Solution	Solving Time (s)	Notes
Scenario 1	Yes	0.08	
Scenario 2	No	120.00	No solution found due to strict skill thresholds
Scenario 3	Yes	0.02	Same solution as in Scenario 1
Scenario 4	Yes	0.01	Same solution as in Scenario 1

Scenario 1, which includes skill thresholds, gender balance, and academic background diversity, produced a feasible solution in 80 milliseconds. **Scenario 3**, which removes the gender constraint, and **Scenario 4**, which enforces full diversity, also returned feasible solutions with faster runtimes of 20 ms and 10 ms, respectively. All three scenarios resulted in the *same team composition*, indicating that the team found in Scenario 1 already satisfied the relaxed constraints in Scenarios 3 and 4.

In contrast, **Scenario 2**, which applied stricter skill thresholds, did not yield a feasible solution. Even with a timeout set to 120 seconds, the solver was unable to find any valid team assignment. This demonstrates the model's sensitivity to constraint tightness and the importance of realistic skill thresholds when ensuring solvability.

5.4. Illustrative example of fair team formation

Our SMT-based team formation model was tested across four different scenarios using a synthetic dataset of 50 students. Because this evaluation relies on only a single dataset instance, the results should be understood as an illustrative example that demonstrates how the model responds to different constraint configurations—not as findings that can be broadly generalized.

In Scenarios 1, 3, and 4, the solver produced the same team composition, assigning exactly five students per team. Each of these teams met all the fairness criteria, including required totals for five skills (Programming, Design, Math, Creativity, and Science), balanced gender representation, and academic diversity with members from Arts, Engineering, and Science.

To provide a concrete example, Table 3 shows one of the teams generated under Scenario 1, which also satisfied the stricter constraints of Scenarios 3 and 4. Although the team composition remained unchanged, the computation time varied depending on the scenario's complexity: 80 milliseconds for Scenario 1, 20 milliseconds for Scenario 3 and 10 milliseconds for Scenario 4.

Table 3. Example of a fair team 10 generated in Scenarios 1, 3 and 4.

Member	Gender	Background	Prog.	Design	Math	Creat.	Sci.
Umar	Male	Engineering	5	2	5	1	4
Vera	Female	Art	1	5	1	5	1
Will	Male	Science	4	1	5	2	5
Xena	Female	Art	3	4	3	4	2
Yusuf	Male	Science	2	4	2	5	2
Total			**15**	**16**	**16**	**17**	**14**

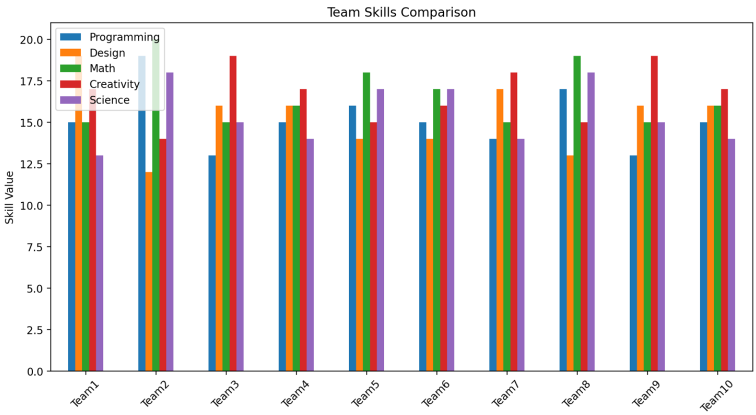

Figure 2. Team skills comparison across Scenarios 1, 2, and 4.

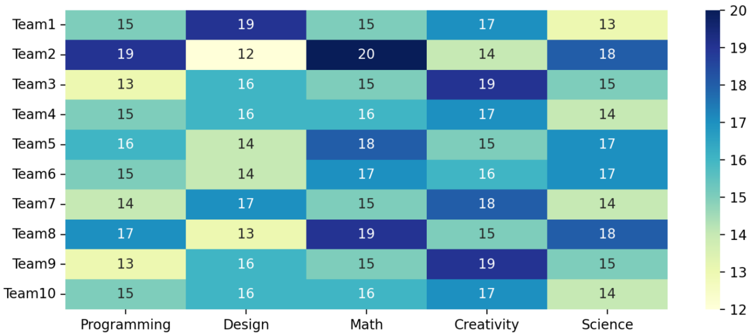

Figure 3. Heat map of individual skill contributions in the same team.

Figure 2 and Figure 3 present visual analyses of the generated teams: a total skill comparison chart and a heat map of individual skill contributions, respectively. These figures are identical across Scenarios 1, 3, and 4, as the solver produced the same team in each of these scenarious. The visuals confirm that the skill levels are well-balanced and fairly distributed within the team.

6. Conclusion and future work

This study introduced an automated and efficient framework for forming equitable student teams in STEAM education using Satisfiability Modulo Theories (SMT). By integrating diverse constraints such as team size, minimum skill levels, gender balance, and academic background diversity, our model ensures fair and well-rounded team formations. The use of an SMT solver allowed us to encode complex rules with clarity and generate satisfying teams in under a second, significantly reducing the manual effort typically required by educators. Our experiments demonstrated that the system consistently satisfied strict constraints and met diversity goals, making it a practical tool for real-world applications. A user-friendly web interface was also developed to support visualization of team assignments and constraint satisfaction. While the results are promising, the effectiveness of the system is closely tied to the quality of the input data. Inaccurate or incomplete student information can affect the fairness and balance of the resulting teams. Additionally, scalability may become a concern as dataset sizes and constraint complexity increase. Looking ahead, we plan to evaluate the framework on larger and more heterogeneous student datasets and explore customizable constraint weighting, enabling educators to prioritize specific fairness criteria based on their institutional goals.

These consistent outcomes across different configurations underscore the solver's capability to uphold fairness principles with minimal computational cost, demonstrating both its scalability and effectiveness.

Looking forward, we plan to extend the tool to accommodate larger and more heterogeneous student datasets. Future enhancements will include support for soft constraints with adjustable priority levels, allowing educators to tailor team formation preferences dynamically. Additionally, feedback from real-world classroom use will be incorporated to improve the system's usability, adaptability, and educational value.

Data availability

Researchers or educators interested in using the dataset for replication or educational purposes may contact the corresponding author Ali Adil Adil at ali.adil@inf.unideb.hu.

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A. Web application

To interact with our SMT-based team formation tool, users are first prompted to upload a dataset in '.json' format. The web interface, built using Streamlit, automatically validates the structure of the file to ensure it contains:

- A list of students, each with attributes like ID, name, gender, background, and skill ratings.
- A project requirements section specifying the team size and minimum required skills.

Once uploaded, the system checks for the presence of all required keys and values. If the dataset is valid, the solver begins processing, and the user is presented with:

- A summary of team sizes and total number of teams.
- Charts showing gender balance and skill distribution across all teams.
- A download button to export the results in Excel format.

This interactive design allows educators or administrators to quickly validate student team assignments and analyze team diversity before final implementation as shown in Figure 4, the interface provides a simple and intuitive way to upload and validate the dataset before team formation begins.

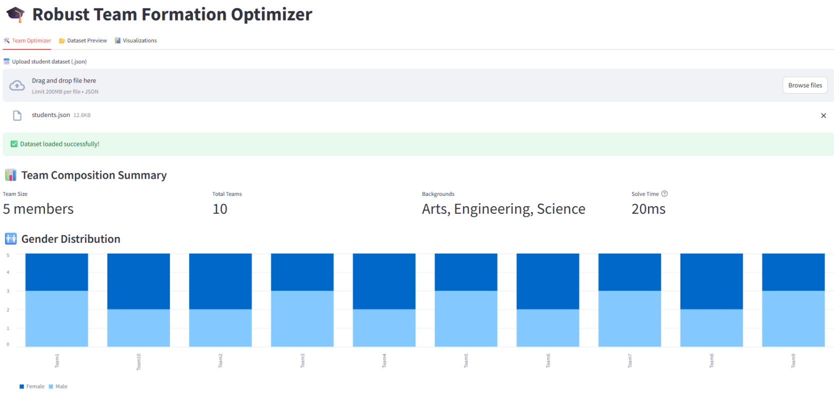

Figure 4. Interface view for dataset upload and validation.

The platform provides summary statistics and allows students to see which team they have been assigned to, as shown in Figure 5.

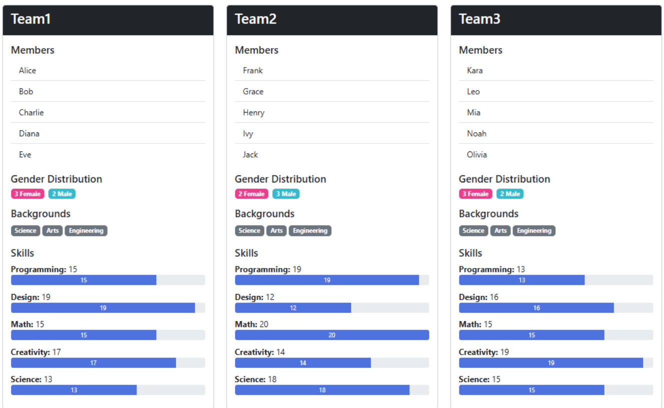

Figure 5. Web interface displaying team assignments and summary statistics.