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Linear Programming as a Tool for Managing the Training Process of Esports Teams

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Abstract

Background. Linear programming, with its ability to account for multiple constraints and optimize linear objective functions, is a promising tool for solving training planning tasks. This method enables the development of individualized plans tailored to the specific goals of each player and the team as a whole.

Objectives. This study aimed to develop linear programming variants for automating the planning process of esports teams' training schedules, enabling the allocation of workloads and determining the optimal distribution of time across various types of training while considering the individual characteristics of esports athletes, constraints, and diverse strategic goals.

Materials and methods. A comprehensive analysis of scientific, methodological, and specialized literature was conducted to ascertain the optimal use of resources, expert evaluation methods, linear programming, as well as statistical methods. Reliable statistical methods were employed: the dichotomous scale (results were processed using Cochran's Q concordance coefficient, which determined the consistency of expert opinions regarding each type of training); and the ratio scale (ranking) – the consistency of opinions was analyzed using Kendall's W concordance coefficient.

Results. An algorithm for determining the distribution of training workloads was proposed, which takes into account expert-defined ratios and constraints. To optimize the planning of the training process for esports teams, linear programming variants were developed, describing the distribution of time between different types of training as a linear programming task. Variant 1 serves for static time allocation between various training types without optimizing the distribution for specific goals. Variant 2 optimizes the time allocation, considering the individual characteristics of athletes and the strategic goals of the team. It incorporates constraints such as the total weekly training hours, the minimum required time for each type of training, and other limitations. The MS Excel Solver linear optimizer was used to find the optimal time distribution. Variant 2 facilitates the investigation of different scenarios for planning the training process of esports teams, demonstrating how the distribution of time across training types changes depending on set goals and preparation phases.

Conclusions. Based on the proposed algorithm, linear programming variants were developed, successfully addressing the task of automating the planning of esports team training. In contrast to Variant 1, Variant 2 offers an optimal distribution of time among different types of training (team training, individual training, physical activity sessions, etc.), considering the individual characteristics of players and the strategic goals of the team. It demonstrates high flexibility and adaptability to various esports disciplines, thereby allowing the investigation of different scenarios. The proposed approach can serve as a foundation for creating more advanced systems for managing the training process. Future research prospects include expanding the functionality of linear programming by incorporating additional factors such as psychological aspects, social dynamics within the team, and the physiological indicators of athletes.

Keywords: esports, management, training process, linear programming, workload, optimization.

Introduction

Esports, as one of the most dynamic sports disciplines, is characterized by rapid development and intense competition. However, despite significant progress, the training process for esports athletes still largely relies on the intuition of coaches and the individual experience of players, as noted by Chyzmar (2021) and Shynkaruk (2024). The lack of scientifically grounded methods that consider the individual characteristics of athletes and the fast-paced development of esports limits their potential and leads to inefficient use of time and resources. This inefficiency manifests in overtraining or undertraining, difficulty adapting to changes in the game, and decreased motivation.

The optimal distribution of training workloads is an important yet underexplored area of modern scientific research. One of the promising approaches is the use of linear programming. Linear programming enables the optimization of training programs, prediction of outcomes for various scenarios, and the creation of personalized training plans. The use of innovative tools based on linear programming will enhance the efficiency of planning the training process for esports athletes, ensure their sustainable development, and help achieve higher performance outcomes.

An analysis of recent studies and publications reveals that Bahrololloomi (2023), Nagorsky, and Wiemeyer (2020), and Novak et al. (2020) investigated phenomena and processes in sports, including esports, applying mathematical and statistical methods to confirm or refute hypotheses and identify new patterns. Several authors, including Shynkaruk et al. (2024), Byshevets et al. (2024), and Lazko et al. (2021), proposed predictive models and identified factors most influencing team victory.

Zhuk (2023) provides evidence of using mathematical modeling methods to develop simulation models aimed at improving the efficiency of detecting potentially suspicious match-fixing in football. According to Zhuk (2023), these methods can be adapted for identifying suspicious matches in other sports. Modeling issues have been addressed in works by Kostiukevych et al. (2023, 2024), Bezmylov (2024).

Chyzmar (2021) proposed a clear logic for formalizing the processes of esports development in Ukraine, revealing the basic mechanisms of the evolution of its subsystems (developers/publishers of games classified as esports disciplines, esports events, esports disciplines). This approach allows for assessing the impact of esports subsystems on the emergence of new communities and target formal groups and on diversifying esports disciplines.

Additionally, van Doornmalen (2023) and others highlighted the use of integer programming methods for tournament scheduling under a round-robin system, proposing solutions for cases of double round-robin systems where pairs meet twice in competitions.

A review of the scientific literature shows that existing mathematical models for optimizing the training process are often too complex for practical use in esports due to intricate mathematical apparatus and a focus on a narrow circle of specialists. This complexity arises from numerous formulas, abstract concepts, and the need for deep mathematical knowledge, as highlighted by Chyzmar (2023) and Shynkaruk et al. (2024).

On the other hand, Byshevets and co-authors (2020), as well as Hepler, Thangarajah, and Zizler (2016), demonstrate the successful application of linear programming methods using the MS Excel Solver optimizer in the training of specialists in physical culture and sports. Given the versatility and accessibility of this tool, we propose its use for solving similar tasks in esports. The MS Excel Solver allows for easy formulation of optimization problems in tabular form, parameter adjustments, and obtaining results in an understandable format. Furthermore, Techawiboonwong and Yenradee (2023) highlight that the linear programming algorithm employed by MS Excel Solver is well-studied and widely used in various fields, ensuring its reliability and efficiency. This approach enables coaches and athletes to independently create individual training plans without requiring specialized expertise, thereby simplifying the preparation process and increasing its effectiveness.

Despite significant progress in esports development, there remains a shortage of scientific research dedicated to creating individualized training plans that consider not only gaming skills but also the physical and psychological state of the athlete. While studies have been conducted on statistical data analysis and forecasting in esports, the potential of other mathematical methods, such as game theory, machine learning, and optimization, remains underexplored.

Linear programming, with its ability to account for multiple constraints and optimize linear objective functions, is a promising tool for solving training planning tasks. This method enables the development of individualized plans tailored to the specific goals of each player and the team as a whole.

The research hypothesis suggests that the application of linear programming using the MS Excel Solver optimizer will enable efficient planning of training workloads, potentially enhancing the performance of esports teams.

The purpose of the study was to develop linear programming variants for automating the planning process of esports teams' training schedules, enabling the allocation of workloads and determining the optimal distribution of time across various types of training while considering the individual characteristics of esports athletes, constraints, and diverse strategic goals.

Materials and Methods

Research Methods

The study involved a review and analysis of scientific, methodological, and specialized literature on the optimal use of resources, identifying the prospects for applying linear programming in the practice of esports.

Expert Evaluation

Expert evaluation played a key role in identifying the main types of training workloads in esports, their relative importance, and time constraints. This stage of the study involved professional esports athletes and specialists, providing a reliable foundation for further modeling and analysis.

Evaluation Parameters

The expert group consisted of 11 individuals: 7 professional esports athletes and 4 esports specialists. The experts provided assessments regarding the importance and duration of various types of training required for the development of both beginner and professional players. The evaluations were conducted based on two main criteria:

1. Selecting the most important types of training from the proposed options.
2. Assessing the relative importance of each type of training in the preparation process.

Evaluation Methods

Reliable statistical methods were employed to analyze the data obtained from the experts:

Dichotomous Scale

Experts assessed training types using "Yes" or "No" responses. For example, they were asked to select the three most important types of preparation for beginners from seven options. The results were processed using Cochran's Q concordance coefficient, which determined the consistency of the experts' opinions on each type of training.

Ratio Scale (Ranking)

Experts ranked different aspects of training preparation by their level of importance. The consistency of their opinions was analyzed using Kendall's W concordance coefficient, enabling the identification of the most prioritized aspects.

Results of the Expert Evaluation

The experts identified the main types of training as the most crucial for the development of esports athletes, including:

- Technical training (improving game mechanics).
- Tactical training (strategies and team coordination).
- Psychological preparation (resilience to stress).

Time constraints and priorities were also established for each type of preparation, forming the basis for constructing mathematical models. The collected data provided the foundation for developing training task programs and optimizing the allocation of time across different types of workloads in esports.

Linear Programming

Linear programming was employed to design and optimize training plans for esports athletes. This method enabled a structured analysis of training processes, taking into account constraints and numerous variables to ensure precise and efficient workload distribution (Shynkaruk, Byshevets, Serhienko, Yakovenko, & Usychenko, 2024). Two variants of linear programming were developed to address different levels of complexity:

Linear Algebraic Equations (3×3)

The simpler variant (1) focused on the basic components of training. It provided insights into the primary relationships and dependencies between variables in the training process. By simplifying the system to a 3×3 matrix, variant 1 clearly visualized the key factors affecting training outcomes and offered a framework for optimizing these components with minimal computational complexity.

Linear Algebraic Equations and Inequalities (7×7)

The more complex variant (2) incorporated a broader range of variables and constraints. These equations described the intricate structure of the training system, accounting for complex interrelations and dependencies. Expanding the system to a 7×7 matrix enabled the simultaneous evaluation of multiple training scenarios, considering both fixed parameters and adjustable constraints. The inclusion of inequalities provided flexibility for exploring various training approaches and allowed variant 2 to account for specific limitations, such as maximum available time or resource constraints.

Linear Programming Approach

Both variants were formulated as linear programming tasks aimed at the optimal allocation of resources and workloads. Linear programming systematically supported decision-making by ensuring compliance with all constraints and maximizing or minimizing a defined objective function, such as overall training efficiency or time utilization.

Implementation with MS Excel Solver

The linear programming variants were solved using the MS Excel Solver optimizer. This tool delivered efficient computations and visualization of optimal solutions within the set constraints. The Solver's functionality allowed researchers to explore various scenarios by adjusting parameters and constraints, dynamically enhancing training plans for esports athletes. The solutions provided practical recommendations on resource and time allocation across different training components to achieve strategic goals.

Statistical Analysis

To ensure the reliability of data obtained during the study, several methods of mathematical statistics were employed. These methods focused on assessing the consistency of expert opinions and the significance of the findings.

1. Cochran's Q Concordance Coefficient

Cochran's Q criterion was applied to evaluate data assessed on a dichotomous scale (e.g., "Yes" or "No"). The primary purpose was to determine the degree of agreement among expert assessments in tasks requiring the selection of the most important types of preparation from a predefined set. The Q formula accounts for the variability in expert choices and evaluates whether their assessments are random or consistent. The significance of the results was tested by comparing the computed Q value with the critical χ^2 value at a significance level of $\alpha = 0.05$.

2. Kendall's W Concordance Coefficient

Kendall's W coefficient was used to measure the consistency of expert opinions when ranking the importance of various preparation aspects. Unlike dichotomous assessments, Kendall W considers the order of importance assigned by each expert. The W value is calculated based on the deviation of individual rankings from the average ranking, which reflects the level of agreement among experts. A high W value indicates strong agreement. The significance of the results was also tested using the χ^2 criterion at $\alpha = 0.05$.

3. Statistical Verification

All concordance coefficients were subjected to significance testing to confirm their reliability. The χ^2 criterion was used to test the hypothesis of randomness or agreement in the results. Calculations were automatically performed using the Statistica software package. The statistical significance of the concordance results was tested using the χ^2 criterion at a significance level of $\alpha = 0.05$. This ensured the accuracy and reliability of the collected data. All calculations were performed using the Statistica software package (StatSoft, USA).

Results

Given the specifics of esports, planning training sessions with different focuses is a particularly complex task. Based on the results of a comprehensive review of scientific and methodological literature on optimizing various types of planning tasks under limited material and time resources, as well as personal experience, we believe that planning diversified training for esports athletes requires special attention.

We begin with a simplified problem of time allocation among various types of training for esports players at the initial stage of preparation. To mathematically describe the real system that represents the planning of esports athletes' training processes, experts identified the most effective training types necessary for successful mastery of an esports discipline by novice players. They also established the types of mathematical relationships (equations, inequalities) and interdependencies among these elements.

Below is an example illustrating the consistency of expert opinions regarding the most effective types of training for novice esports athletes and their weekly durations. In the first case, experts were asked to select the most effective training types for beginners in esports, and in the second case, to specify the number of hours needed for each type of training (Table 1).

Similarly, relationships between the types of training were identified, confirming the consistency of expert opinions ($p < 0.05$).

Then, the problem statement for **Variant 1** is as follows: In the esports training program for novice athletes, there are three types of training focuses: tactical, technical (game mechanics), and psychological. The coach plans to allocate a total of 15 hours to these three types of training as follows: the time allocated to tactical training should be twice that of technical training, and the time allocated to game mechanics training should exceed that of psychological training by 3 hours. How many hours should be allocated to each type of training?

Solution. To solve the problem, we formulated a linear programming variant as a system of linear algebraic equations. Let *x, y, z* represent the hours allocated to tactical, technical, and psychological training, respectively. Then, the SLAE describing the stated requirements is as follows:

$$\begin{cases} x + y + z = 15 \\ x = 2y \\ y = z - 3 \end{cases} \tag{1}$$

We can write the problem in the form of a system of linear algebraic equations (SLAE), ensuring that all unknown variables are on the left side of the equals sign and all constant terms are on the right side:

$$\begin{cases} \mathrm{x} + \mathrm{y} + \mathrm{z} = 15 \\ \mathrm{x} - 2\mathrm{y} \quad = 0 \\ \mathrm{y} - \mathrm{z} = -3 \end{cases} \tag{2}$$

Here:

x represents the hours allocated to tactical training.

y represents the hours allocated to technical training (game mechanics).

z represents the hours allocated to psychological training.

The system of linear equations can be written in matrix form as *AX* = *B*, where:

$$A = \begin{pmatrix} 1 & 1 & 1 \\ 1 & -2 & 0 \\ 0 & 1 & -1 \end{pmatrix}; \quad X = \begin{pmatrix} \mathrm{x} \\ \mathrm{y} \\ \mathrm{z} \end{pmatrix}; \; B = \begin{pmatrix} 15 \\ 0 \\ -3 \end{pmatrix} \tag{3}$$

Here:

A is the coefficient matrix.

Table 1. Determination of Linear Programming Variant Parameters

Training Focus	Expert Agreement (Focus Type) Q = 13.309; df = 6, p < 0.0384		Weekly Duration (Hours)	Expert Agreement (Duration) Q = 16.363; df = 6, p < 0.0119	
	No, %	Yes, %		No, %	Yes, %
Theoretical Training	54.5	45.5	5	81.8	18.2
Physical Training	45.5	54.5	10	90.9	9.1
Tactical Training	9.1	90.9	15	45.5	54.5
Game Mechanics (Technical Training)	-	100.0	20	90.9	9.1
Teamwork and Communication	45.5	54.5	25	100.0	-
Psychological Training	36.4	63.6	30	90.9	9.1
Self-Game Analysis	54.5	45.5	35	100.0	-

Note: Q – Cochran's concordance coefficient; df – degrees of freedom calculated as (n–1)(n-1)(n–1), where n is the number of evaluated objects; "No," "Yes" – percentage of experts who chose a specific response to a question

X is the column vector of unknowns (x, z).

B is the column vector of constants.

It should be noted that the elements of matrix A reflect the relationships between different types of training, while the elements of matrix B represent the constraints on the training load times. The main matrix of the system combined with the matrix of constants forms the augmented matrix of the system:

$$A^{\sim} = \left(\begin{array}{ccc|c} 1 & 1 & 1 & 15 \\ 1 & -2 & 0 & 0 \\ 0 & 1 & -1 & -3 \end{array}\right) \quad (4)$$

Let us solve the problem using the MS Excel Solver linear optimizer.

The key parameters for finding solutions are:

Constants – the augmented matrix of the SLAE.

Changing cells – the matrix X, which contains the unknown variables , representing the distribution of hours allocated to different types of training (for convenience, the matrix X is represented as a row rather than a column).

Objective function (OF) – the resulting indicator for which the linear optimizer selects the best values (it should be noted that in the absence of a predefined function to be optimized, any cell containing a formula can be used as the objective function).

Constraints – these are the conditions that must be considered during the optimization of the objective function.

Let us consider the algorithm for applying linear programming and the MS Excel Solver optimizer, adapted to our task, which will have the following structure (Fig. 1).

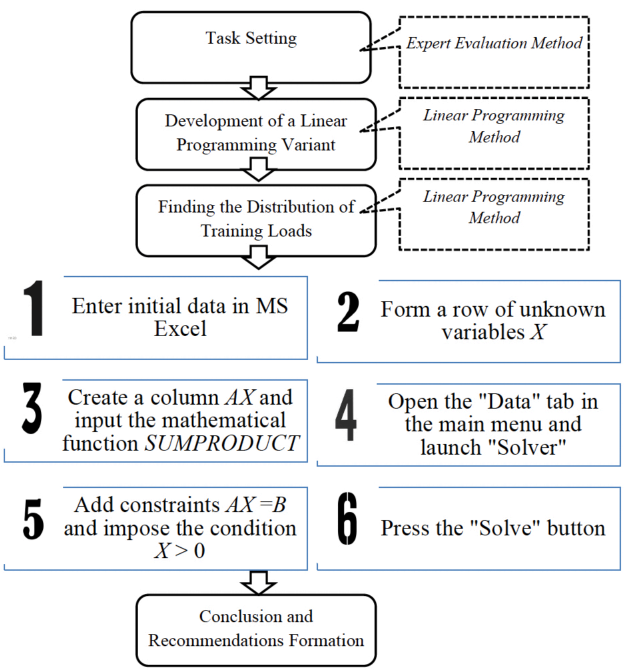

Fig. 1. Algorithm for Determining the Distribution of Training Loads Considering Expert-Defined Ratios and Constraints

The result of the training load distribution using MS Excel tools is presented in the figure (Fig. 2).

Thus, novice esports players at the initial stage of preparation should allocate 6 hours to tactical training,

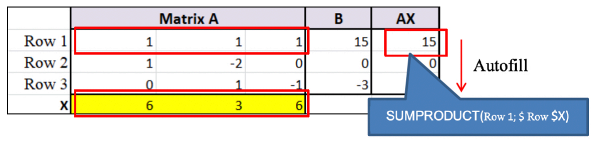

Fig. 2. Result of Training Load Distribution

3 hours to technical training (game mechanics), and 6 hours to psychological training. Using this approach, we were able to optimally distribute training time among various types of loads, considering all imposed constraints.

Let us consider a more complex scenario where various factors need to be taken into account and multiple indicators need to be optimized simultaneously.

We adapt the proposed algorithm for determining the distribution of training loads, taking into account the ratios and constraints identified by experts. It is important to emphasize that the parameters of the linear programming variant were also determined based on expert experience and the consistency of their opinions on each aspect of the training process considered in the variant. It should be noted that as the complexity of the planning task increases, changes will occur at step 5 of the training load distribution process. This step will be supplemented by step 6 – the introduction of an objective function, ensuring the optimal distribution of time for different types of training and allowing for the exploration of various scenarios.

Variant 2. A team of 5 esports athletes needs to distribute time and resources among various types of preparation to optimize their performance before an important tournament. Several key areas are involved in preparation: team training, individual training, match analysis, use of technical resources, working with the coach, psychological support, and recovery (physical activity sessions).

Solution. Let us define the following variables: x_1– time for team training (hours); x_2 – time for individual training (hours); x_3 – time for match analysis (hours); x_4 – use of technical resources (units); x_5 – time for working with the coach (hours); x_6 – time for psychological preparation (hours); x_7 – time for recovery through physical activity (hours).

The problem includes the following conditions and constraints:

Total time and resources are limited to 50 hours per week. Individual training should take 1.2 times more time than team training. Time for match analysis should be 5 hours more than time spent working with the coach. Psychological support should take 3 hours less than recovery. Technical resources should be proportional to the time spent on match analysis, with a coefficient of 0.8. Time spent on working with the coach and team training together should be at least 15 hours. Recovery time should not exceed 10 % of the total time.

Thus, the mathematical model of the problem is a system of 7 linear algebraic equations and inequalities.

As in the previous case, we will input the initial data and configure the necessary settings to obtain the solution using the Solver add-in. Specifically, we will:

Form the column AX: Use the SUMPRODUCT function to calculate the sum of the products of the rows of matrix A and the row of unknowns X.

$$\begin{cases} x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7 = 50 \\ x_2 = 1{,}2 \cdot x_1 \\ x_3 = x_5 + 5 \\ x_6 = x_7 - 3 \\ x_4 = 0{,}8 \cdot x_3 \\ x_1 + x_5 \geq 15 \\ x_7 \leq 0.1 \cdot 50 = 5 \end{cases} \Rightarrow \begin{cases} x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7 = 50 \\ -1{,}2x_1 + x_2 = 0 \\ x_3 - x_5 = 5 \\ x_6 - x_7 = -3 \\ -0{,}8x_3 + x_4 = 0 \\ x_1 + x_5 \geq 15 \\ x_7 \leq 5 \end{cases}$$

Apply the calculation to the entire column: Extend the formula to include all rows.

Step 5 adjustments (Figure 1) add the constraints to the Solver configuration:

$J$2:$J$5=$I$2:$I$5 (The first four components of the system are equations);

$J$6:$J$7>=$I$6:$I$7; $J$8<=$I$8 (The last three components are inequalities);

$B$9:$H$9>=1 (The esports athlete must complete all types of training);

$B$9: $H$9>= whole (The training time must be an integer).

These steps ensure the proper setup of the problem within MS Excel Solver to find an optimized solution based on the defined mathematical model and constraints. Click the "Find Solution" button to obtain the result (Fig. 3).

	A	B	C	D	E	F	G	H	I	J
1		Matrix A							B	AX
2	Row 1	1	1	1	1	1	1	1	50	50
3	Row 2	-1,2	1						0	0
4	Row 3			1		-1				
5	Row 4									
6	Row 5			-0,8	1				0	6
7	Row 6	1				1			15	16
8	Row 7							1	5	4
10	X	15	18	3	8	1	1	4		

SUMPRODUCT(B2:H2;$B$9:$H$9)

Fig. 3. Result of weekly training load planning for esports athletes

Thus, each player in the esports team should plan for 15 hours of team training, 18 hours of individual preparation, 3 hours for match analysis, 8 hours of training with technical resources, 1 hour for working with the coach, 1 hour for psychological preparation, and 4 hours for physical activity per week.

The proposed variant is based on linear programming methods and allows for the exploration of different training process scenarios, adjusting the balance between team and individual training, analyzing gameplay situations, physical activity sessions, and more. However, in real-world tasks, it is often the case that multiple competing objectives exist, requiring a compromise solution.

Therefore, in the process of planning training load durations, we can introduce an objective function that enables formalizing the set tasks and finding the optimal allocation of resources. Even if the basic variant has a single solution, introducing an objective function allows us to make it more flexible and adaptable to various scenarios. For example, we may aim to allocate more attention while balancing the duration of activities such as team and individual training and physical activity sessions. In this case, the objective function would take the following form:

$$Z = x_1 + x_2 + x_7 \rightarrow \max \tag{5}$$

It can be observed that the introduction of the objective function (OF) significantly altered the distribution of time among different types of training. Specifically, the time allocated for physical activity increased to 5 hours. With the time distribution shown in the row in the figure (Figure 4), the objective function will reach its maximum value of 38 hours allocated to the specified types of training. At the same time, the total weekly training duration remains unchanged at 50 hours.

	A	B	C	D	E	F	G	H	I	J
1		Matrix A							B	AX
2	Row 1	1	1	1	1	1	1	1	50	50
3	Row 2	-1,2	1						0	0
4	Row 3			1		-1			2	2
5	Row 4						1	-1	-3	-3
6	Row 5			-0,8	1				0	1
7	Row 6	1				1			15	17
8	Row 7							1	5	5
9	Z	1	1					1	OF	38
10	X	15	18	4	4	2	2	5		

Fig. 4. Result of optimizing weekly training load for esports athletes

Similarly, the coefficients in the objective function can be adjusted to observe how this affects the distribution of time allocated for training. This approach allows us to understand how sensitive the result is to changes in the input data (Fig. 5).

It should be noted that the constraints ensure the minimum inclusion of all types of loads, while the objective

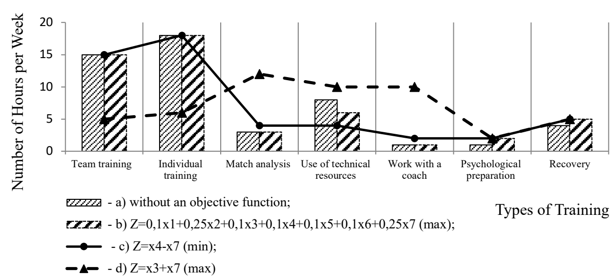

Fig. 5. Optimization of time allocation in the training process of esports athletes: comparison of different scenarios

function determines which types of loads are prioritized. The figure sequentially presents the following graphs:

Without an objective function – for distributing the training load volume under predefined conditions.

With an objective function, that maximizes the overall effect of the training process, prioritizing individual training and physical activity.

With an objective function aimed at minimizing the imbalance between time spent at the computer and physical activity to ensure balanced athlete development.

With an objective function, that shifts focus toward maximizing and balancing time spent on match analysis and physical activity while distributing other types of loads considering predefined constraints.

The proposed Variant 2 for allocating time to different types of training can be applied both to an esports team, taking into account the coach's objectives, and to individual players to address weaknesses and develop strengths.

Thus, the developed Variant 2 of linear programming, aimed at supporting decision-making in the planning of esports teams' training, is flexible and accommodates priority objectives, training phases, and the individual characteristics of each athlete.

Variant 2 enables the exploration of various training process scenarios and determines the optimal allocation of time among training types, considering the individual characteristics of players, constraints, and diverse strategic goals.

Discussion

The study revealed that potential applications of mathematical methods in esports include optimizing team composition, where the problem can be formulated as a system of linear equations with unknowns. The coefficients in these equations represent the effectiveness of each player for a specific role. Moreover, this approach opens avenues for an in-depth analysis of game data, where systems of linear algebraic equations (SLAE) can be effectively employed to determine relationships between various game parameters (e.g., the number of opponents defeated, deaths, assists) and match outcomes. It has also been demonstrated that linear programming can be successfully applied to strategy development by representing different game scenarios as SLAEs, with the unknowns being the optimal actions of the players.

The findings from this study highlight the versatility of linear programming for solving planning tasks in esports training processes. The proposed approach to workload distribution allows for easy adjustments of task conditions and facilitates the exploration of various scenarios depending on set objectives, making it a practical tool for esports.

An algorithm for distributing training workloads was proposed, taking into account expert-defined proportions and constraints. This algorithm is flexible and can be adapted to address a variety of planning tasks in esports training.

Two linear programming variants were developed to model the training process of esports players, describing the allocation of time across different types of training while considering established constraints, such as the total number of training hours per week. Using the simplex method of linear programming, implemented via the MS Excel Solver add-in, an optimal allocation of time that best aligned with set objectives was determined in each case.

Further programming, involving adjustments to the weighting criteria for training duration in the objective function of Variant 2, enabled an examination of how priority changes affect the optimal time distribution among different types of training.

The results align with the findings of Matos et al. (2022), Techawiboonwong, Yenradee (2023), and Yang et al. (2024). For instance, Techawiboonwong and Yenradee (2023) outlined an algorithm for developing an optimal aggregate production plan that includes data collection, problem formulation, solution determination using the MS Excel Solver add-in, solution evaluation, and implementation in production. This approach demonstrated effectiveness in project planning, particularly in scheduling tasks to achieve minimum total project costs. Our findings extend and validate the work of Valenko and Klanšek (2017), who proposed addressing project time optimization problems using the MS Excel Solver add-in, with subsequent data transfer to MS Project for further management and presentation of optimized time planning solutions.

Authors such as Alexander, Le, Tsiango (2018), and Minami et al. (2024) share the view, which we fully support, that implementing linear programming in well-known software environments enhances its practical applicability.

Summarizing the data from scientific and methodological literature and our own positive experience in applying linear programming in physical education and sports (Byshevets et al., 2020; Shynkaruk, Lut, Pinchuk, Vasyliyev, 2024), we proposed employing a similar approach to address practical challenges in esports. Our previous research demonstrated the effectiveness of using linear programming with the MS Excel Solver in decision-making for esports management (Shynkaruk et al., 2024), enabling continued exploration in this area.

Conclusions

Linear programming enables the consideration of multiple constraints, such as time, resources, and players' physical capabilities, which are inherent to the challenges of planning training regimens for esports athletes. The use of the MS Excel Solver add-in automates the search for an optimal training time allocation plan, allowing esports coaches and players to make scientifically informed decisions regarding training schedules, thereby enhancing their overall efficiency.

Based on the proposed algorithm, linear programming variants have been developed that successfully address the automation of training plan optimization for esports teams. Unlike Variant 1, Variant 2 provides an optimal distribution of time across different types of training (team training, individual training, physical activity sessions, etc.), taking into account the individual characteristics of athletes and the strategic goals of the team. It demonstrates high flexibility and adaptability to various esports disciplines and allows for the exploration of different scenarios. The proposed approach can serve as a foundation for the creation of more complex systems for managing the training process.

This study clearly illustrates how linear programming methods can be utilized to substantiate training plans, paving the way for new opportunities to improve the preparation of esports athletes.

Conflict of Interests

The authors state that there is no conflict of interests.

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Лінійне програмування як засіб управління тренувальним процесом команд в кіберспорті

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Авторський вклад: A – дизайн дослідження; B – збір даних; C – статаналіз; D – підготовка рукопису; E – збір коштів

Реферат. Стаття: 10 с., 1 табл., 5 рис., 23 джерела.

Історія питання. Лінійне програмування, завдяки своїй здатності враховувати множинні обмеження та оптимізувати лінійні цільові функції, є перспективним інструментом для вирішення задач планування тренувань. Цей метод дозволяє розробляти індивідуальні плани, які відповідають конкретним цілям кожного гравця та команди в цілому.

Мета. Розробити варіанти лінійного програмування для автоматизації процесу планування тренувального процесу кіберспортивних команд, які дозволять розподіляти навантаження та знаходити оптимальний розподіл часу між різними видами тренувань з урахуванням індивідуальних особливостей кіберспортсменів, обмежень та різних стратегічних цілей.

Матеріали і методи. Аналіз науково-методичної та спеціальної літератури з питань оптимального використання ресурсів, методи експертних оцінок, лінійного програмування, статистичні методи. Застосовувалися надійні статистичні методи: дихотомічна шкала (результати оброблялися за допомогою коефіцієнта конкордації Кохрана (Q), який визначав узгодженість думок експертів щодо кожного виду тренувань); шкала відносин (ранжування) - узгодженість думок аналізували за допомогою коефіцієнта конкордації Кендалла (W).

Результати. Запропоновано алгоритм знаходження розподілу тренувальних навантажень, який передбачає урахування визначених експертами співвідношень і обмежень. Для оптимізації планування тренувального процесу кіберспортивної команди розроблено варіанти лінійного програмування, які описують розподіл часу між різними видами тренувань як задачу лінійного програмування. Варіант 1 слугує для статичного розподілу часу між різними видами тренувань, не оптимізуючи цей розподіл під конкретні цілі. Варіант 2 оптимізує розподіл часу, враховуючи індивідуальні характеристики спортсменів та стратегічні цілі команди. Він враховує такі обмеження як загальна кількість годин тренувань на тиждень, необхідний мінімальний час на кожен вид тренування та інші обмеження. Для пошуку оптимального розподілу часу було використано лінійний оптимізатор MS Excel Розв'язувач. Варіант 2 дозволяє досліджувати різні сценарії планування тренувального процесу кіберспортивної команди, демонструючи, як змінюється розподіл часу на види тренувань залежно від поставлених цілей та фази підготовки.

Висновки. На основі запропонованого алгоритму розроблено варіанти лінійного програмування, які успішно вирішують завдання автоматизації планування тренувань кіберспортивних команд. На відміну від варіанту 1, варіант 2 пропонує оптимальний розподіл часу між різними видами тренувань (командні тренування, індивідуальні тренування, заняття руховою активністю тощо) з урахуванням індивідуальних особливостей спортсменів та стратегічних цілей команди. Він демонструє високу гнучкість та адаптивність до різних дисциплін кіберспорту і дозволяє досліджувати різні сценарії. Запропонований підхід може бути використаний як основа для створення більш складних систем управління тренувальним процесом. Перспективами подальших досліджень є розширення функціоналу лінійного програмування шляхом включення додаткових факторів, таких як психологічні аспекти, соціальна динаміка в команді та фізіологічні показники спортсменів.

Ключові слова: кіберспорт, управління, тренувальний процес, лінійне програмування, навантаження, оптимізація.

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