A Comparative Analysis of Mathematical and Industrial Approaches for Sublevel Caving Long-Term Production Scheduling Optimization

Soroush Khazaei[1] and Yashar Pourrahimian[2]

[1,2] School of Mining and Petroleum Engineering, University of Alberta, Edmonton, Canada

ABSTRACT

Efficient production scheduling is critical for optimizing the performance and profitability of sublevel caving (SLC) mining operations. This paper presents a comprehensive comparative analysis of mathematical and industrial SLC long-term production scheduling approaches, utilizing a mixed-integer linear programming (MILP) optimization model and the GEMS/PCSLC software. The MILP model incorporates various operational constraints, including the maximum number of active levels, continuous mining, mining and processing capacities, vertical and horizontal precedencies, and grade blending, ensuring a robust and realistic representation of the SLC mining method. The model's primary objective is to maximize the net present value (NPV) of the mining project. The formulations are developed, implemented, and verified in the Jupyter Notebook environment and solved using the CPLEX Python API. The production scheduler aims to maximize the NPV of the mining operation while it has control over defined constraints. To benchmark and validate the performance of the MILP model, Production Control System for Sublevel Caving (PCSLC)- the only available software designed for SLC production scheduling- has been employed. By applying different mining directions and strategies to the MILP model and PCSLC, this study provides an in-depth understanding of the project's income over the mine's life. Application and comparison of the models for production scheduling using 541 mining units over 22 periods are presented. The comparative analysis demonstrates the mathematical model's efficiency in optimizing production scheduling and highlights potential improvements in decision-making processes for SLC mining operations. The findings underscore the advantages of the mathematical model to enhance the economic outcomes of sublevel caving projects.

1. Introduction

The sublevel caving (SLC) mining method involves blasting all material for extraction, unlike block cave mining which relies on natural fragmentation through gravity and stresses. This necessitates a systematic network of tunnels due to the blasting requirement [1, 2]. A significant challenge in SLC project design is to create an accurate scheduling plan that considers the complexities of SLC mining, such as cave initiation and propagation, minimizing dilution, and preventing undermining. Conventional mathematical models often struggle to model these aspects effectively [3].

The complexities and technological advancements inherent to SLC necessitate comprehensive mine planning approaches that optimize SLC operation's performance and encompass critical SLC mine

ISBN: 978-1-55195-520-9

components. A robust SLC mine plan integrates all technical facets strategically, with production scheduling playing a pivotal role in determining the most cost-effective mining sequence over the mine's life [4].

Underground production scheduling involves discrete and continuous decisions regarding extraction location, timing, mining unit allocation over the mine's life, and vertical and horizontal precedence relationships [5]. The objective of a production schedule is to optimize the extraction sequence to meet market specifications efficiently while satisfying operational constraints and demand requirements [6]. Mathematical programming models offer precise algorithms that can optimize multi-time-period schedules operationally, providing superior alternatives to manual and heuristic methods [7]. In SLC scheduling, the MILP models are effective in capturing both the continuous and discrete nature of decision variables, ensuring a detailed and accurate approach to managing the complexities of sublevel caving operations [8].

The GEMS/PCSLC software is specifically designed for sublevel caving projects, making it the only commercial scheduling software for this type of mining operation. The PCSLC module employs powerful engines to optimize the production scheduling of SLC operations. This software ensures that the extraction sequence is efficient and meets operational and market requirements. By leveraging advanced algorithms, the PCSLC module enhances the ability to plan and execute complex mining schedules, reducing the reliance on traditional manual and heuristic approaches. This makes PCSLC an invaluable tool for mining engineers seeking to maximize productivity and operational efficiency in SLC projects [2, 9].

This paper introduces a comparative analysis of long-term SLC production scheduling using both theoretical and industrial approaches. In the theoretical part, the MILP method is employed, which is powerful as a deterministic approach to finding the optimal solution and maximizing the NPV of the entire operation. PCSLC software is used as a benchmark to validate the developed mathematical model. This dual approach is highly beneficial for analyzing the results of both methods, gaining insights into SLC mining aspects, and understanding industry practices.

2. Summary of Literature Review

Sublevel caving is a widely used underground mining method known for its high production rates and operational flexibility. Recent research highlights the application of advanced mathematical programming models, particularly mixed-integer programming (MIP), to optimize production scheduling in sublevel caving. These models address unique challenges such as material flow complexity and ore-waste mixing during blasting. Studies by Khazaei and Pourrahimian [10] and Shenavar et al [11, 12] emphasize maximizing net present value (NPV) through refined technical constraints and block model processing.

Innovative tools and algorithms have also been developed to enhance scheduling efficiency. Villa and Diering [13] introduced an application for planning sublevel caving projects, focusing on ore recovery and dilution modeling, while Diering and Breed [14] developed the Footprint Finder tool for rapid layout evaluation and draw factor optimization. Case studies, particularly at LKAB's Kiruna Mine, demonstrate the practical benefits of these approaches, with research by Kuchta, Newman, and

Topal [15], Newman et al. [16], and Martinez and Newman [17] showcasing significant cost savings and improved production target adherence. Overall, integrating advanced mathematical models and innovative tools is crucial for optimizing sublevel caving production scheduling, promising enhanced efficiency and economic outcomes.

While all mentioned studies have explored methods to present SLC production scheduling, few have explicitly validated their developed models against real-world data. These studies have primarily focused on developing and optimizing mathematical models rather than validating them through practical application in mining operations. In this study, the PCSLC is leveraged to create the input data for the MILP model. A comparative analysis of both the model and PCSLC schedules is then conducted to evaluate the capabilities and advantages of using the model in real-world SLC scenarios. This approach aims to bridge the gap between theoretical model development and practical application, providing a robust validation of the scheduling models in operational environments.

3. Problem Statement

Manual planning methods and heuristic algorithms in commercial software often fail to ensure optimal production schedules for sublevel caving (SLC) mines. Although mathematical models for SLC optimization have been developed to address these issues, previous studies primarily focus on production sequencing without incorporating a validation process. This gap limits the reliability of these models for real-world mining applications.

This study aims to bridge this gap by developing an SLC scheduling model that optimizes the extraction sequence while meeting the head grade requirements of the processing plant. The model captures all complexities of SLC operations, including cave propagation control and undermining prevention. The goal is to generate a strategic long-term production schedule that maximizes net present value (NPV) while addressing all operational and technical constraints. These constraints include mining and processing capacities, continuous extraction, the number of active levels in each period, grade blending, and the sequencing of mining units.

To achieve this, PCSLC (Production Control System for Sublevel Caving) has been utilized to create the input data for the Mixed-Integer Linear Programming (MILP) model. A comparative analysis has been conducted between the MILP model and PCSLC schedules to evaluate the capabilities and advantages of the MILP model in real-world SLC scenarios. This approach aims to validate the model's effectiveness in practical applications, enhancing SLC operations' overall efficiency and economic viability. Through this validation, the study seeks to provide a robust and reliable framework for optimizing SLC production schedules in actual mining environments.

4. Methodology

This paper introduces a comprehensive MILP model for long-term production scheduling in SLC mines. The model includes all facets of mining operations, focusing on providing optimal production schedules while efficiently addressing all technical and operational constraints. The employment of MILP as a precise algorithm enables the determination of maximum NPV and optimal mining sequences.

The study includes a rigorous verification and validation process. The verification step involves calibrating the model on a small-scale SLC case to ensure that constraints such as mining and processing plant capacities, continuous mining, the number of active levels, and vertical and horizontal precedencies are functioning correctly. It also involves analyzing NPV for different gap tolerance values to assess financial impacts and conducting sensitivity analysis by varying key parameters to confirm the model's robustness under different scenarios and assumptions.

Following verification, the validation process involves comparing the MILP model schedules with those generated by the PCSLC. This comparative analysis evaluates the capabilities and advantages of the MILP model in real-world SLC scenarios. This approach aims to validate the model's effectiveness, improve the efficiency and profitability of SLC operations, and provide a reliable framework for optimizing production schedules in real mining environments. The methodology and workflow, including the steps for model development, verification, and validation, is illustrated in Figure 1.

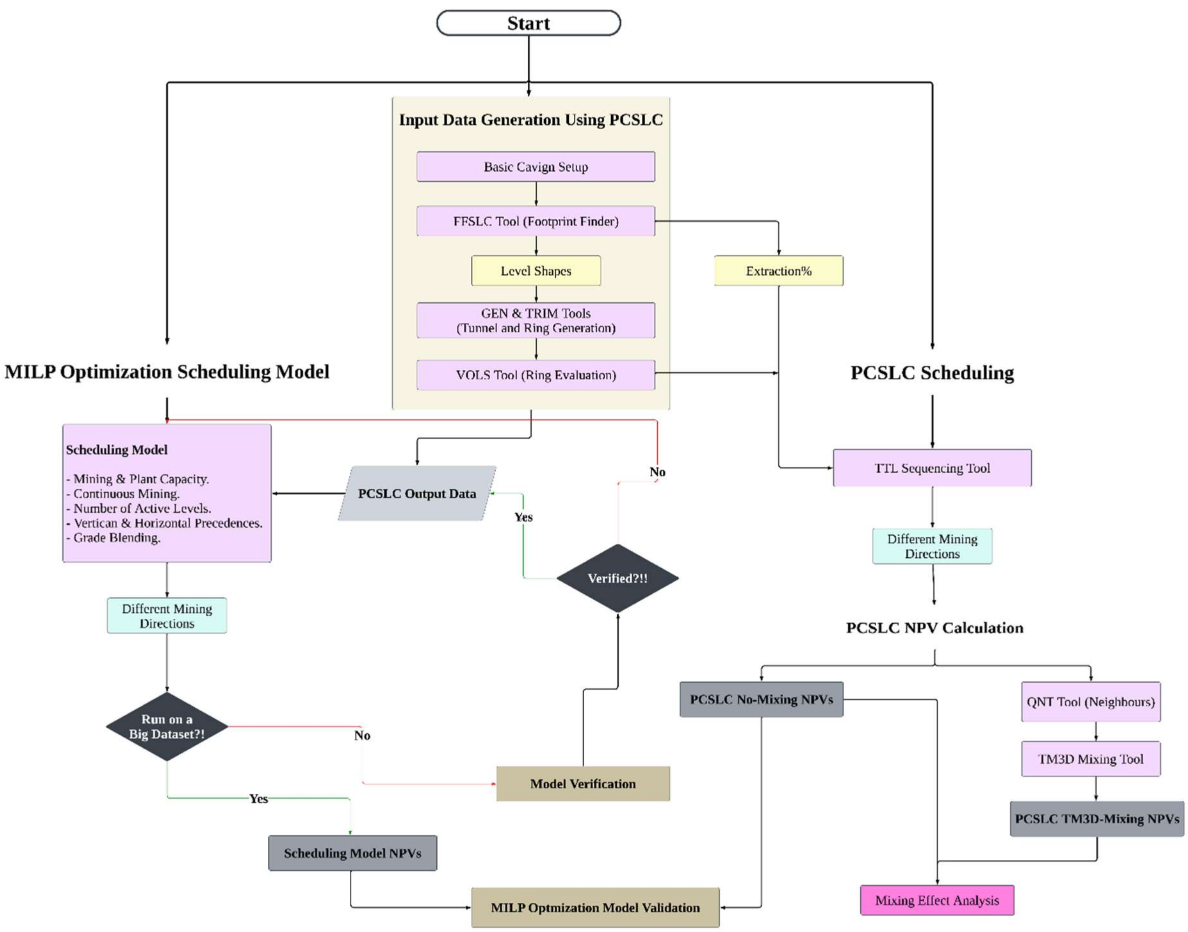

Figure 1. The workflow of the research.

4.1. Key Terminology

Production drift: A horizontal underground excavation serves as a primary pathway for ore extraction and transporting mined ore from the mining unit to the orepasses through a perimeter drift that connects several production drifts within a specific production area and level (see Figure 2).

Ring: A production ring is the quantity of the in-situ ore that will be fired at any one time by a blasted ring (see Figure 2).

Mining unit: A mining unit is where the Load-Haul-Dump unit (LHD) operates, which contains one production drift and several production rings along that drift (see Figure 2).

Level (or sublevel): Levels represent the successive horizontal sublevels situated at different depths, including multiple production drifts driven along the orebody's strike. The sublevel height is generally measured as the vertical floor-to-floor distance between the levels (see Figure 2).

Both mining units and rings consist of attributes like coordination, tonnage, grade, percentage of dilution, and economic data. The model determines which mining unit starts being mined in each period over the horizon to maximize the NPV. Furthermore, the model satisfies constraints such as development activities, mining, stockpile inventory management, processing capacities, continuous mining of scheduling units, restrictions on the allowable number of active production faces, grade blending, and vertical and horizontal sequencing.

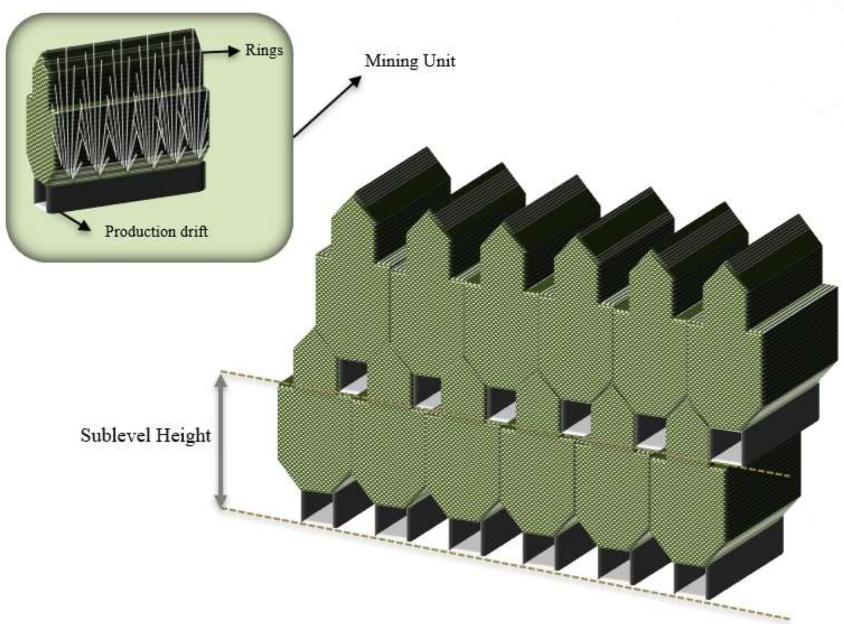

Figure 2. Typical view of mining unit, production ring, and sublevel in an SLC mine.

4.2. GEMS/PCSLC Scheduling

The Geovia GEMS software, especially the PCSLC module, was employed to prepare the input data for the model by generating tunnels and rings [18]. This process ensures that all quantitative parameters like tonnage, grade, and density are transferred from the block model level to the MU level. Figure 3 illustrates all the steps from data preparation to scheduling in the software.

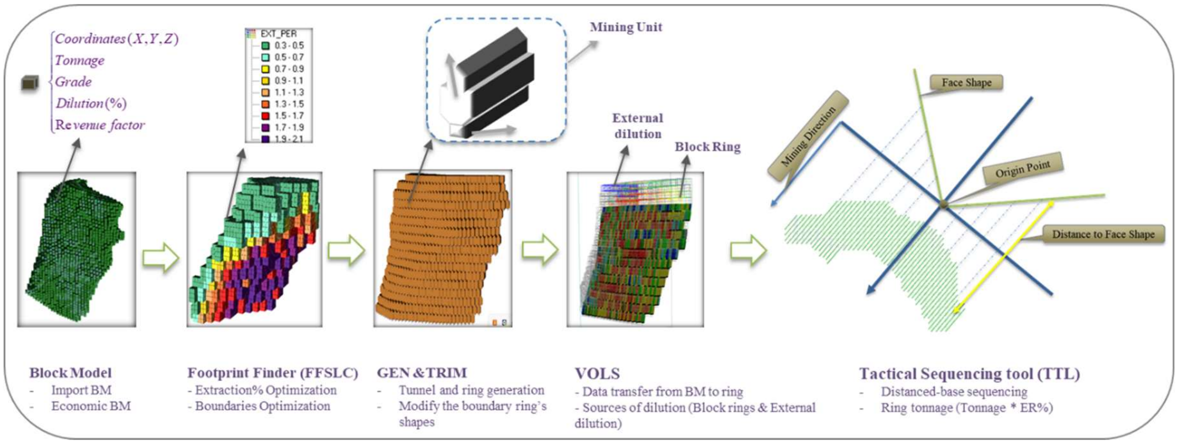

Figure 3. All steps from data preparation to scheduling in GEMS/PCSLC.

4.3. Mathematical Model Scheduling

The scheduling MILP model aims to provide a production schedule that represents the various limitations of an SLC operation. This includes constraints on mining and processing plant capacities, meeting the processing plant's head grade requirements common among all mathematical scheduling models, and SLC-specific constraints. These constraints involve controlling the continuity of mining unit extraction due to the nature of caving, determining the number of active levels to manage cave propagation, imposing the vertical and horizontal precedence rules to manage the lead-lag rules between adjacent mining units and the units in the levels above to prevent undermining and minimize the impact of stress and explosive damage on neighbouring units.

Continuous decision variables track development activities and mined material for each mining unit in each period, while binary variables govern the starting extraction time of mining units and whether a mining unit is being mined in a specific period.

The SLC production scheduling formulation involves defining sets, parameters, and decision variables for V production areas, L levels, and M mining units to be mined over T periods.

4.4. Indices

$m = \{1, 2, ..., M\}$ Index for mining units, where M is the total number of MUs.

$l = \{1, 2, ..., L\}$ Index for levels, where L is the total number of levels.

$t = \{1, 2, ..., T\}$ Index for periods, where T is the scheduled time horizon.

4.5. Sets

S_{M_l} Set of MUs in all production areas on the level l.

$S^{V}_{M_m}$ Set of MUs whose start period is restricted vertically by MU m.

$S^{H}_{M_m}$ Set of MUs whose start period is forced by adjacency to MU m.

4.6. **Parameters**

P	Profit (Selling price minus selling cost) per ton of metal ($/ton).
C^P	Processing cost per ton of ore material ($/ton).
C^M	Mining cost per ton of ore material ($/ton).
δ^t	Discount factor at period t.
o_m	Ore tonnage in mining unit m.
M_m	Metal obtained after mining and processing mining unit m (ton).
$\underline{Q_m^t}$	Lower bound on mining capacity at period t.
$\overline{Q_m^t}$	Upper bound on mining capacity at period t.
$\underline{Q_p^t}$	Lower bound on ore processing capacity at period t.
$\overline{Q_p^t}$	Upper bound on ore processing capacity at period t.
$\underline{g_p^t}$	Lower bound on an acceptable average grade by processing plant at period t.
$\overline{g_p^t}$	Upper bound on an acceptable average grade by processing plant at period t.
n_l	Number of mining units at the level l.

4.7. Decision Variables

$x_m^t \in [0,1]$	Continuous variable represents the mining unit's portion to be mined at period t.
$x_{m,p}^t \in [0,1]$	Continuous variable represents the portion of mining unit m sent directly to the processing plant at period t.
$bs_m^t \in \{0,1\}$	Binary integer variable equals one if extraction of the mining unit m is started at period t; otherwise, it is zero.
$as_m^t \in \{0,1\}$	Binary integer variable equals one if the mining unit m is active at period t otherwise, it is zero.

4.8. Objective Function

The optimization model maximizes the NPV of caving operations in Eq. (1), subtracting the cost of all development activities from the revenue obtained from ore extraction.

$$Max \sum_{t=1}^{T} \delta_t \left[P(\sum_{m=1}^{M} M_m \times x_{m,p}^t) - C^P (\sum_{m=1}^{M} O_m \times x_{m,p}^t) - C^M \sum_{m=1}^{M} O_m \times x_m^t \right] \tag{1}$$

4.9. Mining and Processing Capacity

Eq. (2) enforces the mining capacity, using continuous decision variable x_m^t, between the acceptable lower and upper limits of the total available equipment capacity in each period. Eq. (3) controls the quantity of mill feed using continuous decision variable $x_{m,p}^t$.

$$\underline{Q_m^t} \leq \sum_{m=1}^{M}\left[(o_m \times x_m^t)\right] \leq \overline{Q_m^t} \qquad \forall t \in \{1,2,...,T\} \tag{2}$$

$$\underline{Q_p^t} \leq \sum_{m=1}^{M}\left[(o_m \times x_{m,p}^t)\right] \leq \overline{Q_p^t} \qquad \forall t \in \{1,2,...,T\} \tag{3}$$

4.10. Active Number of Levels

Eq. (4) to Eq. (6) determine the number of active levels (λ^t) which is controlled by adding the decision variables L_l^t. This is critical for effective cave initiation and propagation. Multiple levels help redistribute stress, promote consistent caving, and ensure smooth ore flow, reducing blockages and hang-ups. They also improve ore recovery, minimize dilution, and manage subsidence more evenly, enhancing overall safety and operational flexibility. This balance ensures successful and efficient SLC operations.

$$(1/n_l) \times \sum_{m \in S_{M_l}} as_m^t \leq L_l^t \qquad \forall l \in \{1,2,...,L\}, t \in \{1,2,...,T\} \tag{4}$$

$$\sum_{m \in S_{M_l}} as_m^t \geq L_l^t \qquad \forall l \in \{1,2,...,L\}, t \in \{1,2,...,T\} \tag{5}$$

$$\sum_{l=1}^{L} L_l^t \leq \lambda^t \qquad \forall t \in \{1,2,...,T\} \tag{6}$$

4.11. Continuous Mining Constraints

Each mining unit must be continuously extracted after opening until closing. Eq. (7) forces variable as_m^t to be zero if no portion of the mining unit m is extracted at period t, while Eq. (8) changes the value as_m^t to 1 when a portion of the mining unit m is extracted at period t. Eq. (9) ensures that if extraction from the mining unit m is started during or after period two, at least a portion of the mining unit is extracted until all of the material within that mining unit has been extracted; otherwise, the mining unit must be closed. Eq. (10) ensures that if extraction from the mining unit m is started in period one, the related variable as_m^t for the mining unit is equal to 1.

$$as_m^t \leq M \times x_m^t \qquad \forall t \in \{1,2,...,T\}, m \in \{1,2,...,M\} \tag{7}$$

$$x_m^t \leq as_m^t \qquad \forall t \in \{1,2,...,T\}, m \in \{1,2,...,M\} \tag{8}$$

$$as_m^t - as_m^{t-1} \leq bs_m^t \qquad \forall m \in \{1,2,...,M\}, t \in \{2,...,T\} \tag{9}$$

$$as_m^1 - bs_m^1 \leq 0.5 \qquad \forall m \in \{1,2,...,M\} \tag{10}$$

4.12. Processing Plant Grade Control Constraint

Eq. (11) meets the ore quality specification of the processing plant within the predefined limits.

$$\underline{g_p^t} \leq \frac{\sum_{m=1}^{M} M_m \times x_{m,p}^t}{\sum_{m=1}^{M} O_m \times x_{m,p}^t} \leq \overline{g_p^t} \qquad \forall t \in \{1,2,...,T\} \tag{11}$$

4.13. Vertical and Horizontal Sequencing Constraints

In SLC mining, strict operational rules govern ore extraction. According to Figure 4, vertical sequencing mandates that MU10 extraction begins only after MU6 and MU7 reach a specified extraction percentage. Additionally, horizontal sequencing dictates that MU10 extraction starts after MU9 sufficiently retreats past its neighbouring level.

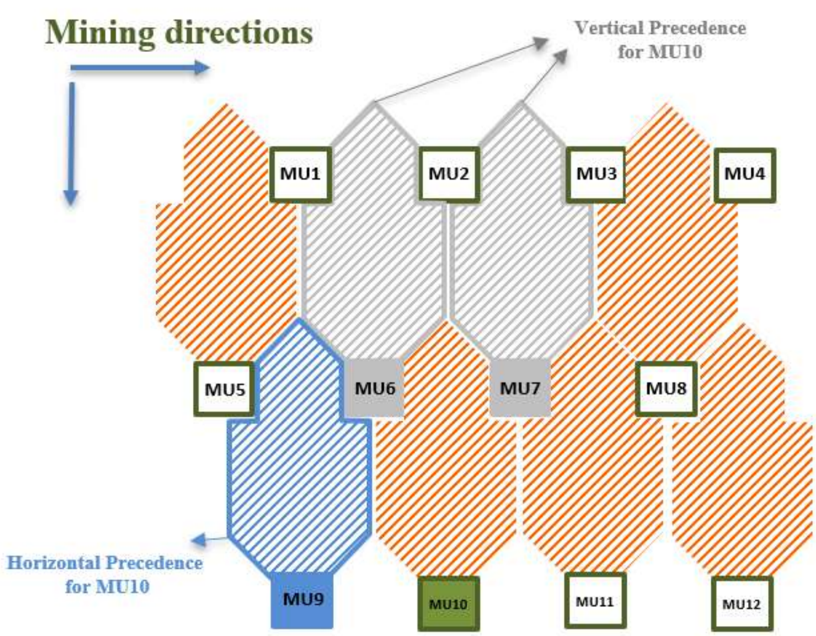

Figure 4. A vertical cross-section of eight MUs in two sublevels.

Eq. (12) and (13) ensure vertical and horizontal sequencing between mining units in the long-term resolution. Vertical and horizontal precedencies and required extraction percentages for predecessor MUs enforce these operational rules. Eq. (14) and (15) ensure that mining operations in both the MU and its precedencies occur, with production in precedencies ahead of the MU. Eq. (16) and (17) prevent further mining of horizontal and vertical precedence positioned at the upper level and the back of mining unit m once extraction in mining unit m is completed. This prevents re-mining precedencies due to caving propagation. Eq. (18) encourages extracting the maximum feasible quantity from mining unit m in each period to minimize vehicle relocation and improve ore blending.

$$bs_m^t - \sum_{t'=1}^{t} x_{m'}^{t'} \le \delta_m \% \qquad \forall m \in \{1,2,...,M\}, t \in \{1,2,...,T\}, \forall m' \in S_{M_m}^V \tag{12}$$

$$bs_m^t - \sum_{t'=1}^{t} x_{m'}^{t'} \le \delta_m \% \qquad \forall m \in \{1,2,...,M\}, t \in \{1,2,...,T\}, \forall m' \in S_{M_m}^H \tag{13}$$

$$\sum_{t' \le t} x_{m'}^{t'} - \sum_{t' \le t} x_m^{t'} \ge as_{m'}^t + as_m^t - 2 \qquad \forall m \in \{1,2,...,M\}, t \in \{1,2,...,T\}, \forall m' \in S_{M_m}^V \tag{14}$$

$$\sum_{t' \le t} x_{m'}^{t'} - \sum_{t' \le t} x_m^{t'} \ge as_{m'}^t + as_m^t - 2 \qquad \forall m \in \{1,2,...,M\}, t \in \{1,2,...,T\}, \forall m' \in S_{M_m}^H \tag{15}$$

$$(as_m^{t+1} - as_m^t) + 1 \ge as_{m'}^{t+1} \qquad \forall m \in \{1,2,...,M\}, t \in \{1,2,...,T-1\}, \forall m' \in S_{M_m}^V \tag{16}$$

$$(as_m^{t+1} - as_m^t) + 1 \ge as_{m'}^{t+1} \qquad \forall m \in \{1,2,...,M\}, t \in \{1,2,...,T-1\}, \forall m' \in S_{M_m}^H \tag{17}$$

$$x_m^t - x_m^{t+1} \ge 1 - as_m^t \qquad \forall m \in \{1,2,...,M\}, t \in \{1,2,...,T-1\} \tag{18}$$

4.14. Variable Control Constraints

Eq. (19) enforces the extracted material from each mining unit to be sent to the processing plant in each period. Eq. (20) to Eq. (21) ensure that the total fraction of material mined and sent to the processing plant is less than one over the scheduling periods. Eq. (22) prevents a mining unit from being mined more than once. Eq. (23) ensures that all continuous decision variables in the model are between zero and one. Eq. (24) guarantees that all binary variables are non-negative and integers.

$$x_{m,p}^t = x_m^t \qquad \forall t \in \{1,2,...,T\}, m \in \{1,2,...,M\} \tag{19}$$

$$\sum_{t=1}^{T} x_m^t \le 1 \qquad \forall m \in \{1,2,...,M\} \tag{20}$$

$$\sum_{t=1}^{T} x_{m,p}^t \le 1 \qquad \forall m \in \{1,2,...,M\} \tag{21}$$

$$\sum_{t \in T_m} bs_m^t \le 1 \qquad \forall m \in \{1,2,...,M\} \tag{22}$$

$$x_m^t, x_{m,p}^t \in [0,1] \tag{23}$$

$$bs_m^t, as_m^t \in \{0,1\} \tag{24}$$

5. Case Study- Implementation of the MILP Model on a Real SLC Mine

The SLC method was selected for mining an iron ore underground mine after evaluating various qualifying factors, including ore strength, host rock strength, deposit shape, size, orientation, ore grade, uniformity, and deposit depth. The ore tonnage is approximately 137 Mt at an average grade of 47% Fe.

Figure 5(a) presents a 3D view of the orebody extended in an NW-SE direction with an azimuth of 130. All MUs have been conducted perpendicularly to the strike of the orebody, following the azimuth of NE-40 (Figure 5(b)). The orebody has a maximum length (along the strike) of 900 m and a width of 437 m.

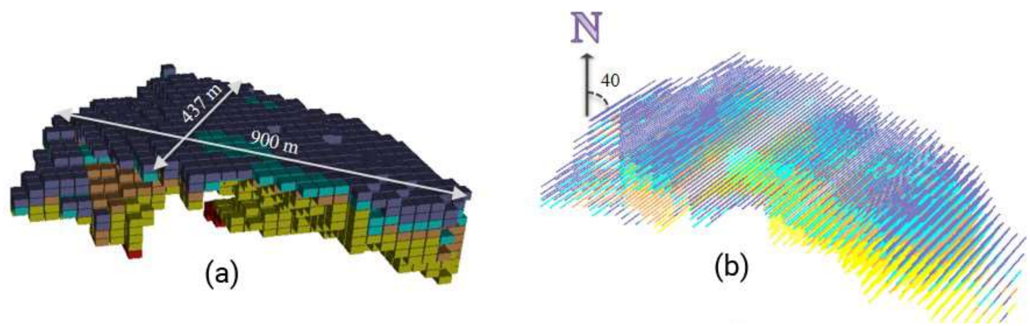

Figure 5. a) Plan view of the orebody; b) Mining units in different levels.

The orebody is situated 500 m below the surface with a 198 m thickness. The analysis includes eleven levels with 541 MUs, each having a production drift of 4.6 m width and 4.3 m height. MUs are spaced at 16 m intervals and have a height of 18 m, matching the sublevel height. The staggered placement of MUs across levels optimizes drilling coverage and material flow. The orebody includes eleven levels, with MUs allocated based on their coordinates to respective levels (Figure 6).

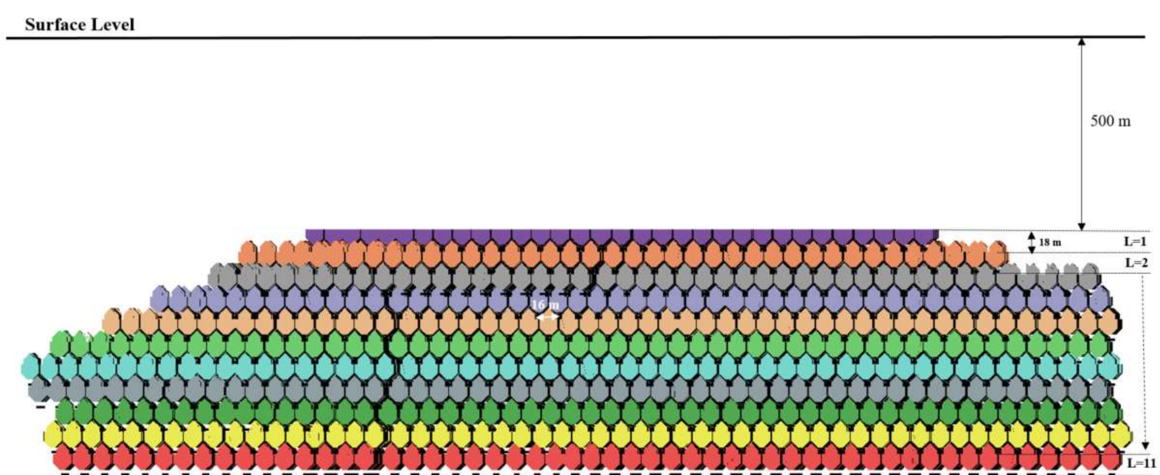

Figure 6. Cross-section view of MUs across 11 levels in the SLC mine.

The SLC mine was organized as follows: eleven horizontal levels, which are horizontal cuts positioned progressively deeper in the earth's surface. In each level, the LHDs load and haul the blasted ore from the production face to the ore passes, where the ore is transported directly to the main haulage level and then hoisted to the surface through the vertical shaft.

In the implemented model, once an LHD starts to mine an MU, that unit must be continuously mined; otherwise, the scheduling unit will be shut down, and the unextracted portion will be left behind. The vertical and horizontal precedence relationships among MUs control the schedule of each MU. The initiation of new MUs extraction in each period is managed to align with mine production requirements, the permissible number of active levels in each period, and the average production grade. Table 1 provides a detailed value of input data used in the model.

Table 1. List of Input data for scheduling model implementation.

Parameters	**Values**
Mine layout	Transverse
Production drifts azimuth	NE-40^0
Mining direction	SW-220^0
Number of MUs	541
Number of levels	11
Mining capacity (first two years of production)	4.5 and 5.5 Mt/year
Mining capacity (from the third year of production to the end of mine life)	6 Mt/year
Processing plant capacity (first two years of production)	4.5 and 5.5 Mt/year
Processing plant capacity (from the third year of production to the end of mine life)	6 Mt/year
Minimum permissible average grade of plant	40%
Selling price	200 $/ton
Mining cost	21.22 $/ton
Processing cost	10.05 $/ton

6. Results and Discussion

All models were run on a PC with the following specifications: AMD EPYC-Rome Processor 2.00 GHz, 128 GB of installed RAM, 64-bit operating system with x64-based processor architecture, running Windows 10 Pro Version 22H2. To optimize resource extraction while considering environmental impact and technical constraints, both the scheduling model and PCSLC have been run in different mining directions at each level: left to right, middle to the sides, and right to left.

Figure 7 to Figure 12 show plots that include a cross-section view of the production schedule for the proposed model and PCSLC for all three mining directions. Inside each MU, the top number is the MU ID, the bottom number is the extraction period, and the middle number is the extraction percentage of the MU in the scheduled period (bottom number). In all the plots, the mining progress starts from the topmost level with the highest Z value to the lowest level with the lowest Z value. The first candidate mining unit at each level is determined based on the mining direction specified in each approach. The differences in mining unit sequencing between the scheduling model and PCSLC are related to the constraints and algorithms defined in the backend of both methods.

Figure 13 to Figure 18 represent the offset plan view of scheduling with both the scheduling model (top of the page) and PCSLC (bottom of the page) across all 11 levels of the SLC mine. According to the chosen colour scheme, as the colour shifts to yellow, the mining operation approaches the end of its life. Colour transition in both methods verifies that both sets of plots adhere to the specified mining directions.

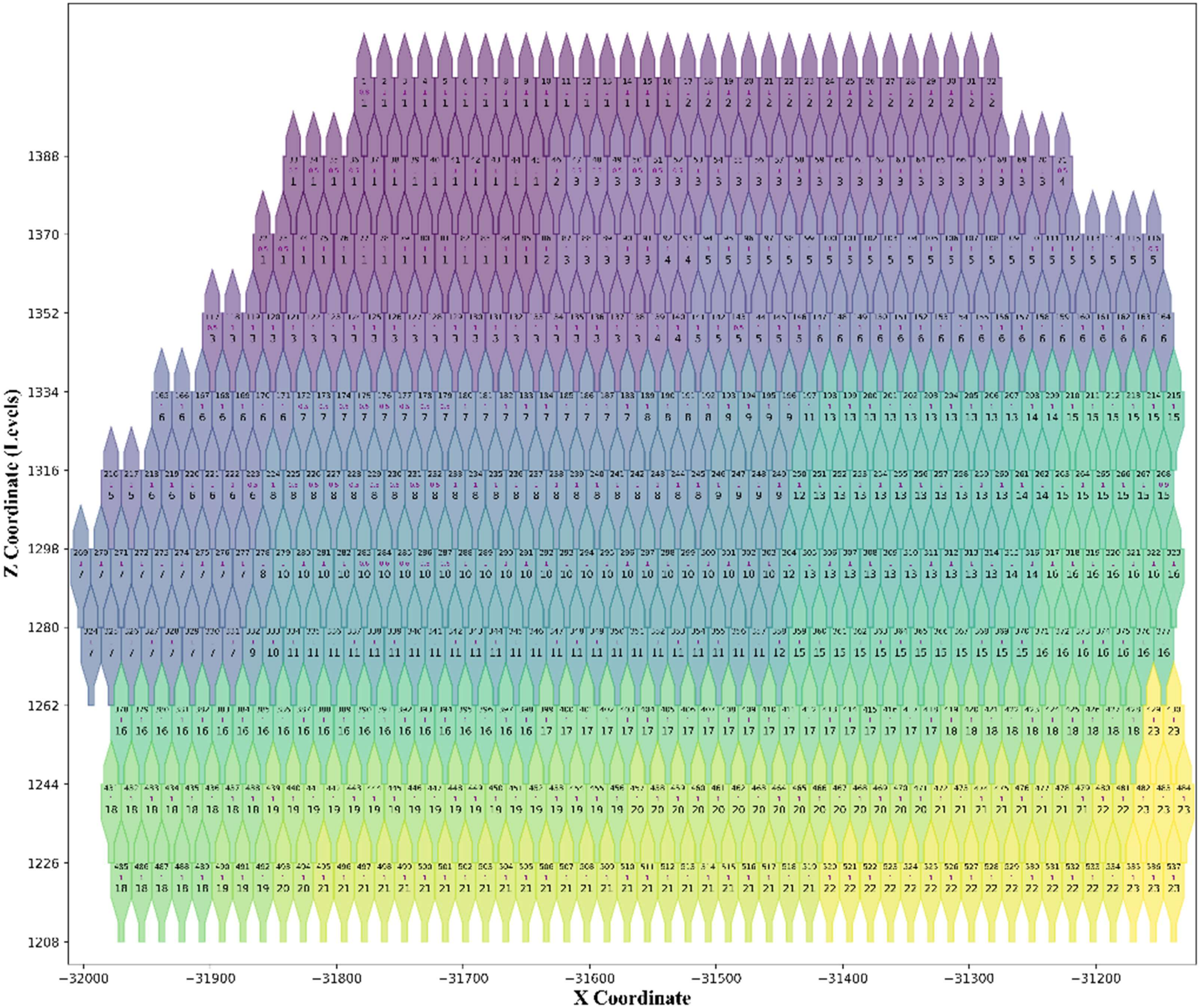

Figure 7. Cross-section view of starting time, and extraction percentage of mining units over the life of mine in scheduling model - Mining direction (Left-to-Right).

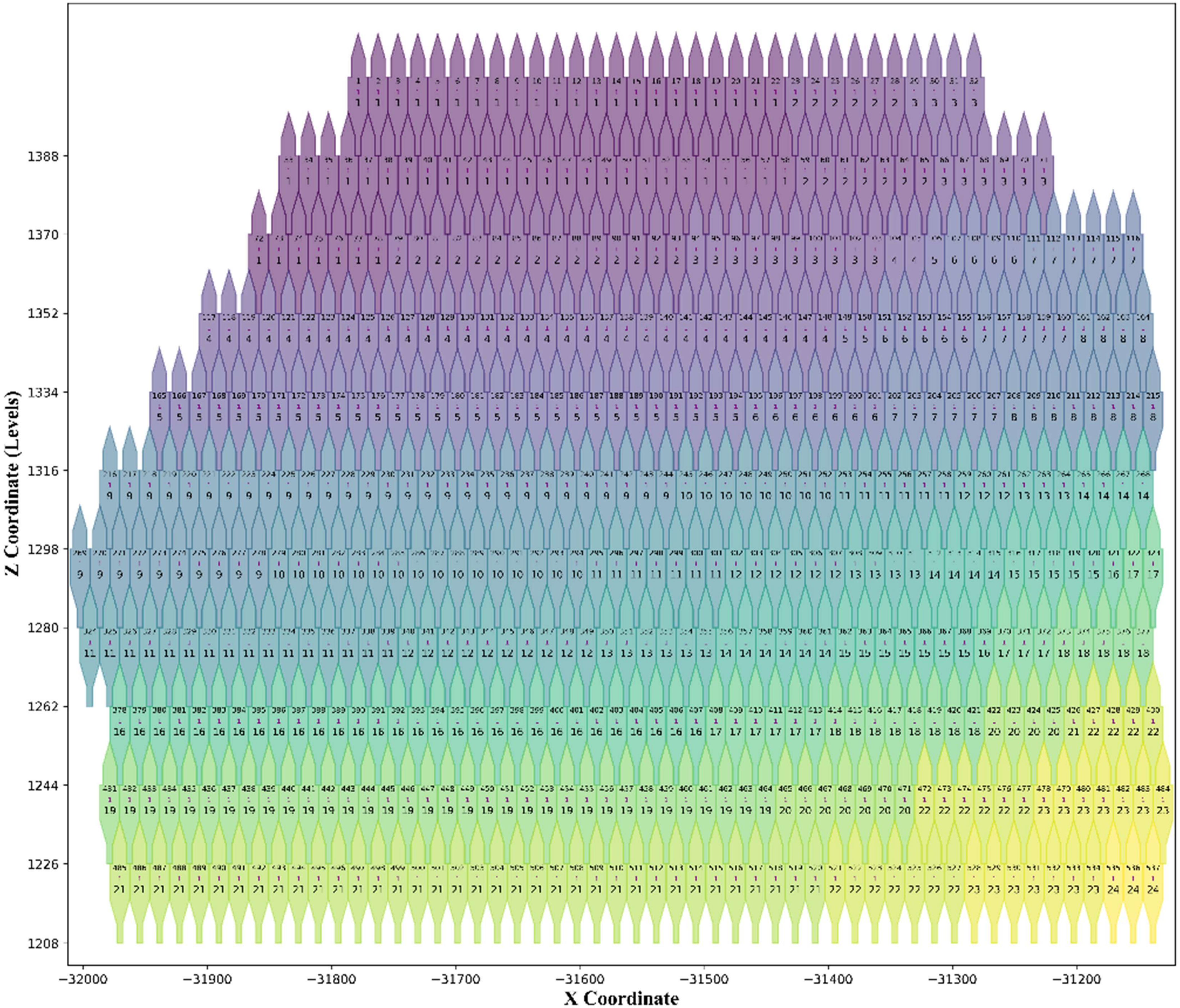

Figure 8. Cross-section view of starting time, and extraction percentage of mining units over the life of mine in PCSLC- Mining direction (Left-to-Right).

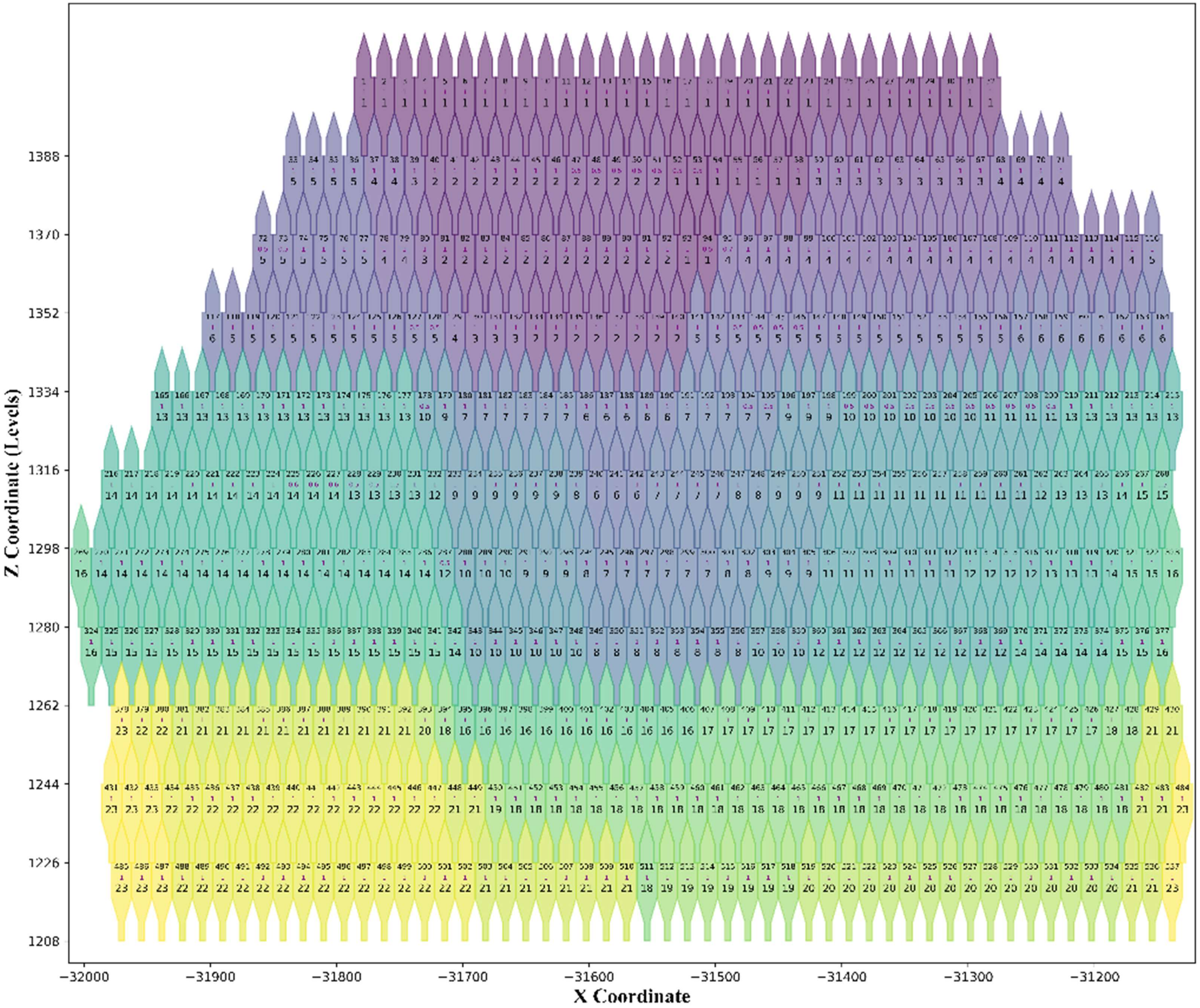

Figure 9. Cross-section view of starting time, and extraction percentage of mining units over the life of mine in scheduling model - Mining direction (Middle).

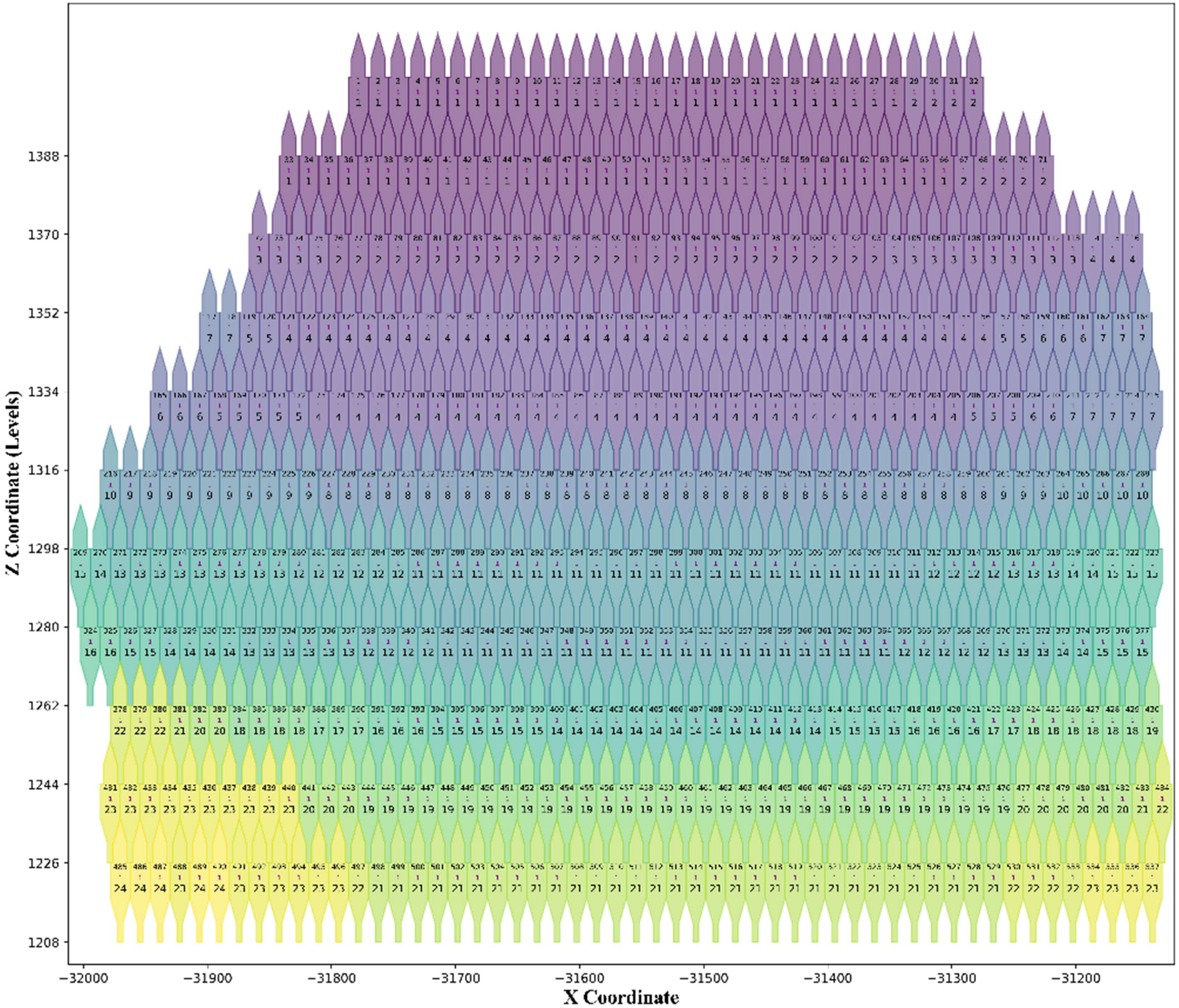

Figure 10. Cross-section view of starting time, and extraction percentage of mining units over the life of mine in PCSLC- Mining direction (Middle).

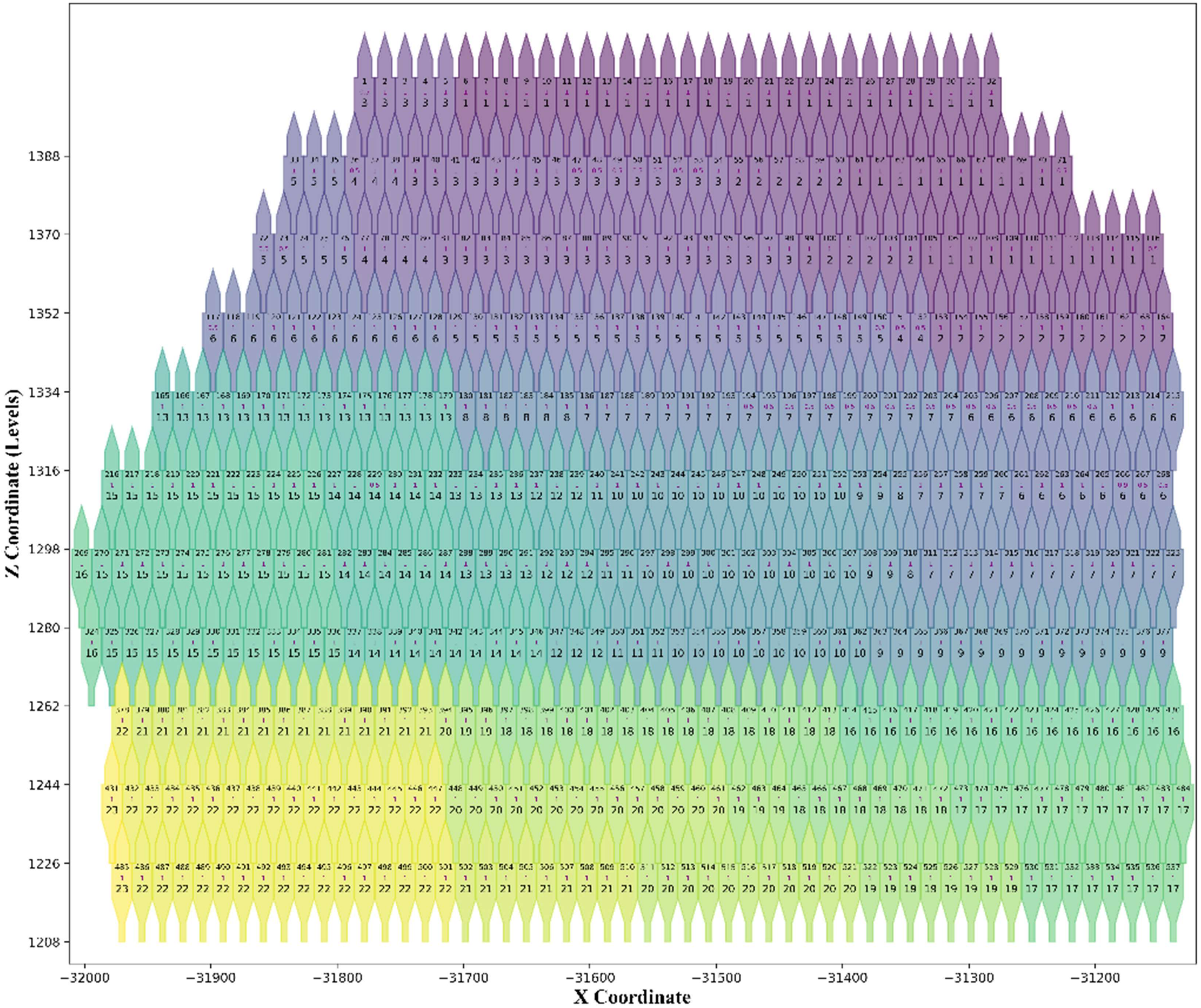

Figure 11. Cross-section view of starting time, and extraction percentage of mining units over the life of mine in scheduling model- Mining direction (Right-to-Left).

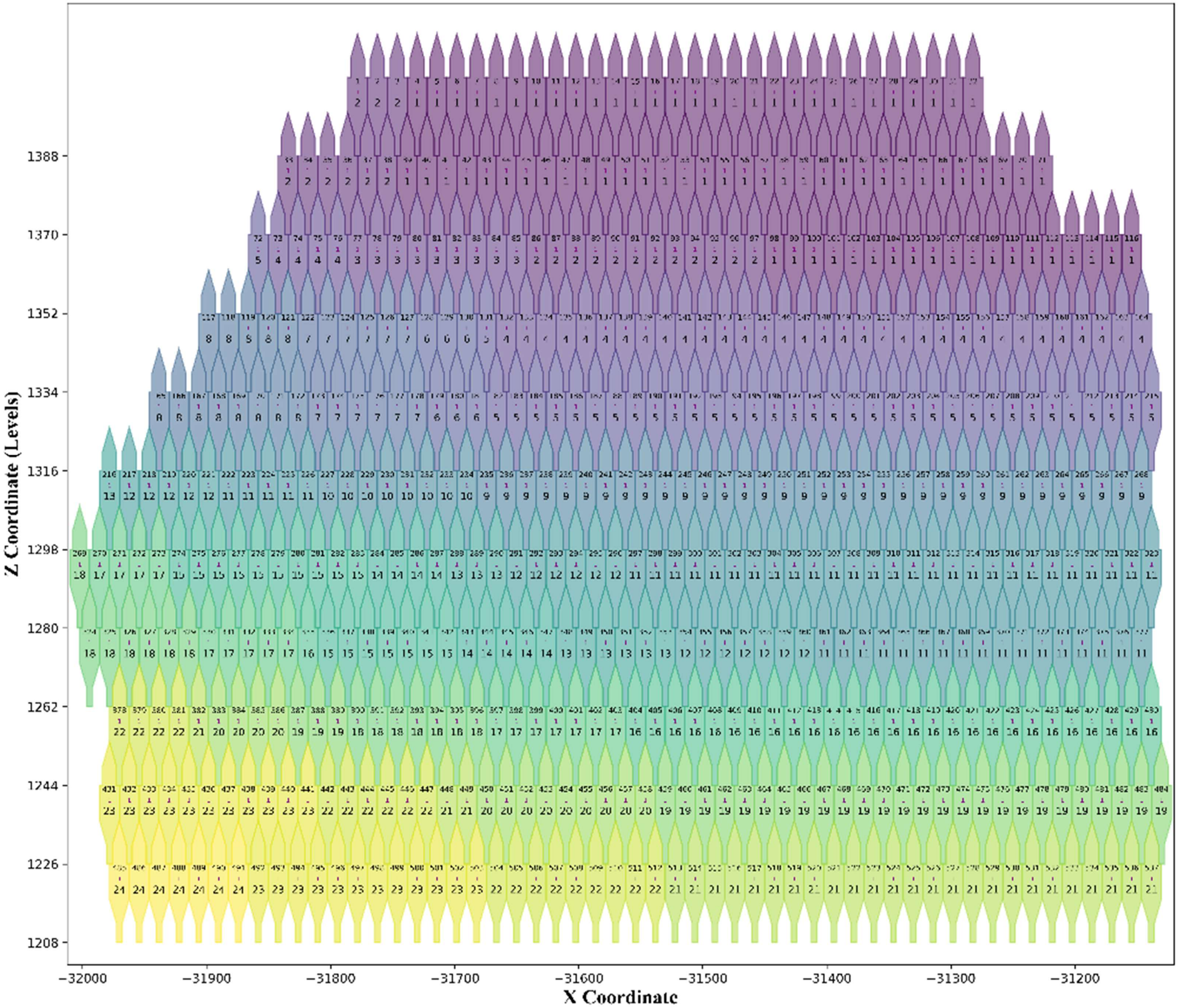

Figure 12. Cross-section view of starting time, and extraction percentage of mining units over the life of mine in PCSLC- Mining direction (Right-to-Left).

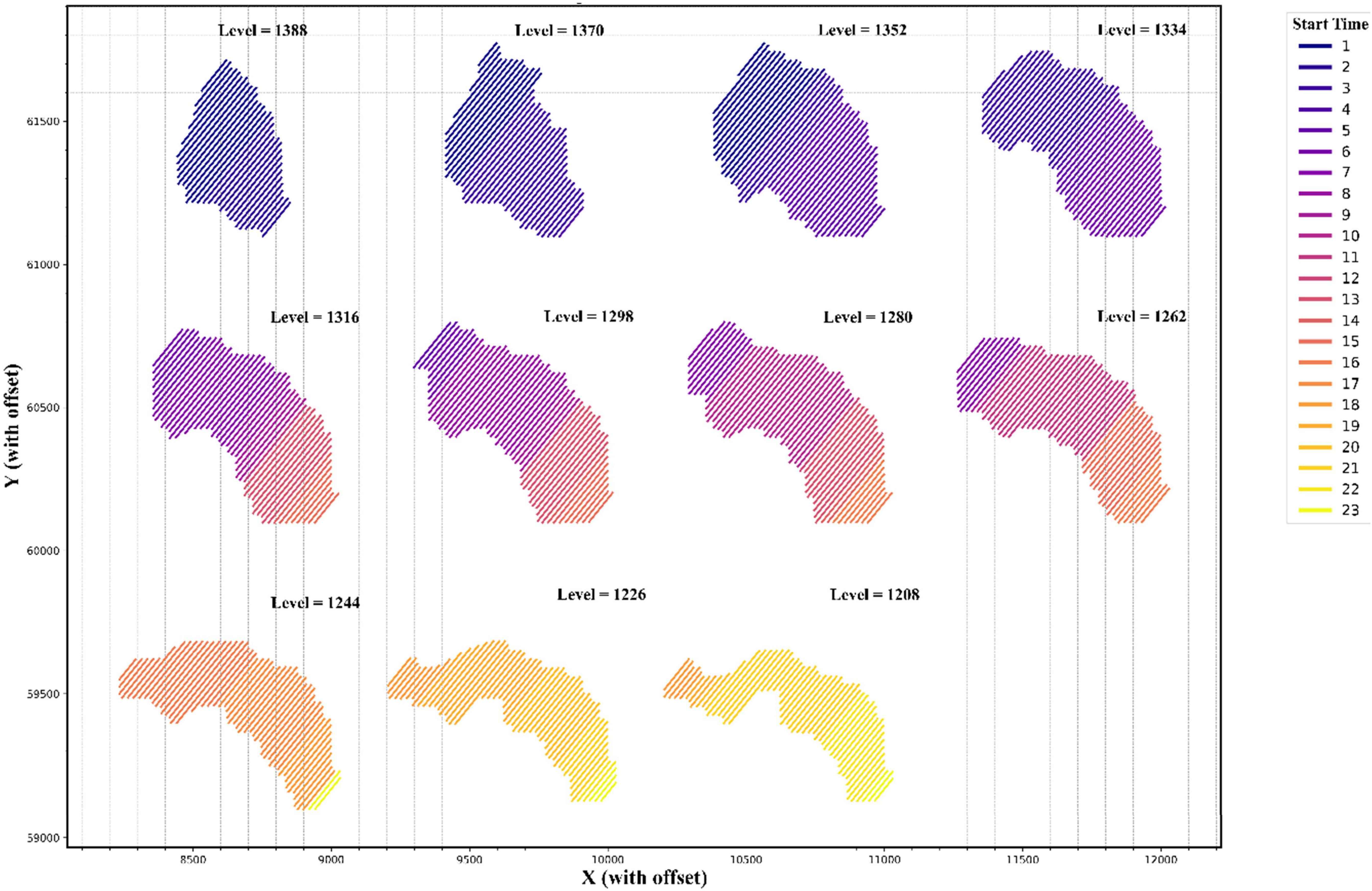

Figure 13. Offset plan view of mining units scheduling in all 11 levels in the scheduling model- Mining direction (Left-to-Right).

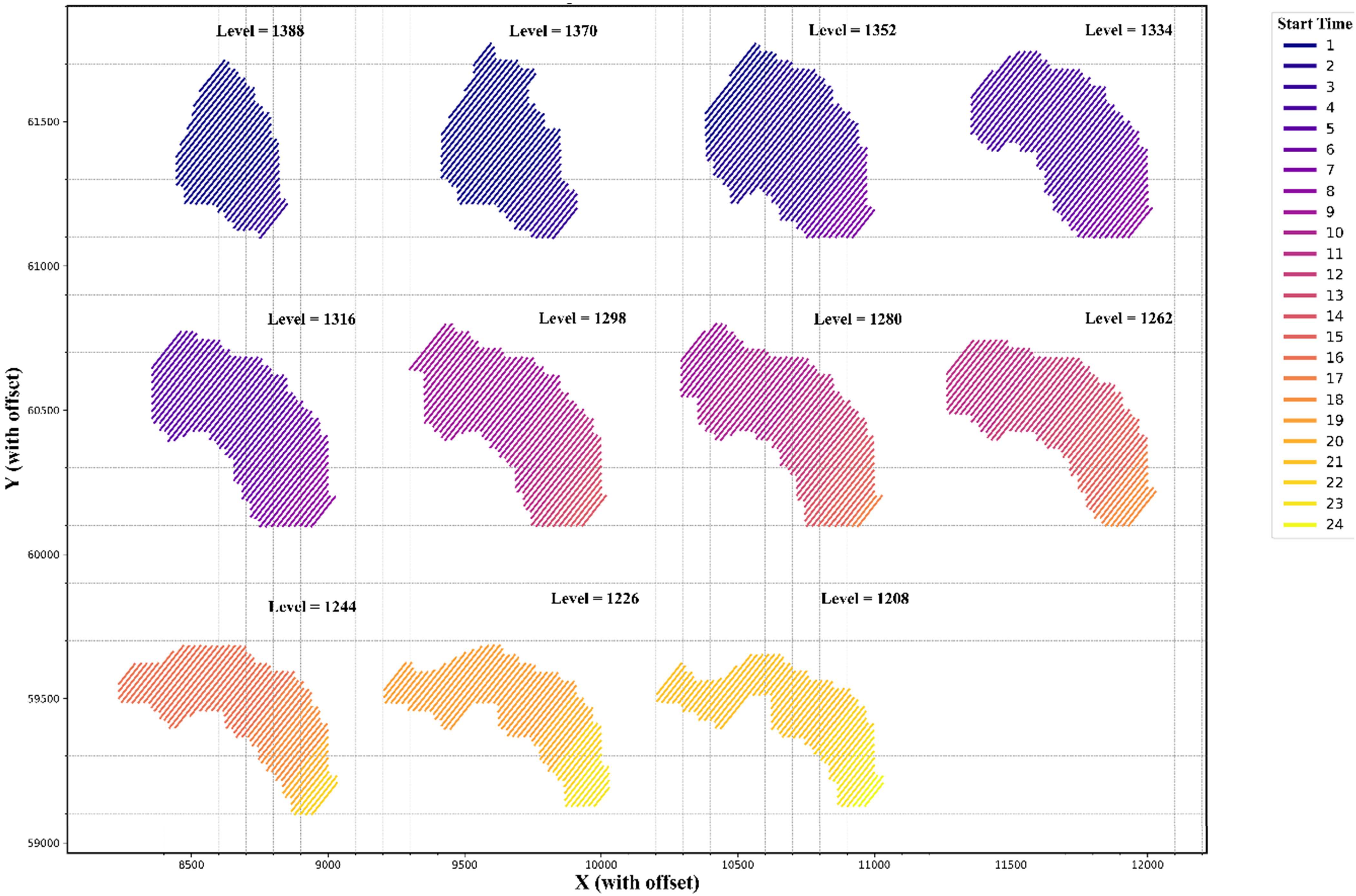

Figure 14. Offset plan view of mining units scheduling in all 11 levels in PCSLC- Mining direction (Left-to-Right).

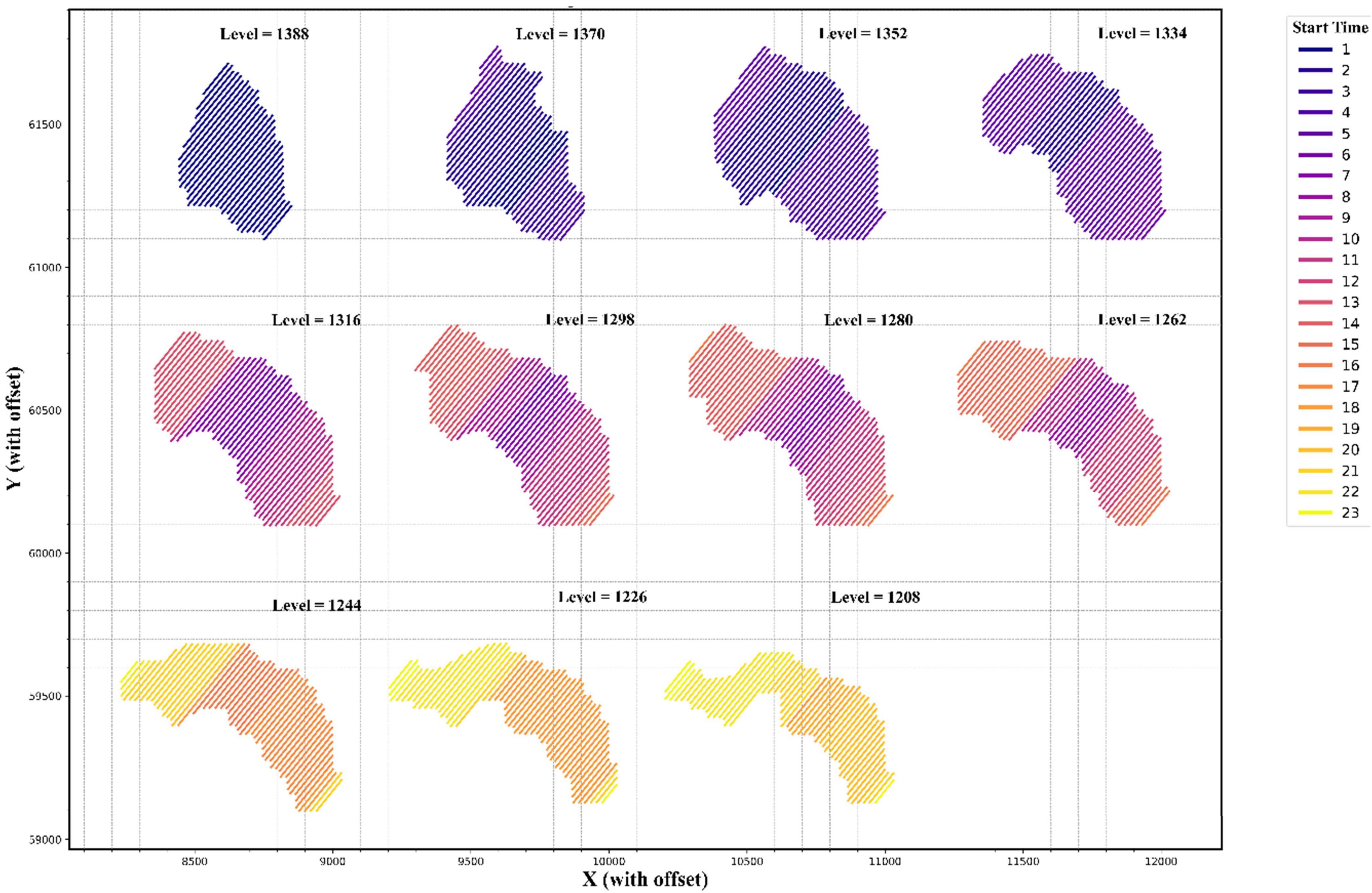

Figure 15. Offset plan view of mining units scheduling in all 11 levels in the scheduling model- Mining direction (Middle).

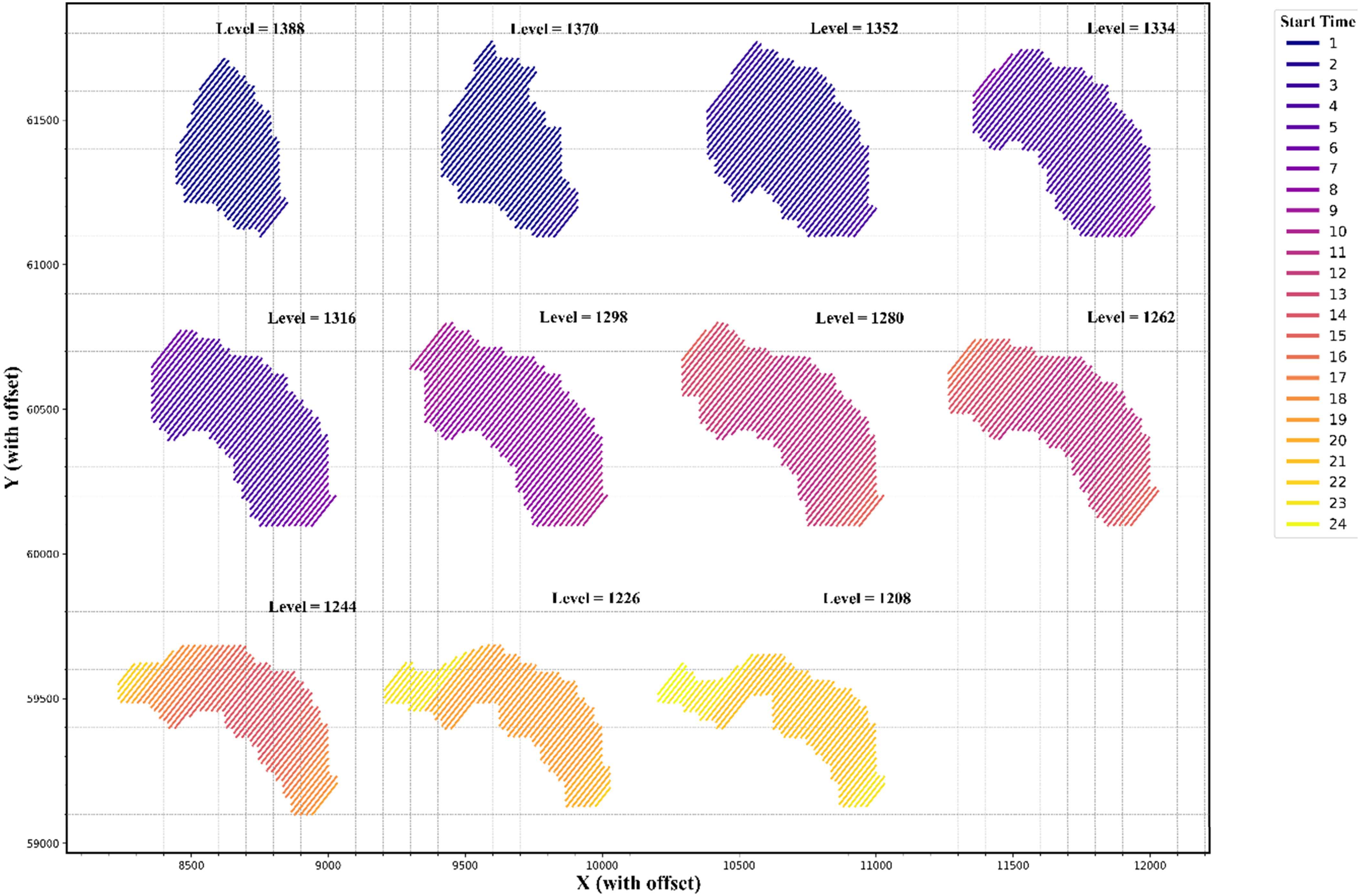

Figure 16. Offset plan view of mining units scheduling in all 11 levels in PCSLC- Mining direction (Middle).

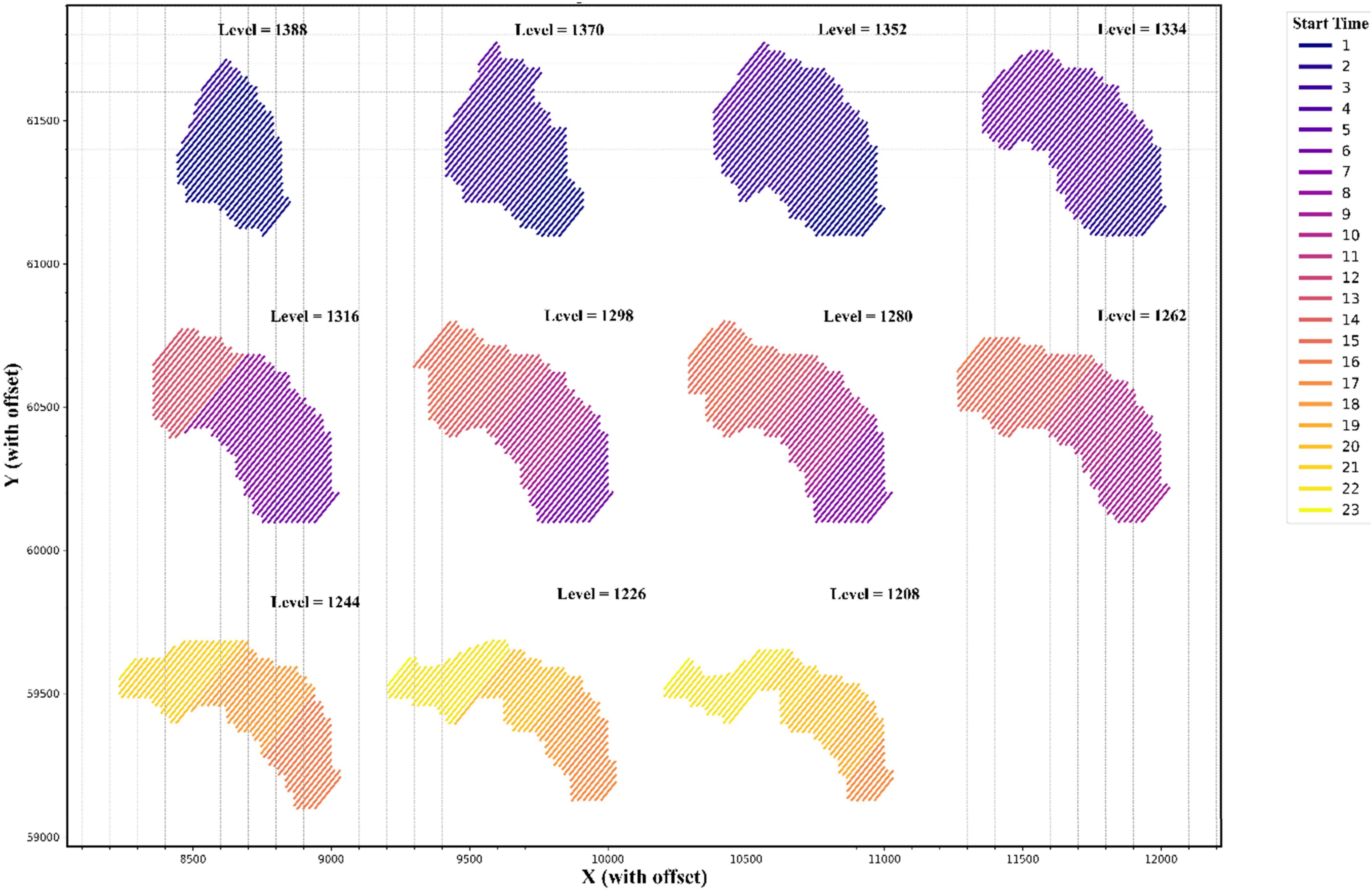

Figure 17. Offset plan view of mining units scheduling in all 11 levels in the scheduling model- Mining direction (Right-to-Left).

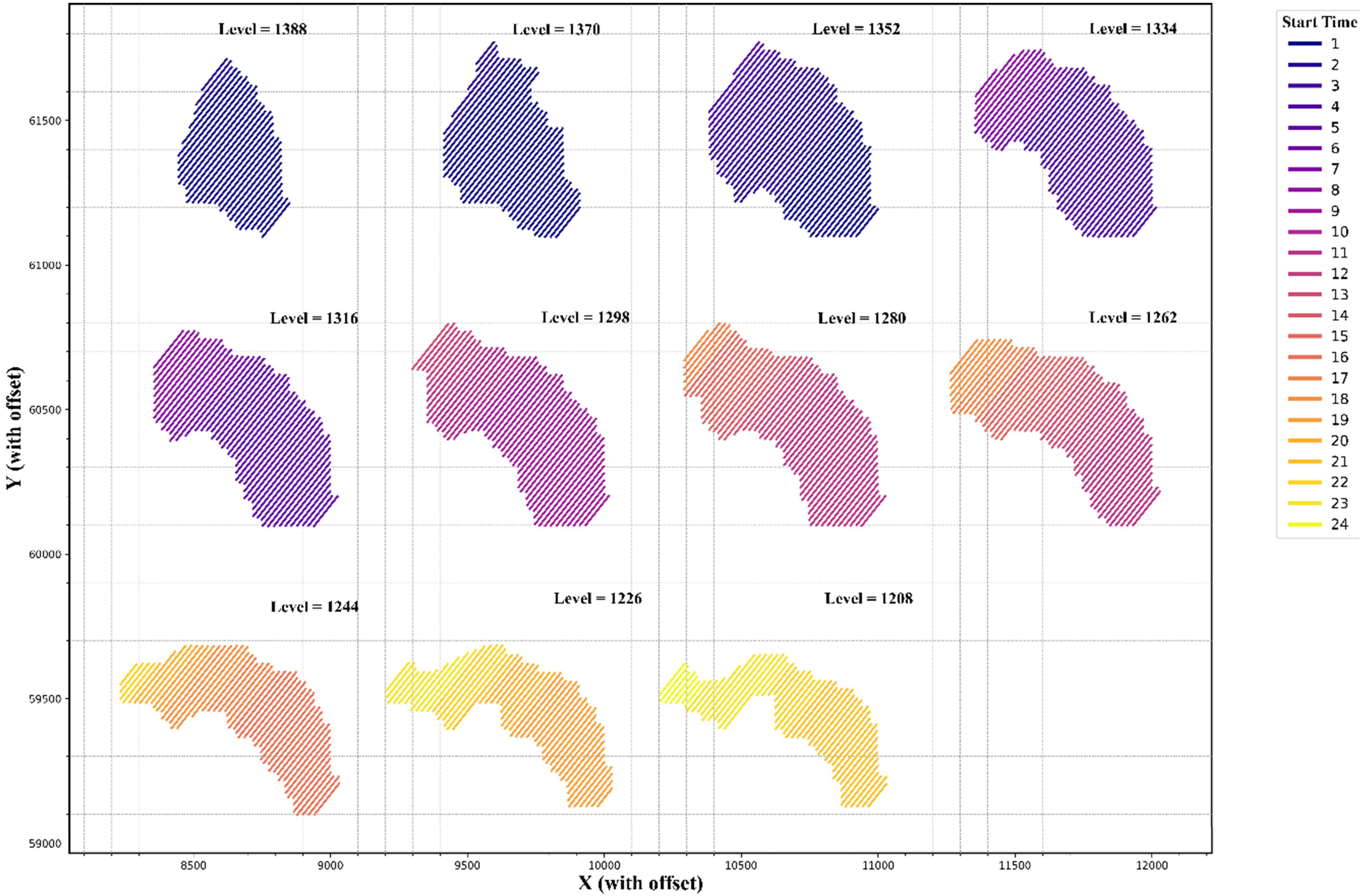

Figure 18. Offset plan view of mining units scheduling in all 11 levels in PCSLC- Mining direction (Right-to-Left).

In Figure 19 and Figure 20, a comparison of the tonnage and average grade for two different scheduling methods, including the scheduling model and PCSLC, is presented. In both plots, tonnage is divided into three categories: Left-to-Right (LtoR), Middle, and Right-to-Left (RtoL), represented by different colours. The average grade for these categories is also depicted with corresponding line graphs. The scheduling model with an 8% gap tolerance completes its operation in 23 years, while the PCSLC schedule finishes within 24 years. For the scheduling model, the tonnage remains relatively stable, with some fluctuations, especially in the final year. The average grade in this model shows more variability, indicating fluctuations in ore quality over the years. In contrast, the PCSLC demonstrates a more consistent tonnage distribution with a slight decline towards the end. The average grade in the PCSLC also shows fluctuations but appears to be more stable than the scheduling model.

Figure 19. Tonnage-Average Grade plot in all mining directions (LtoR, Middle, RtoL)- Model.

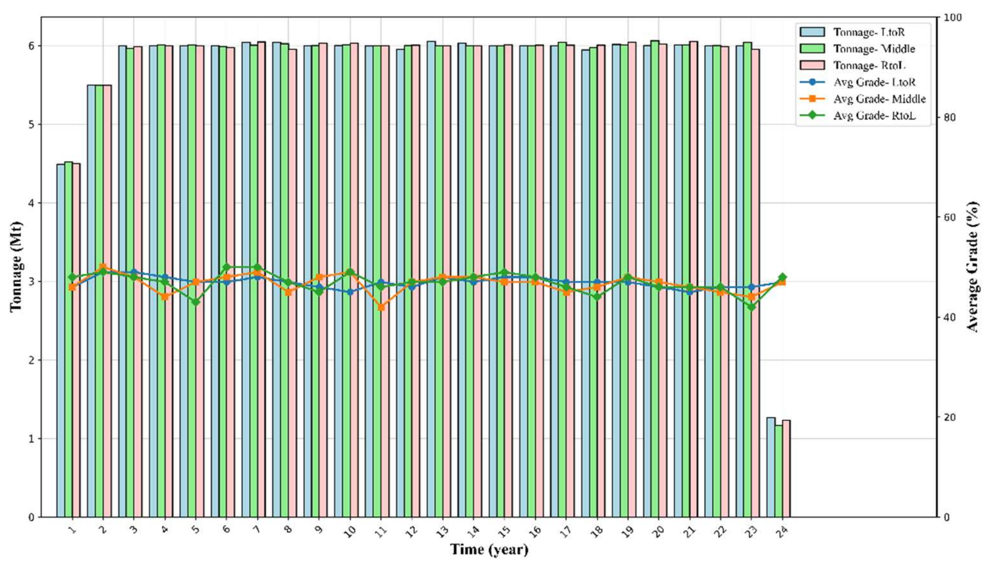

Figure 20. Tonnage-Average Grade plot in all mining directions (LtoR, Middle, RtoL)- PCSLC.

Figure 21 compares the NPV values for the scheduling model and PCSLC across three mining directions: LtoR, Middle, and RtoL. In both the LtoR and RtoL directions, the presented model achieves slightly higher NPV values than the PCSLC, with differences of 2.29% and 2.26%, respectively. However, the most significant difference is observed in the Middle approach, where the model outperforms PCSLC by 3.20%, indicating its maximum NPV advantage. Overall, the scheduling model demonstrates better performance compared to the PCSLC schedule, which indicates that the scheduling model generally provides higher economic values in all mining directions.

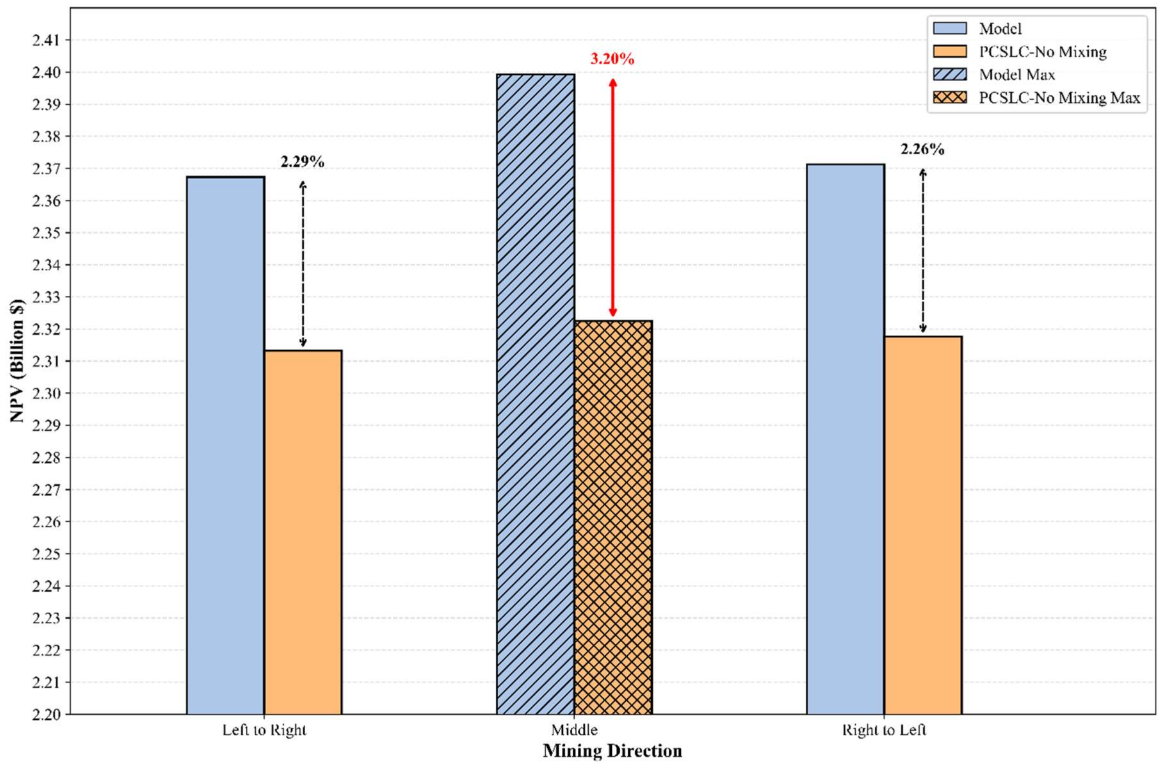

Figure 21. NPV values of the model (run on the gap tolerance of 8%) and PCSLC for different mining directions (LtoR, Middle, RtoL).

7. Conclusion

This study was a comparative analysis to validate the scheduling model developed for SLC long-term scheduling using PCSLC as a benchmark. The model constraints were designed to align closely with PCSLC scheduling setups while incorporating model-specific constraints. The performance of PCSLC, as the only commercial software for SLC scheduling, is undeniable in generating model input efficiently.

The comparative analysis reveals that the presented model and PCSLC exhibit distinct performance characteristics. The scheduling model with an 8% gap tolerance completes operations in 23 years, whereas the PCSLC finishes in 24 years. The PCSLC demonstrates more consistent and stable tonnage and average grade distribution. However, the presented model generally outperforms

PCSLC in terms of economic value in the LtoR, Middle, and RtoL mining directions, with NPV differences of 2.29%, 3.20%, and 2.26%, respectively.

Overall, while PCSLC offers some advantages in specific scenarios, the presented model provides better overall economic value. Additionally, the main advantage of using PCSLC is its significantly faster processing time compared to the scheduling model, making it a highly efficient tool for SLC scheduling. These findings can inform future decisions and methodologies when selecting the most appropriate scheduling approach to reduce solution time for real-world mines with large datasets.

8. References

[1] Darling, P., SME Mining Engineering Handbook. 2011,

[2] Salinas, D.V., *Calibration of a mixing model for sublevel caving*. Thesis, 2012. University of British Columbia.

[3] Shekhar, G., A., Gustafson, K., Jonsson, J., Martinsson, and H., Schunnesson, *Development of an optimal draw control strategy for a sublevel caving operation at Malmberget mine.* Mining Technology, 2020. **129**(2), pp. 104-112.

[4] Campeau, L.P., and M., Gamache, *Short-term planning optimization model for underground mines.* Computers & Operations Research, 2020. **115**, p. 104642.

[5] Pourrahimian, Y., H., Askari–Nasab, and D., Tannant, *Mixed–integer linear programming formulation for block–cave sequence optimisation.* International Journal of Mining and Mineral Engineering, 2012. **4**(1), pp. 26-49.

[6] Mousavi, A. and E., Sellers, *Optimisation of production planning for an innovative hybrid underground mining method.* Resources Policy, 2019. **62,** pp. 184-192.

[7] Khodayari, F., Y., Pourrahimian, *Mathematical programming applications in block-caving scheduling: a review of models and algorithms.* International Journal of Mining and Mineral Engineering, 2015. **6**(3), pp. 234-257.

[8] Khazaei, S., and Y., Pourrahimian, *An Integrated Mixed-Integer-Linear-Programming Model for Long-term Production Scheduling Optimization of Sublevel Caving Mines.* Mining Optimization Laboratory, 2022. **1**(780), p. 348.

[9] Khodayari, F., and T., Diering, (2022). *Material flow simulation using marker mixing*, in *Proceedings of Caving 2022: Proceedings of the Fifth International Conference on Block and Sublevel Caving*. 2022. pp. 1387-1396. Australian Centre for Geomechanics.

[10] Khazaei, S., and Y., Pourrahimian, *Mathematical programming application in sublevel caving production scheduling.* Mining, 2021. **1**(2), pp. 180-191.

[11] Shenavar, M., M., Ataee-pour, and M., Rahmanpour, *A new mathematical model for production scheduling in sub-level caving mining method.* Journal of Mining and Environment, 2020. **11**(3), pp. 765-778.

[12] Shenavar, M., M., Ataee-pour, and M., Rahmanpour, (2019). *Production scheduling in sublevel caving method with the objective of NPV maximization*, in *Proceedings of Proceedings of the 27th International Symposium on Mine Planning and Equipment Selection-MPES 2018*. 2019. pp. 153-163. Springer.

[13] Villa, D., and T., Diering, *A new mine planning tool for sublevel caving mines*, in *Proceedings of Proceedings of the Second International Symposium on Block and Sublevel Caving*. 2010. pp. 237-251. Australian Centre for Geomechanics.

[14] Diering, T., and F., Breed, *Footprint finder tool for sublevel caving*, in *Proceedings of Caving 2018: Proceedings of the Fourth International Symposium on Block and Sublevel Caving*. 2018. pp. 283-296. Australian Centre for Geomechanics.

[15] Kuchta, M., A., Newman, and E., Topal, *Implementing a production schedule at LKAB's Kiruna Mine.* Interfaces, 2004. **34**(2), pp. 124-134.

[16] Newman, A.M., M., Martinez, and M., Kuchta, *A review of long-and short-term production scheduling at Lkab's Kiruna Mine.* Handbook of Production Scheduling, 2006. pp. 265-286.

[17] Newman, A.M., and M.A., Martinez, *A solution approach for optimizing long- and short-term production scheduling at LKAB's Kiruna mine.* European Journal of Operational Research, 2011. **211**, pp. 184-197.

[18] Morad, A.M., M., Pourgol-Mohammad, and J., Sattarvand, *Application of reliability-centered maintenance for productivity improvement of open pit mining equipment: Case study of Sungun copper mine.* Journal of Central South University, 2014. **21**(6), pp. 2372-2382.