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Data Diagram Design and Data Management for Visualisation and Analytics Fusion in The Mining Industry

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Abstract

The adoption of advanced technologies in mining has resulted in large amounts of data. Yet, according to recent research, our ability to collect and store massive amounts of data far outstrips our ability to manage and analyse ever-increasing data, such as data exchange, information sharing, and multi-dimensional data fusion. In this paper, in order to facilitate the development of automated visualisation and multidimensional data-oriented analytics, we propose a visual analytics-oriented data diagram and data processing workflows. Firstly, we introduce visual model data as a new modality in data management and analytics by standardising drawing data. Then, we extend the visual analytics into 3D spaces for enhanced interactive visualization and various data access. This also enables the development of a new schema for a comprehensive data-driven model for visualisation, which can be an alternative to the conventional solid model and perform well in scalability and lifetime support. Furthermore, based on the unified data diagram and tile index concept, a multidimensional and multi-modality data management strategy is proposed for system scalability and lifetime support. Lastly, effective data management targeting data fusion and 3D visual analytics is implemented, providing constant data support in the trial of mining digitalization. Moreover, the outcome of this paper can provide further technical support for constructing a digital twin system.

Keywords: Data diagram; Underground mining data management; Data fusion; Data-driven model development; 3D visual analytics.
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1. Introduction

The state-of-art technologies, such as the Internet of Things (IoT), automation, and sensing, have accelerated data generation in the mining industry.[1-6] Yet, our ability to collect and store massive amounts of data far outstrips our ability to manage and analyse the collected data.[7-10] Hence, the mining industry requires innovative solutions in the field of data management to facilitate the advancement of data-driven visualization and data fusion techniques.[11-15] To accomplish this, the industry necessitates streamlined access to diverse datasets facilitated by an efficient data management and fusion framework. These datasets may include geological information, survey reports, production data, and more. This imperative has propelled recent research efforts in mining digitalization towards a focus on enhancing data management strategies.[16-18]

Data management normally refers to data processing sections, for instance, data diagrams, data storage, data exchange, data cleaning, *etc*.[15-20] The prevalent cloud service aims to integrate data management sections and provide efficient and stable data storage solutions. Industry cases present that the development of data management can improve data utilisation and drive long-term value in operations, such as applications in health care, manufacturing, and civil engineering.[16,17,21-28] However, based on the existing literature, it is apparent that the majority of mining researchers predominantly concentrate on the application of cloud platforms,[29-32] often neglecting crucial aspects such as data diagram standardisation, data exchange, and interrelated workflows. While this emphasis on cloud platforms may provide a short-term solution for accommodating data volume growth, it does not effectively address the challenges associated with the increasing diversity of data. Therefore, this paper will focus on these rarely considered domains, including data diagram unification, data exchange, and workflows, so as to facilitate data management across different applications, such as data visualisation, data-driven model development, data fusion, and visual analytics.

On the other hand, data fusion looks forward to multi-source and spatial-temporal data analytics.[7,8,33,34] However, various non-unified raw data cannot be integrated and

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analysed due to lacking shared attributes, such as coordinates and timestamps. Furthermore, data exchange is a critical process for implementing information sharing, containing data conversion, matching, cache, *etc*.[15,35,36] Data exchange across different applications also requires unified data to improve efficiency and compatibility. Some studies[37,38] proposed the so-called 4D data management and analytics framework based on static/dynamic data in underground mining. The proposed framework improved the data management efficiency and revealed the fusion of visualisation and analytics to some extent. Yet, the data diagram was still non-unified, resulting in a complex data conversion and matching process. In addition, recent literature presents that various data classifications broadly exist in different mining information systems, such as static\dynamic data, production/geology data, routine\business data, *etc*.[15,39,40] Non-standard classification hinders data diagram unification.

Besides, applications such as data visualisation and analytics are always limited to a specific scope, making the system lack compatibility and scalability in lifelong maintenance. For example, typical visualisation applications are arbitrarily developed considering collected data but not compatible with other datasets or other practices.[15,41] Finally, the information island, which is also well-known as data silos, broadly exists by paralleled, non-unified data diagram-supported information systems.[1,15,42-45] From the data management perspective, the information island can hinder information sharing and data exchange. Then, data fusion is hard to achieve in this context.[14,46-51] From the visualisation perspective, according to recent works, solid model-relied visual model reconstruction may not meet real-time and near real-time visualisation. In which solid models refer to all prefabricated visual models by 2D drawings.[52,53] In this context, data-driven model development, such as building information modeling (BIM) and parametric modeling,[54-57] has emerged as alternatives in visualisation. Therefore, the unified data diagram necessitates not only routine data but also visual model data, which has become essential for effective data management.

As a result, considering the status of various existing information systems, in this paper, we target a unified data diagram to simultaneously meet the requirements in visualisation, analytics, data fusion, and visual analytics. Regarding the proposed unified data diagram, visual model data can be one new dimension of multi-sources data. Then, a data-driven model development design is proposed to make visualisation-oriented data fusion and visual analytics possible. Also, the visualization process can lead to a finer model, which in turn enables various analytics. Correspondingly, data exchange and processing workflows following data management and fusion are discussed. Thus, spatial-temporal data analytics, visualisation, and information sharing can be possible during lifetime operation.

2. Challenges in current mining information systems

2.1 Various information systems

Currently, information systems in mining are mainly focusing on data collection and simple visualisation, such as 2D data trend presentation and statistical charts.[42] Some typical information systems driven by different motivations are listed in Table 1. In the table, dynamic data refers to the data that can vary over time, for example, ground stress variation, environmental factors, *etc*. Specifically, dynamic data accumulation is driven by the adoption of IoT/Industrial IoT techniques.[5,6,58,59] Static data means intrinsic geological data, such as rock mass quality index, lithology, and geology information. Due to different motivations from isolated management sections, various information systems are formed and run separately. Multiple information systems running in one mine site make data distributed in different databases and form information islands, which can cause low data utilisation and complex data exchange.

Table 1. IoT-based various information systems in mining.

Content	Focus	Data type
Device maintenance system[60,61]	Device\Vehicle operationand safety	Dynamic data andstatic data
Environment monitoring and alarming system[62-67]	Health, safety, and environment (HSE)	Dynamic data
Support system monitoring[7,68,69]	Geological and production	Dynamic data
Tunnel deformation and geo-stress variation[8,70]	Geological	Dynamic data

In order to reduce the impact of information island, cloud services-oriented systems are developed to facilitate system integration, including cloud databases, web-based frameworks, cloud computing, *etc*.[29,71] However, a cloud platform without a uniform data diagram may not be able to integrate various data sources. In addition, the complexity of data has been upgraded from traditional 3D to time-series 4D. Data sources have presented more than numerical data; images and various documents have become standard in data collection. A unified data diagram becomes imperative to address data integration and the challenge of data category increments. This poses pressure to relational databases due to the complex and various connections across data collections. Thus, the non-relational databases (NoSQL) database has arisen as a solid alternative.[72,73] In contrast to a relational database, a NoSQL database is one that is less structured\confined in format. This allows for more flexibility and adaptability. Nonetheless, due to the non-relational structure of the NoSQL database, the application requires a uniform data diagram to facilitate data sharing. There are four main types of NoSQL databases: Key-value, Wide column, Document-oriented, and Graph-oriented. The comparison and discussion are listed in Table 2.

Table 2. NoSQL databases comparison.[31,72-74]

Category	NoSQL databases	Scopes
Key-value	Hazelcast, Redis, Mem base\Couchbase, Riak, Voldemort, Infinispan	A key-value database maps data items to a key space that is used both for allocating key\value pairs to computers and to efficiently locate a value, given its key. Generally utilised in web content management.
Wide column	Hbase, Hypertable, Cassandra	Wide column or Column Families databases store data by columns and do not impose a rigid scheme to user data, which means that some rows may or may not have columns of a certain type. This solution can be led to geological survey and visualization data involved in a data management system.
Document-oriented	CouchDB, MongoDB, Terrastore, RavenDB	Document-oriented or document-based databases can be seen as Key-value databases. The value has a known structure—service for complex, uncertain survey management and human factor collection data management systems.
Graph-oriented	Neo4J, InfiniteGraph, InfoGrid, HypergraphDB, AllegroGraph	Generally used for presenting large real-world entities, such as maps and social networks. Image recognition-based systems, such as core recognition, lithology boundary detection, and coal detection systems.

Considering the visual analytics and fusion requirements, wide column databases can guarantee system compatibility, which helps the information system handle the increasing data and its variation. However, the key issue of fusing various data and extending the analysis to the spatial-temporal domain remains a burden for data exchange and information sharing, which can be addressed by a unified data diagram.[75-77]

2.2 Visualisation and data fusion

In the data-driven context, data visualisation systems by solid models have limitations in system scalability and expansibility. Updating visual models to map physical ones is a time-consuming process that cannot even be possible in a real-time mechanism. Given that, visualisation system construction is pursuing ways to get rid of solid model reliance. Hence, BIM and parametric modeling are proposed to achieve automatic model generation using structured model datasets.[53,54] The development of BIM\parametric modeling requires digitalising the model into datasets and following up with standard reconstruction policies, which needs the help of efficient data management and reliable data diagrams.

Figure 1 shows the layers for Industry Foundation Classes (IFC) standard in mining working BIM system, mainly referring to the IFC framework from building and construction engineering.[52,53,56] It contains a series of information description modules in which each layer can only reference the information from the same or lower (right) layer. For example, the resource layer is the basic layer, and any other layers can be referred to for general information. The core layer represents the information on the product and process, which can be quoted from the resource layer. The interoperability layer refines the components of systems as well as the main components of the project. The domain layer is the top-level layer that defines entity types for different domains. This strict relation indicates the importance of data streaming in a visual model development solution.

As visual drawings can be digitalized into datasets, data fusion can be realized involving visual model information. For example, fusing model data and various geological data to realise time-series data visualisation and analytics. Some studies have conducted research on the preliminary fusion of data visualization and analytics.[37,78,79] Multi-geological data

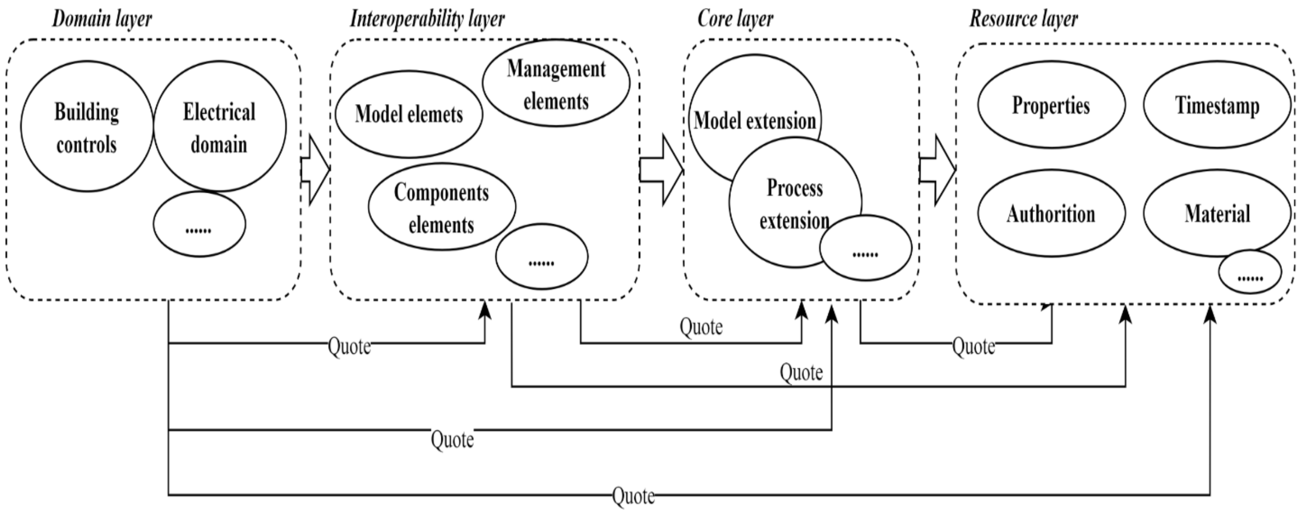

Fig. 1 The system architecture of IFC standard for mining workings.[52,53,56]

was fused into the 3D visual model, and then a single computational 4D statistical analysis of the groundfall hazard assessment model was completed. The attempts at data fusion provided new insights and ideas into mining hazard discrimination and prediction. However, the fusion model lacks the capability of time series accumulation. There are still challenges in this fusion model with uniform data diagram support. Hence, this paper focuses on a data-driven model development solution to address data exchange and fusion issues while taking into account visual model data in data analytics.

2.3 Data management challenges

As aforementioned, data management issues in mining engineering can be summarised as uniform data diagrams, data exchange, and correlated workflows. To deal with these issues and consider data sharing and further data fusion, the following key points are proposed with the data management development:

1. Data variety: The current mining industry generates a massive variety of data across the lifecycle, including:
(a) various drawings of mining workings, such as tunnels, shafts, and ore body outlines,
(b) continuously increased structured, semi-structured, and unstructured monitoring data,
(c) geological datasets, such as lithology, rock mass rating survey, and stress distribution.

From the data analysis perspective, each dataset can be a dimension that can be interpreted and analysed independently and comprehensively. Data fusion is a process of comprehensive data analysis with multi-dimensional data. Given the complexity of underground mining, all various datasets will be key dimensions in data analysis. Therefore, an effective data management framework needs the capability to deal with the increasing data categories and merge the new dimension into analytics.

2. Big data and data processing: The data collected from various production sections needs to be stored in the database, then accessed and processed into valuable information. However, the ever-increasing data made data mining more difficult. This has made the utilisation of production data less than 10%.[1-3,73,80,81]

3. Time series data: Dynamic data is generally accumulated along with the production timeline. Current data diagram design seldom records timestamp, which makes data accumulation, storage, and utilisation difficult to meet time series requirements.

4. Data security: With the implementation of cloud services and web frameworks, data security is a new challenge in data management. Concerning data leakage and ambiguity, prevalent technologies, such as blockchain.[82-84] have adapted to ensure transparency and security.[85] There are at least nine potential use cases for blockchain in mining, which include:
(a) digital identity for assets and people,
(b) data integrity,
(c) provenance,
(d) cradle to grave blockchain for assets,
(e) workflow automation in combination with IoT,
(f) supply chain optimisation,
(g) tokenised mines,
(h) workforce health recording, and
(i) human resources management.

5. Data fusion: Non-unified data diagram hinders the development of data fusion in mining engineering. This status becomes worse with the continuous data increase and the expectation of visual model data integration. Therefore, data standardisation and efficient data exchange become crucial for data management in the mining industry.

6. Visual analytics: Visual analytics is mainly based on visualisation, algorithmic data analysis and analytical reasoning, which takes advantage of visualisation and interactions as suitable tools to integrate human judgment into the knowledge discovery process to visually discover explainable patterns (knowledge) and to gain insight into large and complex data sets.[10] As underground mining is more like a black box issue, visualisation plays a vital role in explaining and demonstrating mining procedures. Therefore, visual analytics requires efficient interaction solutions for data demonstration that expects visual model at a high-fidelity level. Moreover, the data exchange schema, such as interaction-oriented data exchange and data feedback by analytics model, will be a vital issue.

In summary, data diagrams play a vital role in all sections of data management and analytics. This paper focuses on uniform data diagrams and data exchange. Comprehensively, visualization data and routine data will be studied in order to create a uniform data diagram. A novel data-driven visual model development schema will be proposed referring to the uniform data diagram and making visual model data part of data analytics.

3. Data diagram design

3.1 Visual model data

Visual models are important for demonstrating underground mining operations, especially in the context of the influx of 3R applications, such as Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR). However, current mining visualization systems mostly rely on solid models.[52,53] The 2D drawings still play a vital role in production design, devices\sensors deployment, and other professional discussions, though the cognition and understanding of 2D mining drawings is an extremely professional skill. For example, different mining operations require different geological supports and reflect different rock properties (stability, solidity, *etc*.). Identifying tunnels, panels, and mining development components by similar polygons (Fig. 2) and digitalising this information into datasets is important in analysis but difficult for those outside of mining. Furthermore, such solid models and 2D drawings may not be processed, stored, and utilised easily compared to routine data by program readable formats, such as csv, text, and binary files. This prevents the visual models from auto-generation and auto-update.

Figure 2 shows the complexity of underground tunnels and panels. The outlines are unforeseen and cannot be designed by parameters like building components. In terms of this, high-fidelity visual models are less achievable than BIM in construction and civil engineering. However, the visual model needs to maintain high fidelity with the physical one to guarantee the precision of geological and spatial information. With the development of visual analytics, highly customized model interaction and data feedback by the visual models are becoming more and more stringent. Finally, an automatic 3D model generation solution using 2D drawings is urgently needed to facilitate data fusion and visual analytics.

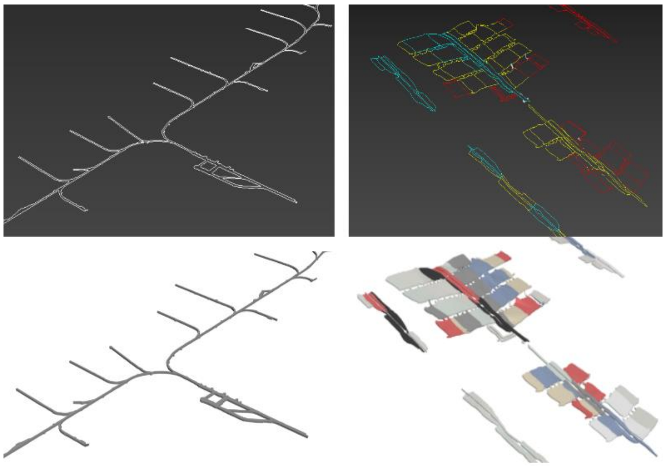

Fig. 2 An example of mining visual model reconstruction.

3.2 Routine data

Routine data refers to all other datasets except drawings, which can include regular surveys, statistical data, monitoring data, *etc*. It can be generated in a structured, semi-structured, or unstructured format, due to different scopes while data collecting and management.[15,20] Structured data are often built on a deliberate relational structure that follows a specific schema. Unstructured data have no clear structure that is often easily recognised by humans but difficult to query and clean by computer. Given that no predefined structure or hierarchy exists in unstructured data, the data exchange and processing will be time-consuming and may get a non-pattern outcome in analysis. Semi-structured data cannot be arranged in a structured way. Similar data cleaning and processing sections are needed. Furthermore, the structured data are generally stored in various data diagram and follow different relation schema. For example, generally existed primary key among data tables can include working area name\ID, level name\ID, coordinate code, sensor ID, *etc*. Since data fusion requires data matching across various datasets, the principle of routine data collection and management in this paper will follow a spatial-temporal schema. Table 3 summarises potential datasets and dimensions across underground mining procedures. According to the shared spatial-temporal attributes, coordinates and timestamp in this paper, unified data diagram is proposed in this section. Moreover, with the advancement of IoT and IIoT techniques, diverse routine data will definitely enrich the sub-type of production data, which makes the data diagram and system compatibility an imperative in lifelong consideration.

Table 3. Potential mining data classification.[8,15,37,38,62,79,86,87]

Data type	Sub-type	Dimension potential
Geological data	Geological, Hydrogeology, Rock mass, Structure, Geo-stress, Seismicity, Blast vibration, *etc*.	Potential for time series accumulation
Environment data	Humidity, CO_2, O_2, Toxic gas, Gas, Ventilation, Water, *etc*.	Time series accumulation
Devices and vehicles data	Device issues, Maintenance, Working cycle, Shaft, Traffic and Transport, *etc*.	Timestamp-based spatial distributed events
Production	Blast, Support, Exploration, Production, Price, Grade. *etc*.	Timestamp-based spatial distributed events and potential for time series accumulation
Hazard	Fall of ground, Rock burst, Failure (roof failure, support failure *etc*.), Water burst, Water and mud inrush, Collapse, Landslides, Surveys\recordings, *etc*.	Potential for time dimensional relevance

3.3 Data-fusion and 3D visual analytics

Considering the complex spatial connections and geological structures, this paper proposes a new multidimensional data management schema. From a macro perspective, one dataset is a dimension, and the increase in data categories means a dimension increase in data visualisation and analytics. Digitalised visual model datasets can be a new dimension in data analytics, which provides geological and spatial information.

Data fusion in this paper mainly includes spatial-temporal fusion and geological data fusion. Spatial-temporal fusion can be implemented by matching location and timestamp attributes in data processing. The matching is based on the unified spatial-temporal diagram. In view of the constant mining activities, temporal fusion can reveal insights into the causes and effects of geological events. Furthermore, the spatial distribution can contribute to the internal linkage of various attributes. Geological data, such as mining workings and geological structures, can be involved in proposed multidimensional data analytics as the same as routine data.

On the other hand, 3D visual analytics is proposed in underground mining scenarios to extend the application of data fusion in visualisation and analytics. It focuses on digitalising geological data into visual models and feedback to data analytics and model training. The implementation requires high-fidelity visual model digitalisation and structured spatial-temporal data. With the design of interaction with visual models, knowledge discovery of mining activities can be well promoted.

3.4 Visual analytics-oriented data diagram

Considering the visual model digitalisation and routine data standardisation, we propose an expansible and scalable data diagram, which is shown in Fig. 3.

The proposed structure is based on the spatial-temporal schema and tile index concept. The tile index originates from 2D mapping, in which the map details can rearrange the tile size. Inspired by the tile index and scalability of the tile size, this paper proposed a 3D tile index schema in multidimensional data management and data-driven model development, in which 3D tile index size can be resized by different data categories and application requirements. In the 3D tile index, every dataset can be generated and located into a 3D grid and follow a timeline variation. Benefiting from the lack of a primary key connection of the NoSQL database, different datasets are linked by implicit spatial information. Fig. 4 shows the samples of different 3D tile index generation. Spatial correlations will be encoded to an attribute in each data collection that services data query and visual analytics. Each routine data will be bound to the nearest visual model grid by tile index, which is flexible for further redirection. To ensure expansibility, this paper divides mining data into three categories by function, including visualisation collection, routine data collection, and reference collection. Among them, reference collection is simple but strict, providing data attribute references such as lithology code, mine site code, *etc*.

4. Proposed data framework

4.1 Data management framework

Referring to the multidimensional data management framework, this paper proposed a data workflow overview in Fig. 5. All collected data will be arranged into a four-layer hierarchy by this workflow, including model data, grid model data, grid data, and cache data. In this work, our model data collection focuses more on the digitalised visual model of the original mining working drawings. It can be recalled after refine gridding operation is conducted by users. The grid model data is generated by our visual model gridding rules, which defines the minimum unit of visual interaction. It can be refined and customised without affecting the original model data. All grid routine data will be processed and stored as well in a collection, and it can be spatially linked to visual model data. Finally, the cache data collection is temporary data storage providing visualisation and analytics datasets. User interaction-oriented data comparison, verification, and validation will depend on it to optimise system response. Based on the idea of 3D tile index, every collection can re-tile refer to its data density, such as routine data dimensions shown in Fig. 4. Due to no primary or foreign key correlation, data re-tile is independent of other data collections, which means every data collection can be processed as one single dimension.

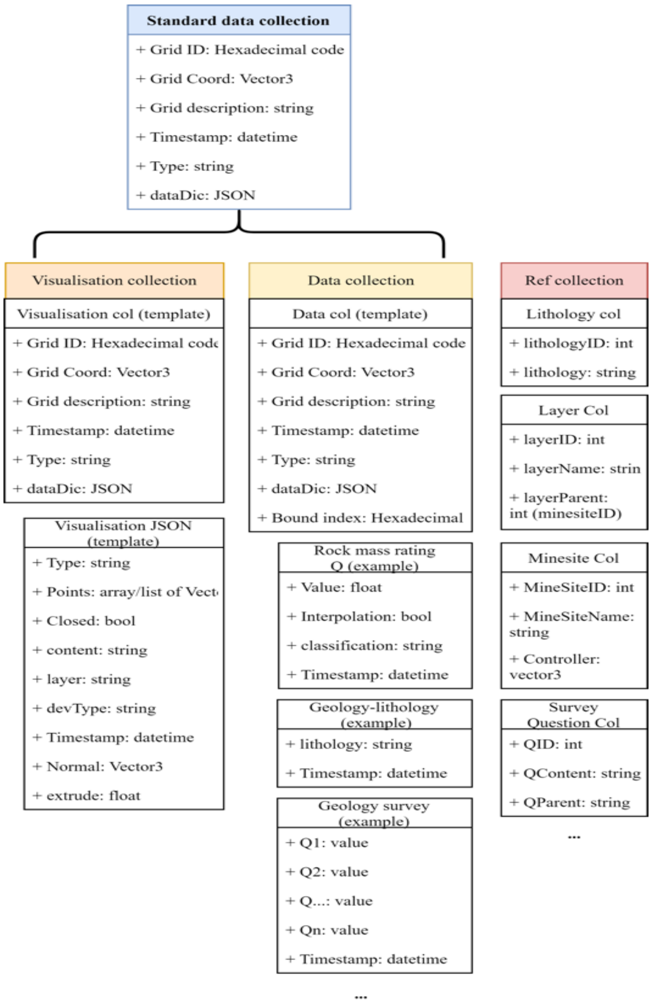

Fig. 3 Proposed data diagram.

4.2 Data-driven model development

Based on the unified data diagram, we proposed the data-driven model development solution for lifetime support in visual model construction. Referring to the idea of tile index, visual model can be digitalised into datasets, grid into specific units, and then reconstructed into visual model by different visual analytics requirements. Such as, 2D wire-frame model with low power cost, 2D plane model for precise physical simulation (pathfinding and emergency plan), and 3D model for fidelity model visualisation.

From the data management perspective, four stages data exchange workflow can be involved in the implementation of data-driven model development, including drawing digitalisation, model gridding, routine data processing and matching, and visual model upgrade and lifetime support.

4.2.1 Drawing digitalisation

Drawing digitalisation focuses on dxf\dwg files-based data conversion and serialisation which finally streams data into

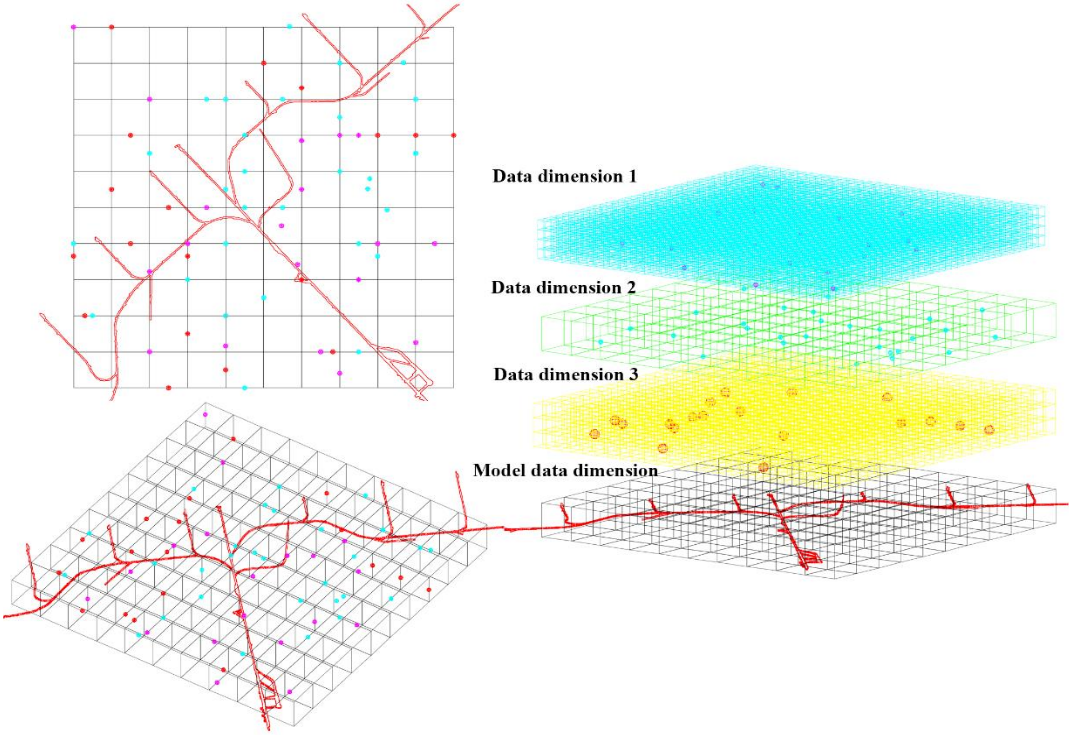

Fig. 4 Data dimension diagram.

the visual model dataset. The data exchange is driven by proposed unified data diagram. We firstly explore the commons and sharing attributes so that digitalisation can get a higher error tolerance. In summary, polyline, line, circle, plane/mesh, and text are most general entities in mining drawing. Polyline and line entities normally construct tunnels and panels. Circle and line are combined to present shaft and inclines in underground mining. Text entities are normally extra information of mining workings. Mesh entities can be 3D geological structures. After concluding the sharing attributes of each drawing entities, model data JSON template is finalised and shown as Fig. 6.

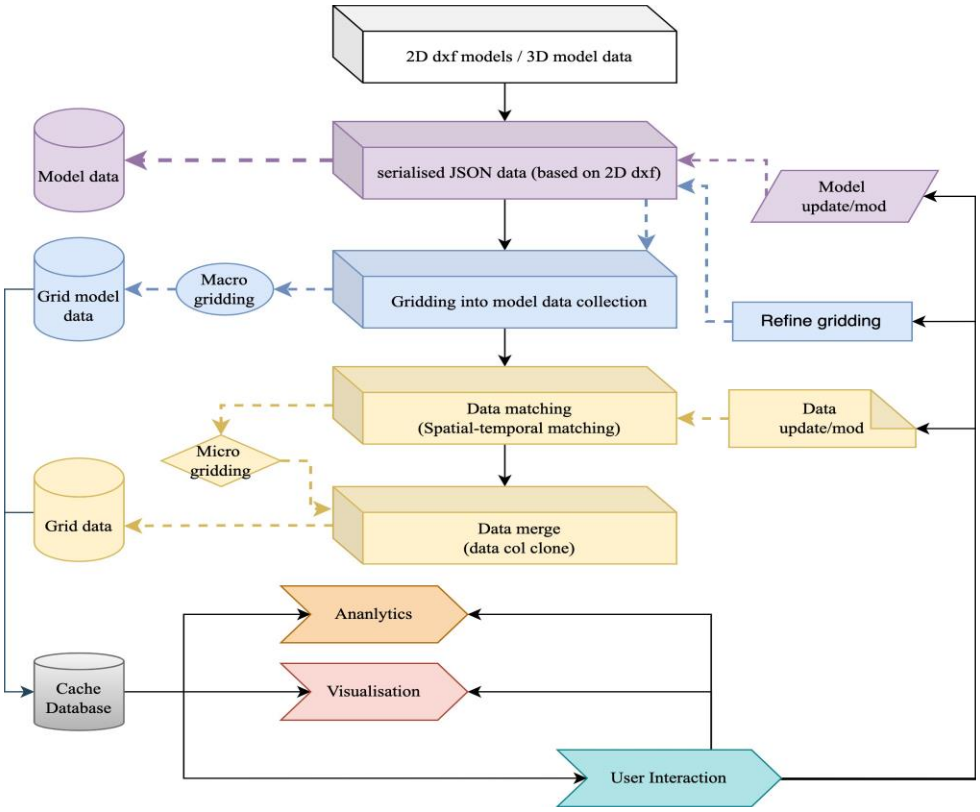

Fig. 5 Proposed platform workflow.

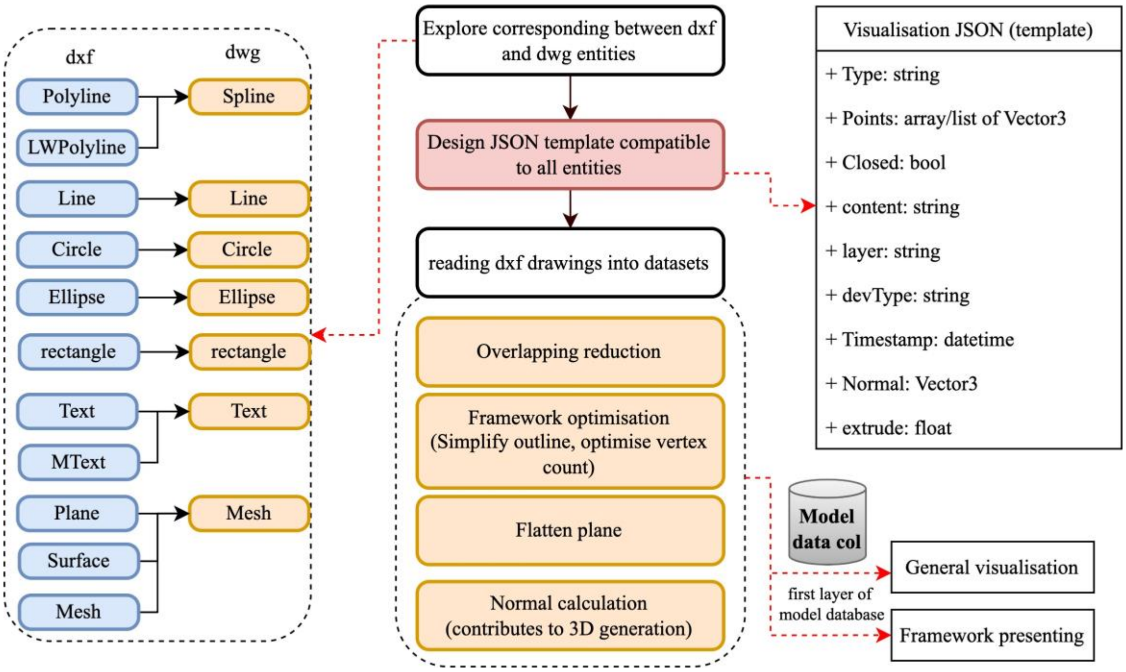

Fig. 6 dxf drawing digitalisation.

Given that mine drawings are not standardised and the complexity of drawings varies from case to case, drawing data cleaning is processed. The cleaning process contains overlapping reduction, framework simplicity, odd plane flattening, and plane normal calculation. JSON serialised data will follow the workflow in Fig. 7 to be stored and transferred to the following process. The original model data collection directly works with bidirectional dxf drawing conversion, and generated gridding data collection then contributes to data-driven model reconstruction and further visual analytics, which ensures the stability of visual model data collection and makes re-grid possible.

4.2.2 Model gridding

Model gridding aims to decompose model entities into grids that will be operated and interacted with in data analytics and visualisation procedures. As underground mine sites cover a wide range of underground space, precise model can pose pressure to system running. From this standpoint, visualisation optimisation can be realised by customised visual schema. The 3D grid model can automatically switch from hidden mode to visible mode as the user's perspective changes. Meanwhile, the multidimensional data linked to the model grid can also follow the render rules to balance the power consumption.

Figure 8 shows the model gridding workflow and involved sections. In view of the multidimensional data framework, model data and grid model data have only one direction of inheritance relationship, which means grid rules can be easily updated without causing any data association issues. From the interaction perspective, layer-oriented control can deal with model filtering to optimise interaction performance. Considering the precise model demonstration, collider component (Unity 3D physical component) will be generated by 2D schema and with a low-consumption mode to reduce physical rendering.

Finally, Fig. 4 shows the partial grid tunnel structure, each grid with explicit coordinates and a timestamp. Each color dot represents a dimension of a dataset that follows its own

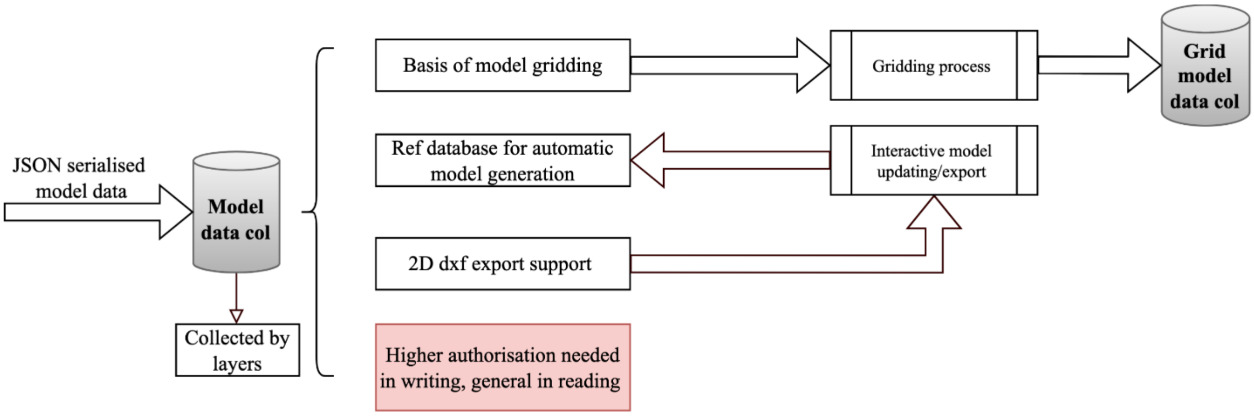

Fig. 7 Model data collection and exchange workflow.

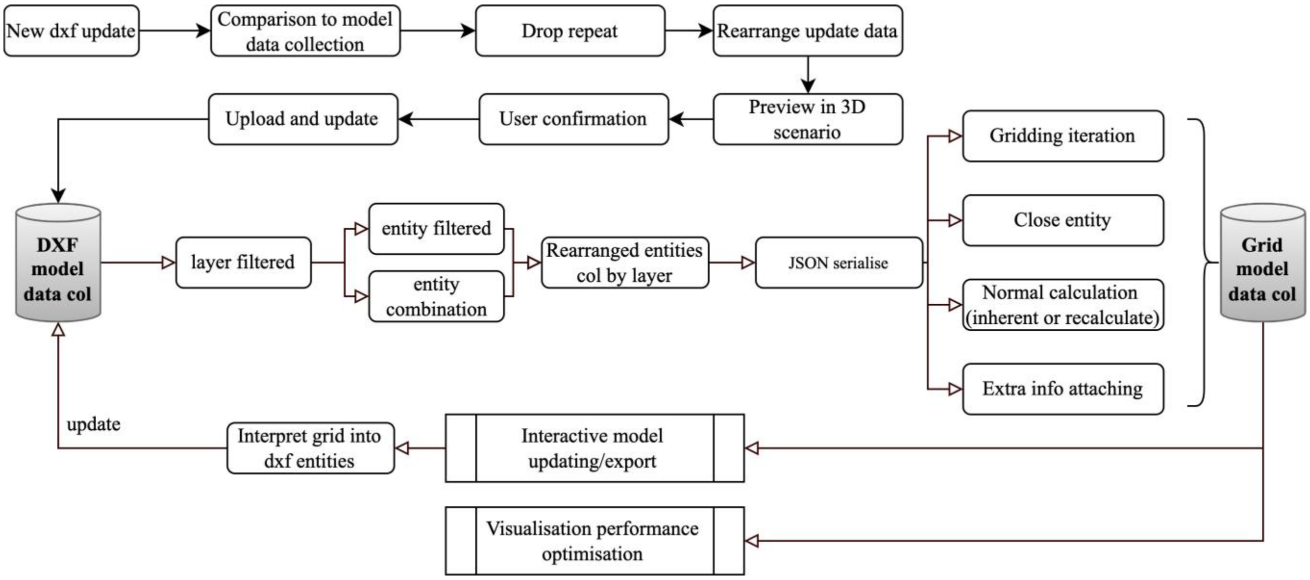

Fig. 8 Model gridding workflow.

gridding rules. Regarding the capability of handling large-scale visual models, Fig. 9 demonstrates the mechanism of visual model optimisation of gridded visual models while the user visualisation perspective changes. In detail, the gridded visual model can be operated by back-end programs, including dynamic visualisation, real-time interoperation, tailored feedback with user manipulation, *etc*. Moreover, the compiled visual model data can also be processed and updated using numerical data.

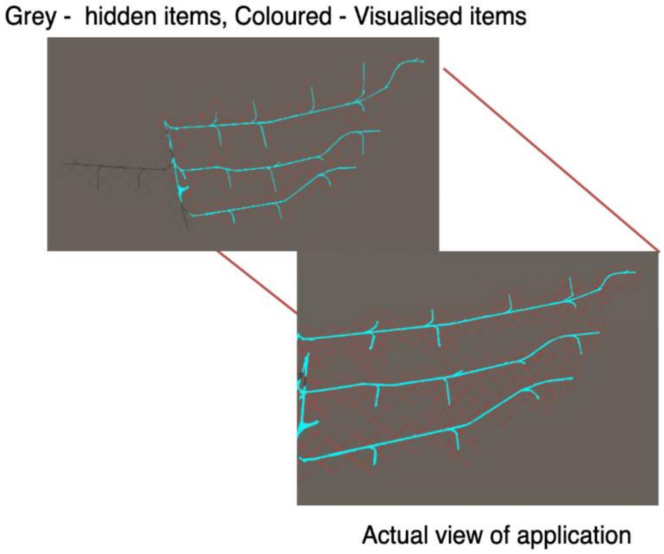

Fig. 9 The mechanism of visual model optimisation while handling large-scale visualisation scenario.

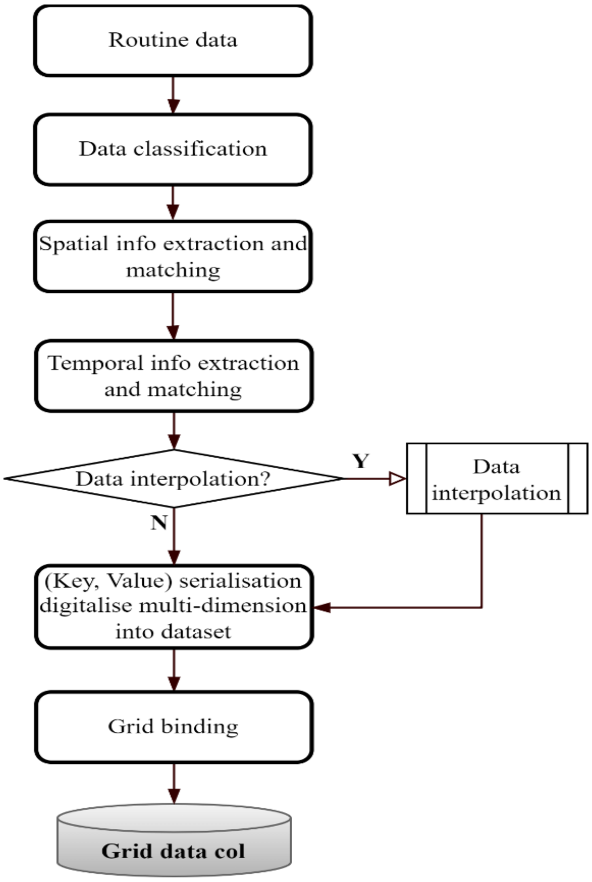

Fig. 10 Routine data processing.

4.2.3 Routine data processing and data matching

Routine data processing also follows tile index rules. Integrated with the multidimensional data management framework, gridding rules can be different in each routine dataset depending on data density and custom setting. The customise is one of the merits of 3D visual analytics that users can re-grid by visualising all valid data to validate its scatter pattern in 3D environment(Fig. 4). Fig. 10 shows the process of routine data gridding and attributes matching. Spatial-temporal traits will be built-in while processing and finally serialised into JSON format. In this workflow, due to unexpected low data volume and unpredicted scattering of geological data, routine data can also be interpolated to get a relatively rich dataset for machine learning (ML) model training and analytics utilisation. From the data analytics perspective, ML model and prediction analytics requires an ideal dataset to explore the data patterns for specific utilisation, which the interpolation can be utilised as an alternative for analytics in data accumulation stage.

To optimise the query efficiency, grid routine data will be attached a model grid index in grid binding. The target index is the closest model grid which contributes to the visualisation interaction, such as render optimisation.

4.2.4 Model update and lifetime support

In terms of lifetime support of the visual model, data-driven model development provides three solutions to guarantee the compatibility and sustainable development.

1. Model re-grid: Considering the grid size can be changed with the data increase and user customisation, grid model data can be rearranged and updated based on model data collection.
2. Model update and interactive development: Fig. 11 shows the visualisation layers and interaction logic. Both model edit and extension will start with one interactive grid, then the data and visualisation steps can guide user finalise the design or model edit procedures. Finally, revised visual model data will stream into model data and grid data collections.
3. Bi-directional dxf data exchange: Referring to the workflow in Fig. 8, model data update can also be realised by dxf drawing import. Firstly, digitalised dxf dataset will be processed for repeat checking comparing to existing model data collection. Then, filtered dxf entities will follow the gridding process for data merging. Similarly, the dxf export can be achieved by dxf interpret process. Finally, a bi-directional drawing transformation can contribute to the lifetime support and model fidelity of the 3D visual analytics.

In summary, with the help of multidimensional data framework and flexible model digitalisation process, visual environment in underground mining can be expanded and updated with the system requirements.

4.3 System expansibility and scalability

Database migration capabilities are the essential work while leading in a new system or platform to take over the ever-increasing data. As aforementioned, due to paralleled information systems, database migration is rarely considered in current study. Here we proposed a basic workflow to deal with the database migration. Fig. 12 shows the basic workflow for database migration. As for most of the mining data has no spatial-temporal properties, batch processing is the most critical work in migration. Data matching and cleaning of all datasets help find out the spatial-temporal connection, then rewrite to the datasets. Then, after series of standardisation and verification, migration can be completed and provide standardised data. Theoretically, database migration can help address the integration of multiple information systems. But more study should be implemented in database migration due to the complexity of historical data. For example, most historical data cannot be traced back to a specific date or coordinates; Some data has experienced adjustments in attributes, *etc*. More efforts should be paid to fix these issues while conducting database migration.

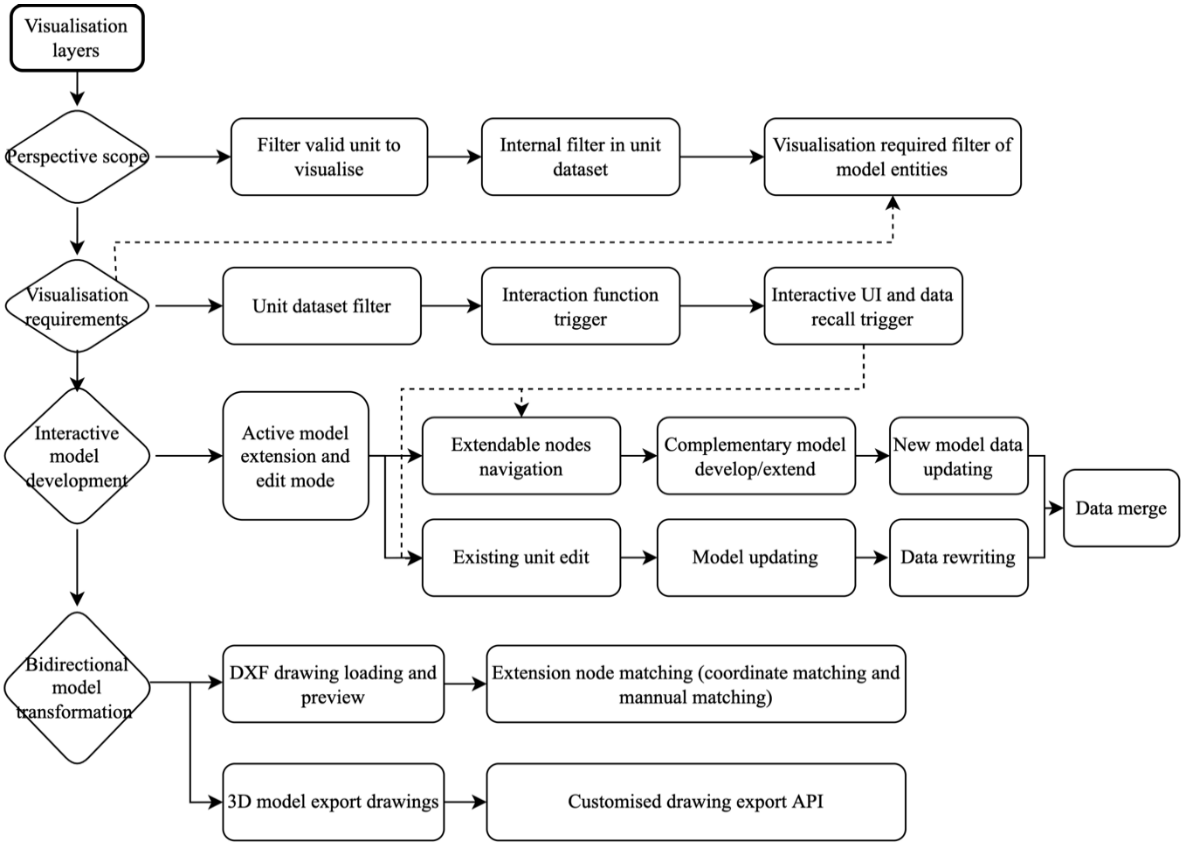

Fig. 11 Visualisation layers and function logic.

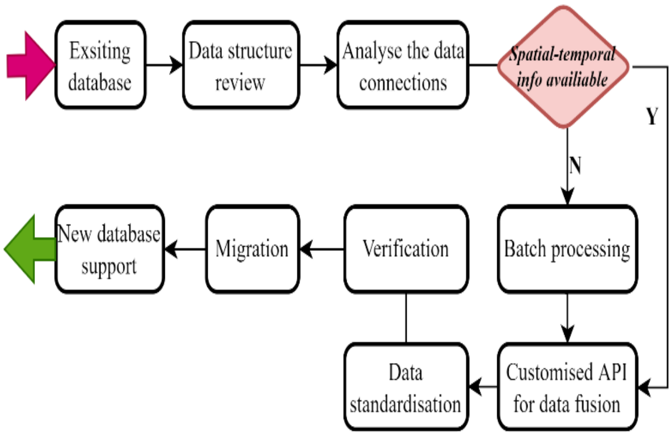

Fig. 12 Database migration workflow.

4.4 3D visual analytics

Interactive visualisation, in this paper, is targeting to provide insights into data analytics by accessing all available data in visual space. Given that, user-oriented model development plays a vital role in 3D engineering design scenarios. It helps to fuse human judgment and human-led interaction into digital information. Fig. 13 demonstrates the visualisation data streaming workflow. It summarises the sections involved in data transformation and visual analytics. Based on the multidimensional data framework, the visualisation platform accesses the database and extracts the model data through query application programming interfaces (APIs) in visualisation data exchange. Then in the visualisation platform, perspective and render optimisation are conducted.

Furthermore, interaction feedback is essential in visual analytics. By data grid, interaction operation can be merged into a data stream and feedback to the dataset. Fig. 11 shows the logic of visualisation layers in different domains. Fig. 14 shows the back-end data preparation for data fusion and visual analytics.

From the analytics standpoint, ML models are constructed in the data analysis layer. Fig. 15 shows the workflow among data clustering, model training by different solutions, and lifetime services in the 3D visual analytics platform. In order to simplify the data exchange and extraction, custom APIs are proposed and listed in Fig. 16. All these contribute to the precision and efficiency of visualisation and analytics completion.

Regarding the lifelong operation of an engineering-based information system, 3D visual analytics in mining requires more human-involved knowledge convey and utilisation. As a result, 3D visual analytics can facilitate the revealing of visual data patterns and the exploration of data connections through multimodal data visualisation. Nonetheless, the development of visual analytics also poses interaction design as an imperative in information system construction, which is part of the data exchange and information sharing.

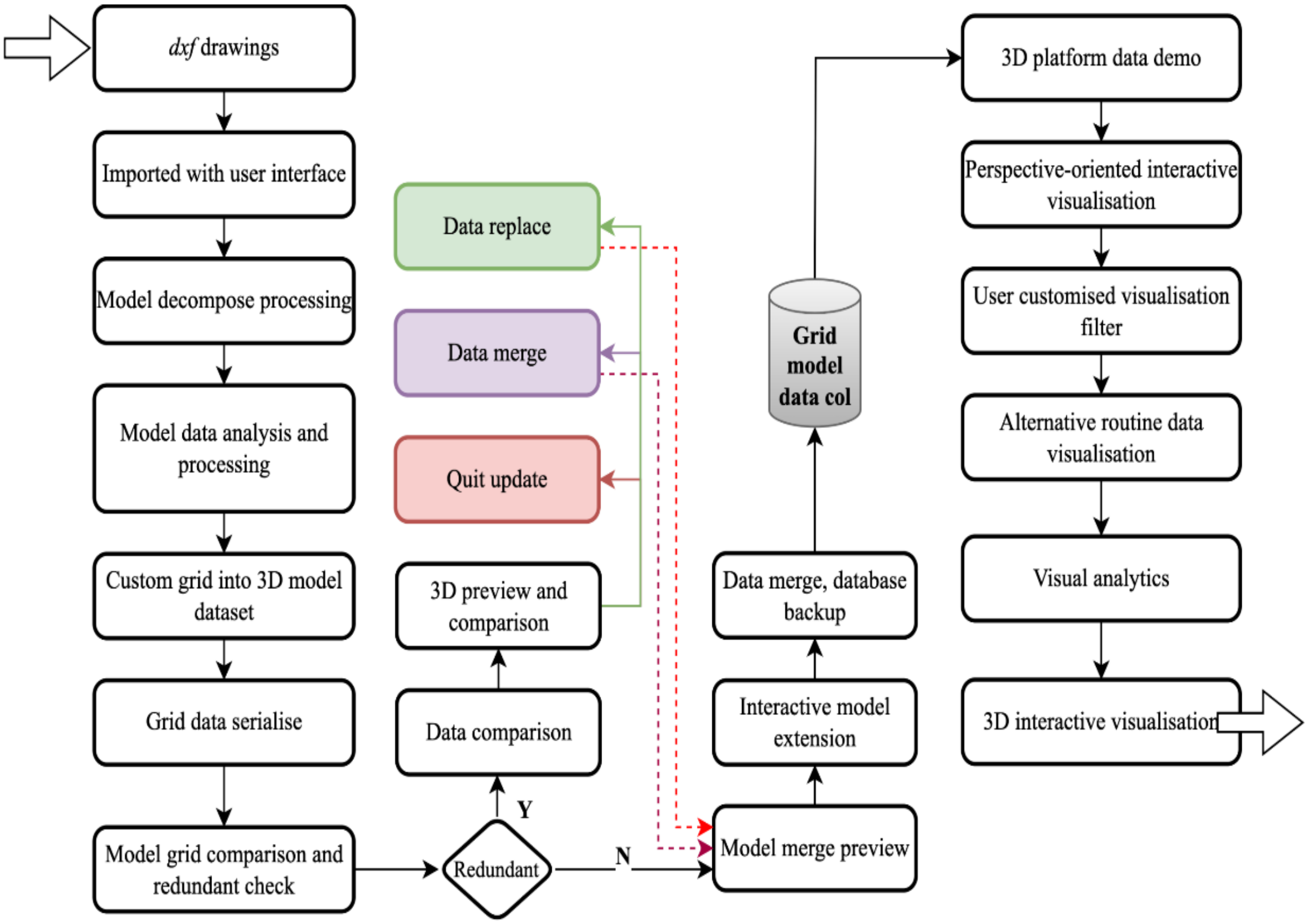

Fig. 13 Visualisation data streaming.

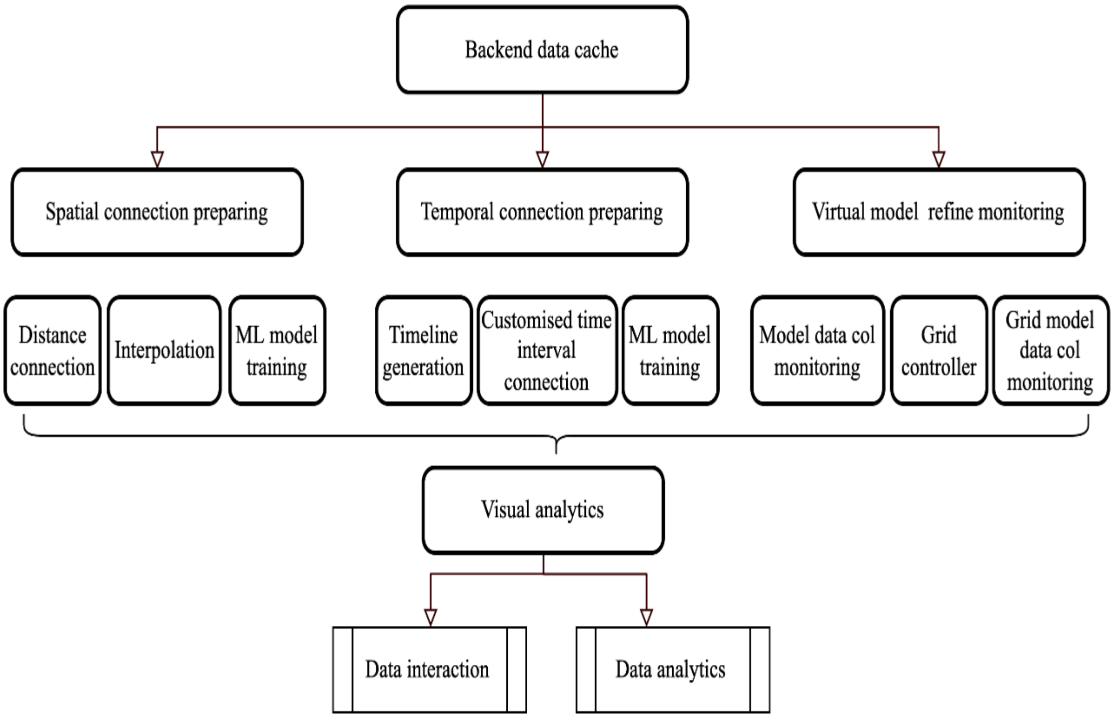

Fig. 14 Data processing.

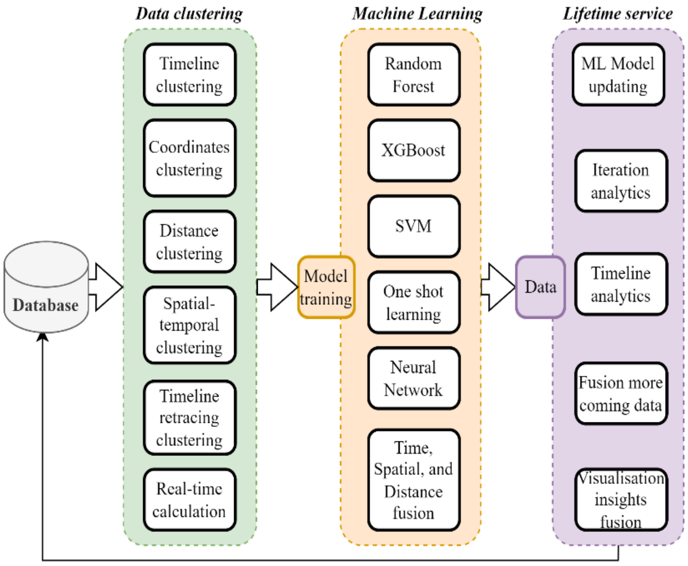

Fig. 15 Analytics-oriented workflow.

5. Future work and insights

This section discusses the future concerns of data management in an integrated mining information system. Regarding compatibility and expansibility, advanced technology-driven insights into mining digital twin systems are discussed as well.

5.1 Data security concerns

Data security can be one important issue with the data management development. Therefore, we discuss some key points in the data security domain here.

1. Data confidentiality

Data confidentiality refers to preventing the active attack of unauthorised parties on the data and to ensure that the information received by the data receiver is completely consistent with the information sent by the sender. Since the production data came from various sections and managed by different groups, confidentiality issues are broadly noticed in processing. The data streaming should be limited under supervision. Once accessed by an authorised user, data confidentiality is compromised, which is irreversible.

2. Data integrity

Data integrity is the reliability of the data, that is, the data cannot be arbitrarily tampered with and replaced. For example, if one mining manager is in charge of one data collection, unauthorised managers, even at a higher level, cannot get access to revise and modify the data. The absence of data integrity can pose serious security issues.

3. Data availability

Data availability emphasises that data can be accessed normally at any time, namely users can access, download, or do some modifications to data in the cloud as soon as they need it. Obviously, this will always follow the rules of data integrity and confidentiality.

4. Completely data deletion

When users no longer use cloud storage, they can completely delete the data outsourced to the cloud server and confirm that the data has been completely destroyed, instead of being cheated by malicious cloud service providers.

5.2 Privacy protection

While users enjoy the convenience of cloud storage, cloud storage providers have captured their private information, such as sensitive data for the enterprise. Privacy security mechanisms are used to guarantee that these data will be kept secret by curious adversaries and malicious employees of

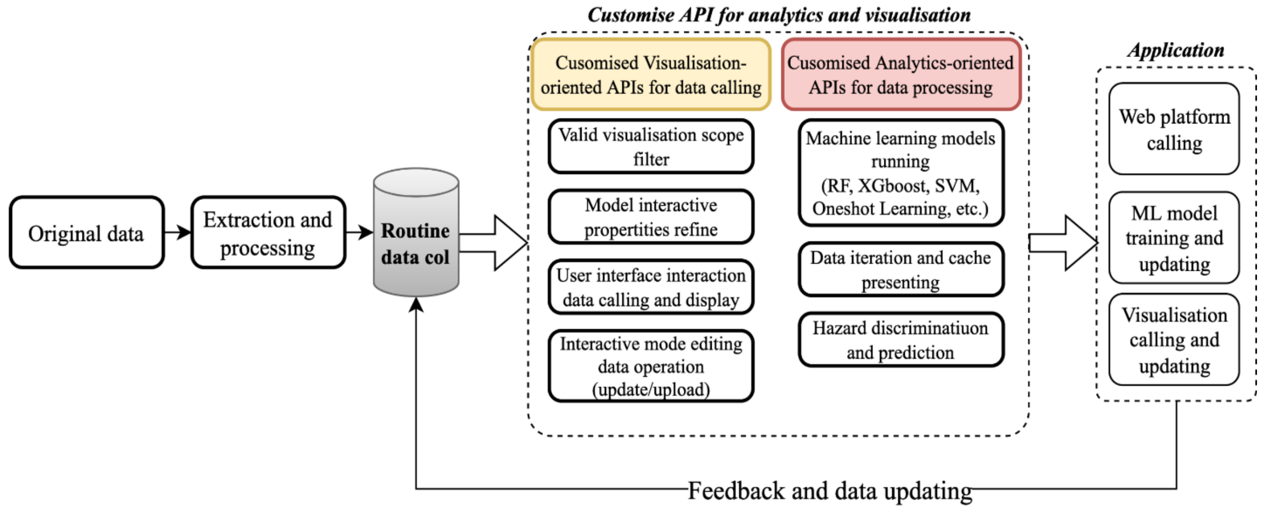

Fig. 16 Custom APIs complemented data exchange.

cloud service providers.

5.3 Insights

Given that the concept of a digital twin system is broadly accepted in industry practice,[47,88-91] effective data management, especially the visual analytics-oriented data diagram, can contribute to the construction and development of a mining digital twin system. Considering the real-time capability and high-fidelity visualisation, the data exchange APIs and model development scenarios will be the core of a mining digital twin system construction.

Furthermore, with the development of SLAM and 3D image modeling, data-driven model development will not be limited to 2D drawings' transformation fusing point cloud data with virtual space visualisation and interaction should be studied in the future. In addition, considering the high precision of SLAM modeling, more scenarios would be possible in a future version, such as (near) real-time goaf evaluation, blasting assessment (over\under blasting), *etc*.

6. Conclusion

In this paper, we proposed a visual analytics-oriented data diagram to facilitate efficient data management to be used in mining. Considering virtual model data, the proposed unified data diagram defines it as a new dimension in visualisation and analytics, contributing to multidimensional data management and analytics. Correspondingly, data exchange workflows are proposed to facilitate data sharing across different applications, such as visual model data digitalisation, data visualisation, routine data standardisation, and visual analytics development. Compared to current data management and analytics solutions in mining engineering, this paper expands data fusion applications into more domains by spatial-temporal connections. Our multimodal data model enhanced visual model makes near real-time underground mining model reconstruction possible, which also lets the visual model data become one possible factor in data analytics. This can be arguably important for the exploration of data fusion in underground mining. Furthermore, the proposed data exchange workflow has provided human-interaction data in a 3D visual analytics framework. As human inputs play an important role in analytics and visual model construction, the tile index-based data diagram can have more potential in data management and interaction construction.

Finally, considering the prevalence of digital twin development, this study provides insights into mining digital twin construction benefiting from efficient data management, such as data flow design (such as APIs, data exchange logic), and visual model development. The complex interaction logic embedding based on the Unity 3D platform needs more effort to perfect and will be a vital part of our future work.

Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable.

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