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Towards fleet power and energy management of parallel hoist operation in underground mines

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ABSTRACT

The EU regulation EB Article 53 (2017/2195) reducing the imbalance settlement period on the electricity market from 1 hour to 15 minutes will open for new needs within the mining industry. The regulation is expected to come into action in Sweden during 2024 for intraday market trading and in 2025 for day ahead trading. Hence, average power over 15 minutes may become more important to monitor and control in the mining operation. One process that can be affected in this timeframe is the hoisting process. Particularly when multiple hoists are in operation, effective control of their usage can significantly impact the average power demand as well as the energy trading dynamics. This paper presents how the hoist system in one of LKABs mines has been modelled in a simulation platform with focus on increasing the control resolution, namely 15 minutes instead of 1 hour. Also, the paper investigates how a slightly more extensive use of the material buffers can move energy demand between timeslots to monitor and control the average power need better. Simulations show how the peak power in a worst-case scenario can be reduced by better fleet management of the hoists to about 25%. In addition, a further reduction of 10% can be reached by also reducing the acceleration of the hoists by 20 % if spare capacity exists in the hoist process. The paper also discusses how energy storage can reduce power variations further and makes an estimation of needed storage size.

1 INTRODUCTION

The introduction of more varying electrical energy sources like solar and wind energy is driving larger price variations. Trading data from (ENTSO-E Transparency Platform) shows an increased variation for the four different electrical day ahead energy bidding zones, SE1-SE4 used in Sweden, shown in **Error! Reference source not found.**. The increased share of weather dependent production is also expected to increase the intraday trading to maintain balance.

The EU regulation EB Article 53 (2017/2195) (European Union, 2017) reducing the imbalance settlement period on the electricity market from 1 hour to 15 minutes is now being introduced and expected to come into action in Sweden during 2024 (Nordic Balancing Model, 2023). Intraday market trading will be implemented first, and in 2025 for day ahead trading.

A market driven way to reduce these variations is to increase the time granularity of the trading horizon. The purpose is then to increase flexibility with a faster price signal to facilitate remedy investments with solutions that provide flexibility at low cost. Example of such technologies in general are battery energy storage, smart charging of electric vehicles, flexibility in conventional power plants but also demand side flexibility.

Large mining operation is both energy consuming and rather variable in demand profiles. Also, load cycles in mining can be both shorter and longer than 15 minutes which can potentially affect the energy profile under the new market conditions. To what extent the end user will become impacted of the new regulations is yet to be seen. However, the price variations on the market are associated with a financial risk which in the end influences the total cost of electricity. Hence, end users may find benefits in better Time of Usage strategies of the demand. Companies that have fast flexible demand might also join the fast frequency response market to increase revenues. The manual Frequency Response Resource (mFRR) market has already been initiated in Sweden (Statnett, 2020) where one can bid in minimum step of 5 MW, full activation within 15 minutes and 60 minutes endurance.

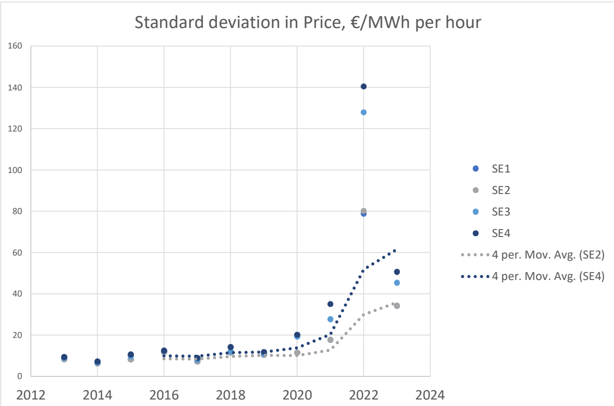

Figure 1 Hourly price variations an the Swedish electricity day-ahead bidding zones SE1-SE (ENTSO-E Transparency Platform) 4.

The updated time resolution on the energy measurements in the grid connection will be hard to follow up without also increasing time resolution in better sub-metering or better process modelling of the power demand.

In this paper, the focus will be on the hoisting process which is interesting for the 15-minutes timeframe. Hoisting normally have material buffers which can be used as storage, cycle time of minutes and also the possibility to reduce acceleration at times with overcapacity in the hoist process. It is also possible to smooth out the demand curve with a relatively small electrical energy storage but where the storage is exposed to many cycles.

2 PROBLEM STATEMENT

In this paper, we address the potential of the new 15-minutes timeframe for power and energy management of hoists, especially in larger mines with several hoists running in parallel. In detail, we want to answer the following questions:

- How can power and energy consumption of hoists be modelled at high resolution?
- How can fleet management be used for reducing maximum power and energy costs, especially with regard to (i) material buffers and (ii) operational settings?

The remainder of this paper includes a detailed explanation of our modelling approach (see Section 3). Also, we discuss hoist fleet management with regard to peak power (Section **Error! Reference source not found.**), buffer utilization (Section 4.2) and variation of operational parameters (Section 4.3). Finally, we summarize our results in Section 5 and propose directions for future work in Section 6.

3 Model and Discrete Event Simulation

The discrete event simulation (DES) stands out as a sophisticated and powerful technique employed across diverse industries (Fishman, 2001), mining being no exception. In general, DES breaks down the physical system into a set of events, each of them influencing the state of the system in a specific way. Entities in the system move through different states triggered by events, and the simulation progresses through these events one by one with time until certain criteria are met. Events, e.g., a truck being loaded, are processed and influence the system's state, causing new events to be scheduled. State variables record the system's changing conditions, and performance metrics can be analyzed using data collected during the simulation.

DES is often applied to modeling and evaluating complex systems and can offer insights that lead to enhanced efficiency and productivity. In mining, DES is a valuable tool used to simulate and improve mining operations (Song, Schlake, & Emmrich, 2022). There are several different DES libraries and software packages available, each with its own strengths and weaknesses. Some of the most popular DES libraries and software packages include AnyLogic (Borshchev, 2014), Arena (Kelton, Sadowski, & Sadowski, 2002), Simply (Scherfke, 2014) and OMNET++ (Varga & Hornig, 2010). In this work, we developed a Python-based DES with special focus on the mining process.

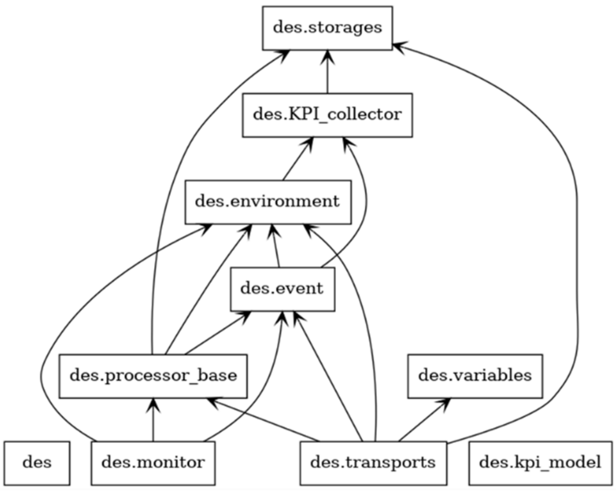

Figure 1 Code structure of discrete event simulation library.

Figure 1 illustrates the code structure and class relations of the DES library developed at ABB and the important classes are:

Event: It represents an individual occurrence or trigger conducting the simulation. Each event corresponds to an action or state change in the system. In the mining process, events can be represented by, e.g., loading material onto a truck, crushing certain quantity of raw materials, etc.

Environment: A general event space that consists of ordered events to be executed. It holds global logic and rules to drive event occurrences.

Storages: Asset management to store corresponding minerals passing through the mining process. In reality, it also often refers to the buffers, which are installed before the processing units, for example, a buffer storage for a grinder.

Processors (*Processor_base*): Processors refer to system entities, which represent objects or elements that are capable of processing assets with specific actions and interact within the simulation system. This class is used to model the mining equipment in general, for example trucks, grinders, etc. *Processor_base* is the base class, and two main derived classes are continuous processors and batch processors that represent two distinguishing processing types. Various specific processors are built and implemented based on them afterwards.

Transports: It consists of rules or logics that control a set of batch processors.

KPI_model: An interface that users can define specific KPI model for processors.

KPI_collector: Collecting KPI calculation from **KPI_model** class, the timestamp of occurrence of calculation is defined jointly by event and environment.

Monitor: Monitoring class that measures that system KPIs and user defined KPIs at a pre-defined frequency. For example, the storage level at each buffer location, power consumption at specific timestamp, etc.

Variables: System parameter model that provides the possibility of using statistical distribution to model variability and randomness inherent in the real-world processes. For example, trucks cannot always drive at a fixed speed, but it is rather a stochastic process conditioned by road condition and human behavior.

4 HOIST FLEET MANAGEMENT

Hoist fleet management is especially interesting for larger mines with more than one hoist and at least one material buffer. In our example, we consider a setup as shown in Figure 2 with hoists on two levels and one material buffer per level.

4.1 Peak Power Shifting

We use the DES library mentioned in the previous section to model the power consumption of LKAB Kiruna's hoisting system (ABB AB Mining, 2024), which haulages the ore from underground to the processing vertically 1.4 km in two stages (Mining Technology, 2020). Figure 2 depicts the layout of the LKAB hoisting system, which has been modeled using our discrete event simulation.

In our discrete event model, direct connections between processors are not allowed. Instead, there is always an intermediary storage unit positioned between them to hold the material and serve as a buffer. Therefore, the model includes three storage units: Bottom Storage, Sub Storage, and Head Storage. In reality, the material lifted from the bottom level originates from another processing unit. However, we intentionally ignore the direct modeling of this part for the sake of simplicity. Instead, the input material flow into the Bottom Storage is modeled using a random distribution.

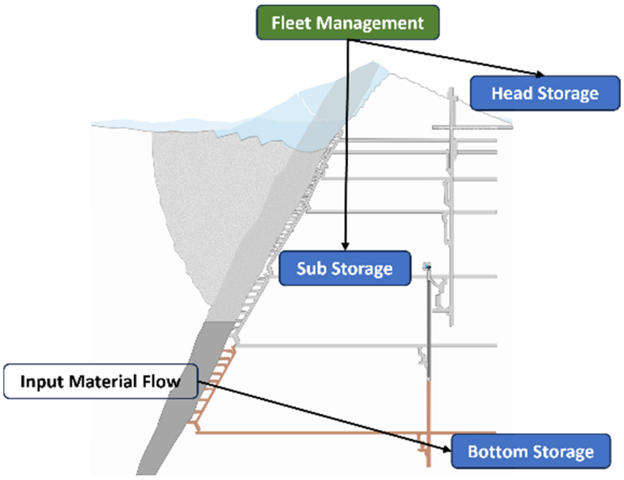

Figure 2 Exemplary two-level mine layout.

As previously mentioned, all hoists are represented by the Processor class in our model. The Fleet Manager coordinates the starting times of hoists to avoid power peak overlaps and minimize power consumption. It evaluates storage levels, selects hoists based on capacity and material volume, and executes them in a specific order. The Fleet Management also pauses other hoists during acceleration phases to prevent power peak spikes. This proactive approach ensures efficient and stable hoist operation.

In our simulation, material input to the Bottom Storage ranges from 1000 to 3000 tons per hour, following a uniform distribution. This variability leads to high total power demand during peak periods. Figure 3 illustrates a non-optimal scheduling scenario, with hoist acceleration phases mostly overlapping. Red lines represent upper power, blue lines represent lower power, and green lines show total consumption, reaching a peak of 60MW in worst case scenario due to overlapping sharp edges in power profiles (see Figure 4).

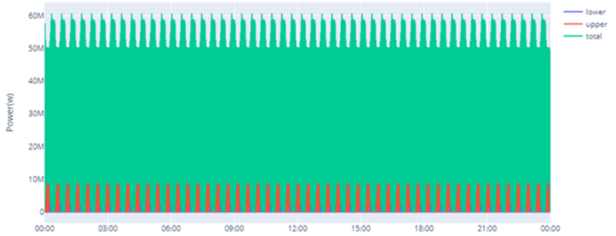

Figure 3 Power consumption with non-optimal scheduling.

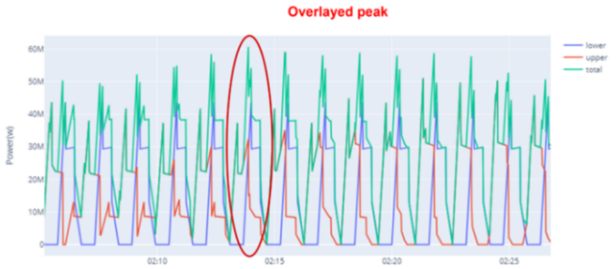

Figure 4 Detail on power calculation for non-optimal scheduling in worst case scenario.

Furthermore, utilizing the discrete event simulation, power peaks can successfully be reduced by implementing a more optimal scheduling approach that aims to prevent the overlapping of power peaks. Upon applying this improved scheduling strategy, Figure 5 illustrates the power consumption results, revealing a peak power of approximately 14MW instead of the 60MW observed in the non-optimal case (Figure 4). The implemented scheduling logic ensures that the execution of each hoist strives to avoid overlapping acceleration phases, as depicted in Figure 6.

This may involve incorporating waiting times if necessary to achieve the desired power peak reduction.

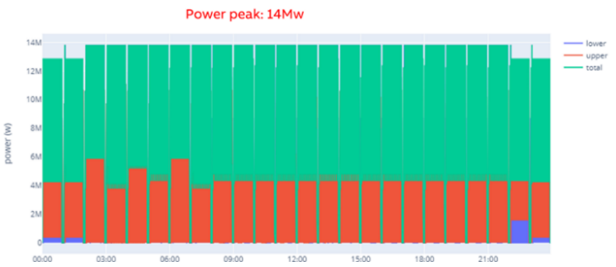

Figure 5 Power consumption with optimal scheduling.

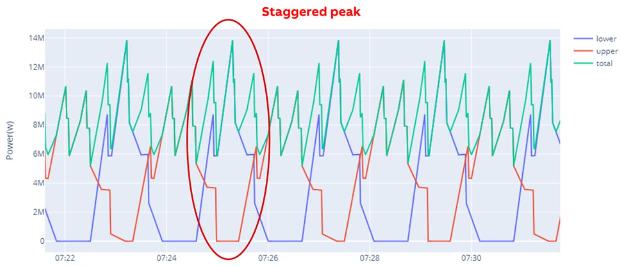

Figure 6 Detail on power calculation for optimal scheduling.

4.2 Buffer and Storage Utilization

In addition to peak power shifting, we also explored the benefits of adding additional energy storage solutions and applying a simplified energy management framework similar to (Sigalo, Pillai, Das, & Abusara, 2021) (Javadi, et al., 2020) (Sorour, et al., 2022). The energy management framework optimally schedules the load coverage, grid usage and battery usage to reduce the overall energy costs and obey all power connections of the network. A consequence of keeping power demand on average power at all times is that grid losses are minimized.

Optimally scheduled hoist cycles as discussed in Section **Error! Reference source not found.** are accumulated per level and then used as input signals to the framework, which can deal with several loads and storage. Figure 7 displays the network being used with accumulated hoist load series for lower level (*load0*) and upper level (*load1*), an energy storage (*battery*) and the *grid*.

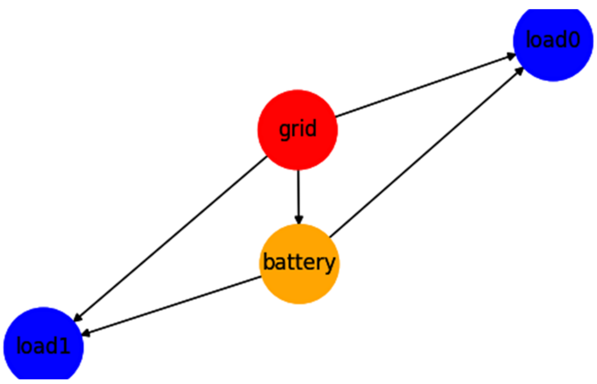

Figure 7 Network for power and energy cost optimization with storage solutions.

Results are displayed with respect to load coverage (see Figure 8) and grid usage (see Figure 9). The goal is to optimally use storage and grid and thereby reduce costs by adapting power consumption to pricing strategies. Results show that the contribution of additional storage helps to reduce power peaks by supplying the average load from the grid and power peaks by the storage (see Figure 8). Results show how the power limit for grid supply is decreased with increasing battery capacity.

Complementary, when switching the perspective to grid usage, Figure 9 highlights the load coverage from the grid over time. In the extreme case of a very large storage (here: 100kWh), the power consumption from the grid shows hardly any variations since power is either used to supply the load or to recharge the storage.

Finally, simulated storage sizes are replaced by realistic storage scenarios. In detail (i) ABB Enviline ESS – Energy Storage System (ABB, 2020), (ii) Flywheel energy storage system (Li & Palazzolo, 2022), and large Lithium-Ion batteries (Hitachi Energy, 2024) have been simulated (see details in Table 1).

For all three storage types, the respective highest power rating and lowest capacity have been selected from the data sheets. It needs to be noted that these storages have been considered as ideal and de-/charging curves and losses have not been considered so far. Please also note that the flywheel is listed here but is still considered a technically challenging solution.

The resulting average grid usage is displayed for the different storage solutions. The optimal solution was reached for the Enviline ESS solution by reducing the maximum power peak by 18 % and thereby reducing dependency from variable pricing.

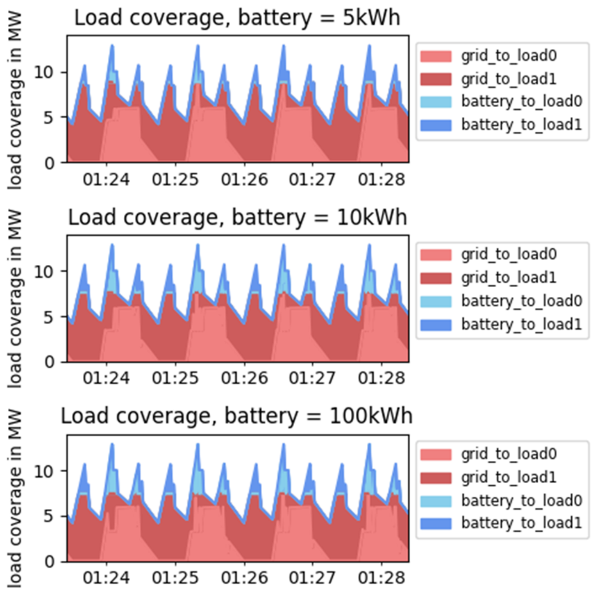

Figure 8 **Load coverage for additional storage sizes (5kWh, 10kWh, 100kWh).**

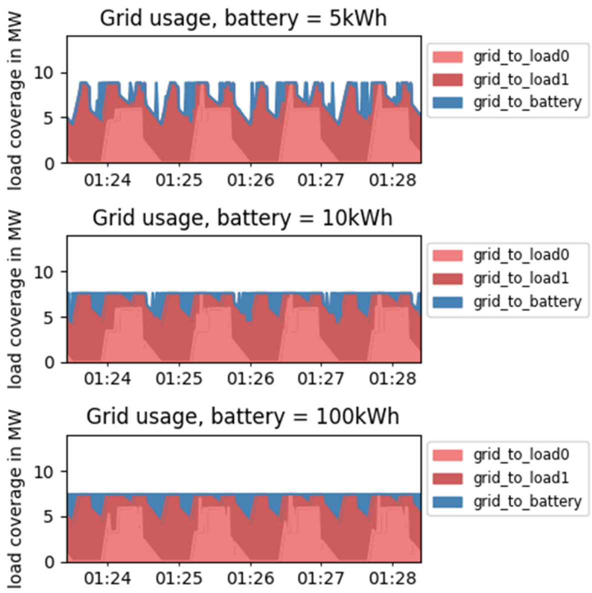

Figure 9 **Grid usage for different storage sizes (5kWh, 10kWh, 100kWh).**

Also, a maximum grid usage of 70.7% could be reached. Concludingly, additional energy storage can support to reduce power peaks and reduce energy costs.

Table 1 **Overview of storage solutions and resulting grid usage (ABB, 2020), (Li & Palazzolo, 2022), (Hitachi Energy, 2024).**

		Enviline ESS	Flywheel	Li-Ion battery
Data sheet	Power rating [MW]	1.35-2.6	2	0.12-0.5
	Capacity [kWh]	100-2500	130	280-812
Results	Avg. power reduction [%]	18.0	14.8	3.1
	Avg. grid usage [%]	70.7	66.7	58.6

4.3 Variation of operational parameters

When contemplating the automated operation of hoists, it becomes apparent that integrating a specific amount of waiting time is crucial to avoid peak overlaps, as highlighted in Figure 5. This implies that even if we were to prolong the acceleration phase of each hoist to mitigate the power peak, comparable performance could still be attained by leveraging the existing waiting time. Therefore, after analyzing the power model, we have opted to reduce the acceleration by 20%. By employing a modified scheduling method that utilizes slower acceleration, the overall power peak could be further reduced while maintaining production efficiency (Figure 10). This adjustment results in a significant decrease in the power peak to approximately 12 MW, largely due to the reduced individual power peaks of the hoists. Additionally, as mentioned earlier (Figure 11), waiting times are minimized, allowing for more efficient utilization of hoists for transportation tasks.

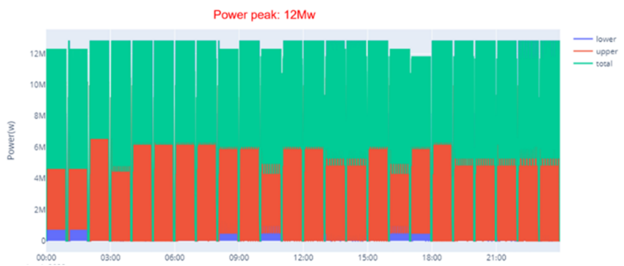

Figure 10 Power consumption for reduced acceleration.

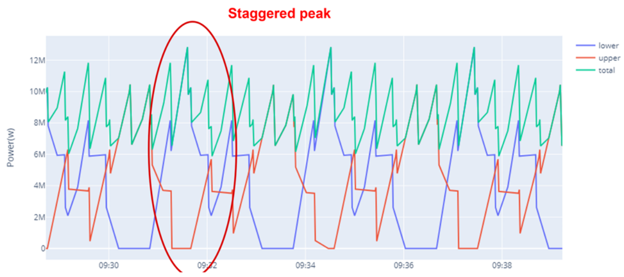

Figure 11 Detail on power calculation for reduced acceleration.

5 CONCLUSION

The reduction of the imbalance settlement period on the electricity market from 1 hour to 15 minutes pose a challenge for time resolution, sub-metering and process modelling in the mining industry. In this paper, we use the example of hoists to showcase the benefits of high-resolution power and energy management. With reference to our problem statement we summarize our results as following:

1) Detailed modelling of power and energy consumption of hoists is key and was addressed by applying a discrete event simulation based on high-resolution modelling. Fleet management can be used to optimally schedule operation of single hoists, thereby reducing overall peak power and corresponding energy costs.

2) An additional reduction of peak power could be achieved in simulations by integrating an energy management framework and testing energy storages of different sizes. A maximum reduction of 18% of peak power was achieved by integrating an Enviline ESS storage. Also, an adaption of operational settings of hoists resulted in a 14% peak power reduction when reducing maximum acceleration of hoists by 20%. It needs to be noted here that a final software implementation would need to balance speed of hoist acceleration with surplus capacity of the hoist, operation time and operation cost.

Hence, we can summarize that a higher time resolution of energy pricing also requires a higher resolution of modelling, and thus bears high potential for new control strategies. Mitigation of power peaks arising from power-intensive equipment can be achieved by varying operational settings, optimizing scheduling strategies or integrating energy storage.

6 FUTURE WORK

Our learnings from this study include both technical and non-technical challenges which are promising to address in future work. First of all, decision making requires detailed knowledge of investment costs and operational costs of additional storage solutions. In addition, integration of renewable energy sources shows potential to further reduce both energy costs and independency of grid and pricing. Trade-offs and cost analysis could be addressed in future work, for example, by evaluating hoist production data from a longer time frame in combination with variable spot prices to derive an estimation of the potential cost saving.

Second, non-technical challenges refer to a change in mindset of operators and shift managers. While performance was measured for decades by throughput only, a change in pricing policy will also initiate potential to save energy by adapting operating policies. Future work can help to incorporate this knowledge in everyday operation, i.e., by visualizing the benefit of adapted performance measurements in everyday mining tools.

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