Monitoring energy usage of heavy-haul iron ore trains with on-board energy meter for improving energy efficiency

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Abstract

Purpose – For billing purposes, heavy-haul locomotives in Sweden are equipped with on-board energy meters, which can record several parameters, e.g., used energy, regenerated energy, speed and position. Since there is a strong demand for improving energy efficiency in Sweden, data from the energy meters can be used to obtain a better understanding of the detailed energy usage of heavy-haul trains and identify potential for future improvements.

Design/methodology/approach – To monitor energy efficiency, the present study, therefore, develops key performance indicators (KPIs), which can be calculated with energy meter data to reflect the energy efficiency of heavy-haul trains in operation. Energy meter data of IORE class locomotives, hauling highly uniform 30-tonne axle load trains with 68 wagons, together with additional data sources, are analysed to identify significant parameters for describing driver influence on energy usage.

Findings – Results show that driver behaviour varies significantly and has the single largest influence on energy usage. Furthermore, parametric studies are performed with help of simulation to identify the influence of different operational and rolling stock conditions, e.g., axle loads and number of wagons, on energy usage.

Originality/value – Based on the parametric studies, some operational parameters which have significant impact on energy efficiency are found and then the KPIs are derived. In the end, some possible measures for improving energy performance in heavy-haul operations are given.

Keywords Energy efficiency, Heavy-haul train, On-board energy meter

Paper type Research paper

1. Introduction

Heavy-haul freight trains have a lower energy usage per tonne of freight hauled than conventional freight trains, providing a measure for increased energy efficiency of the transport. Given the high amount of energy required for powering heavy-haul trains, any further measures to improve energy efficiency can help to save energy. However, for freight operators to achieve energy savings, a good understanding of the energy efficiency of the current operations and potential for future improvements is essential.

Many scholars have contributed to predicting the energy consumption of heavy-haul freight trains. Being a very basic model, Lindgreen and Sorenson (2005) take into account efficiency, the most basic physical principles such as gradient resistance (in a simplified way),

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mechanical and aerodynamic resistance, but excluding curve resistance and the additional resistance due to wind and tunnels. Later, Wang and Rakha (2017) modelled regenerative braking efficiency as an exponential function of deceleration and find that this approach gives lower error for energy prediction than a linear function with constant braking energy efficiency. Bai *et al.* (2009) instead assume an average transmission efficiency but have calculated the gradient and curve resistance in detail by using a mass density function. Zhou (2022) summarise different ways to improve railway energy efficiency in China, where different energy models of the railway system are introduced. Whether a single particle or multi-particle model should be used is discussed in several papers that estimate freight train energy. Lu *et al.* (2018) give arguments for both. They found that single particle models are simpler to analyse but give errors especially for lines with many changes in gradient. On the other hand, multi-particle models are complicated and have a high computational expense, which can be of disadvantage in optimisations. Lukaszewicz (2008) states that single particle models are often used and normally accurate enough, but for long freight trains a distributed mass model should be used. Driver's behaviour has also been considered by many researchers in energy consumption simulation (Lukaszewicz, 2000; Lukaszewicz & Andersson, 2009). Without including the driver's behaviour, an error of 20–30% of energy consumption is reported compared with real train runs (Lukaszewicz, 2008).

To track current energy efficiency performance, key performance indicators (KPIs) are widely used. If chosen properly, they give good indications of current performance and help to identify possible measures for improvement. Continuous monitoring of energy usage can directly reflect energy efficiency of rolling stock and train service (González-Gil *et al.*, 2014). In Sweden, for billing purposes, heavy-haul locomotives are equipped with on-board energy meters, which can record several parameters, e.g. used energy, regenerated energy, speed and position. KPIs can thus be calculated using energy meter data, providing high-resolution data of energy usage on rolling stock level.

Studies on KPIs for energy efficiency of railway operations are scarce and focused on urban rail, see, e.g. González-Gil *et al.* (2015). In another paper it is stated that KPI should be specific, measurable, assignable, realistic and time-related (Scheepmaker *et al.*, 2020). As pointed out by González-Gil *et al.* (2015), in order to have a good overview, the number of KPI should be limited and so it is especially important that they excerpt solely the information that is most relevant. It is, therefore, also a good idea to have a global efficiency (main) KPI, which for instance could be specific energy consumption as suggested in González-Gil *et al.* (2015). For freight train operations, especially heavy-haul, where axle loads are much higher, the characteristics and KPIs are different from these of urban rail operations.

In this study, energy meter data for a standard iron ore train with 30 t axle load and 68 wagons, together with other data sources, is analysed with the aim of identifying significant parameters for describing the energy efficiency of heavy-haul operations. Parametric studies based on a simulation model of the discussed train are performed to generate additional results. The influence of some key operational parameters on energy usage is studied and then KPIs, which can be monitored by the on-board energy meter and from other available sources are derived. In the end, suggestions for appropriate operational measures to increase energy efficiency are given.

2. Methodology

Multiple parameters from several data sources are aggregated for train runs along a predefined route. The train runs that are most similar in terms of operational conditions (number of stops along the route and cargo load) while having the highest difference in net energy usage are compared to assess the influence of defined driver-describing parameters on energy efficiency.

Moreover, a parametric study is performed to evaluate the effects of several operational parameters on energy usage, which are hard to distinguish from running data of trains due to varying driver behaviour. The energy usage for different operational conditions is estimated through simulation of a heavy-haul freight train running along the given route. For this purpose, the heavy-haul iron ore trains, from which data for the running data analysis is sourced, is modelled in the in-house software Simulation of Train Energy Usage (STEC) (Öberg, J., v2.10.b), using a multi-particle approach for gradient and curve resistance.

The train and track models are validated on two different, shorter stretches of track of around 11 km length, using energy usage data from energy meters to validate agreement of measured and simulated energy usage. From the combined results of the running data analysis and parametric study, KPIs are derived for the most significant parameters of interest, considering availability of required data with sufficient resolution from the energy meters or other available sources to calculate the KPIs.

2.1 Setup

The train used in this paper is a typical heavy-haul iron ore train as operated by the company LKAB in northern Sweden and Norway, consisting of two electric IORE class locomotives featuring a regenerative dynamic brake and 68 Fanoo class ore wagons. These trains usually operate close to the limit of 30 t axle load and always with two locomotives and 68 wagons, providing a uniform rolling stock consist and hence a lot of comparable data for analysis. Table 1 presents values of some technical parameters for the rolling stock, which are also used in the simulations.

When it comes to the predefined route for all analysis, the stretch from Kiruna in Sweden to Narvik in Norway is chosen. Figure 1 shows the altitude profile. Apart from being single-track, this route has a challenging topography with gradients up to 1.7% and long steep downhill sections, which amplifies the effect of different driving styles on energy usage. Furthermore, this route is frequented the most by LKAB's iron ore trains, providing the largest set of suitable running data for analysis.

2.2 Data sources

Several data sources have been used to gather running data for the analysis. Firstly, energy meter data has been gathered. The energy meters installed on-board sample several parameters every 5 min together with the accumulated energy usage. The data are saved to internal memory before the data are uploaded to servers using mobile network, which can be

Parameter	2x IORE	1x Fanoo	Unit
Maximum speed	60	60	km/h
Tare mass	360	21.6	t
Payload	0	93.5	t
Length	45.8	10.3	m
Number of axles	12	4	–
Rotating mass contribution	52	1.64	t
Adhesive weight	360	0	t
Maximum power (cont.)	10800	–	kW
Tractive effort	1200	–	kN
Dynamic braking effort	750	–	kN
Drive chain efficiency	88.9	–	%

Source(s): Authors' own work

Table 1. Technical parameter values for rolling stock

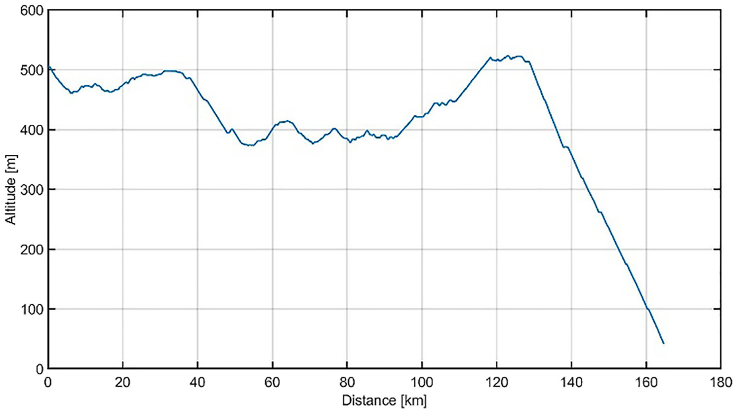

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Figure 1.
Altitude profile for route from Kiruna to Narvik

accessed in an online database. Parameters which are used in this study are total energy usage, total energy regeneration, speed and GPS position.

Given the parameters of energy meter data, further data are manually downloaded from the train event recorder of four pairs of locomotives. Parameters available from this data source that have been used are speed, traction force, regenerative braking force and brake main pipe pressure. Input signals are sampled and saved to the internal memory of the recorder every time a change in speed is detected; however data that have been downloaded is from the long-term memory with a lower resolution than the short-term memory.

Cargo load of each train run is extracted from LKAB's own database, since the trains always pass a scale before departure, ensuring no wagon is overloaded. The reliability of these data is therefore high.

The simulation tool STEC requires inputs of parameters for both train and track in addition to the locations for stops and dwell time. Technical documentation has mainly been studied to obtain required technical parameters for the train. However, average auxiliary power is estimated based on high-resolution instantaneous power data from the data bus of several pairs of locomotives.

High-resolution track data from the Swedish infrastructure owner, Trafikverket, are used to define horizontal and vertical track alignments. These data are input into the simulation tool at a resolution of 10 m, which is equal to the step length used for the calculation of the multi-particle model. For the Norwegian part of the route, older data provided by LKAB are used, though no significant changes have happened to the track alignments over time and altitude checks are performed to ensure accuracy.

2.3 Parameters of interest

Based on a literature review, three main areas which can explain variations in energy efficiency have been identified: driver behaviour, operational conditions and rolling stock performance. For each area, parameters are defined that can be regarded as the most interesting for energy efficiency.

Five driver-describing parameters, depending on the behaviour of the driver, are analysed in the running data analysis. They have been chosen to cover the driver behaviour in the four possible states of the train in motion: acceleration, deceleration, coasting and cruising.

(1) *Powering ratio*: the amount of power used during traction in relation to the rated output power, i.e., a measure of the aggressiveness of accelerations

(2) *Braking ratio*: the amount of braking force used of the maximum available braking force (the combination of electric and mechanical brakes), i.e., a measure of the aggressiveness of decelerations

(3) *Ratio of mechanical and electric braking*: it refers to how much of the total braking during the trip is done using the electric brakes, i.e., a measure of how much of the energy during braking is recovered

(4) *Amount of coasting*: the fraction of the total distance covered by the train during the trip that is spent coasting, i.e., a measure of distance the train covers in the most energy-efficient state

(5) *Maximum speed*: the maximum speed the driver decides to drive at a measure of energy lost due to aerodynamic resistance

Three operational parameters especially relevant for heavy-haul trains, describing conditions beyond the control of the driver, are analysed as part of the parametric study:

(1) *Number of stops*: the number of times the train must stop along the route, for instance, due to train crossings, a measure of the railway traffic situation

(2) *Load factor*: the axle loads the wagons operate at, i.e., a measure of how well the train's maximum hauling capacity is utilised

(3) *Number of wagons*: how close the number of wagons is to the limit defined by the infrastructure, i.e., a measure of how well the train's maximum potential hauling capacity is utilised

Finally, one parameter for the parametric study is defined to describe the performance of the rolling stock from an energy efficiency point of view:

(1) *Efficiency of drive chain*: a measure of internal losses at the locomotives

3. Results and discussion

3.1 Running data analysis

For the running data analysis, data from train runs without any stops between start in Kiruna and end in Narvik have been selected, since this eliminates the influence of the number of stops on energy usage. A total of ten train runs fulfilled the criteria and of these the two train runs with the least difference in cargo load and highest difference in net energy usage are compared.

Table 2 presents key data for the two train runs. As can be seen, the difference in cargo load is only 6 t, meaning the train runs are performed under very comparable conditions in terms of operational circumstances. Furthermore, the same, unique locomotive has been used in both train runs, so the results of the two runs are comparable. This means that the driving behaviour is responsible for most of the significant difference in energy usage.

As a basis for analysis of powering ratio, coasting and braking ratio, Figure 2 has been used, which shows the total traction/braking force at the wheels of all powered axles. It is clearly visible that Train 2 coasts significantly more, so the amount of coasting has explanatory power for energy efficiency and is suitable as KPI, which is expected since coasting is the most energy-efficient state of motion.

The powering ratio is often similar when the more energy-efficient driver of Train 2, hereafter referred to as the "efficient" driver, applies traction compared to the less energy-efficient ("inefficient") driver's ratio. But because Train 2 coasts a lot more, on average the powering ratio gets lower for the "efficient" driver. This confirms the explanatory power of powering ratio, though a KPI should be based on the average powering ratio.

The braking ratio for the electric brake is also often lower for the "efficient" driver because the "inefficient" driver applies higher braking forces for short periods of time. Though, when the "efficient" driver applies constant electric brake forces, it is often higher than for the "inefficient" driver. The difference in average braking ratio is thus less obvious than for the amount of coasting and powering ratio, but still has explanatory power as KPI when taking the mechanical brakes into account, for which the brake pipe pressure can be seen in Figure 3. For a 0.5 bar change in brake pipe pressure from 5 bar, the 68 ore wagons generate a total mechanical brake force of 1420 kN in addition to the electric brake force of the locomotive.

With Figure 3, the ratio of mechanical and electric braking is evaluated. While the "inefficient" (less regenerating) driver uses a higher electric braking force at a higher frequency, the electric braking force is often only applied for a brief time. The "efficient" driver uses a high electric braking force too but uses it constantly for extended periods of time. Thus, in total the electric brake energy recovered gets much larger since the power in combination with the applied time matter for regenerated energy. Interesting to note is that the "efficient" driver closely follows a braking strategy on the long steep downhill sections where constant electric braking is applied, and the speed is adjusted via the mechanical

Table 2.
Key data for compared train runs

Parameter	Train 1	Train 2	Difference
Total gross energy	9994 kWh	8144 kWh	1850 kWh
Total regenerated energy	2936 kWh	5112 kWh	−2176 kWh
Total net energy	7058 kWh	3032 kWh	4026 kWh
Total run time	12591 s	12960s	−369 s
Total distance	168.7 km	168.0 km	0.7 km
Cargo load	6489 t	6483 t	6 t

Source(s): Authors' own work

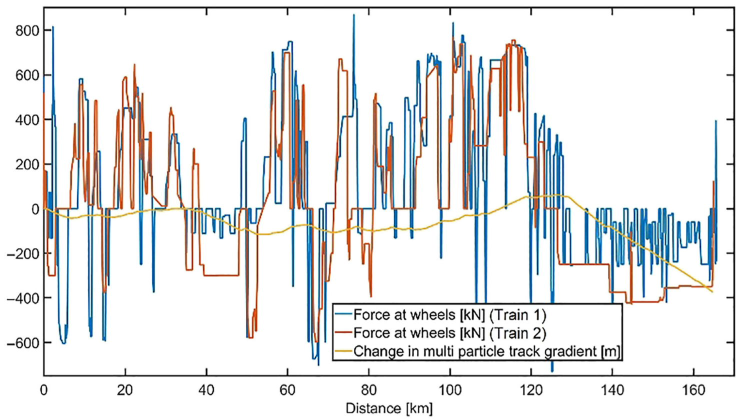

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Figure 2.
Comparison of force at wheels of locomotive

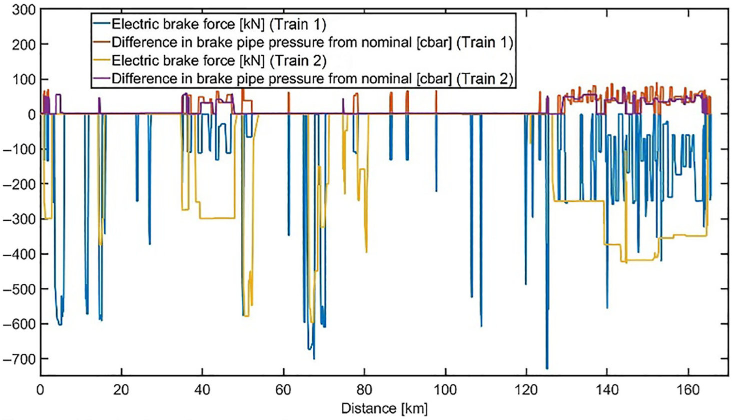

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Figure 3. Comparison of electric brake force and brake pipe pressure difference versus nominal (5 bar)

brakes to keep it below the speed limit. This has been reported to be the most energy-efficient driving strategy on long steep downhill sections (Lin *et al.*, 2017).

The instances where mechanical brakes are used match to a high degree for both runs. So, in total, even though there would probably be a difference in how much energy is braked away mechanically in total for each train, the share of the braking performed with electric brakes is clearly much higher for Train 2. Overall, the ratio of mechanical and electric braking can be concluded to be significant for describing how much energy is regenerated in total and could be useful as KPI.

Finally, the parameter of maximum speed is analysed by comparing the speed profiles of Trains 1 and 2, see Figure 4. The speed for the "efficient" driver is often actually higher than for the "inefficient" driver. A high maximum speed can be of advantage if it means that more of the potential energy on downhill gradients can be converted directly into kinetic energy. This proves that the maximum speed has a low explanatory power as KPI for energy efficiency, given that a high maximum speed is not always negative for energy efficiency.

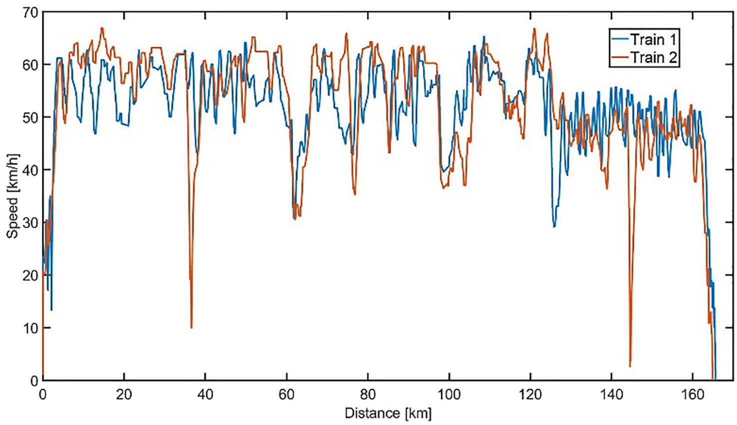

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Figure 4. Comparison of speed profiles

Further, it can be seen in Figure 4 that the "efficient" driver at two instances is close to coming to a stop, probably while waiting for extended movement authority. If these speed reductions would not happen, the difference in net energy would be even bigger.

3.2 Parametric study

When it comes to operational parameters that the driver has no influence over, the number of stops is analysed first. Adding stops at one meeting station along the route at a time with a line speed limit of 48 km/h, it could be seen that additional energy usage of 192.7 kWh is required for each stop on average. Note that this value depends on the start-speed and driving behaviour when it comes to the deceleration before and acceleration afterwards. Therefore, it only applies to the specific start-speed and extremely aggressive driving style in the simulation. In reality, a lower value is expected.

The outgoing gradient is clearly more important than the incoming gradient for the additional energy required, which is expected given that it is here where the kinetic energy of the train has to be built up again. If reasonable run times are to be achieved, the train will have to power to some degree even for acceleration on steep downhills after the stop, making the number of stops significant as the KPI for describing energy usage.

Next, the load factor is investigated which does not result in any saving of gross energy usage, but rather specific energy usage which is used instead for interpreting the results. To be able and simulate varying axle loads, the running resistance must be parametrised in formulas.

For describing running resistance, the simulation software STEC relies on the Davis equation. The coefficients of this equation are based on data received from the provider of a Driver Advisory System (DAS), which has been used on the iron ore trains (Yang *et al.*, 2013). However, only values for a train with 68 wagons and a 95% cargo load factor, equal to 28.77 tonnes axle load, respectively, an empty train have been provided. To allow for a variation of axle load and train length in the parametric study, the A-coefficient is approximated by linear interpolation of the two given values and adjusted for any change in the number of axles for the train, see Equation (1).

$$A \approx \frac{12 + n_{wagons} \cdot 4}{12 + 68 \cdot 4} \cdot (15354.1 + 1191.7 \cdot Q_{tot}) \tag{1}$$

where n_{wagons} is the number of wagons and Q_{tot} the average axle load for the train, considering that the locomotives always have an axle load of 30 t. The equation is structured according to empirical equations which have been established for the similar MV2000 class ore wagon via full scale tests (Lukaszewicz, 2009).

For an approximation of the B-coefficient the equation from Lukaszewicz (2009) is used due to the good agreement with the values from the DAS, see Equation (2).

$$B \approx 0.2 \cdot L_t \tag{2}$$

where L_t is the total train length. Finally, for approximation of the C-coefficient, the formula from Lukaszewicz (2009) is used, adjusted for the discrepancy from values of the DAS by a scaling factor, see Equation (3).

$$C \approx 1.135 \cdot (5.4 + 0.114 \cdot L_t) \tag{3}$$

Due to low speeds, tunnel resistance is expected to have a low influence on energy usage of the train and is thus disregarded in the simulations. Validations show that the simulated running resistance is quite accurate.

Only the cargo load and A-coefficient need to be changed to vary the axle load in the simulations. Figure 5 shows how the specific energy usage changes for typical axle loads from 27.5 t to 32.5 t, where axle loads above 30 t represent a planned future increase of the limit for the iron ore trains. The axle load is expressed as the corresponding cargo load for comparability reasons. Specific energy usage is expressed as kWh per net-tonne-km since that is what a transport company cares about in the context of energy usage. The results indicate that it is advantageous to increase the axle load, but the exact savings shown here only apply to the very aggressive driving style in the simulation.

However, this raises the question of how much energy can be saved for a more reasonable driving behaviour. For this purpose, the planned increase in axle load for the iron ore trains from 30 t to 32.5 t is considered. Several simulations are performed where the driving behaviour is manipulated to gain data points for the change in specific energy for several cases with different driving efficiency performances. Energy savings for drivers with 8,000 kWh gross energy and 10,000 kWh gross energy on the route from Kiruna to Narvik are predicted. For a very energy-efficient driving (based on energy meter data) at 8,000 kWh, 335.6 kWh can be saved when operating at 32.5 t axle load over the distance of 164.73 km. For inefficient driving with 10,000 kWh, a little bit more can be saved at 357.2 kWh. Though these savings are just estimations, they show that the load factor is significant for describing energy usage and should be of interest to track as KPI.

Specific energy usage can also be reduced by adding additional ore wagons, which is analysed by looking at the number of wagons. Here all coefficients of the Davis equation need to be recalculated (using Equations (1)–(3)) together with the multi-particle track input, cargo load, train tare mass and mass contribution from rotational masses, leading to higher uncertainty in the results than for the axle load analysis due to more changes to parameters in relation to the validated standard case (30 t axle load and 68 wagons).

In Figure 5, the change in specific energy usage for different numbers of wagons in the range from 62 to 74 is shown and compared with an adjusted axle load for a standard train with 68 wagons. Though an increased number of wagons reduces specific energy usage, it can be seen that the effect of an increased train length on specific energy usage is lower than for an increased axle load. Even when considering the higher uncertainty of results for the

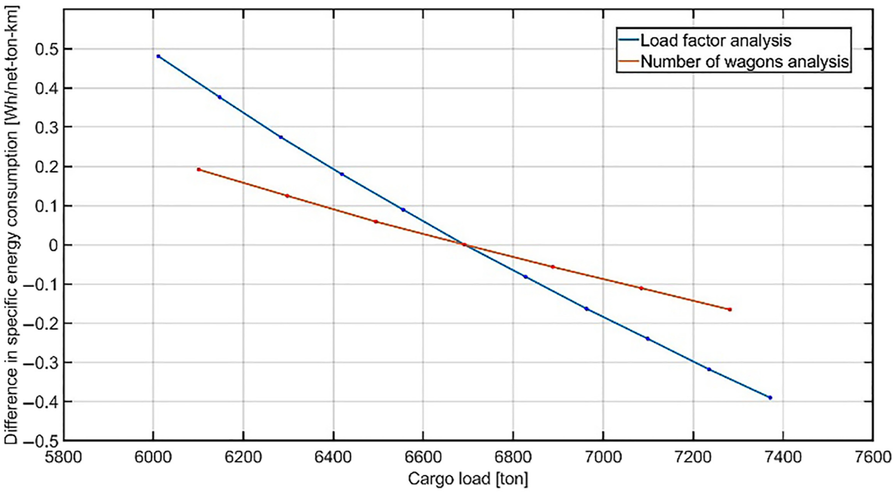

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Figure 5. Comparison of savings in specific energy usage for higher load factor and number of wagons

number of wagons, an increase in axle load is concluded to be superior from an energy efficiency point of view, even though the number of wagons still is significant for describing energy usage and thus of interest to track as KPI.

Lastly, the drive chain efficiency has been investigated as part of the parametric study, which is the only rolling stock related parameter. The traction and regenerative braking efficiency, which are assumed to be the same, are varied and the resulting changes in energy usage are shown in Figure 6.

Looking at the numbers, the influence of a changed efficiency is largest for the net energy usage, since a reduced efficiency means both a higher gross energy intake and lower amount of regenerated energy. For a change of efficiency by 1% compared to the default efficiency, the total net energy changes by around 250 kWh. Keeping in mind that gross energy is lower for a real train run compared to the simulated case with a very aggressive driving style, the change in net energy due to altered drive chain efficiency is expected to be much lower.

It can be concluded that drive chain efficiency can be significant for describing net energy usage, but the suitability as KPI depends on how high variations of the efficiency from the nominal value can be reasonably expected. High efficiency drops down to 70% would mean a major difference, though a locomotive with such a severe defect would probably not be used in regular operations.

3.3 Key performance indicators

Based on the parameters found to be significant in the data analysis and parametric study, KPIs are developed. In Figure 7 they are presented, and the framing colour indicates the availability of data from the energy meters used on-board the locomotives. Blue indicates additional data sources are required and yellow that higher energy meter data resolution is required (the Swedish standard as of today is one data sample every 5 minutes). Further KPIs than the defined ones could also be added in the future if new data gets available or specific energy-saving measures should be tracked in more detail than the defined KPIs allow for.

For measuring overall system performance, a global KPI suitable for heavy-haul freight trains is the *Specific energy usage* measured per net-tonne-km. This requires total net energy usage and cargo loads as an additional data source, though this is usually available to heavy-haul operators.

Then there are three KPIs defined for driver performance, of which the first is *Average traction power*. As running data analysis has shown, even the more energy-efficient driver

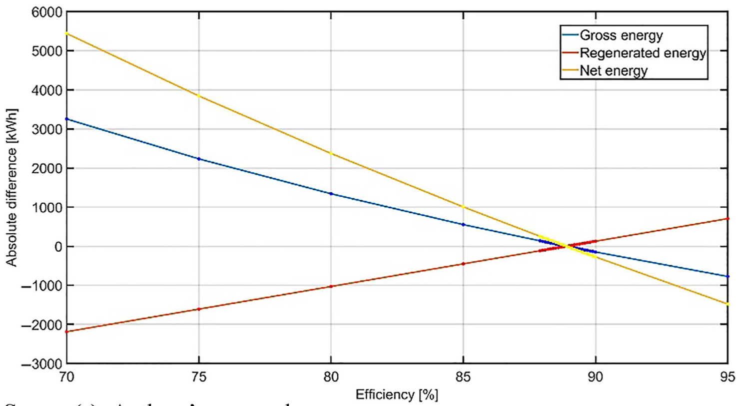

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Figure 6.
Results for drive chain efficiency analysis

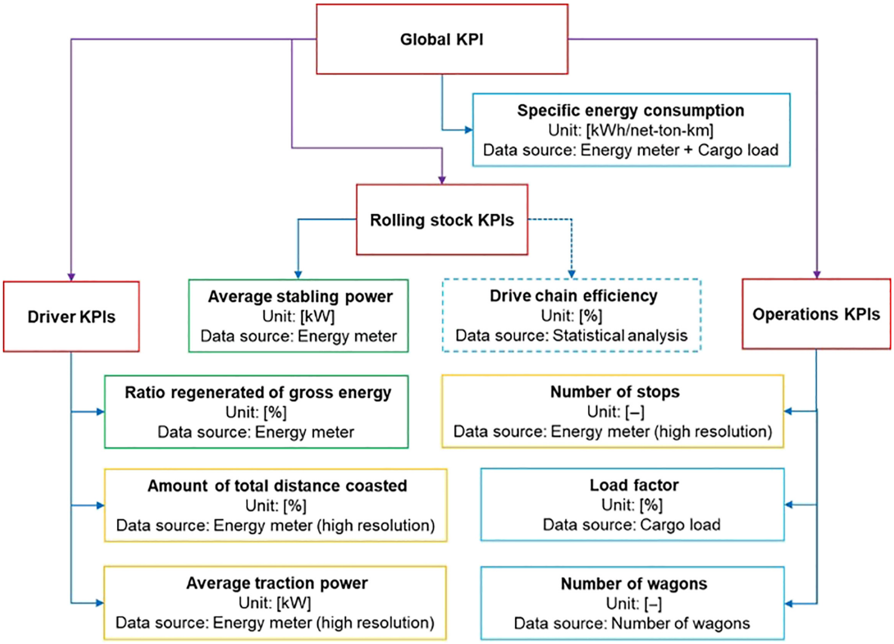

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Figure 7.
Structure for energy monitoring system with KPIs

uses high powering ratios sometimes, but the average powering ratio is lower due to less aggressive accelerations and more coasting. High-resolution power data is needed for calculation of this and the next parameter.

The KPI *Amount of total distance coasted* is directly derived from the corresponding parameter of the running data analysis with the clearest influence on gross energy usage. Defining a certain range within which the power must fall, it can be known when the driver coasts. The distance can then be estimated via the GPS position. For this KPI to work, it relies on drivers being trained to not use coasting extensively where it is not appropriate.

While the braking ratio has some explanatory power, it cannot be distinguished whether measured electric brake force is only applied at the locomotive or results from a brake pipe pressure drop and related mechanical braking of the wagons. It is therefore not possible to track the braking ratio from energy meter data, even though it would be an interesting KPI. Note that differences in local powering ratio and braking ratio along the route often are related to that the "efficient" driver coasts more. In other words, the powering and braking ratio can be explained by the amount of coasting to some extent.

Whenever braking is required, the regenerative brake should be prioritised over the mechanical one. The KPI *Ratio of regenerated energy of gross energy* is thus introduced, which tracks this and penalises excessive use of the regenerative brake at the cost of increased gross energy. It is calculated by dividing the total regenerated energy by the total gross energy for a concluded trip.

Moving on to KPIs related to operations, the *Number of stops* is defined. This can be tracked using the GPS position and recorded speed from the energy meters at a higher resolution. The exact amount of energy that an additional stop adds to the gross energy usage not only depends on the driving behaviour, but the topography of the stops. Performance indicators could hence be introduced that track how frequently each meeting station is used for stops.

For a long-term strategy of reducing the specific energy usage for heavy-haul freight trains, the KPIs *Load factor* and *Number of wagons* should be tracked, especially the load factor. However, in order to use these as KPIs, information from a database that includes cargo load, and the number of wagons is required. Though such databases usually exist for heavy-haul operators.

Finally, for the rolling stock, two KPIs are defined. The first is *Average stabling power* and can be calculated from power data of the energy meters. It is intended to follow up on possible efficiency improvements of the stabling mode of locomotives.

As discussed earlier, the usefulness of *Drive chain efficiency* as KPI depends on the variation of efficiency that can be expected. Due to that power at the wheels is not available from energy meter data, efficiency cannot be calculated and is thus marked as dashed. Instead, it could be evaluated by regression analysis with variables for each locomotive to detect deviations from expected performance, though this requires a huge amount of aggregated data from an established monitoring system.

3.4 Suggestions for energy savings

While working with the data analysis and parametric study, several potential operational measures to increase energy efficiency were identified, applicable to heavy-haul freight train operators.

As the results indicate, operators should in the first-place focus on increasing the axle load before increasing train length to reduce specific energy usage, but both help to increase energy efficiency.

Infrastructure limitations should be removed to allow for the application of regenerative braking force on long downhill sections as much as possible with the mechanical brakes only being used for slight speed adjustments.

To reduce the time lost by applying eco-driving strategies such as coasting, train crossings should be planned to the meeting stations with the most favourable topography for faster acceleration afterwards, which also saves energy.

In the running data analysis, a wide variety of driving styles could be observed with huge differences in net energy usage. Systematic driver training on eco-driving is, therefore, particularly important. To give drivers a better understanding of where coasting and braking are appropriate with regards to the local running resistance of very long and heavy trains, support tools are needed. This could be wayside signboards, a guidance document or a DAS. With an established energy monitoring system, the effect of different driving styles on energy usage can be visualised, which can help motivate drivers to apply eco-driving strategies.

The stabling mode of locomotives has potential when it comes to optimising comfort functions.

4. Conclusion

This work has taken heavy-haul iron ore trains in Sweden and studied energy data recorded by on-board energy meter and from other data sources. Based on analysis of the recorded energy data and some simulation results, parametric studies on the influence of some operational conditions have be conducted.

The work has identified KPIs to reflect the energy performance of the heavy-haul trains. Through this study, it is shown that driver behaviour varies significantly and has the largest influence on energy usage. Operational conditions have also significant impact on energy usage. Through parametric study, it is found that both increased axle load and increased train length can help to improve the energy performance in the operation of the heavy-haul trains, but the increased axle load is superior to the increased train length.

Based on the identified potentials to improve the energy efficiency of heavy-haul freight trains, it is identified that it is necessary for train operators to have a good understanding of the current energy efficiency performance of both their drivers and operations in general. In this study, the use of an energy monitoring system is shown to be a useful tool for them to work with, to implement and to interpret the effect of saving measures in a structured way.

Furthermore, KPIs that are important to describe energy usage and can be tracked by the available on-board energy meter have been defined. To further improve energy efficiency in train operation, additional sources of information and accurate measurement data with higher-than-today resolution are expected. Therefore, this study has laid a foundation for the development of such an energy monitoring system that can be used to track and improve energy efficiency of freight trains over time.

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