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"Distributed Power & Locomotive Assignment: A Model to Minimize Emissions in Rail Freight Transport."

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Abstract

The aim of this study is to develop a logistics model with a focus on sustainability. As the logistics sector, particularly associated with road transportation, has experienced significant growth in recent years and since it emits health harming pollutants that also contribute significantly to climate change, the foundation of this sustainability-oriented logistics model will be the less emission-intensive rail freight transportation.

Specifically, this model aims to enhance the efficiency of operational processes in the railway industry. The objective is to find cost-effective (optimized) assignments of locomotives and trains, as well as to create an operating plan for the route between Vienna and Genoa (Italy). It is intended that 15 trains will travel this route on a weekly basis. There are 122 locomotives of different types available for this purpose. This type of model is referred to as the Locomotive Assignment Problem (LAP) and represents a classical optimization problem. To incorporate another aspect of sustainability into the model, the Distributed Power (DP) technique is applied. In this approach, locomotives are not only positioned at the front of trains but distributed throughout the entire train. This offers various advantages over conventional trains. It enables trains to potentially travel at higher speeds and transport larger quantities of cargo, while simultaneously improving safety, reliability, and efficiency. In the presented model, Distributed Power is supposed to minimize friction and resistance of trains on the rails, leading to fuel savings and associated cost reductions, thereby enhancing the sustainability of the trains. To generate efficient assignments, i.e., solutions to the optimization problem, a metaheuristic approach is employed. Metaheuristics are particularly characterized by their ease of implementation and comprehension, as well as their applicability to various optimization problems. Moreover, they generally yield good or close to optimal results. The Variable Neighbourhood Search (VNS) metaheuristic possesses all these mentioned characteristics and has thus been selected to provide solutions to the underlying problem.

Regarding this sustainability-oriented logistics models, several conclusions can be drawn from this study. In general, locomotives, trains, and routes can be effectively modeled using publicly accessible data and information. However, a detailed quantitative analysis of the impact of Dis-

tributed Power on trains still requires further exploration, especially in the European context. The optimal solution to the assignment problem results in an operating plan with 9 trains operating in DP mode and 6 trains in conventional mode. It has been demonstrated that a solution consisting of trains operating in mixed modes is more efficient than an exclusively DP-based solution. The composition of trains is highly dependent on the randomly chosen initial solution. Therefore, for operational use of the model, the initial solution should be selected based on a rule that prescribes an efficient composition of trains. The VNS heuristic is well-suited for solving this model, and the computational effort, even for larger problem instances, is low.

Zusammenfassung

Das Ziel dieser Arbeit besteht darin, ein Modell im Bereich Logisitk mit Fokus auf Nachhaltigkeit zu entwickeln. Da der Logistikbereich, insbesondere der damit verbundene Straßenverkehr, in den letzten Jahren stark gewachsen ist und gesundheitsschädliche Emissionen verursacht, die auch stark zum Klimawandel beitragen, soll das Fundament dieses nachhaltigen Logistikmodells der weniger emissionsverursachende Schienengüterverkehr sein. Durch diese Maßnahme können Emissionen reduziert und die Straßen von schweren Fahrzeugen entlastet werden.

Konkret handelt es sich um ein Modell, das die betrieblichen Abläufe effizienter gestalten soll. Das Ziel besteht darin, kostengünstige (optimierte) Zuordnungen von Lokomotiven und Zügen zu finden sowie einen Betriebsplan für die Strecke zwischen Wien und Genua (Italien) zu erstellen. Es ist vorgesehen, dass wöchentlich 15 Züge diese Strecke befahren. Hierfür stehen 122 Lokomotiven unterschiedlicher Typen zur Verfügung. Diese Art der Zuordnung wird Locomotive Assignemnt Problem (LAP) genannt, und stellt ein klassisches Optimierungsproblem dar. Um einen weiteren Nachhaltigkeitsaspekt in das Modell einzubringen, wird die Distributed Power (verteilte Traktion) Technik angewendet. Dabei werden die Lokomotiven nicht nur an der Front der Züge, sondern über den ganzen Zug verteilt eingesetzt. Dies bietet gegenüber herkömmlichen Zügen verschiedene Vorteile. Die Züge können dadurch tendenziell schneller fahren und es kann eine größere Menge an Fracht bewegt werden, während gleichzeitig die Sicherheit, Zuverlässigkeit und Effizienz verbessert werden. Im vorliegenden Modell minimiert Distributed Power (DP) die Reibung bzw. den Widerstand der Züge auf den Schienen, was zu Einsparungen bei Kraftstoff und den damit verbundenen Kosten führt und damit die Nachhaltigkeit der Züge verbessert.

Um effiziente Zuordnungen zu generieren, also Lösungen für das Optimierungsproblem zu finden, wird eine Metaheuristik verwendet. Metaheuristiken zeichnen sich insbesondere dadurch aus, dass sie einfach zu implementieren und zu verstehen sind und auf verschiedene Optimierungsprobleme angewendet werden können. Zudem liefern sie in der Regel gute oder nahezu optimale Ergebnisse. Die Metaheuristik Variable Neighbourhood Search (VNS) erfüllt all die genannten Eigenschaften und wurde daher ausgewählt, um Lösungen für das zugrunde liegende Problem zu liefern.

Im Hinblick auf dieses nachhaltigkeitsorientierte Logisitkmodell können in dieser Arbeit einige Schlussfolgerungen gezogen werden. Im Allgemeinen lassen sich Lokomotiven, Züge und die Strecke gut mit öffentlich zugänglichen Daten und Informationen modellieren. Eine detaillierte quantitative Auswirkung von Distributed Power auf Züge muss jedoch noch genauer erforscht werden, insbesondere im europäischen Kontext. Das optimale Ergebnis des Zuordnungsproblems ergibt einen Betriebsplan, bei dem 9 Züge im DP-Modus fahren und 6 Züge im herkömmlichen Modus. Es hat sich gezeigt, dass eine Lösung mit Zügen in unterschiedlichen Modi effizienter ist als eine Lösung, die ausschließlich aus DP-Zügen besteht. Die Zusammenstellung der Züge hängt stark von der zufällig gewählten Eingangslösung ab. Für die Verwendung des Modells im Betrieb sollte daher die Eingangslösung anhand einer Regel gewählt werden, die eine effiziente Zusammenstellung von Zügen vorgibt. Die VNS-Heuristik eignet sich gut, um dieses Modell zu lösen, und der Rechenaufwand, auch für größere Problemstellungen, ist gering.

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Chapter 1

Introduction and Motivation for a Sustainability-Oriented Logistics Model.

The transportation of goods and commodities has historically been conducted on a small scale, primarily limited to local or regional movements between cities, with cross-border journeys occurring less frequently. International transportation endeavors often entailed months or even years of travel. Similar to the distances traveled, the transported freight volume has been a mere fraction of what is possible today. With the advent of industrialization, which rapidly spread across the world, and the subsequent globalization driven by the need to meet ever-increasing demands, international large-scale transport routes have become commonplace. Motorised modes of transportation made it possible to receive goods from the other end of the world in practically no time. In the same manner as distances, these new modes of transportation also changed the sheer volume of freight transported across millions of kilometers. According to data from the Organisation for Economic Cooperation and Development (OECD, 2023) in the European Union $2,226,090$ million tonne-kilometers (a tonne-kilometre represents the transport of one tonne over one kilometre) were transported in 2021. Since this represents an increase of 122% since 1970 it can be deducted that this number will further increase in the future. Efficient logistics networks enabling the transportation of such a significant volume of goods are thus becoming more and more essential. The same OECD report highlights that within the EU, these freight networks are predominantly shaped by road transport. In 2021, a total of $1,768,399$ million tonne-kilometers were transported via road, accounting for 79.4% of the overall volume. Notably, the freight transportation via road has witnessed an increase of 454% since 1970. Seemingly, this road-dominant freight transport setting is efficient enough to maintain the high volume logistics operations in

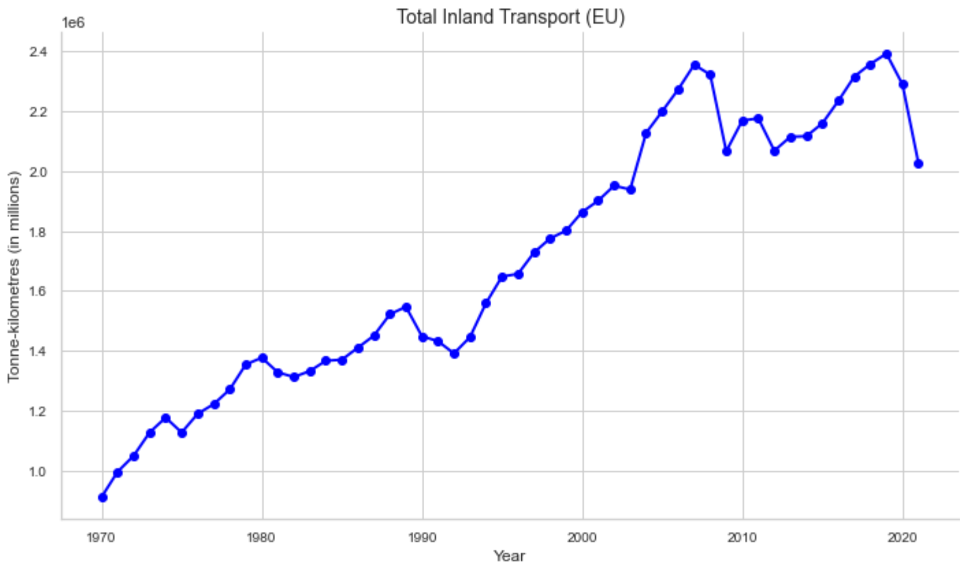

Figure 1.1: The total in-land freight transportation in the European Union from 1970 to 2021. Data source: European-Environment-Agency, 2021.

Europe. Nowadays, such a statement can only be made when neglecting the increasingly important components of transportation like ensuring sustainability, protecting the climate, and avoiding endangering human health. The European-Environment-Agency (2022) reports that road-bound vehicles transporting goods emitted 137 grams CO_2 per tonne-kilometre in 2021, which would make in total $242,239,863$ metric tons of CO_2 emissions. Since many years data and research link emissions of carbon dioxide with the global temperature rising aberrant (Ritchie et al., 2020), causing sea-levels to rise, destroying our living space, habitats, and ecosystems, as well as propagating natural disasters all around the world. To highlight the health harming side of a massive road transport, the European-Environment-Agency (2021) recorded $364,200$ premature deaths in Europe due to the effects of air pollution, to which the road freight transport sector contributes greatly. Road vehicles emit some of the most harmful pollutants in terms of human health (Brusselaers et al., 2023), due to the heavy duty vehicles such as trucks mostly using diesel engines (Breuer et al., 2020).

Another disadvantage of predominantly relying on road transportation for the European logistics network is the relatively small quantity that a truck can carry. Given the significant large overall volume shipped by trucks or similar road vehicles on a daily basis, a considerable number of vehicles would be required accordingly. The industry manufacturing these vehicles emits the same lethal pollutants throughout its entire production chain as when these vehicles are driving (Giampieri et al., 2020). Additionally, the increasing number of trucks is causing congestion on Europe's roads, necessitating further investment in this infrastructure to expand it

to accommodate the growing volume of goods to be transported, even though arguments are being made that such investments should rather flow into more sustainable infrastructure such as rail-roads, bike lanes or walk-able cities. In order to address the aforementioned criticisms of freight transportation, there are various approaches being pursued within the EU. For instance, attempts are being made to replace diesel-powered trucks with more environmentally friendly options such as liquefied natural gas or electric vehicles. While these alternatives are somewhat more environmentally friendly in operation, their production is similarly energy-intensive compared to conventional vehicles. Furthermore, this approach does not solve the problems of road infrastructure congestion or the need for new infrastructure to accommodate more vehicles.
Approaches to become less road dependent include projects like "Shift2Rail"[1], which seeks innovative solutions for improved transportation of people and goods by rail. The focus is primarily on reducing costs, increasing capacity, and improving reliability of trains. Rail transportation cannot entirely replace road transportation, as the latter offers greater flexibility in handling goods, particularly for "last-mile" delivery. Moreover, transporting goods by road is generally more time-efficient compared to rail. Nevertheless, rail freight transportation provides numerous advantages over road transport. To begin with, trains possess a higher overall capacity in comparison to trucks. A single freight train occupies less space than multiple trucks transporting an equivalent volume of cargo, thereby reducing congestion on roads when relying on railways. Furthermore, from an economic perspective of optimizing logistics, it is worth noting that rail freight operations are significantly more cost-effective than truck-based operations (Bína et al., 2014). Moreover, and of particular importance in recent years, trains are considerably more sustainable and emit fewer pollutants than trucks. According to a study by the European-Environment-Agency (2022), rail freight transportation emits only 24 grams of CO_2 per tonne-kilometer. Shifting a significant portion of logistics operations to rail would therefore have positive implications on human health, as well as on nature and the climate. Multiple academic papers such as Pinto et al. (2018) and the before presented statistics prove that rail freight transportation is able to mitigate harmful effects on the climate and on humans and is economically favourable. For these reasons, rail transport suites as a sustainability component in a modern logistics model. In this study, which aims to create a "green", sustainable model for transporting goods from A to B, trains constitute the sustainable foundation, due to them being cheaper and releasing fewer harmful emissions during operation compared to road-based transport modes.
The rail network in Europe is comparatively well established and developed, making it suitable

[1] A list of all projects belonging to Shift2Rail can be found here: https://projects.shift2rail.org

for international freight operations. Managing this network, that is setting strategic goals, making tactical decisions and planning operations is a complex domain which tends to be capital extensive. The strategic stage incorporates long-term decisions, which are the least flexible. On the tactical level mid term decisions are made and the operational level concludes over the short term which can be on a weekly or daily basis. For each of these stages Crainic and Laporte (1997) identify various models that are supposed to assist railway operators in their decision making. As such, on a strategic level location models are deployed, which assist in finding facilities in a railway network to make it as efficient and operable as possible. These networks are then generated using network design models. A railway network is usually expressed as a graph. In a graph there are nodes, which are the facilities or depots in which trains and locomotives are located. These nodes are connected with edges or links which represent the actual rails the trains drive on. A network design model finds and generates suitable and efficient nodes and links on these networks. On the tactical level, one of the most prominent models is the Vehicle Routing Problem (VRP). Here the most efficient routes from one or several depots to one or several customers have to be decided. Fluctuating demand, supply and fleet size have to be considered at all times. Another task occurring on the tactical level is fleet sizing, where the number, type and location of trains and locomotives has to be determined in order to put them into service. Finally, at the operational level, the actual timetable (schedule) for trains must be determined, including efficient assignments of locomotives to trains to ensure their deployment in the schedule. These models are referred to as Locomotive Scheduling (LSP) and Locomotive Assignment (LAP) Problems, where usually time-specific relations as well as the individual type and number of locomotives have to be considered.

As stated before, the model created in the course of this thesis shall utilize railway freight transport to generate a sustainability-oriented framework in the logistics sector. As also previously presented, there are several models available in the freight railway industry that can be employed to enhance operational efficiency. Decisions at the tactical and especially at the strategic levels often have an extended time horizon to be implemented and are difficult to be altered in the short term. Conversely, changes can be implemented swiftly and with minimal cost at the operational level. Due to this, the model underlying this study is designed to take place at the operational level. The main focus of the model is to generate an assignment of locomotives to trains that is highly efficient, cost-effective, and energy saving.

1.1 The Locomotive Assignment Problem.

The Locomotive Assignment Problem (LAP) concerns itself with all the challenges that arise when trying to efficiently assign locomotives to trains. In general, trains can be seen as jobs that have to be scheduled or processed in a certain time frame. Locomotives are the machines that work these jobs. This surrounds a previously defined objective, where quantities like production/travel time, idle time, or costs are to be optimized. Constraints ensuring a feasible operation delimit this optimization, as for example choosing the type or number of locomotives certain trains can be assigned with. An extensive overview of models in this context and the most important variations of them are provided in the survey by Cordeau et al. (1998). The LAP, which according to this survey belongs to the Scheduling Problems is defined as "assigning a set of locomotives to the scheduled trains to satisfy requirements expressed as a number of locomotives or as a measure of the pulling power needed"[2]. They part the model into two main versions, namely in single locomotive models, where only one locomotive is assigned to a train, and the more common and more complex multiple locomotives models, where each train may require more than one locomotive of the same or different type. To introduce a minimum degree of realism into the model underlying this thesis, a multiple heterogeneous locomotive model will be created, which means that there possibly are multiple locomotives assigned to the same train, while there are different types of locomotives available. A detailed overview of the locomotives used in this model can be found in Chapter 5. In the work of Piu and Speranza (2014) an exhaustive re- and overview of the different types of problems and the most important models that solve them is given. Besides single- and multi-locomotive models they also differentiate between a tonnage- and a schedule-based approach. The tonnage-based approach requires trains to be loaded with enough freight, to be able to be scheduled, whereas the schedule-based approach does not regard the loading status of a train, but the train is scheduled when the given time-table intends to do so. However, they argue that the tonnage-based approach is unreliable and leads to poor service provided by the operator. Further, advanced computers and Operations Research algorithms enable an efficient execution of rather complex LAPs, making the more efficient schedule-based approach possible. The multiple-locomotive models are the most complex version of the LAP. Among the first to examine such problems were Florian et al. (1976). Their goal was to minimize costs and capital invested, selecting an optimal number of mixed locomotives. The only restrictions were, that the locomotives had to satisfy the (pulling) power requirements of the train. They tried to solve it using a Benders decomposition, however did not reach optimality, due to the restricted computational power available back then, among

[2]Cordeau et al. (1998), Section 3.3, p. 396

other things. Their model was extended or adjusted to a more realistic use-case by Ziarati et al. (1997) incorporating constraints for dead-hanging or maintenance. They proposed a time-space network approach with a heterogeneous fleet. Dead-hanging is when a locomotive is attached to a train, but it does not actively power the train. This is done for example when a locomotive is required at to some other facility but it is not required to power the train. Their goal was to minimize operational costs. Useful solutions and promising results were generated using the Branch and Bound method in combination with a Dantzig-Wolfe decomposition. The work and models provided by Florian et al. (1976) and Ziarati et al. (1997) lay the founding of the Locomotive Assignment Problems. There are a wide range of additional models that tackle the different requirements of railroad operators (surveyed in Piu and Speranza (2014) or mentioned in Section 2.3). They adapt to a growing number of constraints that reflect lifelike conditions and varying layouts on railroads.

The model relevant to this work incorporates some of the before presented operational constraints. Specific details on the objective and the constraints imposed on this LAP can be found in Chapter 3. The ultimate goal is to generate a green, sustainable locomotive assignment respectively scheduling model. To do so, a technique is introduced, that is known to make freight trains more reliable, safer and efficient.

1.2 The Distributed Power Technique.

The train and the railway industry in general has seen a range of innovations since the steam engine was invented by James Watt, laying its foundations. Nowadays research ranges from trying to find ever more efficient and sustainable ways to motorise trains, experimenting for example with hydrogen fuel cells (Seyam et al., 2022), to developing trains driving autonomous using Artificial Intelligence and Neural Networks (Ciric et al., 2022). However, there exists a relatively simple technique that is used for trains which is supposed to make them safer, faster and more sustainable, called Distributed Power (DP). As the name says, Distributed Power implies distributing the engines that power a train over the whole length of it, instead of only having one or multiple locomotives pulling from the front. These dispersed locomotives work as one engine and simultaneously accelerate and break. Thereby they tap into a range of advantages. According to Murray (2001), DP was first introduced in 1995 at the Union Pacific Railroad Company to replace manned helper engines. Manned helpers are typically used on mountain grades from 1.5% and steeper to support the train. The personnel was connected via radio communication and the driver in the lead engine would give commands to the others whether to apply power or brake. To save personnel costs and to make the braking and accelerating more accurate, they replaced these manned helpers with autonomous locomotives. Whenever the crew in the lead engine applied power, a radio signal instructs the remaining engines to do the same. Company representatives consulted in Murrays article report that DP enables them to employ longer and heavier trains due to a better power and braking distribution. It allows faster acceleration and decceleration

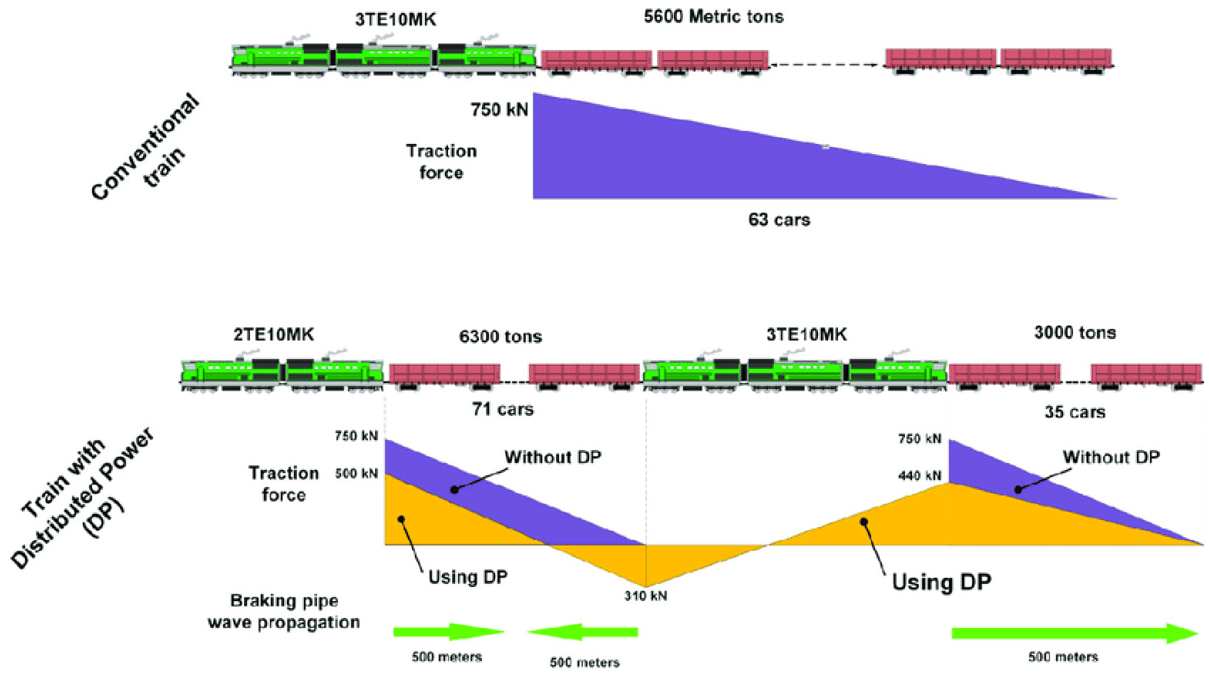

Figure 1.2: A graphical representation of Distributed Power by Davydov et al. (2017). Locomotives are dispersed throughout the train instead of only being located at the front.

and thus time savings, as well as better fuel efficiency due to less rolling resistance. Fuel Savings from 5% up to 11% are reported by GE Harris Harmon (the leading US-manufacturer of DP equipment called Locontrol) and the Railway Company CSX Transportation in Murrays work. Multiple connected units allowing heavier and longer trains is quite obvious. But why does DP allow trains to go faster and why is does it bring enhanced energy efficiency? Mike Volkmar of the Union Pacific Railway Company explains it in Murray (2001), page 60 as the following: "The reason is on a train with all its power on the head end, there is a stringlining effect in which cars try to follow the path of the locomotive by the shortest route available, causing a high degree of resistance in curves. With DP, a portion of the train is always being pushed rather than pulled through the curves". He further explains, that a DP-train rolls exceptionally well compared to a conventional train. Less resistance and a smoother travel through curvy passages permits a faster train (without the danger of derailing or decoupling) and requires less fuel. However, it is also noted that when not needed, DP locomotives impose unnecessary and additional operating cost and should removed at terminals and should only be added when needed. There are also studies that conduct experiments with DP to measure and define its quantitative effect on a trains resistance. In a conference paper David Peltz (Peltz, 2013) presents the basics of Distributed Power and its benefits like fewer broken knuckles (wagon connections), less train car damage as well as fuel savings and improved train handling through reduction of longitudinal forces. By deploying in-train testing methods it is shown that besides this there exist less obvious benefits like diminished lateral forces, especially in curves, from the reduction in longitudinal forces. Peltz presents an empirical relationship between longitudinal train forces and lateral train forces in curves which should allow track and wheel wear savings by employing Distributed Power, similar to the claims made by Mike Volkmar. The Indian Railway Company also sees these positives effects for DP in heavy-haul freight trains. For them, to implement DP the research group Kashyup et al. (2022) presents a Wireless Locomotive Control System where up to five electric locomotives can be accessed and controlled remotely instantaneous and without delay in a master and slave configuration. Their Distributed Power Wireless Control System realizes the aforementioned benefits (like reduction of coupler forces, faster application of brakes in long-haul freight trains and less required crew to operate them) when implemented in the daily operation and trains could reach an overall length of over 3.5 kilometers. The paper by W. Li et al. (2020) also proposes a Distributed Power control system, especially designed for locomotives of different types communicating with each other. Synchronism and communication of the system and quality of control of the locomotives shall be improved whereas the latency of instruction and information transfer between different types of locomotives shall be reduced. Tests that they conduct confirm the efficiency of the control system's synchronism optimization, which guarantees enhancing the differential wireless multi-traction synchronous control system for coupled trains and thus improving train control. Kiselev and Pudovikov (2020) concern themselves with the automatic speed control systems of trains with distributed traction and try to optimize the parameters related to quality of control. A automatic system provides the desired control quality under all types of movement (traction, speed stabilization, braking). In-train forces, coupler damages and longitudinal compressing forces are being monitored. When these parameters are optimized in the related work, the authors report that when Distributed Power was employed, the quality of speed control of the train motion substantially improved, which encouraged better safety of train motion. As mentioned before, Shift2Rail is a Project launched by the European Union to promote "research and innovation (R&I) and market-driven solutions by accelerating the integration of new and advanced technologies into innovative rail product solutions" and to make the European Rail Industry more competitive. In the course of this project Cantone and Toubol (2019) investigate compositions of two or more trains in terms of safety. They find that a train with two traction units (e.g. operating in DP) where the train on the front is 400 meters long and a second train is attached at the back and the total hauled mass is up to 2800 tons, operates safer than existing (conventional) trains in use. For the same project Cantone et al. (2021) find that long trains with two and up to four tractive engines are equally safe as classic, shorter trains with only one traction unit. Further they find that when coupling multiple trains together to form a 1500m train, it is not favourable to connect trains of similar mass an length. They recommend to rather couple trains having a decreasing length and hauled mass to increase safety. Due to increasing freight volumes on the Russian Baikal-Amur mainline Davydov et al. (2017) are trying to find a solution to increase the capacity of this railway section and to pass higher cargo volumes. They discuss a Distributed Power setup with new stronger locomotives. They find that without DP a locomotive consist of 3 locomotives at the front with a traction force of 750 kilo Newton (kN) can carry a train with 63 cars attached, considering that the train must pass mountain sections while maintaining a considerable high speed, to ensure a minimal travel time. Using DP with two traction units at the front and three in the mid, the train can carry 106 cars and thus significantly increase the hauled freight, while travel time and speed remain the same (see also Figure 1.2). The research conducted by Roney et al. (2010) finds similar to other research presented, that when introducing Distributed Power (and a Friction Control System) at the Canadian Pacific Railway Company it resulted in the reduction of damaging lateral forces, rail wear, and system fatigue, as well as increases in velocity and network capacity. In addition to that they conduct real-world test and analysis of the effect that Distributed Power has on lateral forces when the train operates in different locomotive configurations (as in where the locomotives are placed in the train). They find that some configurations enable reductions in average lateral forces of up to 17% and an increase in velocity of up to 35%.

It has been shown by multiple international research groups that Distributed Power has positive effects on trains. It has been especially thoroughly tested in countries that employ particularly long freight trains such as the United States, Canada, Russia, China, or India. In Europe research on this topic is quite limited yet. Arguments could be made, that since in Europe there are many mountainous and twisted sections in railroads, the DP technique could be beneficial, although freight trains are typically shorter in Europe. In general it can be concluded, that DP introduces a sustainability or "green" factor to trains. This work is supposed to further contribute to collecting information of the usage of DP on (freight) trains in general and especially in an European context. The exact effect Distributed Power will have on the trains in this scheduling model is presented in detail in Section 5.5.

The preceding introductory statement is supposed to motivate this work and the underlying model. Further, the two most important components to make it a sustainability-oriented logistics model were introduced. The remainder of this thesis is structured as follows: In Chapter 2 the existing research on green scheduling models and on LAPs incorporating the DP technique will be presented. Further, Chapter 2 will illustrate why a metaheuristic suits best to solve this particular problem and further research employing different metaheuristics to the LAP or LSP will be presented. The subsequent Chapter 3 discusses the how the efficiency (costs) of the trains will be assessed and the mathematical formulation of the problem including objective function and constraints are shown. In Chapter 4 the solution approach with the implementation of the chosen metaheuristic can be found. Chapter 5 presents the input data for the heuristics and explains how locomotives and trains are simulated in the model. Finally, in Chapter 6 the results of this approach are shown and Chapter 7 concludes.
In the course of these Chapters and this study, the goal is to answer the following main research questions:

- Is it possible to model and simulate a logistical railway model using only publicly available data? If so, what are the main challenges and where is a lack of information, especially in regard of the Distributed Power technique?

- What is the effect of Distributed Power on trains? How to DP-trains compare to conventional trains in the results of the model? Does Distributed Power introduce an appropriate sustainability factor to the model?

- Are metaheuristics well suited to be applied to this kind of model? In particular, how does the ultimately chosen Variable Neigbhourhood Search metaheuristic perform?

By addressing these questions, this study contributes to making rail freight models more accessible and sustainable by utilizing only publicly available data, employing an easily comprehensible solution approach, and implementing the efficiency enhancing Distributed Power technique at the operational level, which can be achieved without significant capital expenditure.

Chapter 2

Exploring Approaches on Sustainability, Distributed Power and Metaheuristics in Locomotive Assignment.

In this chapter, the aim is to establish a benchmark and enhance our comprehension of the current research landscape by examining relevant academic literature on similar models. The primary focus revolves around the following key aspects, which are also crucial to the model underlying this work:

- Sustainability-oriented, green train models.
- Models that solve the Locomotive Assignment Problem and incorporate Distributed Power.
- Research that uses metaheuristics to solve the LAP respectively LSP.

By doing this, it shall be identified, how this work can add value to the existing research and further improve railway logistics.

2.1 Sustainable & Green Train Scheduling Models.

In recent years, research in railway models has emerged, that has as objective to make train operations more sustainable and to reduce emissions. Often this is done minimizing costs related to harmful emissions. One such way, that is also crucial to this thesis, is reflecting cost by measuring the fuel consumption of a train. Fuel consumption of a train can not only be seen as a cost driver, but also as a parameter that measures the sustainability of ones operation. X. Li et al. (2013) propose a *green* scheduling model measuring and minimizing energy and carbon emission costs. Like Ghoseiri et al. (2004) they measure energy costs (respectively fuel consumption) based on resistance. The resistance of a train is given by the Davis formula. In his book "The Tractive Resistance of Electric Locomotives and Cars" from 1926, W. J. Davis derived an equation based on a trains mass, certain resistance coefficients and velocity to calculate a its resistance. Both research groups incorporate resistance (among other measures) in their objective function to be minimized. Ghoseiri et al. (2004) solve their model using a two-step approach determining the Pareto frontier and then performing multi-objective optimization using the distance-based method and X. Li et al. (2013) apply a fuzzy multi-objective optimization algorithm. Hu et al. (2013) also try to minimize operational costs (fuel consumption and allowances for emission reduction) and passenger time with a solution provided by a fuzzy algorithm. Their approach differs in the operational constraints. They incorporate constraints in their model that restrict the exhaust emissions on certain segments the train drives on. They report significant reduction in energy consumption compared to existing models and a trade off between operational costs and passenger trip time. In the work of Jafarian-Moghaddam (2021) operational sustainability is achieved by minimizing resistance by assessing the optimal length and speed (and thereby weight and resistance) of the train. They develop a multi-objective model where the objectives conflict and thereby restrict each other. The model assesses the optimal train length and minimal travel time, while lowering energy consumption. The fact that the train length is variable makes their model an Elastic Train Model. The model is solved by the Genetic Algorithm metaheuristic and the results promise a revenue increase of 48% and a increase in time savings of 25%.

2.2 Employment of the Distributed Power Technique in the LAP.

The research discussed in the previous Section 2.1 all incorporate some measures or constraints to design their model somewhat sustainable. As mentioned multiple times, in this model the measure shall be Distributed Power. The first to incorporate DP in the LAP are Ortiz-Astorquiza et al. (2021). Similarly to Peltz (2013), Murray (2001) and Roney et al. (2010) they claim a reduction in in-train forces, the possibility of increased weight and length of trains, and the reduction of fuel consumption, reduction the wear on rails and reduction of the possibility of derailment as the positive effects of DP. However, setting the locomotives up for DP mode is more time-consuming and not all locomotives possess the means to operate in DP mode. Ortiz-Astorquiza et al. (2021) provide a highly sophisticated model for the LAP which determines the optimal assignment of different locomotive types to trains. They also try to find the optimal choice of train operating mode that reduces total costs, while satisfying multiple constraints that are crucial to the Canadian National Railway Company, like power requirements and flow balance for a given seven-day train schedule. The DP technique comes to play at the power requirements constraint. They assume, that a train assigned with locomotives operating in DP mode has lower power requirements than a conventional train and thus saves costs. To obtain feasible solutions they employ two versions of a Benders decomposition based algorithm, which when used with real world data delivers potential benefits. In contrast to that, this model DP does not effect the power requirements of a train (i. e. when driving with DP it needs less locomotives), it effects the resistance of a train and thus lowering the total costs. Details regarding this can be viewed in Chapter 3.

2.3 Literature on Metaheuristics Utilized to Solve the LAP.

This section provides an insight into the method that solves this Locomotive Assignment Problem. It briefly explains the concept of metaheuristics and the reason for their frequent use. Further the most prominent research using metaheuristics to solve the LAP is presented. Detailed information which exact metaheuristic is applied in this thesis and why it is the most suitable is provided in Section 4.1, Section 4.2 and Section 4.2.1.

A metaheuristic is a higher-level problem-solving strategy that guides the search for solutions by exploring the solution space using a set of heuristics. Unlike simple heuristics, metaheuristics can be applied to a wide range of optimization problems, and they do not rely on specific problem knowledge. Metaheuristics can be viewed as problem-independent algorithms that are designed to find near-optimal solutions to complex optimization problems. Metaheuristics are typically used when the problem size is large, and the search space is complex, making it difficult to use traditional optimization techniques such as mathematical programming. Metaheuristics can explore large solution spaces in a reasonable amount of time and can often find good-quality solutions that are close to the optimal solution. This is because metaheuristics are generally known to solve hard problem instances by exploring all of the large and complex solution space. Generally, metaheuristics serve three main purposes: solving problems faster, solving large problems, and obtaining robust algorithms. Moreover, they are simple to design and implement, and are very flexible (Talbi, 2009). It also lies in their nature that they are intuitive and easy to understand. As such they can be deployed by a broad range of operators with little knowledge of optimization systems or computational science. In this thesis the focus is to apply a metaheuristic to solve the underlying Locomotive Assignment Problem. Concerning the solution approach for LAPs there are multiple methods to utilize. In the survey provided by Piu and Speranza (2014) less complex multiple locomotives models were usually solved using some standard heuristic approach like the tree-based branch-and-cut method, some assignment algorithm, minimum cost path algorithms

(Paoletti and Cappelletti (2006), Cordeau, Desaulniers, et al. (2001), Bacelar and Garcia (2006)) or decomposition based methods like a Benders or Dantzig-Wolfe decomposition, as in Florian et al. (1976), Cordeau, Soumis, et al. (2001), Lingaya et al. (2002), and Ziarati et al. (1997). The more complex, real-life applications are mostly too large to be solved by commercial solvers such as CPLEX or GUROBI. The temporal and computational effort required to obtain good solutions is too large. One way to solve complex problems using a commercial solver is through approximate dynamic programming (ADP) which was proposed by Powell et al. (2001). Through ADP a large problem is split in a sequence of small solvable sub problems. Powell puts the ADP framework to use in numerous publications (see for example Powell and Topaloglu (2003), Godfrey and Powell (2002), Topaloglu and Powell (2005), and Topaloglu and Powell (2006)). In Piu and Speranzas Survey research solving the LAP using metaheuristcs occurs only rarely. Ziarati et al. (2005) solve the LAP using a Genetic Algorithm (GA) including a Neural Network module. The GA is a search metaheuristic inspired by natural evolution where only the fittest individuals (solutions) are selected to reproduce in order to generate new (better) solutions, also allowing for random mutations. The problem of solving large MIP formulations of real-life applications of the LAP has also been addressed by Ahuja et al. (2005), who incorporate a metaheuristic in their model to solve a detailed real-life problem. In particular, they propose a decomposition based heuristic approach where near optimal solutions generated by a solver (like CPLEX) which are then used as a starting point for a very large-scale neighborhood (VLSN) search algorithm. This algorithm alters the initial solution until a local optimal solution is found. That way, the authors report solutions are delivered in up to 30 minutes and a significant cost reduction in comparison with traditional methods is achieved. Other research that uses metaheuristics to improve solutions obtained by algorithmic methods is conducted by Sama et al. (2015) who aim to schedule and route trains in a complex and busy network. Initial solutions obtained by a truncated branch-and-bound algorithm are applied to a Variable Neighbourhood Search (VNS) and Tabu Search metaheuristc in order to be improved. Tabu Search is a heuristic optimization algorithm that avoids getting trapped in local optima by using a memory-based search strategy that keeps track of recently visited solutions in a Tabu list and imposes constraints on the search movements based on it. It iteratively explores the neighborhood of the current solution and selects the best move that does not violate any Tabu rule until a stopping criterion is met. VNS is a metaheuristic optimization algorithm that iteratively searches the solution space by alternating between different neighborhoods of the current solution, each defined by a distance measure. The algorithm starts by generating an initial solution and then iteratively applies a shaking procedure to produce new candidate solutions in the current neighborhood, followed by a local search procedure to improve the solution within that neighborhood. If no further improvement is found, the algorithm moves to a different neighborhood with a larger distance measure and repeats the process until a stopping criterion is met. In general the authors find that the VNS is faster than the Tabu Search and it is able to compute new best solutions for some of the tested instances. Chen and Niu (2013) also developed a Tabu Search algorithm to solve a realistic Train Scheduling Problem. The objective is to minimize the train fleet and interval times, while respecting the time-shift and equilibrium constraints. An application to real data on the Beijing-Tianjin line has shown that the algorithm can produce high-quality train scheduling solutions. It is also flexible to be extended to any rail train circulations characterized by high-density trips and large-quantity trains. Habiballahi et al. (2022) apply Adaptive Genetic Algorithm (AGA) and Simulated Annealing (SA) to the LAP for freight trains. Simulated Annealing mimics the annealing process of cooling molten metals to reduce defects. The algorithm iteratively explores the search space and accepts candidate solutions with a probability that depends on the current temperature and the difference between the candidate solution and the current solution. The algorithm gradually reduces the temperature to decrease the probability of accepting worse solutions. They applied the heuristics to a small-scale analysis (10 problem instances) and a large-scale analysis (100 problem instances). In the small-scale analysis the SA could solve 76% of the instances optimally and the AGA could optimally solve 85% of the instances optimally. For the large-scale problems, the AGA also outperforms the SA, however the SA could deliver solutions generally 10 times faster.

Noori and Ghannadpour (2012) apply the Genetic Algorithm in a two-phase approach. Their objective is to minimize the cost of assigning homogeneous locomotives respecting the trains power requirements and precedence relations for train classes and service levels. In the first phase, they convert the multi-depot LAP into a single-depot problem. In the second stage, each depot problem is solved by a hybrid Genetic Algorithm including various heuristics and operators in the evolutionary search. When applied to medium sized examples and compared to branch-and-bound techniques it is shown that this approach is effective in terms of solution quality and timely effort. A similar problem is faced by Ghoseiri and Ghannadpour (2010) who extend the multi-depot homogeneous locomotive assignment problem with a time window constraint. Again the problem, which is formulated as a vehicle routing problem, is converted into a set of single depot problems, which are solved using a hybrid Genetic Algorithm. Again, it is applied to medium sized examples and compared to a branch-and-bound method. The authors report an efficient algorithm. Another group of researchers deploying a genetic algorithm to the LAP is Godwin et al. (2006). Their study concerns itself with freight trains on a passenger rail network. In their two-stage approach they first assign a locomotive to a train and then create a schedule. The assignment should minimize deadheading time and total coupling delay. The assignments are found by a multi-objective genetic algorithm and another GA is deployed to schedule and route the freight trains to minimize total tardiness. This approach is efficient and produces solutions of acceptable quality to the authors.

Chapter 3

Mathematical Representation of a Locomotive Assignment Model using Distributed Power.

The following chapter presents the mathematical formulation of the underlying Locomotive Assignment Problem. It introduces the necessary operational constraints to enable feasible locomotive assignments and train scheduling. Additionally, a detailed examination of the objective function is conducted, with a specific focus on resistance as the main driver of fuel consumption and costs.

Train scheduling and locomotive assignment with their objectives and constraints are usually expressed in the form of a Mixed Integer Program (MIP), which the following section describes. The formulation of a resistance based fuel consumption in the objective function builds on the work of X. Li et al. (2013) to a large extent. The constraints are on the one hand basic operational constraints of the locomotive assignment problem and on the other hand adapted to the speciality of the use of Distributed Power in this model. Variables, coefficients and abbreviations used in this model can be found in Table 3.1 and in Table 3.2.

Variable	**Context**
x_{ij}	Equals 1 if locomotive j is assigned to train i, 0 else.
y_j	Equals 1 if locomotive j is able to operate in DP mode, 0 else.
H_{iq}	Equals 1 if train i traverses segment q, 0 else.

Table 3.1: Table of all variables used in the MIP.

Parameter	Context
R	Resistance (of a train).
A	Davis Coefficient for wheel & track related friction.
B	Davis coefficient for rolling friction dependent on speed.
C	Davis coefficient for air drag.
v	Velocity.
i	Train indicator variable.
q	Segment indicator variable.
j	Locomotive indicator variable.
s	Station indicator variable.
I	Set of all trains.
Q	Set of all segments.
J	Set of all locomotives.
S	Set of all stations.
A_J	Set of all allowed locomotive combinations to be assigned to the same train.
m_i	Mass of train i.
g	Gravitational force $g = 9\ m/s^2$.
δ_q	Track grade of segment q in radians.
M	Axle load in tons.
L_T	Total length of the train.
n_{loco}	Number of locomotives on a train.
n_{ax}	Number of axles of the train.
θ	Distributed Power coefficient.
P_{iq}	Required power of train i on segment. q
d_q	Length of segment q.
r_i	Amount of fuel consumption per unit power output.
c	Cost per unit fuel consumption.
p_j	Power of locomotive j.

Table 3.2: Table of all parameters used in the MIP.

3.1 Modelling a Trains Resistance.

Resistance is an important factor affecting the efficiency of trains. Freight trains are exposed to resistance forced upon air, the track, rolling, axles and so forth. According to the Davis formula (Davis, 1926), the total resistance of a train can be reflected by a third-degree polynomial, quadratic in the velocity of the train:

$$R = A + Bv + Cv^2. \tag{3.1}$$

This formula is derived from the experimental work conducted by Davis and thus has an empirical nature. In Equation (3.1), the variables A, B, and C represent distinct types of resistance. Szanto (2016) provides an overview of these three terms and presents various values for the parameters based on empirical observations of coal and iron trains. According to this research, parameter A

corresponds to rolling friction and track friction, which are independent of speed but depend on factors such as train length or weight. Parameter B is associated with speed-dependent friction, including wheel/rail friction, rail wave action, or curve resistance. The quadratic term Cv^2 relates to air drag, which occurs at the front and end of the train, as well as between cars or in tunnels. Typically, this type of drag increases quadratically with the train's speed. Different approaches exist for applying the Davis formula. For instance, X. Li et al. (2013) define the resistance of train i on railroad segment q as follows:

$$R_{iq} = m_i \left(A_i + B_i v_{iq} + C_i v_{iq}^2 + g \sin(\delta_q) \right), \tag{3.2}$$

where m_i is the mass of train i, A_i, B_i, and C_i are Davis resistance coefficients of train i, v_{iq} is the average velocity of train i on segment q and $g \sin(\delta_q)$ is the grade resistance per mass on segment q, where g denotes the gravitational force. Additionally, they provide the resistance coefficient values for various train types included in their study. These coefficients are typically obtained through empirical derivation using existing models or by conducting real-life experiments with the trains. In this model, it is necessary to determine the appropriate resistance coefficients for the modeled trains. However, the derivation process must align with the characteristics of the trains and locomotives involved to ensure an accurate representation of the behavior of heavy freight trains at high speeds. An analysis and full-scale test of running resistance for freight and passenger trains in Sweden is presented by Lukaszewicz (2007). This study investigates the influence of variables such as speed, number of axles, number of wagons, axle load, track type, and train length. By measuring the energy balance equation and collecting speed and distance data of test trains in the Rolling Stock Laboratory of the Swedish State Railways under varying track conditions, the author examines these factors. The freight trains used in the study are similar to those employed in this model and consist of open wagons, closed wagons, and mixed configurations. The train configurations range from 18 to 36 wagons (each with two axles), with total train masses varying from 798 tonnes to 1470 tonnes and total train lengths between 256 and 514 meters. These measures closely resemble typical Austrian trains utilized in this model. Based on these experiments, Lukaszewicz (2007) determines values for the Davis parameters A, B, and C that are independent of train weight but dependent on the number of locomotives, number of axles, total train length in meters, and axle load in Newton. Table 3.3 displays the resistance coefficients for various types of freight trains. In this case, the parameters of the Davis Formula are not directly dependent on train weight but rather on other train characteristics. The variable n_{loco} represents the number of locomotives, which influences resistance independently of speed. The same applies to M, the axle load, and n_{ax}, the number of axles. The total length of the train (L_T) affects the resistance depending on speed, indicating that longer trains experience

Train Type	A (N)	B (Ns/m)	C (Ns^2/m^2)
Covered Wagons	$2000n_{loco} + (65 + 0.6 \times 10^{-3}M)n_{ax}$	$-22 + 0.6L_T$	$5.1 + 4.9 \times 10^{-2}L_T$
Open Wagons	$2000n_{loco} + (65 + 0.6 \times 10^{-3}M)n_{ax}$	$0.3L_T$	$5.1 + 9.2 \times 10^{-2}L_T$
Mixed Consist	$2000n_{loco} + (65 + 0.6 \times 10^{-3}M)n_{ax}$	$-22 + 0.6L_T$	$5.1 + 8.1 \times 10^{-2}L_T$

Table 3.3: Values for the Davis parameters A, B and C or three different wagon configurations.

increased resistance as their speed increases. Additionally, the train length is the only variable component in the aerodynamic drag coefficient C of the Davis formula. It is worth noting that the coefficients are quite similar across different wagon configurations, with variations primarily observed in terms of B and C. For covered wagons and mixed consists, the influence of speed on resistance appears to diminish, becoming proportionally smaller as the train length increases. At a certain train length, this influence starts to contribute to the overall resistance. In the case of open wagons, the train length consistently exerts a positive influence on the resistance parameter B. As for the aerodynamic coefficient C, it is smallest for covered wagons, indicating that they are the most aerodynamically streamlined wagon type. Open wagons experience the highest aerodynamic drag, while mixed configurations have a slightly lower coefficient. Since the mass of the train is already incorporated into these coefficients, we cannot directly utilize the formula from Equation (3.2). In this model, the mass of the train only affects the resistance when it is ascending or descending hills and mountains. As a result, the resistance in this model is calculated as follows:

$$R_{iq} = (A_i - \theta y_j) + B_i v_{iq} + C_i v_{iq}^2 + m_i \left(g \sin(\delta_q)\right). \tag{3.3}$$

For each train i on a given segment q, the terms A_i, $B_i v_{iq}$, and $C_i v_{iq}^2$ are calculated based on the train's characteristics and the values provided in Table 3.3. The corresponding speed v and grade δ for each segment can be obtained from Table 5.1. When a train operates in Distributed Power (DP) mode, indicated by the assigned locomotives being in DP mode ($y_j = 1$), the Distributed Power coefficient θ is subtracted from the resistance parameter A. This adjustment is supported by the insights derived from the research presented in Section 2.2, indicating that DP affects the resistance of the trains on the track. Since the experiments were conducted independently of speed, DP will be applied to the resistance parameter A which is not influenced by the velocity of the train.

3.2 Assessing a Trains Fuel Consumption Driven by Resistance.

The trains resistance discussed in the previous section is the main driver of fuel consumption, which is to be minimized. To calculate the fuel consumption, the effort required to pull a train needs to be assessed. For a train to maintain a continuous velocity, the tractive effort has to be equal to the resistance. According to basic Physics and following X. Li et al. (2013), the required power of train i on segment q is given as

$$P_{iq} = R_{iq}v_{iq}. \tag{3.4}$$

Therefore, considering that the amount of fuel consumption per unit power output is given by r_i, fuel consumption is given by $R_{iq}d_qr_i$. Hence, the fuel consumption of train i on segment g is given by

$$E_{iq} = \sum_{i\in I}\sum_{q\in Q} R_{iq}d_qr_iH_{iq}, \tag{3.5}$$

where H_{iq} equals 1 if train i traverses segment q and 0 otherwise.

3.3 Objective Function of the Locomotive Assignment Problem.

The ultimate goal of this model is to reduce carbon emissions of freight trains. This is measured via fuel costs which are to be minimized. By denoting c as the cost on unit of fuel consumption and combining it with Equation (3.5), we can assess the cost on fuel consumption:

$$E = \sum_{i\in I}\sum_{q\in Q} cR_{iq}d_qr_iH_{iq}. \tag{3.6}$$

Now, if the train operates in DP mode, its resistance decreases by the DP factor θ. Thereby the cost of fuel consumption in Equation (3.6) reduces and we are left with the Distributed Power influenced objective function:

$$E^{DP}_{min} = \sum_{i\in I}\sum_{q\in Q} c\left(R_{iq} - \theta y_j\right)H_{iq}d_qr_i. \tag{3.7}$$

The decision variable y_j equals 1 if the locomotive j assigned to a train is in DP mode and 0 else. Note that the exact deduction of the DP parameter θ is performed as displayed in Equation 3.3 and not as depicted here. The representation in Equation 3.7 is simplified with regard to the deduction of the resistance by the DP-factor.

3.4 Operational Constraints Imposed on the LAP.

For the LAP to be feasible a set of operational constraints has to be satisfied. For this model it is assumed that there is no consist busting or deadheading. All locomotives assigned to a train are active powering units and the order of assignment is arbitrary.

Power Requirement, Locomotive Type & Mode Constraint. There must be enough power (locomotives) assigned to a train, such that the power supplied by the locomotives is greater than or equal to the power required by the train to be pulled:

$$\sum_{j \in A_J} x_{ij} \cdot \mathrm{p}_j \geq \mathrm{P}_{iq} \quad \forall i \in I, \quad \forall q \in Q, \tag{3.8}$$

where x_{ij} is a binary variable equalling 1 if locomotive j is assigned to train i. The variable p_j indicates the total available power of locomotive j and P_{iq} is the power required by train i on segment Q.

By summing over the set A_J which incorporates every allowed locomotive combination to be assigned to the same train, it is ensured, that only locomotives of the same type (Vectron, Hercules, etc.) and of the same mode (DP or conventional) are assigned to the same train.

Unique Assignment Constraint. Each locomotive j in the set of all locomotives J can only be assigned once per schedule:

$$\sum_{i \in I} x_{ij} \leq 1 \quad \forall j \in J. \tag{3.9}$$

Distributed Power Constraints. If a train i operates in DP mode, that is it only has DP enabled locomotives assigned, there need to be at least 4 locomotives assigned:

$$3 \cdot y_j + 1 \leq \sum_{j \in J} x_{ij} \quad \forall i \in I. \tag{3.10}$$

If a train operates in conventional mode, there is no particular restriction on the minimum number of locomotives. The minimum number of locomotives required to pull a train (and that every train is served) is ensured through Equation 3.8.

Flow Conservation Constraint. The trains movement has to be ensured to be without any longer stopping or waiting times. For the train to choose the right path, we assume when the train runs from station $s-1$ to station s it should choose exactly one segment q to go into station s and choose exactly one segment to go out of station s.

$$\sum_{q \in Q_{is}^{I}} H_{iq} = \sum_{q \in Q_{is}^{O}} H_{iq} \quad \forall i \in I \quad \forall s \in S. \tag{3.11}$$

Q_{is}^{I} represents the set of segments pointing into station s which can be used by train i and Q_{is}^{O} the set of segments pointing out of station s which can be used by train i.

Variable Range Constraint. The variables used in this model are assumed to take the following values:

$$H_{iq}, x_{ij}, y_j \in \{0, 1\} \quad \forall j \in J, \quad \forall i \in I. \tag{3.12}$$

The feasibility of these constraints has been checked using the CBC MILP Solver version: 2.10.3, build date Dec. 15 2019, implemented in Python 3.9 using the PuLP package. Due to the complexity and non-linearity of the objective function a simple proxy has been used that minimizes the total power assigned to a train. The feasibility of the objective has been extensively studied in other research mentioned before.

Chapter 4

Selecting and Implementing the Heuristic to Solve the Locomotive Assignment Problem.

The optimization model described in Chapter 3 shall be solved using a heuristic approach. The heuristic itself should be easy to understand and of simple nature. Further, this approach shall ensure, that the solution is generated in a timely manner and as efficient as possible. A solution of the underlying problem can generally be seen as an assignment of locomotives to a set of trains, while respecting the model constraints (see Section 6.1 for a detailed presentation of solutions). Further this solution should provide the costs of the computed schedule. To generate such solutions the field of metaheuristics provides a set of possibilities to tackle the underlying problem. In the following chapter the selection of an appropriate metaheuristic, the implementation of the specific model will be discussed. The subsequent Chapter 5 presents the input data for this algorithm.

4.1 Selection of Metaheuristic & Implementation of Schedule.

As seen in Section 2.3 there are many metaheuristics that have been applied to solve the LAP. The Genetic Algorithm or adapted versions of it seem to be particularly popular to be deployed to compute solutions to the Locomotive Assignment and Scheduling Problems. To find the appropriate metaheuristic for this model, the most important demands imposed on the solution methods have to be recalled: The method should generally be applicable to any given problem such that if the circumstances of the underlying problem or model change it is still possible to adapt the algorithm easily. It should be rather trivial and easy to understand, easy to be implemented and operated, and it should produce solutions in a timely manner. Factors to include into the choice of metaheuristic are also the underlying problem type and data structure. In this particular assignment problem, we have have a set of available locomotives of varying type with different features. The set of trains the locomotives are assigned to is rather small as the schedule is on a weekly basis. Thus, there are many similar solutions, enabling many local optima and few global optima. An algorithm or a heuristic always runs the risk of being stuck in a particular solution unable to find a better one. Thus, a metaheuristic should explore all of the solution space efficiently and it also should be able to escape local optima. However, when escaping a local optima the metaheuristic should not jump to a completely different solution, and thereby risking not finding a potential global optimum close to the local optimum. There are many heuristics that avoid being trapped in local optima like, Simulated Annealing, Tabu Search, or Genetic Search. However, they usually do not fulfill the requirement of simplicity and that often makes it hard to find the reason of their effectiveness (Mladenović and Hansen, 1997). A local search heuristic, on the contrary, is generally known to be simple and applicable to any problem, easy to implement and efficient. Using the novel idea of neighbourhood change during the search Mladenović and Hansen (1997) propose a new heuristic, as effective as other metaheuristics and as simple as a local search, called Variable Neighbourhood Search (VNS). They find that VNS is at least as effective as other metaheuristics and due to its simplicity it is worthy of being studied further. In their successive work (Hansen and Mladenović, 2001) they confirm their findings by proposing several desirable properties of a metaheuristic, and by showing that VNS fulfills all of them to a great extent. The principles go along with the desired characteristics imposed in this thesis and are: Simplicity, Coherence, Efficiency, Effectiveness, Robustness, User-friendliness, and Innovation. They compare VNS to a range of benchmark problems and the VNS solves them exactly or very close to the optimum. VNS also outperforms other widely known and popular metaheuristics. As a result of this and since it complies with all desired properties, the Variable Neighbourhood Search metaheuristic is chosen to solve the underlying DP-LAP. In the subsequent section the problem-specific adaption of the VNS is presented.

4.2 The Variable Neighbourhood Search Metaheuristic.

In another paper Hansen et al. (2010) present the background of the VNS idea and explain the underlying principles in detail, among other things. The VNS algorithm basically builds around a local search heuristic to solve combinatorial and global optimization problems. A local search heuristic takes a solution x that is chosen beforehand and finds a direction to descent from there within the neighbourhood of the solution $N(x)$. A neighbouring solution is another solution similar to the initial solution, that usually differs only little from the initial solution. Large Neighbourhoods can however imply, that some neighbour of the initial solution resembles the initial solution only in few parts. The local search moves towards the minimum of $f(x)$ in $N(x)$ in a descending direction. Usually it takes the steepest direction which is also called *BestImprovement*. The basic VNS algorithm (Algorithm 1) has three main inputs. The initial

Algorithm 1 Variable Neighborhood Search (VNS)

```
function VNS(x, k_max, t_max)
    repeat
        k ← 1
        repeat
            x′ ← Shake(x, k)                          ▷ Shaking
            x″ ← BestImprovement(x′)                   ▷ Local search
            NeighbourhoodChange(x, x″, k)              ▷ Change neighbourhood
            k ← k + 1
        until k = k_max
        t ← CPU_Time()
    until t > t_max
end function
```

solution x is the key input, and it refers to any feasible solution to the underlying problem. There are numerous ways to construct this initial solution. Various approaches include generating it randomly, applying a some principle or rule to ensure an efficient starting point, or consulting another optimization method. The parameter k_{max} defines the number of neighbourhood structures to be generated. The metaheuristic also requires a stopping criterion. In the initial proposal by Pierre Hansen and Nenad Mladenović the algorithm stops at a certain time t_{max} that has to be defined by the user. Other commonly used stopping criteria are to stop after no further improvements have been made or after a certain level of fitness (optimality) has been reached. The basic idea of the VNS works as the following:

1. By using the *Shake* function on the existing solution x, a new solution x' is created. The *Shake* function is in charge of producing a new solution that is comparable to the existing one but distinct enough to permit investigation of an alternative area of the search space.

2. x' is then submitted to the *BestImprovement* function. The local search method examines the vicinity of the current solution and provides the best solution found x'' within that

area.

3. The best discovered solution, x'', the current value of k, and the current solution x are then passed to the *NeighbourhoodChange* function. It is up to the *NeighbourhoodChange* function to decide whether to accept x'' as the new current solution or whether to continue exploring the search space by incrementing k and generating a new solution using *Shake* ("move or not").

The VNS algorithm iteratively explores the search space (see Figure 4.1), by using the *Shake* function to create new solutions, the *BestImprovement* function to improve those solutions, and the *NeighbourhoodChange* function to decide whether or not to accept or reject those improvements. The VNS method is very flexible and any optimization problem can be addressed by adapting the neighbourhood structures and the shaking procedures to the respective optimization problem.

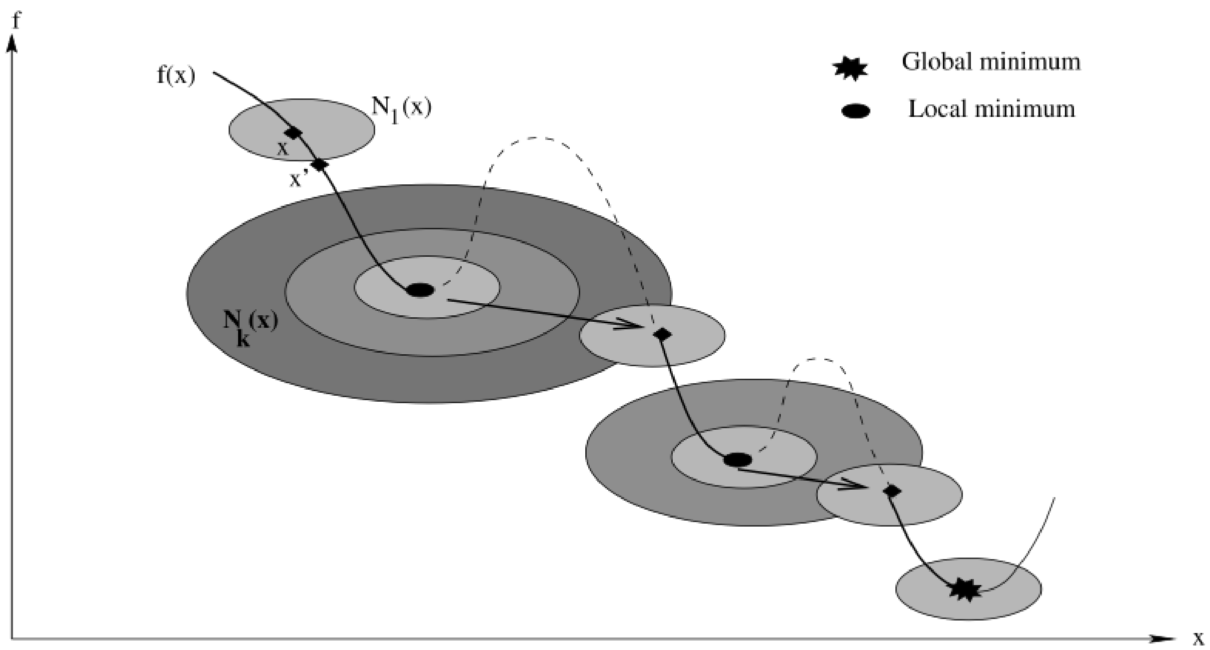

Figure 4.1: This visualization from Hansen et al. (2010) represents how the VNS algorithm iteratively searches the solution space.

4.2.1 Implementation of the VNS for the Underlying DP-LAP (First Stage).

The basic idea and the structure of the VNS has been described in the previous Section 4.2. However, in order to solve this particular Locomotive Assignment Problem (described in Chapter 3) a number of adjustments have to be made. To fit the problem, it is necessary to define the neighborhood structures and set up the shaking procedure. Crucially, all modified solutions generated by the shaking process and explored neighborhoods must adhere to the constraints imposed by the given LAP (see Section 3).

To begin, it is necessary to generate a feasible initial solution. In the case of this VNS implementation, the solution is created by assigning locomotives to trains randomly. This is based on the assumption that the locomotives in the initial depot are not in any particular order and will be assigned to trains in the order they are parked. The procedure for generating these initial assignments ensures that the constraints of the models are complied with. This includes verifying that all assigned locomotives to the same train are either equipped with the Distributed Power technique or not, if a locomotive has already been assigned (as each locomotive can only be assigned once) and if the locomotives assigned to the same train are of the same type. It is assumed that only locomotives of the same type can power a train, although this constraint could potentially be relaxed for future research, allowing multiple locomotives of different types to power a train. Additionally, it ensures that if a train has DP-locomotives assigned, there must be at least four locomotives assigned. Lastly, the initial solution generating procedure checks if the train has enough power (locomotives) assigned to be pulled. If this requirement is met, the procedure stops; otherwise, it continues assigning locomotives to the trains. The VNS algorithm utilizes the initial solution as its starting point. In addition to this, the VNS algorithm for the underlying DP-LAP (Algorithm 2) takes input regarding locomotives and trains, including information such as required power, power available, locomotive type, and details about the train route network such as inclines and segment lengths. The algorithm begins by tracking information about run time and the number of iterations. The initial solution is designated as the current (incumbent) solution, and its objective value is computed. The function employed to calculate the objective value, utilizes information about locomotives and trains such as length, weight, and cost related to diesel and electricity, in order to evaluate the cost of each assignment. The current solution, denoted as X, is then subjected to the shaking swaps. To address the assignment problem, three distinct shaking procedures have been developed, each generating different solutions. These shakings are concised and illustrated as pseudocode in Algorithm 3. Depending on the state of k the incumbent solution gets altered in a different way. When designing these shakings it was deliberately ensured that they do not change a solution too drastically. Large Swaps could be seen equivalent to random restarts every time the shaking procedure is being called and the idea of the metaheuristc would be useless. Since in every assignment there are usually between three an seven locomotives on a train, only one locomotive will be changed in these swapping procedures. The difference in these swaps lies in the choice of the locomotive that is being removed. In order to ensure, that the solution improves, the first shaking ($k = 1$) removes the locomotive

Algorithm 2 DP-VNS

function VNS($inital\_solution, train\_data, loco\_data, track\_data$)
  $start\_time \leftarrow time()$
  $num\_iter \leftarrow 0$
  $best\_iter \leftarrow 0$
  $X \leftarrow inital\_solution$
  $Z \leftarrow Objective\_Value(X, train\_data, loco\_data, track\_data)$
  while True **do**
    $num\_iter \leftarrow num\_iter + 1$
    $k \leftarrow 0$
    while $k < length(Shakings)$ **do**
      $X' \leftarrow Shaking(X, loco\_data, k)$ ▷ k different Swaps
      $o, X'' \leftarrow get\_neighbors(X', loco\_data, track\_data)$
      $Z'' \leftarrow \texttt{min}(o)$ ▷ Best Improvement
      if $Z'' < Z$ **then** ▷ Local Search
        $X \leftarrow \texttt{list}(X''[o.\texttt{index}(Z'')])$
        $Z \leftarrow Z''$
        $best\_iter \leftarrow num\_iter$
      else
        $k \leftarrow k + 1$
      end if
    end while
    if $time() - start\_time > 60$ and $k \geq 3$ **then**
      `break`
    end if
  end while
  `return` $X, num\_iter, best\_iter$
end function

with the most power (kilo watt, kW) from the respective assignment. This is done for the reason that it often occurs, that there is only a small amount of power required to pull the train left to be fulfilled by a locomotive and the algorithm finds and assigns a powerful locomotive, that overshoots the target by a large amount. By removing a strong locomotive, a less powerful loco-

Algorithm 3 Shaking Swaps

```
function SWAP(X, loco_data, k)
    loco_to_remove = None
    for every assignment in X do
        calculate total kW of locos
        if total kW of locos == kW required by train then
            pass
        else
            if k == 1 then
                find loco with most kW
                loco_to_remove = loco_most_kW
            end if
            if k == 2 then
                find loco with least kW
                loco_to_remove = loco_least_kW
            end if
            if k == 3 then
                find random loco that fulfills the constraints
                loco_to_remove = loco_random
            end if
            X.remove(loco_to_remove)
            X.add(random(loco_data))
        end if
    end for
    return X
end function
```

motive could be added and hence improving the solution[1]. Similarly more than one locomotive could be removed and their space could be taken by one (powerful enough) locomotive.

A similar thought is behind the second swap (remove the locomotive with the least power). If the VNS adds a very powerful locomotive at the end, it could be that a weak locomotive can be removed without needing another one added, and thus the assignment requires less locomotives

[1]Note that this does not imply improving the solution in the sense of a cheaper assignment, but the gap between power required and power supplied decreases, which is also seen as an improvement in terms of solution quality.

in total, reducing costs and optimizing the total solution. The random shaking swap was added to take another non-deterministic factor into the model. This swap simply chooses a random locomotive of the assignment to be removed.

Subsequent to the shakings, the neighbours of the perturbed, incumbent solution are generated. For the neighborhood the nearest-neighbour (1NN) method is chosen. This implies that for every current solution (X') a copy is taken and one locomotive in one assignment is changed using another, unused locomotive. This represents one neighbour of the incumbent solution. This is done for every locomotive in all assignments. As such, a list of solutions (aka neighbours) is generated. In the same procedure, the objective value for every solutions is calculated and also appended in that list of neighbours. That way, after generating the neighbours and assessing their fitness, the VNS can perform a local search where the solution with the best objective value (Z'') is chosen. If this value improves the current best objective value, it is saved and this iteration is also noted as the best iteration. If it does not improve, the solution will be sent to the next shaking ($k + 1$). This whole process is carried out until the total running time exceeds 60 seconds (considering that all three shakings have been performed). 60 seconds is a sufficient run time, since tests showed, that the VNS usually finds the best solution way before the time runs out.

4.2.2 Implementation of a Weekly Freight Train Schedule (Second Stage).

The VNS metaheuristic described in Section 4.2.1 iteratively selects locomotives for trains while aiming to find optimal assignments by evaluating and minimizing costs. The cost primarily depends on the resistance of the trains, which also determines the number of locomotives needed to pull a train. This requirement typically varies across different segments of the freight train route, considering inclines and declines. Therefore, the assignments obtained from the VNS alone are not sufficient for the entire route. The optimized assignments produced by the VNS serve as input for the second stage, which generates the complete schedule.

In the second stage, costs and required power (both influenced by resistance) are calculated for each route segment. In some segments, the train's power requirements exceed the power supplied by the assigned locomotives. To address this, depots have been established at specific stations, where additional locomotives can be added to the train to meet the remaining power needs. In the context of this model, depots are present in both Innsbruck and Trento. This is due to the significant incline that trains encounter when crossing the Alps. After ascending the incline, the additional locomotives that are no longer necessary can be unloaded at the depot following the declining segment. It's important to note that in this case, the locomotives added at the first depot may not necessarily be the ones that need to be removed at the second depot. Instead, other locomotives, potentially more favorable, can be chosen for removal. In practice, however, it is often more efficient to remove the most recently added locomotives (Last in, First out - LiFo). To elaborate, the second stage functions as follows:

1. Take the final assignments of the VNS as input. The input assignments have to have enough traction power to overcome all the inclines between Vienna and Innsbruck, since there is no depot in between.
2. Calculate the total cost for every train on every segment.
3. In Innsbruck, check for every train if additional locomotives are required.
4. In Trento, check if locomotives can be removed because they exceed the total required power by more than their own power. Still, make sure that there is enough power and the remaining inclines until Genoa can be overcome by the trains, since their are no more depots in between.

This approach produces a freight train schedule that includes the number of trains being scheduled, the locomotive count on each train, train types, traction types (DP equipped or conventional), and assignment costs. Additionally, it calculates the total job costs from Vienna to Genoa. It's important to note that in this context, the term "schedule" does not refer to specific time windows for train departures or arrivals at stations. Instead, it pertains to organizing the trains that will fulfill orders and generating an operational schedule within a given time frame, such as a week.

Chapter 5

Modelling Input Data for the Sustainability-Oriented Logistics Model.

To ensure the resulting schedule reflects a high level of realism, it is crucial to consider accurate input data such as locomotives, trains, and track characteristics. Since this model is designed for the Austrian context, locomotives and trains utilized in Austria are represented in the model. To obtain realistic data, reliable sources, including actual railway operators, are consulted. Additionally, relevant research papers and similar efforts provide valuable information. Data pertaining to railway tracks is gathered from a mapping tool specifically designed for railroads.

5.1 The Train Route Network.

In order to realistically model the schedule and incorporate a sufficient level of detail, it is necessary to implement a real-life train route within the model. To achieve this, a train route network diagram is utilized, which represents the railway network using graph-based structures (refer to Figure 5.1).

The train route network is built upon principles of graph theory, with nodes and edges representing specific locations and possible routes within the railway network, respectively. Each node corresponds to a location, while each edge represents a potential route between two locations. Moreover, each edge is associated with specific characteristics of the corresponding route or segment. These characteristics may include factors such as length, incline, or maximum allowable speed for that particular section of track. Based on these characteristics, costs related to the route can be determined, encompassing factors like fuel consumption or maintenance costs.

In the context of the LAP, a train network typically includes depots in addition to nodes and edges. Depots serve the purpose of storing locomotives that can be added to trains as needed. For instance, a depot is typically present at a starting node where a train awaits its schedule and requires locomotives. Depots can also be necessary at nodes preceding steep inclines, where additional power in the form of locomotives is required by the train. As illustrated in Figure 5.1,

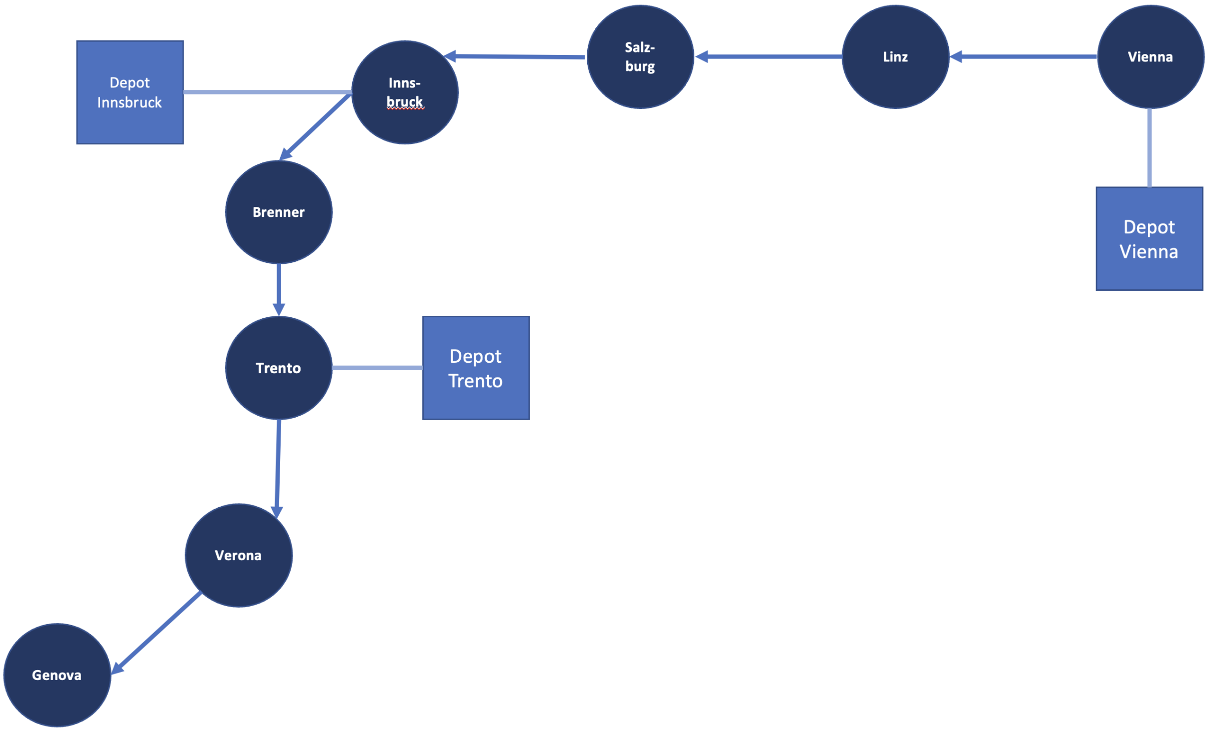

Figure 5.1: A graphical representation of the train route network as a directed graph. The nodes are represented as circles and the depots as squares.

the train network includes a depot in Vienna for the initial assignments and depots in Innsbruck (Austria) and Trento (Italy). The segment between the Innsbruck and Brenner nodes traverses the Austrian Alps, characterized by steep inclines. It is possible that trains may need to load additional locomotives from the Innsbruck depot to successfully navigate this segment. However, in Trento, these additional locomotives can be unloaded since they are no longer needed for the remaining track.

Determining optimal paths within such a network can be accomplished by assessing segment costs and employing graph-based methods to find optimal solutions. Previous to that, algorithms such as linear programming or problem-specific metaheuristics, are used to generate schedules and assignments based on the problem's constraints and objectives.

In this case, the model adopts a two-stage approach. The segments themselves do not directly influence locomotive-train assignments. In the first stage, assignments are generated using the

VNS metaheuristic, which has been discussed in the preceding Section 4.2.1. These assignments aim to minimize costs based on specific train and locomotive data, such as weight, length, number of wagons, required power, and available power. The assignments are calculated to ensure that trains possess sufficient tractive power to overcome inclines at the desired speed until they reach the next depot, where additional locomotives can be added to the train.

This is where the second stage of the model comes into play. In the second stage, the actual "schedule" is computed. For each train, the cost and number of locomotives required for each segment are calculated using the initial assignments as input data. If the calculated required power exceeds the total tractive power of the currently assigned locomotives, additional locomotives are added at the depot. Conversely, if the locomotives are no longer necessary, they can be removed at the next depot.

5.2 Simulating a Real-World Freight Railroad.

To conduct experiments, the theoretical train-route network needs to be mapped onto a real-world railroad route. In this case, the chosen route is from Vienna to Genoa, passing through Austria, Germany, and Italy, as depicted in Figure 5.2. The scheduled trains are intended to commence their journey from Vienna Westbahnhof (the start node) and proceed to their destination, Genoa Pra (the sink node).

This particular route is selected because it represents a significant freight railway corridor that facilitates the transportation of Austrian or Italian manufactured goods to Genoa. Genoa is home to one of the largest cargo ports in Europe, enabling the shipment of goods to various destinations worldwide by sea. Likewise, the track provides efficient and sustainable means of importing goods from around the world, with Genoa serving as the entry point. These goods can then be transported by train to Vienna, where they can be potentially distributed throughout Europe. The train route between the start and sink nodes includes several intermediate nodes, namely Linz, Salzburg, Innsbruck, Brenner, Bolzano, Trento, and Verona. While the train is not obligated to stop at any of these nodes, they are modeled because each node delimits a segment with its own unique characteristics (see Table 5.1). These distinct circumstances in each segment ultimately dictate the number of locomotives required and the operational cost of the train on that segment.

With a total length of approximately 1050 kilometers, this track serves as a representative approximation of a real-life long-distance freight railway. It is well-suited for heavy-haul freight trains with extended lengths. The track's profile consists of several flat segments, some of which are significantly long. Other segments present challenges with relatively steep inclines, a com-

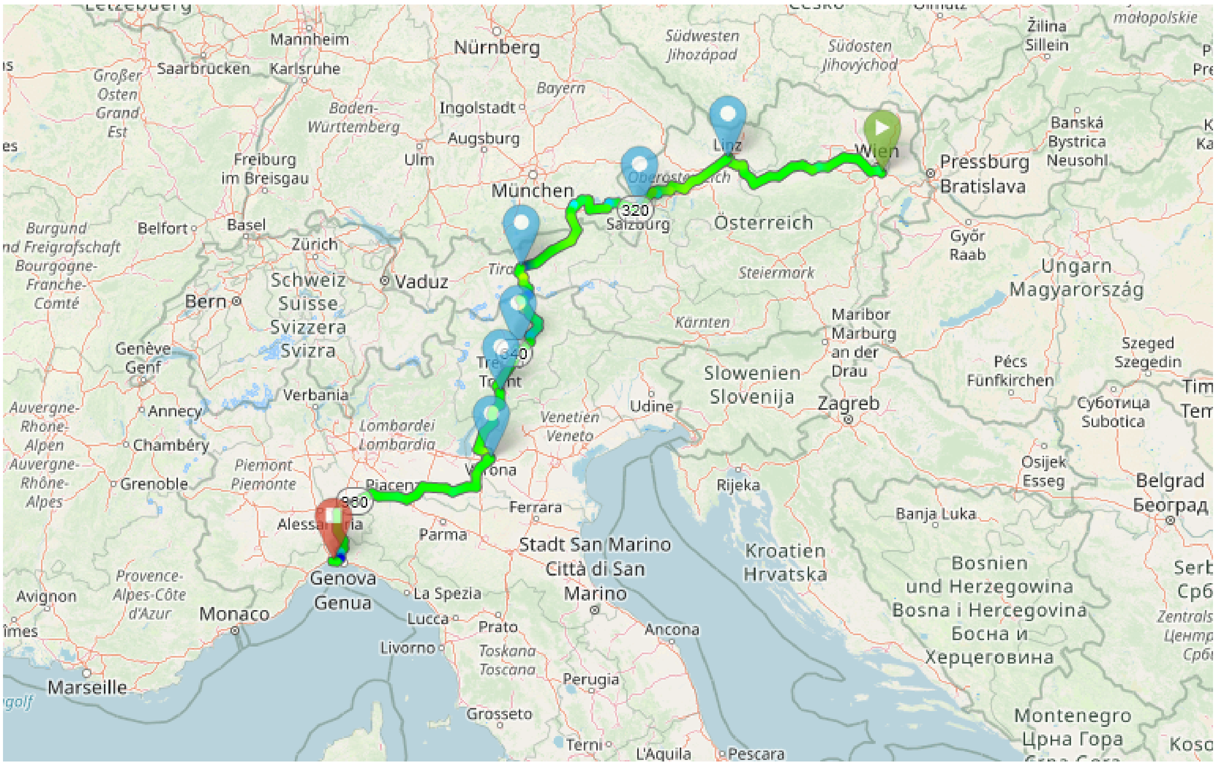

Figure 5.2: Depiction of the actual freight railway route from Vienna to Genova, passing through various major cities along the way. (Source: OpenStreetMap.org/BRouter)

mon occurrence for heavy trains in Europe. Notably, between Innsbruck and Bolzano, the trains must traverse the Austrian and Italian Alps, adding to the complexity of the route. Even tough

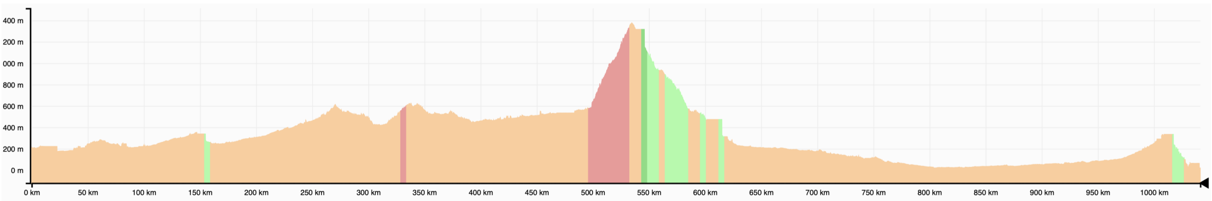

Figure 5.3: Depiction of the track profile from Vienna to Genova, crossing the Alps between Innsbruck and Bolzano. (Source: OpenStreetMap.org/BRouter)

most of this is route is staffed with tunnels the track can reach an inclination of up to 2,4% and decline up to 1,3% (see Figure 5.3 or Table 5.1). Before and after the segments with these steep sections the depots mentioned in Section 5.1 are located. In these inclines some heavy trains require more locomotives to climb the mountain at a reasonable high speed. Conversely when riding downhill, the train requires enough braking power to stop its mass, respectively to hold it at a reasonable low speed. The speed limits depicted in Table 5.1 do not take effect in this model as heavy freight trains typically travel slower and in this model an average speed of 25 m/s (approximately) 90 km/h for all trains on all segments is assumed. The track reaches its highest

Segment	Distance (km)	avg. Slope (%)	max. Speed (km/h)
Vienna - Linz	$182,8$	$0,17$	250
Linz - Salzburg	$125,1$	$0,35$	160
Salzburg - Innsbruck	$193,6$	$0,28$	160
Innsbruck - Brenner	$37,5$	$2,4$	110
Brenner - Bolzano	89	-1, 3	180
Bolzano - Trento	$55,9$	-0, 12	155
Trento - Verona	$91,1$	-0, 14	150
Verona - Genova	273	$-0,02$	300

Table 5.1: The most important characteristics of each segment of the underlying freight track.

point at approximately 1376 meters above sea level, which is at the border between Austria and Italy (Brenner). On the other hand, the lowest point is found in the harbor of Genoa, at around 3 meters above sea level. This diverse route provides a valuable insight into the performance of trains equipped with Distributed Power in such an environment.
To accurately model the track and capture its intricacies, data from reliable sources such as *OpenRailwayMap.org* and *BRouter* is consulted. These sources are based on the comprehensive mapping platform *OpenStreetMap.org*, ensuring detailed and accurate representation of the track's features.

5.3 Simulating Locomotives for the Model.

Austria is home to multiple freight train operators, with the largest being OeBB (Austrian National Railway Company) and its subsidiary Rail Cargo Austria. Other freight train operators in the country include Cargoserv, TXLogistik, and ecco-Rail. Information and data about locomotives can be accessed publicly on the OeBB website, which serves as a reliable source for this model.
For the sake of simplicity, this model utilizes locomotive data obtained from the OeBB website. According to their provided information, approximately 75% of their locomotive fleet is electrified. Diesel locomotives are primarily used as "shifting locomotives", which are employed for moving trains within a station from one track to another. Additionally, diesel engines are used

when operating on rail segments that are not electrified[1]. In this model, a specific set of locomotives will be considered. The selection includes various electric locomotives, with the exception of shifting locomotives. Additionally, a particular type of Diesel locomotive will be included, along with the new and powerful Vectron locomotive type (see Table 5.2). Although the use of Diesel

Loco	**Type**	**Amount (Pcs.)**	**Weight (t)**	**Tractive Force (kN)**	**Driving Force (kW)**
Taurus 1	Electric	50	88	300	6.400
Taurus 2	Electric	282	88	300	6.400
Tfz 1144	Electric	180	90	300	5.000
Vectron	Electric	113	90	340	6.400
Hercules	Diesel	100	80	250	2.000
Sum		725			

Table 5.2: A selection of Locomotive types used in Austria and their main characteristics (Source: OeBB).

locomotives does not align with the sustainability-oriented goals of this model, they have been included to observe their behavior. It should be noted that most Austrian railway operators have minimized the usage of Diesel locomotives. However, their inclusion in this model allows for an examination of their characteristics and behaviour in comparison to electric and DP-locomotives. Generally, diesel locomotives are considered to be less powerful and more costly to operate.

The power, or tractive force, of traction units and vehicles, such as locomotives, is measured in kilo newton and represents the maximum force they can exert when starting from a standstill. The starting tractive force significantly influences a traction unit's ability to initiate the movement of a train. It must be sufficiently dimensioned to overcome the initial resistance forces of the train and accelerate it accordingly (see Figure 5.4). The tractive force finally determines how much power locomotives can supply to a train and thus, depending on the weight of a train, also determines the number of locomotives that have to be assigned to a train.

To incorporate the locomotive data into the model, some modifications are made to the original OeBB data. Firstly, the number of available locomotives in the model is a fraction of the total locomotives owned by OeBB. In this case, only 122 locomotives of the five most common types from a total of 725 locomotives are assumed to be available for this specific job. This accounts

[1]Lokomotiven, ÖBB Produktions GmbH. Link: https://produktion.oebb.at/de/lokomotiven. Accessed as of 10.02.2023

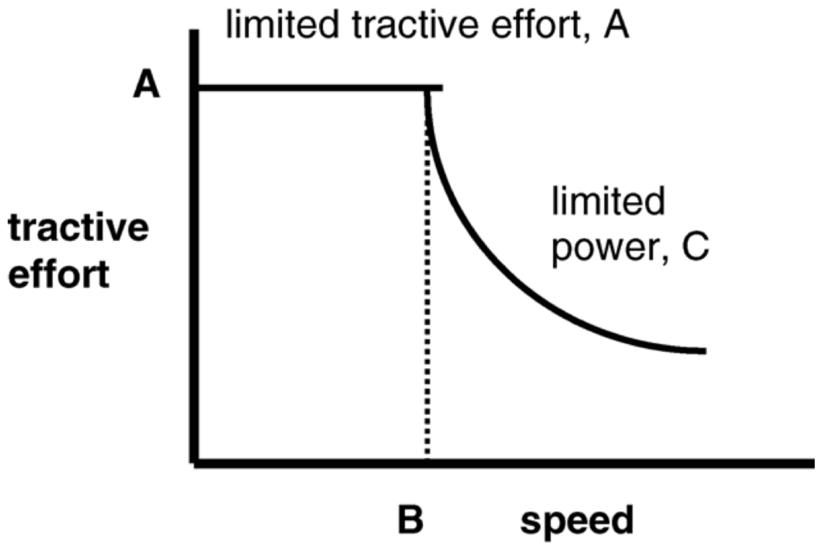

Figure 5.4: This simplified version of a tractive effort curve by Grassie and Elkins (2005), shows the effort required to pull a train at a certain speed.

for approximately 16.8% of all locomotives of these types. The remaining 83.2% are assumed to be utilized in other daily or weekly operations.

Another significant adjustment to the given data is related to the tractive force of the locomotives. As shown in Table 5.2, the tractive force of the locomotives is relatively similar, except for the more powerful Vectron locomotives and the less powerful Hercules Diesel locomotives. In the context of this model, if all locomotives had the same tractive force, assigning different locomotive types and varying numbers of locomotives would have little impact on the solution (assignment). To address this, an assumption is made that due to maintenance, reliability, or safety reasons, the locomotives can only utilize a portion of their total tractive force when powering a train. The available force for the locomotive classes is determined randomly within the range of their maximum force, as indicated in Table 5.3. By assumption, each locomotive type has a range of tractive force available. The range is based around the maximum force they can put out. Further, the DP types that the locomotives can take on are shown in Table 5.3. DP1 represents locomotives that are able to drive in DP mode. DP2 depicts locomotives unable to drive in a DP constellation. DP is only available to the electric units, although not all of them have the DP technology built-in. This assumption is made to facilitate a meaningful comparison between trains that utilize Distributed Power and those that do not. All Vectron locomotives are DP enabled. It is important to note that the Diesel locomotives, typically older, less used, and weaker Hercules locomotives are not able to be used in DP mode. The table also shows the actual number of locomotives used in the model.

However, since the weekly scheduled trains vary in terms of weight and length, the full impact of

Loco	**Amount (Pcs.)**	**avail. Tractive Force (kN)**	**DP Type**
Taurus 1	24	190 - 290	1 & 2
Taurus 2	40	190 - 300	1 & 2
Tfz 1144	26	190 - 300	1 & 2
Vectron	16	280 - 340	1
Hercules	16	190 - 250	2
Sum	122	30300	

Table 5.3: Characteristics and number of actual locomotives used in this model.

DP on them cannot be accurately measured. The assignments themselves cannot be influenced as they are solely determined by the VNS algorithm. To address this limitation and enhance the comparability of different modes, three distinct data sets are generated for input into the algorithm. These data sets differ in the composition of DP and non-DP units, allowing for a more comprehensive analysis and evaluation. Table 5.4 illustrates that two of the data sets are biased

Data Set	**Amount DP units**	**Amount non-DP units**	**Power Distribution**
60_DP1-40_DP2	73	49	DP1: 59,2% DP2: 40,8%
50_DP1-50_DP2	61	61	DP1: 49,4% DP2: 50,6%
40_DP1-60_DP2	49	73	DP1: 39,5% DP2: 60,5%

Table 5.4: Data sets of varying DP proportions used to test the VNS model.

towards a particular type of DP mode, while one data set is approximately evenly balanced. The three different data sets have a different distribution of DP and non-DP units. When splitting the locomotives into different portions (e.g. 40-60, 50-50, and 60-40), it was ensured, that the distribution of power force (column Power Distribution) also approximately follows this split, to keep the data balanced and comparable. This variation allows an observation of how the VNS algorithm performs under different circumstances or environments. Depending on the specific weekly schedule, there may be instances where more or fewer DP units are available. The crucial question is whether the VNS algorithm shows a preference for the supposedly more efficient DP mode or if it tends to favor the mode that dominates in the given dataset.

5.4 Simulating Trains for the Model.

The locomotives discussed in Section 5.3 are responsible for pulling the trains they are assigned to. To effectively model these trains, it is essential to collect information regarding their length, the types and quantities of wagons, and their overall weight. This data plays a critical role in calculating operational costs and, more importantly, determining the required power for locomotion. Unfortunately, specific details about individual trains or wagon configurations are typically not publicly available or published by railway operators. Similarly, there is a scarcity of accessible data concerning the precise characteristics and schedules of freight trains operating in Europe.

Consequently, it is necessary to model a freight train and simulate them as realistically as possible, while respecting the European context. To do so, again online data is consulted. The freight subsidiary of the OeBB has developed new modular freight cars called “TransANT” aimed at boosting productivity and efficiency. According to their own statement[2] these wagons are especially lightweight, allowing up to four additional tons of freight being hauled, by reducing the cars weight by about 20% compared to other wagon types. These wagons are well-suited for modeling freight trains in a sustainability-oriented approach. Additionally, they offer several other advantages, including their flexibility in train assembly and during the journey. The

Wagon	**Weight (tons)**	**Cargo Load (tons)**	**Volume (m^3)**
Flat BOX	22,2	67,8	109
Cover BOX	23,6	66,4	123
Multi BOX	20	70	79
Bulk BOX	19	71	40

Table 5.5: Characteristics of wagon types used to model trains. (Source: TransANT, 2020).

[2] Rail Cargo Group, TransANT Product Advantages. Link: https://www.railcargo.com/en/services/wagonload/equipment/freight-wagon/transant/advantages, accessed as of 17.02.2023

TransANT project developed four different variants of freight wagons, representing the four most popular types used worldwide, excluding tank cars typically carrying liquid or gaseous materials in bulk. Tank cars are often used in block-trains or whole-trains, where only the same type of rail car is employed due to safety concerns regarding hazardous materials. Hence, this freight train model is focused on the four wagon types presented in Table 5.5. In TransANT (2020), the main attributes of these wagons are presented. The Flat Box type wagon is used for example to transport long logs of wood or blocks of steel. A Cover Box type is used when shipping for example general goods that have to be protected from weather. A Multi Box is similar, however open at the top. It is easier to load, but goods are less protected. The Bulk Box is as the name says used for bulk goods such as coals or raw iron.

The length of the wagons, or their platforms, can vary between approximately 10 meters and 23 meters (33 feet to 70 feet). For simplicity, a standard length of 23 meters is assumed for all wagons.

To determine the power required to pull a train in the model, the total weight of the train must be calculated:

$$f_{w_i}(n_{car}, n_{loco}) = n_{loco} \cdot 88 + n_{car} \cdot 0.8 \cdot (w_{flat} + w_{cover} + w_{multi} + w_{bulk}) \,. \tag{5.1}$$

Here, w_i is the weight of train i and n_{car} is the number of wagon types on the train and n_{loco} is the number of locomotives assigned to the train. In the last term of Equation (5.1), the total maximum weight (cargo weight and own weight) of every wagon type is summed up. It is assumed, that the train is loaded up to 80% of its maximum payload capacity, hence the factorisation by 0.8. Additionally it is assumed, that the wagon types are evenly distributed over the scheduled freight train. Hence, the amount of each wagon type (n_{car}) in the train is required and is then multiplied by the number of rail car types (four). When adding this to the weight of the locomotives (where the average locomotives weighs 88 tons), the total train weight can be assessed.

To provide clarity an example of the weight calculation process shall be presented. Assume a train has 19 cars of mixed type and is approximately 500 meters long (including locomotives). The experienced operator is aware, that such a heavy-haul train requires 5 locomotives that have to carry their own weight[3]. To begin with, the number of wagons of each type has to be assessed. There are 19 wagons in total and there are 4 different types of wagon. Hence the number of cars

[3]Note that this is only a starting assumption for the algorithm. When the heuristic assigns locomotives to the train it again calculates weight and required power of a train. Thus the number of locomotives required per train is subject to change.

per type is

$$\frac{19}{4} \approx 5.$$

Now, that the number of wagons per type and the number of locomotives is known, this can be put into Equation (5.1).

$$f_{w_i}(5, 5) = 5 \cdot 88 + 5 \cdot 0.8 \cdot (89 + 89 + 90 + 90) \approx 1872.$$

The total weight of a 500 meters long trains with 19 cars and 5 locomotives weighs approximately 1872 tons. Now to calculate the power required to pull such a train from a standstill, respectively to calculate its resistive force, the trains weight has to be employed in another function:

$$f_{rR_i}(w_i, \delta_q) = w_i \cdot (0.5 + 9.81 * \sin \delta_q). \tag{5.2}$$

Again, w_i is the weight of the particular train and δ is the average grade incline of the respective segment q. It is assumed, that the train accelerates $0.5m/s^2$. The gravitational force ($g = 9.81$), also has an impact on the resistive force of the train. To continue the example from before, the resisitve force of a 1872 ton train is calculated as the following:

$$f_{R_i}(1872, 0.001295) = 1872 \cdot (0.5 + 9.81 \cdot \sin 0.001295) \approx 960.$$

Thus, a train of 1872 tons requires approximately 960 kN of pulling force, when the average incline is 0.1295% and it accelerates at a rate of 0.5 m/s^2 on average. A similar calculation is carried out for all fifteen trains in Table 5.6 of varying length between 400 and 800 meters. In total, a resistive force of $17,295$ kN has to be pulled by the available locomotives. The approximate length of the trains resembles the average freight train length in Europe.

5.5 Determining a Suitable Distributed Power Factor.

Although the positive effects of Distributed Power are widely recognized, its usage in Europe is limited. In North America, Distributed Power is a fundamental component of freight trains, since they can reach lengths of up to 4300 meters. Nonetheless, the impact of Distributed Power should not be neglected in Europe (where trains are considerably shorter), and the possibility of fuel or general cost savings should be researched. The length of a train is not the only factor that would justify the use of DP. The technique could also prove itself advantageous in mountainous regions in Europe where the rail tracks are curvy and twisted, enabling longer, faster and safer trains, while costs improve.

In general, public research, literature or data on Distributed Power is limited. There is some research that concerns itself with Distributed Power and how to operate with it or which effects

ID	Power required	Wagons	Length
"Train 1"	768	15	390
"Train 2"	960	19	494
"Train 3"	1152	23	598
"Train 4"	1230	26	676
"Train 5"	1490	30	780
"Train 6"	770	16	416
"Train 7"	1115	23	598
"Train 8"	1216	26	676
"Train 9"	813	18	468
"Train 10"	1351	29	754
"Train 11"	1281	25	650
"Train 12"	1505	30	780
"Train 13"	1552	31	806
"Train 14"	1310	27	702
"Train 15"	782	17	442

Table 5.6: All 15 modeled trains to be scheduled in this model and their main characteristics.

in general it has (see Section 1.2). However, this is usually not in the European context (but in countries that typically employ longer, heavier trains as the USA, Canada, Russia, India, or China). When consulting Austrian Railway Operators (in this case Rail Cargo) about Distributed Power, they argued that DP concepts have few applications in Europe (see Appendix B). They generally only know DP from countries with longer trains. In Europe trains have a length of around only 700 to 740 meters. The main reasons for the shorter train lengths are:

- The infrastructure is not designed for increased train lengths.

- The wagon couplings are not designed withstand forces of larger trains.

To summarize, the lack of information on Distributed Power (DP) in Europe can be attributed to several factors. One reason is that the total train length is limited due to network characteristics, and longer trains would become excessively heavy. However, it can be argued that DP is not exclusively beneficial for long trains. There is a possibility that relevant research would demonstrate cost savings for shorter but heavy or fast trains that employ DP, or that DP is advantageous when trains encounter steep inclines or declines.

Another reason for the limited popularity of DP can be discussed in terms of its impact on in-train forces, such as coupler forces. Trains with a length of 2000 meters and more experience extreme forces in the couplings, since the locomotives and wagons at the front pull the whole weight of the attached train. When DP is envisioned as composing five 700-meter trains, with each train having its own locomotives, the total train length would be 3,500 meters. In such a scenario, the coupler forces could be managed since a new train with its locomotives begins after every 700 meters, deacreasing the in-train forces. These considerations aligns with the conclusions of studies conducted by Cantone et al. (2021) and Cantone and Toubol (2019)).

Unfortunately, there is a scarcity of publicly available sources that provide quantitative data on the actual effects of DP on resistance. However, the work of Roney (referenced as Roney et al. (2010)) offers a comprehensive investigation and measurement of the impact of distributed power on train speeds and lateral forces. Roney's study examines longer and heavier trains than those used in this model, involving steel and aluminum cars with significant train lengths and weights. His findings indicate a substantial reduction in the frequency of high lateral/vertical forces (L/V) for a specific locomotive assignment configuration (2-1-1). A 2-1-1 constellation indicates, that there are two locomotives at the front of the train, one locomotive at the mid of the train and one locomotive at the back of the train. The L/V forces are the most detrimental to track structure degradation and are responsible for the highest train resistance on the track. Roney also observes a reduction of 9% in average low rail lateral forces for aluminum cars and 17% for steel cars in the 2-1-1 model, compared to the standard 2-0-1 model. DP has particularly positive effects on curves in rail tracks, as reported by Roney.

Given the lack of alternatives for determining the DP factor in this model, we rely on the factor determined by Roney. To maximize the benefits of DP, considering the use of steel cars (albeit lighter ones), a DP factor of 17% will be employed. Therefore, it can be stated that

$$\theta = 0.17.$$

Where θ is the DP factor that has a diminishing effect on the resistance as presented in 3.3. It has to be noted that θ can not be deducted from the total R_{iq} as in Equation (3.7) constituted. R_{iq} has to be seen as in Equation (3.3) and θ is to be deducted from the Davis parameter A, since this parameter corresponds to the rolling friction on the track independent on the speed of the train. Furthermore it is clear that when a train operates in DP mode it is always assumed that it operates in the beneficial 2-1-1 constellation. If more than four locomotives are assigned it operates in a 3-1-1 constellation, 3-2-1 constellation or 3-2-2 constellation and so forth going.

Chapter 6

Results from the Two-Stage Heuristic Solving the Underlying Locomotive Assignment Problem.

The model described and proposed in Chapter 3 and implemented in Chapter 4 is tested, and its behavior is observed using the data presented in Chapter 5. This chapter focuses on discussing the solution to the underlying problem and presenting different types of solution structures. Finally, the results of the algorithm are presented, its general behavior is observed, and the computational effort involved is assessed.

6.1 Solution Structures Generated by the Heuristic.

The model is able to produce different types of solutions with varying degree of detail. Each solution structure has its own scope of application. The smallest but most detailed solution is on the single train level. A detailed breakdown of the train-level solution is presented in Table 6.1. This solution showcases the assignment for Train 2, which necessitates a power of 950 kN to be hauled. The four Tfz 1144 locomotives provide a total power of 990 kN, indicating a reasonably good solution. However, a more optimal solution could have been achieved by utilizing less total power. It is worth noting that this would not affect the objective value. Nevertheless, it is considered favorable when the assigned power closely matches the required power. Since the assigned locomotives are capable of operating in DP mode (DP 1), the train operates in DP mode. The cost associated with each assignment can be computed using the objective function outlined in Equation (3.7). This detailed solution allows for verification of whether the algorithm complies with the constraints imposed by the MIP Model. These constraints include:

Train 2	950 kN required		
Locomotive	**ID**	**Power**	**DP Mode**
Tfz 1144	1144-2	250 kN	DP1
Tfz 1144	1144-5	230 kN	DP1
Tfz 1144	1144-6	270 kN	DP1
Tfz 1144	1144-3	240 kN	DP1
Cost	**405**		

Table 6.1: A simulated solution for the scheduled Train 2. This type of solution - on the single train level - is the most detailed.

only incorporating locomotives of the same type (e.g., Tfz 1144) within the same train train, with either all DP1 type locomotives (DP enabled) or all DP2 locomotives (conventional units), ensuring that each locomotive is assigned only once by verifying the uniqueness of their ID in the schedule, guaranteeing that the power supplied by the locomotives is greater than or equal to the power required by the train, and ensuring that a train operating in DP mode has at least four locomotives assigned. Upon inspection of the solution presented in Table 6.1, it is evident that all constraints are satisfied.

In a less detailed solution structure, the assignments for all trains of a schedule can be seen (see Table 6.2). This second-level solution structure provides an overview of each scheduled train,

Train	kN requried	Locomotive	DP Type	Num. Locos	Cost
Train 1	768	Taurus 2	1	4	391
Train 2	960	Tfz 1144	2	4	477
Train 3	1152	Vectron	1	4	519
Train 4	1230	Tfz 1144	1	5	609
Train 5	1490	Hercules	2	7	749

Table 6.2: A a less detailed solution for five trains in a weekly schedule.

including information such as train type, locomotive type, DP type, required power, and cost, as seen in the more detailed solution structure. However, in this structure, only the number of assigned locomotives is displayed, without specifying the exact locomotives assigned. It is not possible to verify whether the algorithm adhered to all constraints based on this structure alone. By examining this solution, it can be observed that three trains operate in DP mode, while the remaining two do not. One train in the solution is assigned Diesel-powered locomotives (Hercules). The total number of locomotives employed in this solution is 24. The heavier or larger trains require up to 7 locomotives, and the DP-equipped trains are assumed to operate in a 3-1-1 or 2-1-1 configuration. The resulting schedule yields a total cost of 2.745. The final schedule solution structure resembles the second solution structure presented in Table 6.2. It provides the assignments for each train across the entire train network from Vienna to Genova. One notable aspect revealed by this solution structure is the utilization of depots in Innsbruck and Trento. As indicated in Table 6.3, the first three trains from Vienna to Innsbruck require four locomotives each, while the remaining two trains require six locomotives. Upon reaching Innsbruck, each train loads an additional locomotive to traverse the Alps between Innsbruck and Trento. Although not shown in this excerpt, in Trento, each train uncouples one locomotive, resulting in the same train-locomotive assignments as before crossing the Alps. Two important points should be noted: To begin with, it is unknown which specific locomotive is decoupled in Trento, whether it is the one that was connected in Innsbruck or another locomotive. Further, there is no predetermined requirement for the same number of locomotives to be assigned to a train after crossing the Alps as before.

6.2 Operational Results for the DP-LAP Model.

In order to analyze the algorithm's behavior and gather insights regarding DP usage, locomotive assignments, and costs, multiple solutions similar to the one presented in Table 6.3 were generated. For each data set type, a total of fifteen weekly schedules were compiled to assess the overall variability of the model and examine the behavior of different DP mode constellations. The results were then aggregated and evaluated in the subsequent sections.

6.2.1 60% DP1 - 40% DP2 Data Results.

Considering the first data set presented in Table 5.4, we evaluate the most favorable scenario among the three. In this scenario, the assumption is made that only a mix of locomotive modes is available, rather than having an ideal abundance of DP-enabled locomotives. To analyze the behavior and potential variations in the results, the algorithm proposed in Chapter 4 was executed 15 times using the 60% DP1 and 40% DP2 data set as input. This allows us to observe

Train	kW req.	Loco	DP Typ	Num. Locos	Cost
Vienna to Linz					
Train 1	768	Tfz2	2	4	598
Train 2	960	Tfz2	1	4	665
Train 3	1152	Vectron	1	4	758
Train 4	1230	Taurus 2	1	6	934
Train 5	1490	Taurus 2	2	6	1077
Linz to Salzburg					
Train 1	768	Tfz2	2	4	409
...	...	...	...	...	...
Salzburg to Innsbruck					
Train 1	761	Tfz2	2	4	633
Train 2	906	Tfz2	1	4	704
Train 3	1052	Vectron	1	4	803
Train 4	1141	Taurus 2	1	6	989
Train 5	1432	Taurus 2	2	6	1140
Innsbruck to Brenner					
Train 1	1057	Tfz2	2	5	133
Train 2	1260	Tfz2	1	5	146
Train 3	1462	Vectron	1	5	166
Train 4	1586	Taurus 2	1	7	202
Train 5	1991	Taurus 2	2	7	231

Table 6.3: This solution type of structure incorporates the total schedule. In this excerpt the legs from Bolzano to Genova and a part of the assignment from Linz to Salzburg are omitted.

the overall behavior of multiple schedules and assess any differences in the generated solutions. Table 6.4 presents a summary of the results obtained with the 60/40 data set (detailed results for

KPI	Total Cost	Locos Used	DP1	DP2	Power DP1	Power DP2	Cost DP1	Cost DP2	Num Iterations	Best Iteration
Mean	131675	73	9	6	75031	55743	40503	91172	288	53
Min	95684	69	8	6	64444	46891	35207	53858	253	2
Max	151539	77	10	7	83114	65711	44207	112210	308	265
		Sum	131	94					**Median**	9
									Mode	4

Table 6.4: Aggregated results for 15 schedules. 15 trains had to be assigned with 122 locomotives available in total. Locomotive data split: 60% DP-locomotives, 40% conventional.

schedules of all data sets are available in Appendix A). Various metrics, including costs, number of locomotives, and power usage, are analyzed using statistical measures. The average cost of a weekly schedule with 15 trains is shown to be $131,675$. Among the 15 schedules, the best solution achieved a minimum cost of $95,684$, utilizing a total of 69 locomotives. Within this solution, 9 trains operated in DP mode, while 6 trains operated conventionally. One notable aspect of the best solution is the distribution and proportion of locomotives used (a summary of locomotive distribution for all 15 schedules can be found in Table 6.5). In comparison to other inferior solutions, this solution demonstrates a relatively even distribution of locomotive types, with a smaller occurrence of the Hercules type. Another observation from Table 6.4 is that, with the dominance of DP-locomotives in the data set, DP-equipped trains continue to dominate the results. Across all 15 schedules, there are more DP trains than non-DP trains, with an average schedule consisting of 9 DP trains and 6 conventional trains. A similar (60/40) proportion is observed in the power supplied by locomotives of the respective modes and the associated costs of the trains. Regarding the performance of the VNS metaheuristic, it completed a total of 288

KPI	Taurus 1	Taurus 2	Tfz-1144	Hercules	Vectron
Mean	15	22	16	11	10
Min	11	15	13	4	6
Max	19	30	22	14	12
Total	222	328	242	162	143

Table 6.5: Distribution of locomotives in the assignments generated with the 60/40 data.

iterations within its 60-second run-time. Each iteration concludes when all shaking operations have been executed (refer to Algorithm 2). The range between the minimum and maximum number of total iterations indicates a relatively small variation. The "Best Iteration" column signifies the iteration in which the best solution value was found. Based on the median best iteration, it can be inferred that the best solutions are typically discovered early in the process, although there are a few outliers. For instance, in these 15 schedules, the best schedule was found during the fourth iteration out of a total of 308 iterations.

As mentioned earlier, Table 6.5 presents the distribution of locomotives used in the 15 schedules. The average and total distribution aligns with the data distribution. In the data sets, the locomotive type Taurus 2 is the most frequently employed, with 40 locomotives. This pattern is also reflected in the generated schedules, where Taurus 2 is used on average 22 times. The second most commonly used locomotive is Tfz 1144, which is also the second most prominent locomotive type in the solutions. Although Hercules and Vectron locomotives have equal representation in the data set, the less efficient Hercules is favored in the 60/40 solutions. This behavior is generally undesirable, and it warrants an assessment of whether the model should be revisited and updated in this regard.

6.2.2 50% DP1 - 50% DP2 Data Results.

This section examines whether the algorithm favors potentially more efficient DP-enabled locomotives or trains, and whether the overall solution quality improves when the ratio of DP and non-DP locomotives is balanced in the data set.

Based on the aggregated data in Table 6.6, it can be inferred that the balanced data set does not yield cheaper schedules compared to the 60/40 data set in the 15 generated schedules. The best solution in terms of cost has a total cost of $101,356$ and utilizes 70 locomotives. Among the fifteen trains in this solution, eight operate in DP mode and seven in conventional mode. Similar to the best solution in the 60/40 data set, the best solution in the 50/50 data set minimizes the use of the Hercules type locomotives. However, the distribution of other locomotives in this solution is not as even as the distribution observed in the best solution of the 60/40 data set. Since the 50/50 dataset contains an equal share of DP and non-DP locomotives, the proportion of trains operating with DP-enabled locomotives is also nearly equal in the generated schedules. Although the average solution tends to use more DP trains, there are a total of 113 trains with DP and 112 with conventional locomotives. Among the 15 schedules, 8 schedules favor DP-enabled trains, while 7 schedules favor conventional trains (see Appendix A). The power distribution between DP and non-DP units is also fairly balanced on average. However, compared to the 60/40 data

KPI	Total Cost	Locos Used	DP1	DP2	Power DP1	Power DP2	Cost DP1	Cost DP2	Num. Iterations	Best Iteration
Mean	127894	73	8	7	64528	65932	34674	93220	292	58
Min	101356	70	6	6	46936	54131	25948	62109	252	2
Max	144584	77	9	9	75564	82940	40615	111276	311	201
		Sum	113	112					**Median**	19
									Mode	3

Table 6.6: Aggregated results of 15 schedules generated with the 50% DP and 50% non-DP data.

set results, there is a stronger discrepancy in costs between the two train modes. This indicates that allowing the model to choose fewer (cheaper) DP locomotives and trains, and opting for more conventional units, has a negative impact on the cost of a schedule. Regarding the algorithmic behavior, the results are consistent with the previous findings. The total number of iterations performed ranges between 250 and 300. However, the best solution is typically found in earlier iterations. On average (median), it takes 19 iterations to discover the best solution. The most frequently occurring (mode) best iteration is the third iteration.

KPI	Taurus 1	Taurus 2	Tfz-1144	Hercules	Vectron
Mean	14	25	15	10	8
Min	9	21	9	5	5
Max	19	29	19	13	13
Total	213	382	220	147	126

Table 6.7: Distribution of locomotive type usage in the assignments for the 50/50 data set.

Regarding the distribution of locomotives used (see Table 6.7), a similar pattern emerges as observed in the 60/40 data set results. The Taurus 2 locomotive type is even more prevalent than before, and once again, the less efficient Hercules locomotive is favored over the Vectron locomotive type.

6.2.3 40% DP1 - 60% DP2 Data Results.

It is generally assumed that having fewer locomotives equipped with Distributed Power (DP) is undesirable. To examine this assumption and determine if the model can still find satisfactory or optimal solutions under such circumstances, an evaluation is conducted using a data set where 60% of the available locomotives are unable to utilize the DP technique. Table 6.8 provides a summary of all 15 generated schedules for this data set. Interestingly, the model is able to

Solution	Total Cost	Locos Used	DP1	DP2	Power DP1	Power DP2	Cost DP1	Cost DP2	Num Iterations	Best Iteration
Mean	132835	73	6	9	55077	75642	29331	103504	284	78
Min	100675	69	5	8	47152	66498	25121	66878	246	2
Max	155385	78	7	10	66092	86273	34299	129349	297	272
		Sum	95	130					**Median**	43
									Mode	-

Table 6.8: Aggregated results for the data set with a 40/60 split of DP modes.

achieve better solutions using the 40/60 data set compared to using the 50/50 data set. The best schedule obtained has a total cost of 100,675, utilizing 7 DP-enabled trains and 8 conventional trains. It can be inferred that the efficient solutions prioritize maximizing the utilization of DP trains. Similar to the best solutions in other data sets, the distribution of locomotive types is generally even, with the exception of the extensive usage of the Hercules type. Among the 15 generated solutions, none of them incorporated more DP trains than conventional trains. The most extreme schedule only employed 5 DP trains out of 15.

On average, the solutions in this data set employed 6 DP trains and 9 conventional trains, which is the exact opposite of the average solution generated with the 60/40 data set. Notably, the average cost of these solutions is the highest among all the data sets. This confirms the assumption that a situation where the majority of trains lack DP equipment is indeed undesirable to a certain extent. This is also evident in the cost distribution between DP and non-DP trains. The

Solution	Taurus 1	Taurus 2	Tfz2	Hercules	Vectron
Mean	15	22	16	11	9
Min	13	15	13	5	5
Max	20	27	23	15	13
Sum	225	330	237	163	142

Table 6.9: Distribution of locomotive types the model generated when fed with the 40/60 locomotive data.

extensive usage of conventional trains and locomotives significantly drives up the costs compared to solutions derived from other data sets.

While there is no significant difference in the total number of iterations performed by the algo-

rithm using the 40/60 data set, it is noteworthy that more iterations are required to find the best solution. Both the median and average best iterations are considerably higher compared to when the algorithm was fed with the 60/40 or 50/50 data sets. It appears that the algorithm encounters challenges in finding favorable solutions when the data situation is unfavorable.
The distribution of used locomotive types in the schedules generated using the 40/60 data set (refer to Table 6.9) closely resembles the distribution observed in other data sets. However, the presence of Hercules locomotives is slightly more prominent in these results.

6.2.4 100% DP1 & 100% DP2 Data Results.

To contextualize these results and evaluate whether the solution quality improves significantly when there is no mixture of locomotive modes in the input data, the model was tested using a data set consisting exclusively of DP-enabled locomotives. To compare these results an exactly opposite data set containing only conventional units is created and evaluated.
In Table 6.10, a summary of the results generated with the data set containing only DP-enabled locomotives is presented. Interestingly, the best solution among the 15 generated schedules is worse than any of the solutions generated with the mixed data sets. This particular solution requires a total of 71 locomotives. The maximum number of locomotives used in any solution is 79, which is the highest for all solutions generated so far. Additionally, this solution is also the most expensive among all generated solutions, involving 13 Hercules locomotives. Despite the variation in solution quality, the exclusive use of the 100% DP1 data set had no significant impact on the computational effort of the algorithm, as results on the average and best iterations are similar to those observed before. Table 6.11 presents the results obtained from the data set

KPI	Total Cost	Locos Used	Num. Iterations	Best Iteration
Mean	126345	74	281	27
Min	101428	69	247	2
Max	139860	79	297	236
			Median	5
			Mode	3

Table 6.10: The most important metrics of the results of the model when the initial locomotive data is composed of only DP-enabled units.

consisting exclusively of conventional (non-DP) locomotives. As expected, the solution quality decreases compared to the 100% DP1 data set and all other data sets. In general, the model is

KPI	**Total Cost**	**Locos Used**	**Num. Iterations**	**Best Iteration**
Mean	129306	73	280	45
Min	103952	69	251	3
Max	150774	76	294	273
Sum			**Median**	8
			Mode	3

Table 6.11: Aggregated results for 15 schedules, where the in initial data were only non-DP locomotives.

able to find good solutions using only 69 or 70 locomotives. However, since the cost calculation in the objective function does not take into account the Distributed Power factor, the total costs remain consistently high. It is worth noting that there are no significant changes in terms of computational effort required when using this type of data.

6.2.5 Analyzing the Models' Sensitivity.

To evaluate the model's performance in handling changes in the data structure, specifically an increased number of trains and available locomotives, tests were conducted. The train data was expanded to include an additional 15 trains of similar length and power requirements, resulting in a total of 30 trains. To accommodate this increased train load, the locomotive data was doubled, providing a total of 228 available locomotives. Among these, 114 locomotives were DP-enabled, while the remaining 114 were conventional locomotives, maintaining a balanced 50/50 split.
The aggregated results of the 15 generated schedules using this expanded data set can be found in Table 6.12. Comparing the results for scheduling 15 trains using the 50/50 data in Table 6.6 to the results obtained with an increased train and locomotive data, there are no significant differences in overall solution quality. The average total cost for 15 trains is $127,894$. Doubling this cost for twice the number of scheduled trains results in an approximate cost of $255,788$, which is relatively close to the average cost for a schedule with 30 trains. Similarly, the number of locomotives used roughly doubles for each schedule, indicating that the increased train size does not significantly impact the results.

KPI	Total Cost	Locos Used	DP1	DP2	Power DP1	Power DP2	Cost DP1	Cost DP2	Num. Iterations	Best Iteration
Mean	253076	144	15	15	132670	128032	71466	181610	164	33
Min	216912	139	13	13	108928	108264	58152	146101	107	2
Max	295387	151	17	17	151776	150288	81649	237235	256	112
		Sum	230	220					**Median**	10
									Mode	3

Table 6.12: The aggregated results the model generated when the feature size was increased. Data: 30 trains, 228 locomotives. The locomotive data is in a 50/50 split.

However, the increased train and locomotive data size does have a negative effect on the computational effort required by the algorithm. The average number of iterations performed with this larger data set is only 164, compared to 292 for 15 trains and 122 locomotives. In 60 seconds, the heuristic is only able to perform half the number of iterations when the data size is doubled. Thus, to achieve the same 300 iterations as before, it would require approximately 120 seconds. When examining the iterations that find the best solution, it can be observed that the increased computational effort does not affect the result significantly, as the best solutions are still usually found in early iterations.

To further investigate the model's behavior under different circumstances, tests were conducted by fixing the number of trains to be scheduled while increasing the number of available locomotives. The results in Table 6.13 were generated using input data with the initial 15 trains and double the number of locomotives (228 in total), with a 50% split between DP-mode and non-DP-mode locomotives. The total number of iterations performed is similar to that of the original data, averaging around 280 iterations, and the best solutions are typically obtained in early iterations. Therefore, it can be concluded that increasing the locomotive data size while maintaining the train data size does not significantly affect the computational effort required to produce solutions. An important observation from these results is that increasing the size of the

KPI	Total Cost	Locos Used	DP1	DP2	Power DP1	Power DP2	Cost DP1	Cost DP2	Num Iterations	Best Iteration
Mean	117914	74	7	8	61267	69599	32791	85123	278	26
Min	102461	72	6	7	50829	56362	26972	62615	265	1
Max	144543	76	9	9	74677	79456	40411	108512	290	150
		Sum	106	119					**Median**	4
									Mode	1

Table 6.13: The aggregated results for the analysis of increasing the locomotive size to 228, but holding the trains size fixed at 15.

locomotive data improves the average solution quality. Although this data does not yield the best overall solution, the generated schedules tend to have lower costs in general. However, it is noteworthy that in these results, the model consistently favored non-DP units, with only 2 out of 15 schedules utilizing more DP units than conventional trains. This bias towards non-DP units may lead to inefficiencies and warrants further investigation and revision, as it likely contributes to the absence of an overall best solution.

Chapter 7

Concluding Statement.

This section presents the concluding remarks on the key aspects discussed in this thesis. It summarizes the findings regarding the overall utilization of Distributed Power and its feasibility in the DP-LAP model. Additionally, an evaluation is conducted to determine the effectiveness of the VNS metaheuristic in solving the optimization problem. Finally, general insights on the capabilities of this model in simulating trains, locomotives, and track conditions as well as the resulting most efficient schedule are provided.

7.1 Findings on Distributed Power.

Distributed Power (DP) is commonly utilized in long heavy-haul freight trains, particularly in challenging mountainous railway sections with steep gradients and curves. This technique synchronizes the efforts of locomotives, providing several advantages over conventional trains, as discussed in Section 1.2. These benefits include increased speed, enhanced safety, reliability, and efficiency, as confirmed by numerous sources and research papers (see Section 1.2 and Section 2.2). However, despite the existing literature on DP, there are two crucial areas where there is a lack of information regarding this thesis.

Firstly, in modeling and simulating trains, the available data from online resources and academic research papers were insufficient to accurately represent the detailed impact of DP on trains. While some sources confirm the positive effects of DP, a comprehensive quantitative analysis of different train configurations on various track conditions is not readily accessible. To achieve more precise results, further experiments focusing on resistance and behavior of different train configurations, especially in hilly and curvy sections, need to be conducted.

Secondly, the utilization of Distributed Power (DP) in Europe remains largely unexplored, with minimal available information and publications on this technique. Unlike countries such as the

USA, Canada, Russia, India, or China, where DP in trains is well-documented, there is a scarcity of data specifically related to DP usage in European trains. While DP is commonly employed in high-speed passenger trains to enable faster travel, it is often argued that the benefits of DP cannot be fully realized in freight trains in Europe due to their shorter lengths and infrastructure limitations.

In Europe, it is frequently mentioned that freight trains are not long enough to fully leverage the advantages of DP, and the existing infrastructure does not support the operation of extended train lengths. Although the Austrian Federal Railways' (OeBB) freight subsidiary, Rail Cargo, acknowledges the concept of DP, referred to as "double heading and tandem operation", they do not disclose specific details regarding its implementation or the benefits they derive from it[1].

The Distributed Power usage in Europe remains relatively limited, with a lack of available information on its application in trains. While DP is commonly associated with high-speed passenger trains, its feasibility and benefits for freight trains in Europe are often questioned due to train length limitations and infrastructure constraints. Although Rail Cargo acknowledges DP, they do not publicly share comprehensive information about its deployment or the advantages it offers for them.

In conclusion, DP presents a promising technique for improving the safety, reliability, speed, and efficiency of trains, benefiting the logistics sector. The implementation of DP at a (freight) railway company can be achieved with minimal capital expenditure. However, to effectively implement DP in practice, more comprehensive information, data generation, and exploration are required, particularly within the European context.

7.2 Findings on the VNS Heuristic to Solve the LAP.

The Locomotive Assignment Problem (LAP) is a well-established optimization model within the logistics sector, and its formulation and solution methods have evolved over time. In its early stages, LAPs were relatively simple and could be solved using basic optimization techniques. However, as railway operations became more intricate, the problem complexity increased, prompting the development of advanced solution methods.

Researchers introduced various approaches, including decomposition-based methods and the Approximate Dynamic Programming method, to address the growing difficulty of solving LAPs. Concurrently, metaheuristics gained popularity as effective solution methods for LAPs. Notably, in Section 2.3, prominent metaheuristics like Tabu Search and the Genetic Algorithm were applied to LAPs, demonstrating promising results compared to benchmarks and other state-of-

[1]DP at Rail Cargo: https://blog.railcargo.com/en/artikel/eisenbahn-einfach-erklaert-doppeltraktion

the-art techniques. Given their simplicity, efficiency, and versatility, a metaheuristic approach was chosen to solve the underlying problem.

Specifically, the Variable Neighbourhood Search (VNS) method was selected due to its straightforward implementation and proven efficiency (refer to Section 4.2). The VNS framework proved to be a suitable solution method for the problem at hand. It successfully integrated and implemented the relatively complex model, which involved dynamic cost calculation, a nonlinear objective function, and a set of constraints.

While there is no benchmark available to validate the quality of the solutions generated by the model, the VNS heuristic demonstrated its effectiveness by delivering results rapidly and with minimal computational requirements. It consistently performed well, even with larger problem instances and input features. As a result, the model can be deployed on systems with limited computational resources and used by individuals without expertise in algorithms or optimization problems.

In summary, the chosen metaheuristic VNS effectively addresses the Locomotive Assignment Problem by providing feasible locomotive assignments and efficient schedules in a short time and with minimal computational effort. Its implementation demonstrates its suitability for practical use and its ability to support users unfamiliar with the intricacies of the subject matter.

7.3 General Findings on this Model.

This master thesis presents the development of a comprehensive railroad logistics model. The model includes various features that needed to be accurately represented and simulated. The initial step involved selecting a suitable railroad track and designing stations, depots, and other key characteristics such as segment lengths, inclines, declines, and speed limits. Online mapping tools were used to assist in this process, allowing for the creation of a railroad route and gathering relevant information. Additionally, existing data on popular European railroad segments were utilized to determine the cities and stations to be connected within the model.

Simulating the trains operating on the railroad track was the next task. Since precise information about the specific composition and freight of these trains was not publicly available, assumptions and rough estimates were made. Parameters such as the typical total length and approximate weight of European trains were used to generate these assumed train configurations. Publicly accessible data on wagon and rail car characteristics facilitated this process. Similarly, detailed information on locomotives, including their types, typical quantities used, and exact specifications such as length, weight, and power, was obtained from relevant sources provided by Austrian railway companies.

Various metrics within the model, such as train resistance and fuel cost calculations, were extensively documented in academic sources. However, detailed quantitative information specifically related to Distributed Power (DP) was limited. Nonetheless, with the available information, a realistic train scheduling and locomotive assignment model was created, relying solely on publicly accessible sources.
To observe the behavior of the model, a range of schedules using different types of input data was generated. The most efficient schedule obtained by the model had a total cost of $95,684$ and included 15 scheduled trains requiring 69 locomotives. Among these 15 trains, 9 trains utilized the Distributed Power technique (i.e. had DP-enabled locomotives assigned) while 6 trains operated in conventional mode. The cost of the DP-trains was $41,826$ and the cost of conventional trains was $53,858$. This optimal schedule was found during the fourth iteration out of a total of 308 iterations performed. The data set used favored the generation of schedules where DP trains predominated over conventional trains by having 60% of the locomotives capable of driving in a DP constellation and 40% as conventional type. Such schedules, where more DP trains are employed, appear to be more efficient, and data sets with a higher proportion of DP units facilitate their creation. The initial random assignment of locomotives to trains also has a significant impact on the composition of a schedule. If in a data set is a dominance of DP units, it is more likely that they will also dominate in the random initial assignment. Conversely, when conventional units dominate the data set, they may also dominate in the random initial assignments, resulting in a less favorable solution quality. This is due to the fact that the VNS metaheuristic is not able to alter the DP/non-DP composition of the initial solution. If the initial solution incorporated 8 DP-trains and 7 conventional trains, so will the final resulting solution. Thus, it is recommended that for further usage of this model or research, a predominately defined rule or other method should determine a beneficial initial assignment that can then be optimized by the metaheuristic, to prevent initially unfavorable assignments.

In conclusion, this study demonstrates that trains in Europe can be effectively modeled and simulated using the available information. By leveraging this data, a framework can be developed to optimize operational efficiency and reduce costs. In general, a schedule with a combination of DP and conventional trains is favorable, with DP-trains comprising the majority. It is recommended to apply a rule for generating efficient initial assignments before optimization. In this regard, metaheuristics prove to be a suitable solution method. In certain areas, generating and publishing more detailed information may be necessary to enable the construction of even more realistic models.

Finally to answer the main research questions enclosing this thesis:

- Regarding locomotives and their features, the Austrian railway operator OeBB provides extensive material that allows for a realistic simulation within the Austrian and European context. Similarly, when it comes to trains, precise data on the typical composition of freight trains in Europe or Austria is not available. However, rough estimates regarding the length and weight of trains are known. Furthermore, the OeBB publishes information on the key characteristics of the four most commonly used types of wagons in freight trains. Since a train consists of connected wagons, it is possible to model them with sufficient detail using publicly accessible data.
  To simulate the behavior of trains, relevant research provides guidance on factors such as resistance, fuel consumption, and the power required to pull a train. While there is some research on the impact of Distributed Power (DP) on trains, there is insufficient data and information available to model DP in trains with a high level of detail. This limitation is particularly noticeable within the European context.

- In this model, Distributed Power (DP) was incorporated to reduce the trains' resistance, leading to lower fuel consumption and improved cost efficiency. This reduction in fuel consumption has been supported by research, which indicates that DP trains experience reduced rolling resistance and wheel-rail friction compared to conventional trains. Consequently, DP trains consistently exhibit lower fuel consumption and operational costs in this model compared to conventional trains. However, when considering the overall schedule of trains, the results demonstrate that a combination of DP trains and conventional trains yields the most efficient operation. This mixed approach proves to be optimal in terms of achieving operational efficiency.
  In summary, the implementation of Distributed Power in railroad operations offers significant sustainability benefits. Its proven efficiency, enhanced safety, and reliability make it a suitable factor for improving sustainability in rail operations. Furthermore, the implementation of DP in the operation is cost-effective and straightforward, since only locomotives have to be equipped with the DP technique.

- Metaheuristics have been employed to address various versions of Locomotive Assignment Problems, each with different levels of complexity. In the case of this model, the metaheuristic approach was particularly effective in dynamically calculating the costs associated with trains. The Variable Neighbourhood Search (VNS) heuristic demonstrated its flexibility in handling challenges related to cost calculation, offering a comprehensive and easily understandable solution methodology.

Implementing the VNS heuristic was straightforward, requiring minimal effort to understand and execute. Furthermore, the computational requirements for generating solutions remained consistently low, even when dealing with larger sets of features and data. The efficient generation of a initial solution to the VNS could be a valuable supplement. As it has been shown, that the solution quality is dependent on the initial solution, employing some rule or heuristic to create an efficient input to the VNS is recommended for the operational purpose.

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Appendix A

Detailed Results.

In this appendix A the detailed results corresponding to the aggregated results in Chapter 6 are presented. For each generated schedule the total costs of this schedules, the total number of locomotives used, the power distribution and cost distribution are shown. Additionally, the distribution of locomotive types can be observed for each of the schedules. Similarly the total number of iterations performed to generate each schedule and and the iteration where the best solution has been found is depicted in each table.

The operator could employ the schedules as follows: The “Total Cost” column presents the financial implications of each solution, enabling stakeholders to compare and determine the most cost-effective option. The “Locos Used” column indicates the resource allocation required for each solution, aiding in evaluating operational requirements and associated costs. The presence and quantity of distributed power units (DP1) and conventional units (DP2) are captured in the table. The DP-units reduce forces within the train and on the tracks, potentially leading to energy savings. Assessing the deployment of DP units helps in understanding their impact on system efficiency. Cost considerations related to distributed power units are also highlighted. The cost of implementing DP1 and DP2 is provided, assisting researchers in evaluating the economic viability of utilizing distributed power units. The quantities of different locomotive types, including Taurus 1, Taurus 2, Tfz2, Hercules, and Vectron, are listed. Understanding the locomotive composition contributes to comprehending the system dynamics and performance. Additional information includes the number of iterations performed during the study, indicating the level of optimization, and the best iteration for each solution, highlighting the most favorable outcome achieved and computational effort required.

Solution	Total Cost	Locos Used	DP1	DP2	Power DP1	Power DP2	Cost DP1	Cost DP2	Taurus 1	Taurus 2	Tfz2	Hercules	Vectron	Num Iterations	Best Iteration
1	130454	77	9	6	75495	58200	40955	89499	19	24	16	11	7	259	4
2	142501	77	9	6	72126	61568	38588	103913	13	27	16	13	8	253	5
3	130050	72	9	6	83114	46891	44207	85843	16	20	13	11	12	293	11
4	132403	75	8	7	76390	56893	40150	92253	12	30	13	11	9	262	3
5	121160	73	9	6	76590	53594	42071	79089	16	21	19	9	8	291	7
6	141373	72	8	7	70748	58950	37831	103542	14	15	19	12	12	302	6
7	139233	73	9	6	73240	56904	40754	98479	14	20	19	12	8	297	2
8	151539	74	8	7	74321	56131	39329	112210	12	20	16	14	12	294	116
9	125360	72	9	6	77221	52787	41359	84001	16	22	14	9	11	296	265
10	130606	73	8	7	72710	57294	39074	91532	15	22	16	11	9	294	53
11	135138	72	10	5	80018	49804	43858	91280	16	18	14	12	12	295	191
12	135498	72	9	6	71667	58294	39305	96193	16	21	15	12	8	286	70
13	124582	73	9	6	79857	50916	43033	81549	17	27	14	9	6	287	42
14	95684	69	9	6	77528	52209	41826	53858	11	22	22	4	10	308	4
15	139547	73	8	7	64444	65711	35207	104340	15	19	16	12	11	307	9
Mean	131675	73	9	6	75031	55743	40503	91172	15	22	16	11	10	288	53
Min	95684	69	8	6	64444	46891	35207	53858	11	15	13	4	6	253	2
Max	151539	77	10	7	83114	65711	44207	112210	19	30	22	14	12	308	265
		Sum	131	94				**Sum**	222	328	242	162	143	**Median**	9
														Mode	4

Table A.1: Detailed results from the 60% DP1 / 40% DP2 data.

Solution	Total Cost	Locos Used	DP1	DP2	Power DP1	Power DP2	Cost DP1	Cost DP2	Taurus 1	Taurus 2	Tfz2	Hercules	Vectron	Num Iterations	Best Iteration
1	129905	77	8	7	67419	66146	36036	93869	18	21	17	11	10	252	3
2	134064	71	6	9	46936	82940	25948	108116	16	25	13	11	6	290	3
3	134511	72	8	7	67350	62397	36498	98013	15	29	9	11	8	294	102
4	138727	73	8	7	66235	64274	35814	102913	10	22	19	12	10	296	78
5	132877	72	7	8	57029	73114	30887	101990	13	25	18	11	5	298	198
6	124173	72	8	7	62710	67181	34315	89858	11	25	18	9	9	296	54
7	109634	71	9	6	75564	54131	40615	69019	15	28	12	7	9	311	201
8	135824	73	7	8	58547	71691	31829	103995	15	24	15	10	9	293	19
9	133707	74	7	8	64629	65829	34685	99022	19	26	13	11	5	290	85
10	144584	75	7	8	67283	65843	35071	109513	14	26	12	13	10	261	3
11	102856	70	8	7	62785	66683	33899	68957	14	25	18	5	8	305	2
12	143521	75	7	8	60341	70387	32245	111276	15	27	16	12	5	290	3
13	127429	73	8	7	71370	59130	37901	89528	19	25	10	10	9	289	112
14	101356	70	8	7	72899	56454	39247	62109	10	26	16	5	13	305	2
15	125241	70	7	8	66821	62779	35118	90123	9	28	14	9	10	304	2
Mean	127894	73	8	7	64528	65932	34674	93220	14	25	15	10	8	292	58
Min	101356	70	6	6	46936	54131	25948	62109	9	21	9	5	5	252	2
Max	144584	77	9	9	75564	82940	40615	111276	19	29	19	13	13	311	201
		Sum	113	112					213	382	220	147	126	**Median**	19
														Mode	3

Table A.2: Detailed results from the 50% DP1 / 50% DP2 locomotive data.

Solution	Total Cost	Locos Used	DP1	DP2	Power DP1	Power DP2	Cost DP1	Cost DP2	Taurus 1	Taurus 2	Tfz2	Hercules	Vectron	Num Iterations	Best Iteration
1	130011	74	7	8	66092	66927	34299	95712	13	22	16	11	12	265	66
2	125236	72	7	8	63065	66636	32980	92256	17	23	14	9	9	296	170
3	136740	72	6	9	50643	79016	27537	109203	14	20	17	12	9	286	81
4	134788	73	6	9	53328	76911	28348	106440	14	21	14	11	13	297	43
5	136509	73	7	8	62529	67528	33260	103249	15	15	23	11	9	293	5
6	134632	78	6	9	53545	80416	28500	106132	16	27	15	12	8	246	2
7	136426	74	6	9	48759	81745	26357	110069	14	22	15	12	11	286	182
8	137239	75	7	8	53537	77332	29628	107611	20	24	13	11	7	297	9
9	100675	71	7	8	63554	66498	33797	66878	13	25	16	5	12	283	113
10	129316	72	5	10	51320	78419	26111	103205	16	23	13	10	10	295	192
11	125130	69	6	9	51145	78115	27166	97964	14	20	16	10	9	297	4
12	137777	73	7	8	57831	72497	31061	106716	18	21	14	11	9	291	19
13	132259	71	7	8	54789	74861	29767	102492	14	21	14	11	11	289	272
14	140406	76	6	9	47152	86273	25121	115285	14	24	18	12	8	252	3
15	155385	74	5	10	48870	81457	26036	129349	13	22	19	15	5	281	13
Mean	132835	73	6	9	55077	75642	29331	103504	15	22	16	11	9	284	78
Min	100675	69	5	8	47152	66498	25121	66878	13	15	13	5	5	246	2
Max	155385	78	7	10	66092	86273	34299	129349	20	27	23	15	13	297	272
		Sum	95	130				**Sum**	225	330	237	163	142	**Median**	43
														Mode	-

Table A.3: Detailed results from the 40% DP1 / 60% DP2 locomotive data.

Appendix B

RailCargo Interview.

In this appendix B the e-mail correspondence with a spokesperson from RailCargo in relation to the usage of Distributed Power at OeBB or in Europe and Austria is presented (translated from German to English).

B.1 Inqury.

Dear Sir or Madam,
As part of my research work/Master's thesis, I am investigating the application of Distributed Power (DP) (or multiple-unit train operation) in freight trains in the European and Austrian context. It is known that DP reduces the energy consumption of freight trains by reducing forces within the train and forces exerted on the track. However, since there is very limited data and publications available in this area, I wanted to inquire whether you have any data or publications related to DP that you can provide or share (if necessary, under confidentiality).
Thank you in advance for your assistance.
Best regards,
Severin Lehner

B.2 Answer RailCargo.

Thank you for forwarding the inquiry.
Personally, I am more familiar with the concept of "Distributed Power (DP)" in countries where freight trains operate with significantly longer train lengths than in Europe, such as Australia and the USA. For example, in the USA, the length of a freight train can reach up to 4300 m. These trains operate with groups of distributed locomotives (power units) = DP.
In comparison, the maximum train length in Europe is much shorter: ÖBB Infra: 700 m, DB

Network: 740 m.

Therefore, DP concepts have limited application possibilities in Europe. The main reasons for shorter train lengths are:

- Infrastructure is not designed for longer train lengths.
- Screw couplings cannot transmit higher forces.

That is my assessment of the situation.

Best regards.