Decision Support System Considering Risks in Combined Transport

With a Case Study of Risk Management in Railway Transport

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Abbreviation

ANN	Artificial neural network
APP	Application software
BP	Back-propagation algorithm
BPNN	Back-propagation neural network
CFR	Căile Ferate Române
cf.	confer
CT	Combined transport
DB	Deutsche Bahn
DSS	Decision Support System
DynKo	Project Dynamic Consolidation
e.g.	For example
etc.	and so on
EC	European Commission
ERP	Enterprise Resource Planning
EOC	European Operation Centre
EU	European Union
Eq.	Equation
GA	Genetic Algorithm
GSM-R	Global System for Mobile Communications - Rail(way)
GUI	Graphic User Interface
Ibid.	In the same place
ICT	Information Communication Technology
JIT	Just-in-time
LMBP	Levenberg–Marquardt Training
LMS	Least-mean square
IT	Information Technology
IMT	Intermodal transport
KPI	Key performance indexes
km	Kilometre
kg	Kilogram

MAA	Moving annual average
min.	Minute
MLP	Multi-layer perceptron
Mse	Mean squared error
msereg	Mean squared error with regulasation
No.	Number
SC	Supply chain
SD	Standard deviation
SimAL®	SimAL.Scheduler®
p.a.	Per year
VLBP	Variable learning rate
vs	Versus

List of Symbols

b	Bias of an artificial neural network
C	Data set generated in the hidden layer of an artificial neuron network
c	c^{th} neuron in the hidden layer of an artificial neuron network
D	Training data set of an artificial neural network
d	d^{th} output of an artificial neural network
E	Training error of an artificial neural network
e	Error vector of an artificial neural network
f_n	Fitness value in Genetic Algorithm
G	Activation function of an artificial neural network
g	Gradient in Gauss-Newton algorithm
H	Hessian matrix
I	Identifying matrix in Levenberg-Marquardt algorithm
$J(w)$	Jacobian matrix
k	k^{th} iteration of an artificial neural network
N	Population size of Genetic Algorithm
n	n^{th} individual in the population of Genetic Algorithm
p_c	Crossover probability in Genetic Algorithm
p_m	Mutation probability in Genetic Algorithm
R	Input data set of an artificial neuron network
r	r^{th} input of an artificial neuron network
s	Sensitivity factor in Gauss-Newton Algorithm
st	State of an artificial neural network by reinforcement learning
t_d	Targeted value of an artificial neural network
W	Matrix of weight factors of an artificial neural network
w	Weight factor of an artificial neural network
X	Matrix of inputs of an artificial neural network
x_r	Value of rth input of an artificial neural network
y_c	Output of the hidden layer of an artificial neural network
y_d	Calculated output of an artificial neural network

ξ	Modifying factor of variable learning rate of an artificial neural network
ρ	Adjustment factor of variable learning rate of an artificial neural network
η	Learning rate of an artificial neural network
θ	Momentum of an artificial neural network
φ	Regularising parameter in Levenberg-Marquardt algorithm

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1. Introduction

1.1. Motivations

Combined transport (CT) generally refers to the movement of goods by successively using at least two transport modes, where the goods itself remains in the load unit. The major part of the transportation chain is by rail, inland waterways, or sea as well as pre- and post-haulage carried out by trucks.[1]

The starting point of the development of CT was a far-reaching regulatory reform and reorganisation in the major freight modes, i.e., railways, road transport, and air transport, in the U.S. since the mid-1970s. At that time new corporation forms developed in freight transport, the so-called integration of the courier, express, and parcel services sectors. After the nation-state deregulation and privatisation policies of the 1980s in the industrialised countries and the end of the East-West conflicts in the 1990s, targeted measures followed for cross-border liberalisation of freight markets at trans-region level (e.g., North American Free Trade Agreement and European transport internal market). Nowadays, CT plays an active and important role in the logistics sector.

In actual settings, the major part of the journey of CT consists of rail, inland waterway, or sea travel to benefit from economies of scale and to reduce the negative impacts of road travel on the environment. In the dissertation, CT focuses on goods transported by railway as the major part. The regions for this study are limited to Germany and the European Union (EU). The beginning and end of the journey benefit from road transport flexibility. The transition of goods between different modes of transport is normally conducted in a transhipment terminal, wherein change of the transport mode occurs between traffic modes or between transport networks.

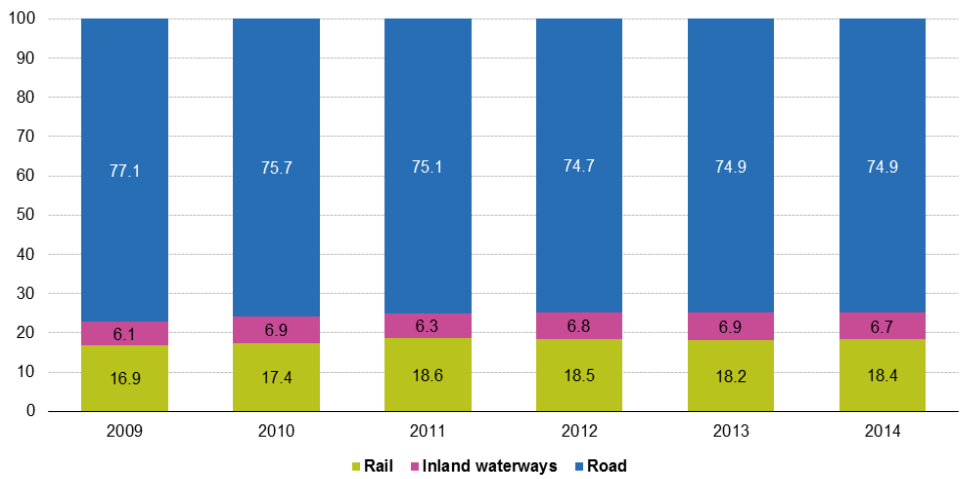
From an environmental perspective, increasing globalisation is expected to enhance the volume of trans-border freight flow. Trucking mode is widely used in freight transport traditionally because of its convenience in relation to pickups and local deliveries. However, it induces road-traffic problems of congestion, the environment, and traffic safety, especially when the amount of shipments is large. The

[1] Cf. (UIC - International union of railways)

increasing dependence of transport on fossil fuels also results in the unsustainability of current transport patterns. Therefore, sustainable transport modes should be developed to address the external effects of transport. CT has received much attention as a prospective and environment-friendly alternative to road freight in medium-to-long-distance corridors.

Nonetheless, CT transport is not competitive in road transportation in practice. For instance, the rapid development of the German economy after the 2009 crisis has increased transport demands in Germany and in Europe as a whole. However, statistics (Figure 1) show that the transport volume of CT has failed to meet expectations in terms of participation regarding the increase in transport volume over time.

Figure 1: Modal split of European freight transport from 2009 to 2014[2]



(1) EU-28 includes rail transport estimates for Belgium (2012-2014) and does not include road freight transport for Malta (negligible).

The decreasing transportation volume of CT has many reasons. The main exogenous causes are as followed: First, the declining freight volume of bulk goods in the primary sectors (agriculture and mining) in comparison with industrial products. A rapidly increasing amount of finished goods is often transported by truck given that these goods are truck-affine.[3] The transport volume of road transport and global containers has increased.[4] Second, orders from small-scale consumers increase. The size of the shipment from the small-scale consumers is smaller than that of the train, or the size of the shipment fits only one or a few wagons. Consequently, railway service is generally less condensed than road service. Finally, CT exhibits serious

[2] Cf. (Eurostat, 2016)
[3] Cf. (Vahrenkamp, 2007)
[4] Cf. (Aschauer, et al., 2010)

drawbacks such as non-transparent regulations regarding freight transport by rail and ships.[5]

The changes in the transport environment require CT to alter its logistic services correspondingly. Previously, the speed of cargo trains was an insignificant factor in the railway transportation. At present, delivery is expected to be reliable, timely, and combined with pre- and post-haulage on trucks. Transport times in rail haul and transhipment must be shortened, and services offered more frequently for short distances.[6] This situation changes railway operation, e.g., scheduled delivery times should be highly more flexible to adapt to market variations. Congestion can also cause bottlenecks on railway lines. For instance, demand variations can constrain capacity at almost any point along the origin, destination, or intermediate rail yard of the railroad.[7]

The dissertation focuses on the endogens reasons for CT. The endogens reasons of CT are generally described as:

When CT is perceived at the "supply-chain" level, the management of CT aims to integrate all activities into a seamless process to enhance the performance of all members. Hence, transportation causes a considerable information flow in order to generate, manage, and follow a tangible flow of goods.[8] Therefore, CT usually performs the transportation tasks according to a considerable amount of information flow.

Organisation issues and coordination of transportation tasks discourage decision-makers to choose CT for freight transportation. If a decision-maker is involved in CT, more uncertainties would affect the logistic service.[9] In practice, the solutions are not enough to make decisions easier at the operational level.[10] Furthermore, the solutions might be weakened by processing and classifying huge amounts of data. The recalibration of their strategies and different rules of engagement are needed to cope with unexpected events.

[5] Cf. (Reis, et al., 2013)
[6] Cf. (Meers, et al., 2017)
[7] Cf. (Chen, et al., 2016)
[8] Cf. (Stadtler, 2011)
[9] Cf. e.g. (Vilko, et al., 2012), (Verbano, et al., 2013) and (Heckmann, et al., 2015)
[10] Cf. (Simchi-Levi, et al., 2009)

Unexpected events lead to less-structured problems, whose solutions can only be vaguely identified. Or, there are several solutions to the same problem, but the priorities of the solutions are too complex to be ranked.[11] Finding a well-structured solution to quickly solve problems in CT is difficult, especially at the operational level. How can decision-makers be supported in CT? This is a major point of concern of this dissertation.

1.2. Objectives and Scope

To enhance the business competitiveness of CT, this dissertation presents a decision support system (DSS). DSS aims to improve the core competence of CT to enhance its operational processes. To realise the aim, the system provides solutions for a number of problems of CT, which were discussed in the previous sections:

1. Enhancing the quality of decision making requires an understanding of risks in a CT. With the risk analysis in CT, DSS develops responses to the environmental dynamism of CT.[12] Decision-makers benefit from the DSS in their dynamic decision-making process, particularly at the operation level, where unexpected events occur more frequently than in the strategy and tactical level.
2. DSS is facilitated with functionalities for organisational arrangements for the planning and design of transportation tasks. Through DSS, users can achieve an overview of the specific transportation task. For any unexpected event, DSS can promptly inform its users using Information and Communication Technology.
3. Transport-Suite is introduced as an example of DSS in this dissertation. The Transport-Suite aims to establish an effective decision-making tool that provides insights on risk management in CT, that is, a DSS to provide solutions to less-structured problems.
4. As a frequently recurring risk in CT, delay prediction is emphasised in the dissertation. Due to the complexity of data, the model is developed on the base of an artificial neural network (ANN) to estimate the time of train delay. To establish and train the ANN, with help of MATLAB® the data of Romaine Railway are applied.

[11] Cf. (Lin, et al., 2016)
[12] Cf. (Gaur, et al., 2011)

Transport-Suite was developed in the frame of the research project Dynamic Consolidation (DynKo),[13] which was financially supported by the Federal Ministry of Education and Research (Bundesministerium für Bildung und Forschung). DynKo was initiated on the premise that not only large investments are necessary for infrastructure but effective measures for the organisational field as well.

1.3. Structure of the Thesis

The thesis is structured as follows:

Chapter 2 presents the definition of CT and introduces the operational background. Moreover, the operational progress and evaluation measures of CT are explained. Given that the railway network is the main research objective presented in this dissertation, the practice of railway network is explicitly described.

Chapter 3 describes the research agenda for the topics involving the main risks in CT from a comprehensive perspective. It investigates the risk sources that cause lateness not only in the railway system/CT but also in the entire supply chain, such as delivery lead time of suppliers and exchange rate fluctuations in international trade. These sources of risk arise from processes that are not directly related to CT but that nevertheless affect the performance of CT.

Chapter 4 describes the framework of the DSS for multiple decision-makers in CT. DSS aims to deliver efficient decisions under complex circumstances to satisfy the requirements of multiple agents in CT. An example of DSS Transport-Suite is introduced. The software is facilitating the use of Transport-Suite with various functionalities. For instance, a genetic algorithm (GA) (applied to solve routing and scheduling problems) and the ANN (applied to demonstrate the functionality of risk management).

Chapter 5 outlines the underlying theory of the delay prediction model. The fundamental theory of ANN is explained, including the learning rules, working principles, and so on. Although ANN is an efficient tool for data mining, its complexity limits its application in practice. Hence, several techniques are introduced to improve the performance of ANN. Except for adding more mathematical parameters directly related to the algorithm of ANN, GA is also introduced to enhance the quality of ANN.

[13] Cf. (Noche, et al., 2014)

Chapter 6 presents a case study of the simulated delay propagation model and discusses the results. Through repeated simulations, the model is trained to assist decision-makers to find solutions in the real system.[14] To estimate the impact of parameters on the performances of the model, the obtained results are discussed.

Chapter 7 ends the dissertation with conclusions and future extensions. This chapter summarises the findings and discusses possible extensions and further work.

[14] Cf. (Hilletofth, et al., 2012)

2. Combined Transport

This chapter focuses on operation background. First, definitions of combined transport (CT) are provided. Second, the fundamentals of railway transport are introduced. Third, the control system of CT is described. Finally, the section is summarised.

2.1. Background of Combined Transport

2.1.1. Definition of Combined Transport

CT is currently among the most widely used transportation types in praxis. Its definition is closely related to those of intermodal transport (IMT). However, no overall consensus has been reached regarding a universal definition in the literature of such types of transport.[15] Crainic, et al. (2007) described this type of transport as the moving of goods from its source to its destination in a process that involves more than one transport mode.[16] Mathisen, et al. (2014) defined IMT as a combination of at least two modes of transport in a single transport chain without changing the process of cargo packing.[17] The goods in load units are transferred among different modes at intermodal terminals. A concept of IMT can also be derived from literature published by the European Union (EU), i.e.

> *"Intermodal transport of goods where the major part of the journey is by rail, inland waterway or sea and any initial and/or final leg carried out by road is as short as possible."*[18]

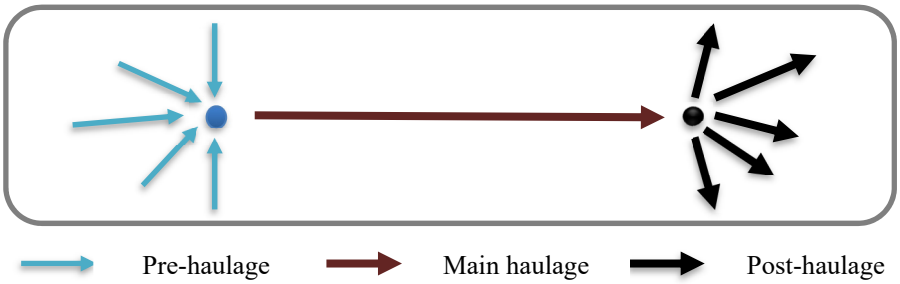
According to EU Council Directive 92/106/EEC, IMT can be defined as CT when the distance travelled by truck (i.e., measured by the shortest route) is less than 100 kilometre (km). The definition of CT is therefore subsumed under that of IMT. Given that this dissertation focuses on the operational level of transport, these two terms are used interchangeably here.

[15] Cf. (Reis, et al., 2013)
[16] Cf. (Crainic, et al., 2007)
[17] Cf. (Mathisen, et al., 2014)
[18] Cf. (eurostat, 2009)

Despite the wide range of CT definitions, all of them imply that CT combines at least two modes of transportation for one journey while commodities are stored in one load unit. Alternatives to the main haulage are cargo trains, inland ships, and overseas vessels. Trucks are used in pre- and post-haulage (the shortest possible pre- and post-haulage by road).

In CT, the longest portions of the transport journey are spent in either trains or ships. Trucks are used only in the pickup of goods from the source and in their delivery to the final destination (Figure 2). Hence, truck travel covers only a small portion of the overall journey, i.e., drayage transport. CT operates on a large scale and relies on the transhipment of load units between transport modes (trains/ships to trucks or trucks to trains/ships). This transport approach combines the flexibility of the truck with the performance of environment-friendly transport modes.[19]

Figure 2: Typical representation of CT[20]



As mentioned previously, "CT" is denoted as a process of transporting goods in which loading units (swap bodies, containers, semi-trailers, or complete trucks) are carried by at least two different modes of transport throughout the journey. It is in contrast to "broken" traffic (which is including changes of loading-unit).[21] In CT, the loading units of goods are not changed in the transport chain.

2.1.2. Policy support

The market shares of continental transportation sectors, i.e., rail, inland waterway, and sea, have dropped in practice and have not reported adequate rates of return. Bureaucratic inefficiency induces a severe bottleneck in the development of rail freight transport.[22] To motivate a modal shift from all-road freight transport to CT/IMT, national/regional governments have initiated a wide range of potential

[19] Cf. (Barta, et al., 2012)
[20] Cf. (Macharis, et al., 2004)
[21] Cf. (Bendul, 2013)
[22] Cf. (Crainic, et al., 2007)

policies. Although the policies discussed in this subsection explicitly support IMT, the development of CT also benefits from them as a subset of this transport type.

From the perspective of regulation support, the European Commission (EC) has explicitly expressed its objective to motivate the shift of transportation from road to intermodal in its transport policy documents. A series of EC transport policies aim to improve the competitive position of IMT.[23] Not only are research and technological demonstration activities financially promoted but the networking activities proposed and managed by international consortia are supported as well.[24]

In the EU, the policy-maker sector has focused on measures to support CT/IMT. For instance, the Belgian government has initiated projects to enable investors to increase their investments in the infrastructures of rail freight transport networks, including transhipment equipment in terminals.[25]

The European rail-based network is characterised by the vertical separation of infrastructure and operations, i.e., the infrastructure managers running the railway network are independent of the rail operators. Both managers and rail operators are supervised by an appointed EC rail regulator. This vertical separation encourages new train operating companies to obtain access to the railway network in Europe because the rail operators in each country do not gain from new entrants.[26]

To support the development of CT, infrastructure conditions have been financed, e.g., Trans-European Networks, Pan-European corridors, and the Transport Corridor Europe–Caucasus–Asia.[27] Straightforward reform measures have been implemented to improve the efficiency of rail traffic. For instance, major steps have been taken toward the deregulation of the rail sector in North America. Similarly, the franchising of such services to the private sector is a popular approach in Japan, South America, and New Zealand.[28]

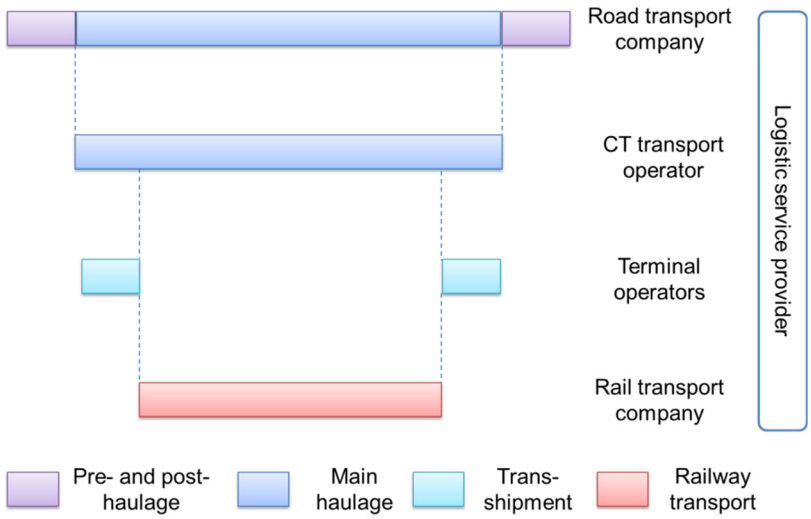
2.1.3. Operational Processes

The entire process of CT is a systematic flow of goods and information. Moreover, the CT is concerned with a broad spectrum of load units (type and size),

[23] Cf. (Caris, et al., 2013)
[24] Cf. (Tsamboulas, et al., 2007) and (Macharis, et al., 2011)
[25] Cf. (Macharis, et al., 2011)
[26] Cf. (Jeong, et al., 2007)
[27] Cf. e.g. (European Commission, 2011) and (European Commission, 2011)
[28] Cf. (Nash, et al., 2008)

rail wagons, and trailer chassis. From the perspective of multiple agents, CT operates in four core areas, as shown in Figure 3:

Figure 3: Processes of CT[29]



- Pre-haulage: After issuing the order, the cargo is handed from consignor over to the carrier. The transport from the source location to the first terminal is handled by the trucking company or freight forwarders.

- Transit in intermodal Terminal: A CT operator serves as the connection to the client. The operator in a so-called "check-in" procedure checks the roadworthy condition of loading units. The compliance of safety regulations for the crane work as well as for the transport of cargo units on the rail should be ensured.

- Railway traffic: A railway transport company takes over the tasks of the shunting of wagons and traction of the train.

- Post-haulage: At the road run, the goods depart from the reception terminal and are further transported to their recipients. The consignee receives the transported goods.

From the viewpoint of a logistic function, the stages of intra-organisational processes are classified into transport, disposition, administration, and additional service (e.g., customer clearance). Under such conditions, the individual network

[29] Cf. (Boldt, 2009)

actors in different fields are closely and interactively connected to perform various CT functions.[30]

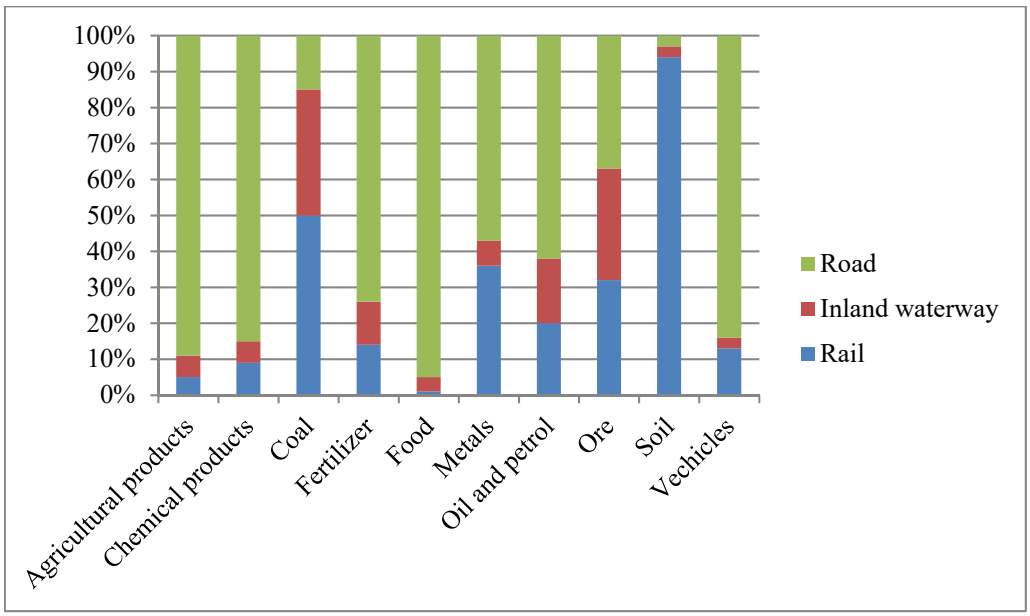
Given that long haulage on railroads is usually integrated with a road hauler, CT can be considered a complete door-to-door service. From this perspective, the synergic connection between rail and road network is important to the railway service level.

2.2. Role of Railway in Freight Transport

Based on Figure 4 coal and oil are successfully utilised in railways. Both products have high weight/volume. Production areas (e.g. coal/oil mine) and centralised end cousumers (e.g. power plant and gasoline station) are few. The quality of coal and soil does not decline over time. These products are also relatively inexpensive per kilogram (kg). Therefore, the goods for rail transport are characterised as follows:

- Heavy goods, especially in large amounts;
- Goods that are not particularly time-sensitive; and
- The transport network has few origin and end points.

Figure 4: Modal share of different goods[31]



[30] Ibid.
[31] Cf. (Reis, et al., 2013)

From the perspective of the statistical data above, goods with a high value/kg (e.g., chemical products) and that require much transport flexibility (e.g., textile) and time (e.g., food) are unsuitable for rail transportation. Table 1 presents an overview of the main advantages and disadvantages of rail freight.

Table 1: Advantages and disadvantages of rail freight[32]

Advantages	Disadvantages
Well suited for mass and heavy loads over long distances	Capital-intensive deployment, operations, and maintenance expenses
Fast terminal-to-terminal connections based on existing infrastructure	Long lead time for the planning and construction of facilities
Favourable transport costs	Low compatibility with borders for national systems and regulations
Environmentally friendly with respect to energy consumption and emissions	Not development of rail network mostly because of the low density of the electricity network
Well suited for combined freight transport	Low capacity and utilisation of rail networks

Traditionally, cargo trains are well suited for the delivery of heavy goods (e.g., machines, automobile parts, and ore) over long distances. Currently, to meet the requirement of customers, rail-based transporters provides various additional services, e.g. short-distance bulk train transport for niche markets. (For certain products, particularly overweight and large commodities, maritime transportation is very useful.[33] However, this topic is beyond the scope of this dissertation).

Railway freight transport also benefits from tax and statutory regulations, such as in Austria and Switzerland. The driving ban is derogated, and the maximum gross weight for trucks is increased, particularly in the mountainous regions of these countries.

In this subsection, the rail network is divided into three components, namely, rail lines, rail networks, and rail terminals. A state-of-the-art railroad is introduced at the end of the subsection.

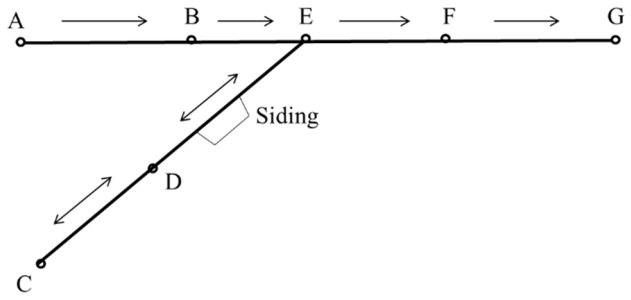
2.2.1. Rail lines

A rail line is a sequence of segments between a starting and an ending point (usually two major freight terminals), with one or more potential intermediate stations.

[32] Cf. (Nuhn, et al., 2006)
[33] Cf. (Eurostat, 2016)

Several junctions of such lines comprise a network.[34] Figure 5 illustrates two types of tracks: segments A–E and E–G are single tracks and C–E are double tracks. In a single-track system, trains move in two directions using the same track. Therefore, the buffer sidings must be adequate so that trains can wait for those running in the opposite direction to pass and prevent potential deadlocks.[35]

Figure 5: Single- and double-track segments in railway networks



In a double-track system, a train is permitted to travel in only one direction while a train in the opposite direction runs on the other parallel track. Signalling facilities can generate signals in both directions. However, signalling facilities are limited to the provision of signals in only one direction per track segment.

A network consists of one or several parallel single tracks, double tracks, and other systems with any number of tracks. In Germany, railway networks are typically composed of double tracks. Nonetheless, the signal system is set up as such that the double-track system can be used for two-way transportation, especially when high-priority trains are given precedence over the low-priority ones.

2.2.2. Rail networks

As mentioned previously, rail lines constitute a rail network. This network is extended by roads. At present, all CT systems are fundamentally organised as hub-and-spoke networks.[36]

In practice, both block (direct) and shuttle trains are used. A block train is a complete train used by a single customer. It runs directly from the consignee to the consignor without other deliveries. A shuttle train provides transportation on fixed schedules and offers its services frequently. A block train is adapted for the specific

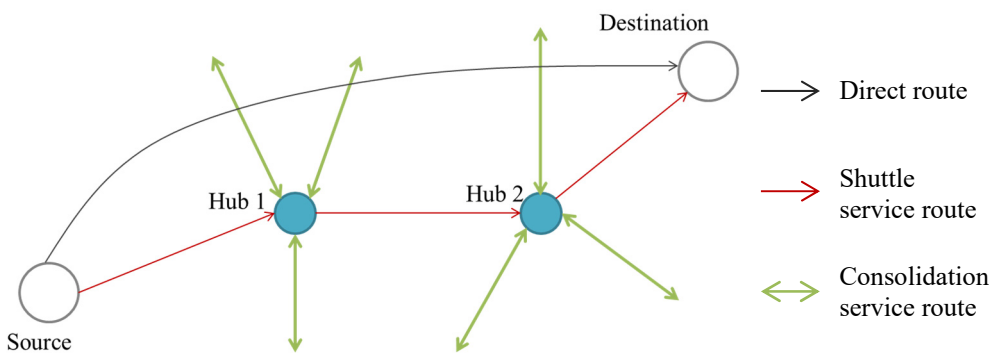
[34] Cf. (Törnquist, 2006)
[35] Cf. (Lu, et al., 2004)
[36] Cf. (Crainic, et al., 2007)

customer/commodity groups, including bulk items such as ore. By contrast, shuttles follow a fixed frequency and have a pre-determined number of wagons. Therefore, they are more suitable for the transport of low-volume orders than block trains are.[37]

Although shuttle trains limit the flexibility of the train operator, the client benefits from the wide range of departure times. An essential feature of the shuttle service is that economies of scale can be achieved through consolidation at terminals, thus reducing cost.[38] As a result, a hybrid transport network is developed. Commodities are transported from a source by block train and arrive at a destination without visiting any hubs. By contrast, the shuttle train transitions from one hub to the next after the consolidation of goods took place. It then proceeds to a destination.

As illustrated in Figure 6, low-volume deliveries are initially transported to Hub 1 (e.g., the rail yard or distribution centre). At this hub, these deliveries are consolidated into large material flows that proceed to Hub 2 through high-frequency and high-capacity logistic services to maximise economies of scale (the red lines). Low-frequency and emergency services are often performed by small vehicles that usually move between the origin and the destination (the grey lines). Consequently, the resource utilisation of railway networks increases.

Figure 6: Movement of goods in a hybrid hub-and-spoke network



2.2.3. Railway Terminals

Terminals are essential facilities in freight systems. They are typically regarded as intermediate locations for trucks and trains. Terminals are varied in terms of layout, handling equipment, storage, operating policies, and the volume of containers

[37] Cf. (Woxenius, et al., 2013)
[38] Cf. (Racunica, et al., 2005)

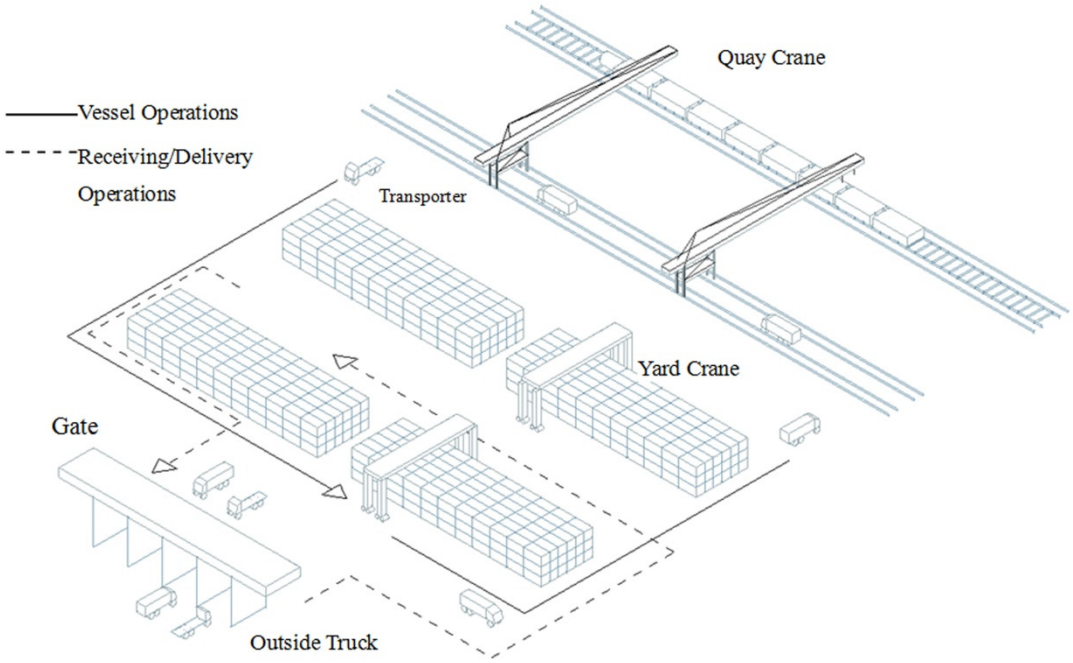
transhipped.[39] A key feature of railway terminals is the interface between short- and long-distance transports. The intermodal transfer of goods between a truck and a rail car typically occurs at rail terminals. To ensure a smooth exchange, highly specialised equipment must be used to handle loading units, primarily yard trucks or automated vehicles that move the loading units into the cargo train/truck. These intermodal-specific transition points are also known as consolidation terminals. Following the exchange of goods between transportation modes, terminals are also assigned to store products. Therefore, terminals can be hybrids, and the available capacity can be utilised for the simultaneous collection and delivery of products.

Some trains consist of traditional rail wagons in one part and flatcars in the other. Intermodal units can be loaded and unloaded conveniently on the flatcars. The assembling, sorting, and deconstruction of freight trains constitute a process called shunting. Railcars are connected to the rear or to the front for easy detachment at a marshalling yard; hence, the train can move rapidly toward the intermodal terminal in which the cargo is expedited. Given that trains can be composed of up to 100 railcars they are often of various origins and destinations, shunting can be a complex task to perform especially when it is frequently required.[40]

As illustrated in Figure 7, packing goods, i.e., containers, arrive at the rail terminal by truck. Unloading begins immediately, and the inbound containers are either directly transferred by the transporter to a rail car waiting in the rail area or moved using transhipment equipment, i.e., yard cranes, to a temporary storage area. Commodities are then picked up from the storage area and loaded onto rail cars that are grouped into trains within a given window of operation. When the train arrives at the subsequent rail terminal, the operations are reversed; outbound containers are either loaded onto trucks for their final transport journey or placed in storage until the assigned vehicle is unloaded.[41] Many railway terminals are accommodating an entire train by using several tracks. The advantages of such depots include resource savings, pollution reduction, and an increase in depot efficiency (the result of shared equipment and infrastructure).

[39] Cf. (Corry, et al., 2006)
[40] Cf. (Reis, et al., 2013)
[41] Cf. (Crainic, et al., 2007)

Figure 7: Example of a container terminal with an indirect transfer system[42]



In an ideal case, when commodities arrive at a terminal per train/truck, they should be directly loaded to the truck/train. If the vehicle has available space, the loading/unloading process should begin immediately. Otherwise, commodities must be stored in terminals until their assigned vehicle is unloaded. The storage of outbound goods is called "double handling".

2.2.4. Status Quo of Railway Transport in the EU and Germany

As mentioned previously, railway transport has two major aspects, namely, rail networks and terminals. In this subsection, the status quo of railway transport in Europe, specifically in Germany, is divided into two facets: railway infrastructure and stations (terminals).

- Infrastructure

The distinguishing operational characteristic of rail infrastructure is vital in train transportation. In German railway networks, some lines are utilised over 100%, thus causing traffic jams on the railways. Moreover, the merging and abandonment of rail lines contributes to the existing congestion in rail network systems.[43]

[42] Ibid.
[43] Cf. (Murali, et al., 2010)

Figure 8 presents an overview of the length of the tracks in the railway network systems in EU countries. Germany, Italy, Poland, and Spain exhibit strong rail networks.

Figure 8: Total length of European railway lines (Unit: km) in 2012[44]

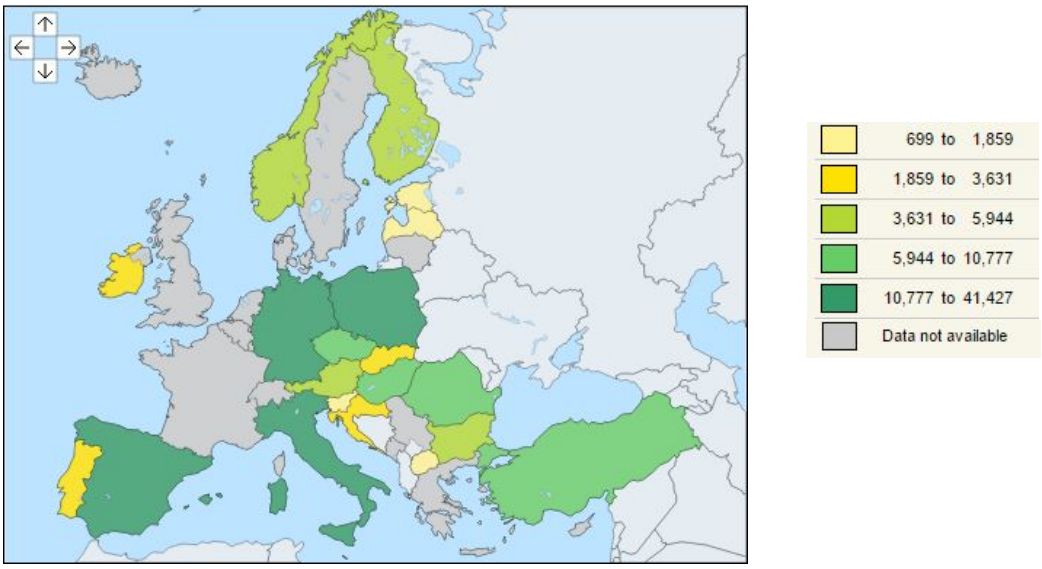
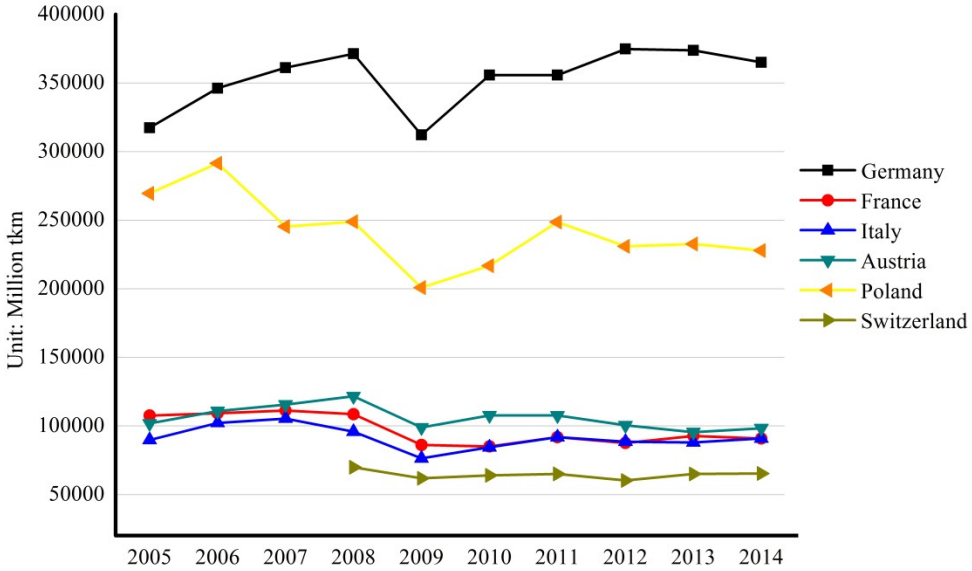


Figure 9 illustrates the development of rail freight transport in key European countries from 2005 to 2014. The volumes of railway freight in Germany, Switzerland, and Austria progressed strongly because of economic development. The Polish economy is highly dependent on foreign trade, and its export sector developed rapidly as a result of its entrance into the EU in 2006. However, its transport volume dropped by 25% in 2009 because of the stagnation of the world economy in 2008 and 2009.[45] Meanwhile, rail freight in France has been on the decline. In fact, the transport volumes in all of these countries and worldwide decreased as a result of this economic crisis.

[44] Cf. (eurostat, 2014)
[45] Cf. (Neumann, et al., 2010)

Figure 9: Development of the transport capacity of European countries from 2005 to 2014[46]



In current CT terminals, roads/rails are available for use as hubs in the form of germ cells such as container terminals and freight villages. The prerequisite for a hub is the presence of a sufficiently large hinterland that guarantees a correspondingly large volume of cargo.

- Stations

Stations are transit terminals that are important components of the railway network. The rail system should link trains and act as intersections to other modes of transport. Stations are connected by rail lines that link to other networks. Therefore, the entire transport chain can be operated efficiently. Cologne Eifeltor is among the most important major CT stations in Europe. Shipments are primarily heading to the north or the south of Europa, such as to Italy or to Spain. The terminal has a capacity of 450,000-unit loads.[47] In the modern logistic system, many parameters are applied to qualify a transit station. Table 2 provides an overview of those parameters.

[46] Cf. (eurostat, 2014)
[47] Cf. (PLANCO Consulting GmbH , 2012)

Table 2: Intermodal service in Deutsche Bahn (DB)-owned transhipment terminals (based on the financial year 2012)[48]

	Kassel	Dresden	Frankfurt (Oder)	Wustermark
Transhipment capacity p.a.	30,000 TEU	60,000 TEU	30,000 TEU	40,000 TEU
Storage capacity at the transhipment terminal	270 TEU	600 TEU	700 TEU	600 TEU
Sidings for transhipment	2	4	2	2
Length of crane runway	402 m	640 m	575– 645 m	660 m
Quantity of gantry cranes	1	2	0	0
Mobile transhipment equipment	1	0	2	2

- Organisation of Railway Companies

Compared with truck-only transportation, rail freight transport has a low level of flexibility and frequency. Given that rail transport companies have little control over the level of usage of cross-border trail networks in the EU (according to Guideline 2004/51/EG), national governments have a major role in improving the infrastructure of a rail-based network.[49] In the rail network, improving lane systems and increasing electrification would significantly enhance the service performance.

As a result of the rapid development of the automobile industry trucks, trucks became more commonly used in CT since the 1960s. Cargo trains sharply lost their transport market share and profitability. To promote rail competition, the railway market opened-up to private railway companies.[50] In 2001, with the revision of the 1999 EU Guidelines (see section 2.1.2), railway companies engaged in cross-border businesses gained access to the European rail freight network. At the same time, foreign companies operated in the German market.

Currently, around 250 private rail freight companies operate in Germany. To accomplish the tasks of an infrastructure operator, the operator should cooperate with rail transport companies in terms of schedules, the offering of available train tracks,

[48] Cf. (DB Intermodal Services GmbH, 2011)
[49] Cf. (Nash, et al., 2008)
[50] Cf. (Engartner, 2008)

and maintenance/repair of networks.[51] Among these railway companies, the subsidiaries of industrial and commercial companies have the common goal of providing flexibility, thus satisfying the demand of clients.[52]

In 2012, the total traffic volume of rail freight in Germany was 110.1 billion ton-km, which corresponded to a share of 23.1% of land transport. The most common cargo included metals and metal products with 13.1 billion ton-km, followed by chemical and mineral products, ores, rocks, soils, and other mining products. Today, bulk and liquid bulk are mainly transported by rail. The railway network in Germany has an available length of 70,000 km.[53]

2.3. Main Performance Indicators of Freight Railway Transportation

Transportation time and costs are the most common performance indicators in the evaluation of freight railway transportation. In addition to these two conventional indicators, environmental-friendliness has also drawn public attention. Because of recent global warming, the occurrence of environmental disasters increase. Therefore, innovative and environment-friendly concepts must be considered at both the business and consumer levels.

2.3.1. Transportation Costs

Railway transportation costs are generally related to the following factors:

- *Transportation distance*: At distances of more than 600 km, CT costs are lower than road transport costs. Railion AG Germany follows a strong economy of scale in the transportation of general cargo by train. Average freight rate is 7.40 cents at a transport distance of 1000 km when converted to freight rates per ton-km. This value is almost 55% lower than that obtained for a distance of 200 km (16.04 cents).[54] Therefore, freight transport over medium- and long distances is more competitive than that of road haulage.

- *Shipment weight*: In practice, the freight rate of cargo train is determined not only by transport distance but also by shipment weight. For instance, rail price varies with the shipment weight of the load. The transport cost rate for goods

[51] Cf. (Boldt, 2009)
[52] Cf. (Nuhn, et al., 2006)
[53] Cf. (Verband Deutscher Verkehrsunternehmen e.V., 2013)
[54] Cf. (PLANCO Consulting GmbH, 2007)

that weigh less than 13.5 ton is 22.87 cents per ton-km. This rate decreases to 17.07 cents (approximately 25.4%) when the consignment weighs 20 tons. Given shipment weighing 30 tons and onward, the rate is 14 cents. This value is almost 39% lower than those of shipments that weigh under 13.5 ton.[55] Thus, rail line-haulage is suitable for heavy items.

- *Network utilisation*: Fixed asset costs decrease with increasing transportation volume and/or transportation distance. Empirical evidence proves that increasing traffic on a single route generally reduces unit cost unless the route is heavily congested.[56]

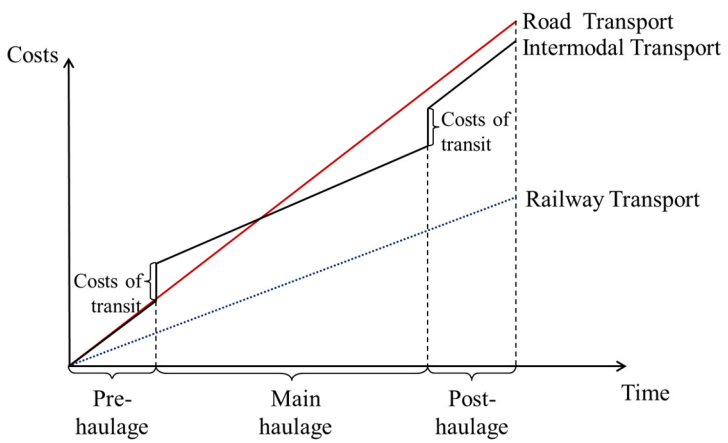
In accordance with the CT process, CT costs are divided into three broad categories, as exhibited in Figure 10:

(1) Transhipment costs in rail terminals (loading and unloading): The line runs parallel to the axis "Costs";

(2) Cost of main haulage (rail): The slope of the train transport line is lower than that of truck transport. That is, the costs per km of the former are lower than those of the latter; and

(3) Costs of pre- and post-haulage by truck: This division depends on the area costs.

Figure 10: Allocation of CT costs[57]



[55] Ibid.
[56] Cf. (Holzhey, 2010)
[57] Cf. (Beresford, 1999)

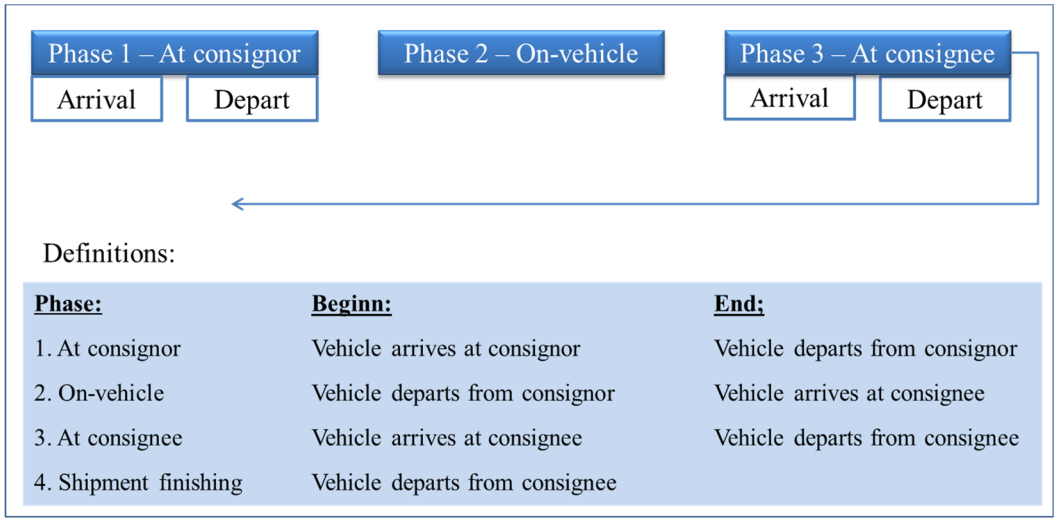
Although the use of railroads can reduce the transportation cost of CT, this reduction must be viewed in the context of the overall CT costs. Costs such as depreciation, maintenance, repair, and insurance are not included in the analysis of CT costs in this dissertation because they are directly associated with the consignment specifications and are therefore carried by either shippers or recipients.[58]

2.3.2. Delivery Time

A shipment is transferred between the origins and the destinations in its itinerary (Figure 11). Simplified rail-specific scheduling includes the following factors:

- Train arrangement: The connection between an inbound and an outbound train must be reasonable to minimise shipment time.
- Available lanes and marshalling yard: In a given time window the number of trains traveling on a track segment is constrained. In other words, a limited number of trains can depart from a terminal in a given time window because available tracks are restricted.
- Crew and locomotive: Prior to being reassignment to the next shipment, crews and locomotives must remain at the terminal for a given (minimum) duration.

Figure 11: Time phases[59]



The main operating components of freight time are its delivery time, i.e., goods-on-vehicle time, transhipment time at terminals, and waiting time because of sequential transport activities at terminals. With the robust development of centralised

[58] Cf. (Janic, 2007)
[59] Cf. (Closs, et al., 2003)

distribution centres and logistic parks, transit time increasingly affects the service reliability of rail shippers and carriers.[60]

Waiting time for permission to use a lane increases the transport time of freight trains, apart from the waiting time for sequential vehicles at terminals. This increase can be observed when link utilisation exceeds approximately 80%. Therefore, capacity utilisation in rail operation is characterised by an output capacity between 80% and 110%. Lines with a capacity of less than 80% display a degraded performance. Rail traffic time increases if more than 95% of rails are utilised.[61]

Another important time component is the handling time at the terminal, which mainly depends on the capacity of the handling machines (e.g., crane) and on the number of goods (usually in containers). Three interchangeable components can be identified in the CT network.

1) The first interchangeable component is the railway network, which consists of terminals, lines, and the flow of goods. Transport activities are associated with the cargo trains that originate from different clients and carry goods to customers.
2) The second interchangeable component involves the terminals in the network. Cargo trains may visit terminals for cargo loading and unloading. Goods transported using different traffic modes are consolidated at these terminals.
3) The third interchangeable component is the rail station. In the network, rail stations serve to accommodate trains. The movement of commodities from truck to train or vs, generally takes place in rail stations. Therefore, rail station operation is one of the most substantial elements that affect the time window for the pickup and shipment of goods.

Scheduling is conventionally studied as an optimisation problem. Correspondingly, numerous optimisation methods have been developed, e.g., genetic algorithms.

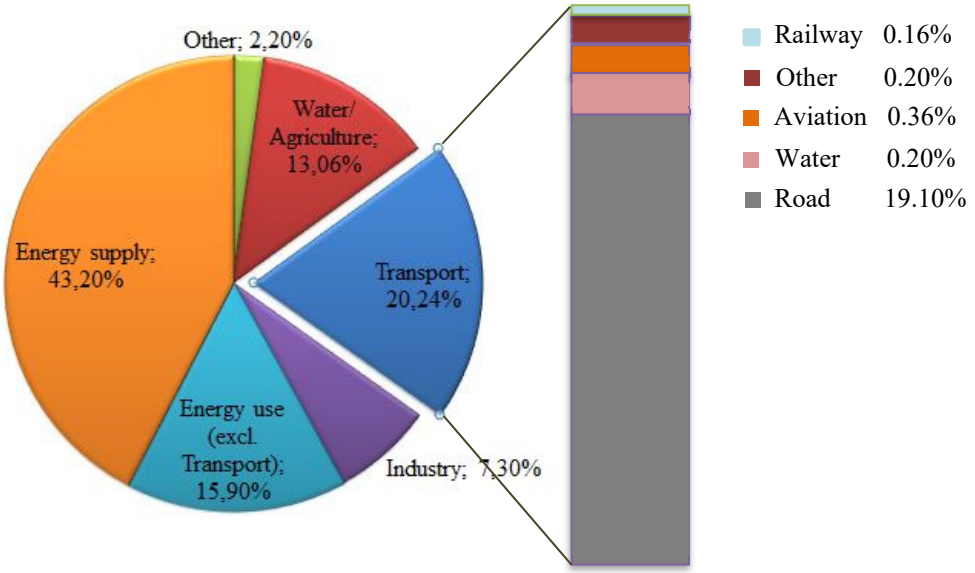
[60] Ibid.
[61] Cf. (PLANCO Consulting GmbH, 2007)

2.3.3. Environment Performance

CT can not only optimise the process of long-distance transport but also enhance its ecological image and sustainability. The main reason is that CT is considered an environmentally-friendly form of transport. In contrast to popular transportation modes via truck, transport on either railways or waterways emits fewer greenhouse gases. In the long-term, forward-looking companies rely on combined traffic to gain a competitive advantage over competitors.

Figure 12 depicts the CO_2 emissions from the different transport modes in Europe in 2011. Indirect emissions generated by rail transport and those from international aviation and maritime transport are not considered. The CO_2 emission from road traffic constitutes almost all the total CO_2 emissions from the transport sector. Hence, these CO_2 emissions can be significantly reduced if the transport volume on the road is shifted to railways given that railways balance CO_2 more effectively.

Figure 12: Emission distribution from economic sectors in 2011[62]



Aside from greenhouse gas emissions, traffic noise, accidents, climate gas, and air pollution are also important issues in freight transport.[63] A major complaint about the railway is the noise volume of trains. At equal exposure, railway noise irritates people less than road traffic noise does.[64] With respect to container transport, the average total external costs of railway transport are 13% less than that of road

[62] Cf. (European Environment Agency, 2013)
[63] Cf. (Janic, 2008)
[64] Cf. (Griefahn, et al., 2006)

transport.[65] The main haulage of CT is performed by environmental modes, such as rail. Thus, its external costs are lower than those of transport on a truck.

Aside from the three main indicators, CT participants seek to formulate comprehensive policies to achieve, maintain, and improve railway freight services as well as the services of pre- and post-haulage. The following indicators are considered by responsible CT participants:

- Reliable transportation (an efficient planning process, clearly defined responsibilities, and well-organised wagon management);
- Safety in the sense that damage-free freight transportation; and
- real-time compliance with information flow among actors. [66]

Railways are an environment-friendly mode through which goods can be moved trans-continentally. Nevertheless, as discussed previously, transportation via rail has constantly declined over the past decade.[67] The research methodologies for CT remain in its infancy.[68] Moreover, the current research focuses on the design and implementation of algorithms to improve the performance of CT. By contrast, the issue of partnership and collaboration in CT draw less research attention.

2.4. Collaborative Partnership in Combined Transport

2.4.1. Necessity of Collaboration in Combined Transport

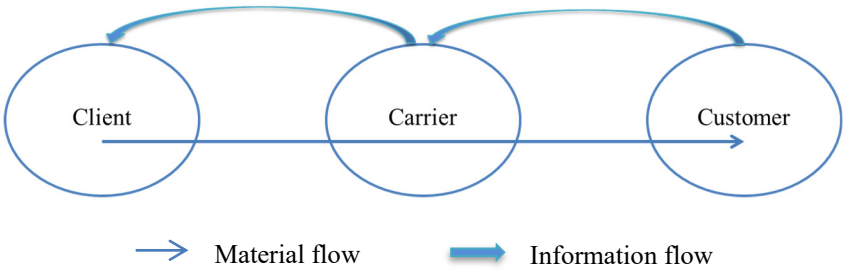
Given the endogenous feature of CT, multiple agents must negotiate to pursue a common purpose. Specifically, a good-quality partnership in CT facilitates joint problem solving and the fulfilment of pre-determined goals. It also avoids complex and lengthy contracts that are costly to write and are difficult to monitor and enforce. Partnership interaction increases the profitability of the transport chain.[69]

The typical actors in a transport chain under a logistic contract are illustrated in Figure 13. These actors include the consignor/client, the carrier (e.g., logistic forwarders), and the consignee/customer. Other participants, such as terminal operators, are involved but are only indirectly connected to such contracts. As

[65] Cf. (PLANCO Consulting GmbH, 2007)
[66] Cf. (Boldt, 2009)
[67] Cf. (European Commission Eurostat, 2013)
[68] Cf. (Crainic, et al., 2007)
[69] Cf. (Srinivasan, et al., 2011)

indicated, commodities are transferred from upstream to downstream participants, whereas information moves from the downstream partners to upstream suppliers. The discussion of collaboration is based on this concept in this dissertation.

Figure 13: Relationship between goods and information in a transport chain



The concept of collaboration has two facets, namely, cooperation and coordination. Cooperation is generally established based on contractual obligations, e.g., outsourcing and subcontracting.[70] Coordination is broadly regarded as the deliberate and orderly alignment or the adjustment of the actions of partners to achieve synchronisation in a CT network. Owing to the integration of independent actors along the transport chain, the collaboration effort in CT is significantly higher than that in mono-modal traffic.

2.4.2. Influence of Collaboration on Combined Transport

Collaboration requires the involvement of individuals or groups from different departments, organisational levels, and even different organisations. For example, the selection of the transportation route is typically undertaken through the collaboration among consignor, carrier, and consignee, who come from different organisations. In addition, the multiple-agent and multiple-goal features of CT increase the financial and organisational efforts.[71]

In logistics practices, information sharing can lead to enhance delivery performance.[72] From a technical perspective, the communication of collaboration in CT is principally an application-based technology that helps multiple users integrate transport processes efficiently. For example, Information communication technology is widely applied to meet this objective.

[70] Cf. (Ketchen Jr., et al., 2008)
[71] Cf. (Zouaghi, et al., 2010)
[72] Cf. (Ketchen Jr., et al., 2008)

2.5. Interim Conclusion

From the perspective of logistic theories, CT is a promising transportation trend because of its four specific benefits, namely, reduced road congestion, increased safety, highly efficient transport-asset utilisation (not only of infrastructures but also of wagons), and reduced total costs.[73] CT is principally suitable for all types of goods that can be transported over long distances.

Nevertheless, CT competes narrowly with mono-transport modes in freight transport. An important cause of this competition is the complex and highly stochastic operation process that is attributed to its endogenous features,[74] such as complex material and information flow, high uncertainty in operations, and high requirements for data exchange. Risk-management as an important element in CT will be explained in the following chapters.

[73] Cf. (Closs, et al., 2003)
[74] Cf. (Christopher, 2011)

3. Main Risk in Combined Transport

Risks in combined transport (CT) are always complicated to study and arises under many different circumstances. Moreover, the transport chain belongs to the supply chain (SC). Thus, this section not only discusses the risks in the transport chain but also those in the SC. This chapter is organised as follows. First, a definition of risks is provided. Second, various risks in the SC/CT are discussed. Finally, to specifically explain the risks in transport practices several case studies of railway transport are presented.

3.1. Definition

In this thesis, the definitions and category of uncertainty/risk are in accordance with the arguments of Ivanov, et al. (2010).[75] In decision theory, the risk is a measure of a set of possible (adverse) outcomes from a single rational decision and their probabilistic values. Uncertainty can exert both positive and negative influences on the SC, whereas risk causes only a negative influence and results in damage.[76] Given that this research focuses on the prediction of negative influence on CT/SCs, risks are defined as a broad term and can be replaced with the term uncertainties in this dissertation.

Risk is an endogenous attribute of a system.[77] It arises from the incompleteness of human knowledge about the environment and the conditions of its development, i.e. unexpected events.[78] Consequently, risk cannot be avoided. It can be measured by the probability and the consequence of not achieving a defined project goal. To identify risk accurately, its sources (the origins of risk) must be identified and clarified.

Discussions on the sources of risks in the transport/SC appeared in the 1990s.[79] In this dissertation, risk is classified into three categories on the basis of its origins, namely, risk related to the operation, organisation, and external environment. The first category is associated with either a focal company or a control system of the focal

[75] Cf. (Ivanov, et al., 2010)
[76] Cf. (Singhal, et al., 2011)
[77] Cf. (Heckmann, et al., 2015)
[78] Cf. (Vilko, et al., 2012)
[79] Cf. (Singhal, et al., 2011)

company, its SC partners, and so on. The second category is interpreted as the source of risk from the perspective of the transport chain. For instance, given that information technology (IT) plays a vital role in CT, the risk that originates from this area is often discussed in the literature. However, this type of risk cannot be divided into any specific operational process. Such a risk originates from the transport organisation. External risks are caused by environmental issues that are outside the control of either the transport chain or the agents in the transport chain. External risks are explained as the fourth category of risks.

3.2. Literature Review of Operational Risk

In terms of the place of origin in the operation process, risk in this category is further classified into three groups, namely, risk related to the consignor (manufacturer/supplier), to the carrier (railway/road shipper), and to the consignor (customer).

3.2.1. Risk Related to the Consignor

The consignor, which is the source of transported goods, is engaged in appropriate management to stabilise the transport chain at its origin. Uncertainty related to the consignor is also interpreted as supply risks, e.g., production capacity constraints, quality problems, and product design changes.[80] A low level of management in consignor organisation also contributes to transport risk. In the context of the transport chain, these uncertainties originate mainly from business processes and the control system within an entity.

The risk in the manufacturing process has been suggested as a source affecting timely order fulfilment.[81] This risk exists mainly in the lead-time of the production.[82] In the perspective of outbound transport, problems in the production process have significant effects on transport performance. Manufacturing problems (e.g., ineffective scheduling) or operational problems (e.g., machine breakdown) can delay product dispatch or cause a high rate of product returns. Operational problems in the storage process, e.g., poor inventory and order management, can affect the quality and create unnecessary returns.[83] Similarly, risks from the operation process can be affected by

[80] Cf. (Srinivasan, et al., 2011)
[81] Cf. (Davis, 1993)
[82] Cf. (Sabri, et al., 2000)
[83] Cf. (van der Vorst , et al., 2002)

the likelihood of full or partial loads being rejected by customers (hence decreasing customer satisfaction).[84]

An obvious trend of the current market is the just-in-time (JIT) strategy. On one hand, the JIT strategy contributes to a sharp reduction in inventory costs in the SC and mitigates potential delivery delays. On the other hand, the freight transport is highly sensitive to production with minimal decoupling points. Thus, freight transport is highly sensitive to production fluctuation, even to subtle ones, because the safety stock of manufacturers is too low.[85]

Some characteristics of specific products can increase the risk of SCs, e.g., innovative products in the fashion industry. Another instance is groceries, such as vegetable, fruits, and other perishable goods. They require air-conditioned transportation to extend storage time and control quality. In the case of defective cold storage in trucks, transportation can fail to satisfy customer demands.[86]

3.2.2. Risk Related to the Carrier

Providing a rail service requires locomotives, wagons, lane, signalling, terminals, and staff, e.g., train crews, rolling stock maintenance, and administration.[87] CT has high requirements in terms of real-time information sharing along the chain because of the integration of different transport modes. For instance, making a load plan for a cargo train (an assignment of weight distribution on the train) is important because the weight of the train needs to be directed toward the front of the train to reduce wear on the braking mechanisms.[88] When a truck arrives late, the original load plan becomes difficult to maintain because the drivers who arrived in advance do not know the exact delay-time of the others.

Risk can also arise from the lack of flexibility of transportation organisation, such as shipment, transport schedules, and vehicle configuration.[89] This phenomenon can result in delays in the delivery process and limit the opportunities to perform load consolidation within the distribution network. Given that it requires one additional packing move and additional time to complete the transportation service, double

[84] Cf. (Rodrigues, et al., 2008)
[85] Cf. (Datta, et al., 2011)
[86] Cf. (Van Dank, et al., 2005)
[87] Cf. (Nash, et al., 2008)
[88] Cf. (Corry, et al., 2006)
[89] Cf. (Seebacher, et al., 2015)

handling increases the number of containers stored in the terminal buffer.[90] Inefficient transport scheduling can cause unpredictable arrival times, thus negatively affecting the efficiency of depots. Rigid routing plans can require extra unnecessary capacity. In practice, a logistics service company sometimes fails to deliver in time because they cannot combine a transport with that of other customers. They would rather pay a penalty than deliver on time. This behaviour increases the risks of delay in CT.

Inefficient fleet management, which is reflected by poor vehicle utilisation or excess empty runs, can adversely influence transport operations.[91] The most suitable vehicles for the work may be difficult to source, particularly under highly specialised conditions.[92]

Risks can result from transport delays caused by technical reasons, such as defective vehicles or lack of drivers.[93] As locomotives are driven manually, a synchronised personnel plan plays a vital role in daily rail operations. Because of the constraints on the legal maximum, working time of a driver can delay journeys. Vehicles may need to wait for a replacement driver in the middle of the delivery process.[94]

3.2.3. Risk Related to the Consignee

Demand risk originates from a large number of sources, e.g., the seasonal demand of customer and mismatch between the forecasts and actual demand of a company. Demand uncertainty is viewed as the potential or actual disruption of product or information flows that exist between upstream actors and their end-customers in the transport chain.[95] Demand variation can result in capacity constraints at almost any point along the transport chain: origin, destination, or intermediate terminal. Such intermittent bottlenecks cause further the service reliability problem.[96]

The bullwhip effect is one of the most typical risks that originate from the demand uncertainty of the downstream tier in CT. End-customer demand fluctuation not only influences production process uncertainty, which affects timely order

[90] Cf. (Corry, et al., 2006)
[91] Cf. (Esper, et al., 2003)
[92] Cf. (Naim et al., 2006)
[93] Cf. (McKinnon, et al., 2004)
[94] Cf. (Lewellen, et al., 1998)
[95] Cf. (Christopher, et al., 2004)
[96] Cf. (McCarren, 2000)

fulfilment, but also lead to the fluctuation of transport volume, which aggravates uncertainties on the side of the carrier and consignor.

An accurate order forecast plays an important role in a stable transport chain. Other activities, such as purchase, production, and distribution, are arranged based on the forecast. The accuracy of the order forecast is closely related to the forecast horizon, i.e., a long horizon means significant inaccuracy and low reliability in forecasts because customer demand fluctuates.[97]

3.2.4. Organisational Risk

CT is characterised as a multi-agent system. Multiple criteria reflect the different requirements of various CT partners. These criteria include freight rate, delivery speed and reliability, flexibility, infrastructure availability and capacity, regulation/legislation, and so on.[98] Every participant has its own goals. The existence of multiple goals in CT leads to decision complexity, which is one of the most important sources of uncertainty.[99] Solutions would be not complicated to find if the number of goals and their multiple constraints decreases.

The relationship between partners is difficult to control because of possible goal conflicts. For instance, the collaborative relationship requires a voluntary investment of resources (e.g., capital, training, and consulting) by one or several of the partners for the common development of all partners in the long term. However, the investment can decrease the profit of the investors in the short term. From this point of view, collaboration increases the risk for partners.[100]

The partnership quality may improve the efficiency of the system because it affects organisational performance by promoting an efficient information/knowledge exchange, improving partner commitment, and enhancing collaboration, and by reducing the transaction costs associated with expensive monitoring mechanisms.[101]

Transport network management can be another significant source of risk.[102] A major cause of concern is the lack of effective information communication between

[97] Cf. (van der Vorst , et al., 2002)
[98] Cf. (Dullaert, et al., 2009)
[99] Cf. (Verbano, et al., 2013)
[100] Cf. (Miles, et al., 2005)
[101] Cf. (Srinivasan, et al., 2011)
[102] Cf. (Cavinato, 2004)

different actors with different transport modes.[103] For instance, limited communication in the ordering process can result in supplier overestimating the demand from customers.

Interactions between partners linked in a transport chain aggravate the influence of unexpected events. When forwarders attempt to integrate their transport work for different clients sequentially, major delays can be compounded, thereby significantly affecting clients toward the end of the work schedule.[104] Collaboration can also expose individual organisations to the risks of other partners and the transport chain itself, e.g., cultural difference.[105]

Investigations on the behaviour of top management teams suggest that senior managers play an important role in maintaining and balancing the relationship of a firm with its circumstances.[106] Changes in strategies in a firm can lead to internal uncertainties as well. Risks that originate from the behavioural perspective are excluded in this dissertation.

3.2.5. Risk Related to Information Technology

Given that IT is widely applied for communicational purposes, dependence on it has increased dramatically, particularly the widespread use of the Internet. However, the wide application of IT and the Internet also has downsides: IT risk increases organisational vulnerability because of the potential threat to the value of an organisation.[107] Inherent IT system failure, e.g., security incidents, will paralyse the business process in CT. Owing to the increasing complexity and reliance on IT and the Internet, the frequency of potential threats from such risks correspondingly increases.[108]

In practice, much data is in the hands of the private sector and is neither visible nor accessible. It further leads to intransparency of information in CT.[109] Incomplete access to relevant information thus leads to faulty planning for some participants in

[103] Cf. (Choy, et al., 2007)
[104] Cf. (Fowkes, et al., 2004)
[105] Cf. (Wittmann, 2000)
[106] Cf. e.g. (Janowicz, et al., 2006), (Beckman, et al., 2007) and (Gaur, et al., 2011)
[107] Cf. (Simangunsong, et al., 2012)
[108] Cf. (Smith, et al., 2007)
[109] Cf. (Caris, et al., 2013)

the transport chain. This phenomenon typically leads to unnecessary transport movement.

A system with high levels of collaboration is exposed to a significant amount of sensitive information and promotes security risks. To improve access to information, information communication technology (ICT) is widely used in CT.[110] However, the dynamic technological development of ICT is a major source of risk. The adoption and assimilation of ICT lead to considerable synergistic effects between social and technological developments.[111]

In addition to the risk discussed above, financial flow is also an important cause of uncertainties. Financial flow means the flows of cash between organisations, e.g., incurrence of expenses and the use of investments for the entire network and the settlements. The risks here include settlement process disruptions, improper investments, and no cost transparency in the entire network.[112] This source of risk is neglected in this dissertation.

3.2.6. External Risk

External risk arises from the complexity of the environment of an organisation, e.g., competitor actions (i.e., the interaction between members), technological innovation, consumer tastes and preferences (i.e., socio-political actions), and fluctuations in macroeconomic markets.[113] External uncertainties have significant effects on organisational processes.[114] Risks emanating from external sources, such as variations in key transport macroeconomics, demand unpredictability, and road congestion, is not under the control of the logistics partners.[115] Despite the modern advanced technology and risk management, the failure caused by such external uncertainties cannot be precisely predicted.

- Technological Change and Macroeconomic Fluctuation

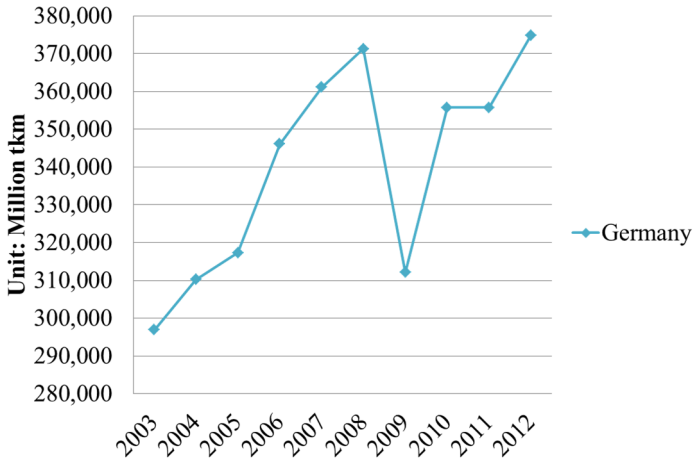
Technological innovations lead to the discovery and development of new products, services, and process opportunities in the market. Although participants in the network benefit from innovations, SCs have often been noted for anecdotal

[110] Cf. (Wang, 2012)
[111] Cf. (Zhang, et al., 2011)
[112] Cf. (Rangel, et al., 2015)
[113] Cf. (Verbano, et al., 2013)
[114] Cf. (Gaur, et al., 2011)
[115] Cf. (Rodrigues, et al., 2008)

examples of how they constrict or prevent innovation.[116] A major cause of concern is the high investment involved in the replacement of current equipment and products. Employees also need time and effort to adapt to innovations. In the worst-case scenario, the innovation can cause structural unemployment, i.e., employees lack the skills needed for the innovations. From the perspective of a well-developed industry, innovations can cause risks, particularly on the level of strategic management.

Another main concern that results in an unstable transportation volume results from macroeconomic fluctuations. In the last major worldwide economic crisis in 2009, the quantity of freight transported decreased by approximately 16%. A loss of approximately 59 million tons of commodities solely on the railway network in Germany was incurred in comparison with that in 2008.[117] Figure 14 shows a noticeable decline in German transportation volume in 2009.

Figure 14: German transportation volume from 2003 to 2012[118]



A good economic situation promotes freight flows. For instance, the largest share of Chinese rail freight can be found in Asia and Oceania, followed by North America and Russia. China represents approximately 70% of rail-freight transport performance throughout Asia and Oceania, i.e., an enormous share with over 2400 billion ton-km in 2010 with an upward trend.[119] Such a performance benefits from the continued strong economic growth in specific regions.

[116] Cf. (Cavinato, 2004)
[117] Cf. (Statistisches Bundesamt, 2010)
[118] Cf. (eurostat, 2014)
[119] Cf. (UIC - International Union of Railways, 2011)

A number of authors have stated that fuel prices vary the transportation costs[120], which further results in logistic uncertainty. For instance, in the case of high fuel prices, the strategy of a distribution centre with a high inventory level is needed in the network because large quantities are shipped to decrease the unit transportation costs.[121]

- Political Policies

Changes in political policies may affect the activities involved in transportation. For instance, country boundaries, such as mountains, cause environmental worries and slow speeds in any case. Due to these concerns, both Switzerland and Austria limit transalpine truck movements in their countries. As a result, border-crossing intermodal road-rail transport has a large market share across the Alps. Between Italy and Belgium, 50% of goods flow is performed by intermodal road-rail transport.[122]

Considering the heterogeneity of administration in EU countries (see section 2.1.2), and depending on the respective national regulations, railway operators should work together with government agencies or ministries either comprehensively in the planning, construction, and operation of roads or in individual sections of the infrastructure, such as bridges or highway segments.[123] This decoupling of railway infrastructure operators and cargo train operators leads to irregular and opaque information flow.

Given that rail-based transportation largely depends on the support of government and other policymakers, e.g., government intervention on employment and investment is another key source of uncertainty for the rail operating environment.[124]

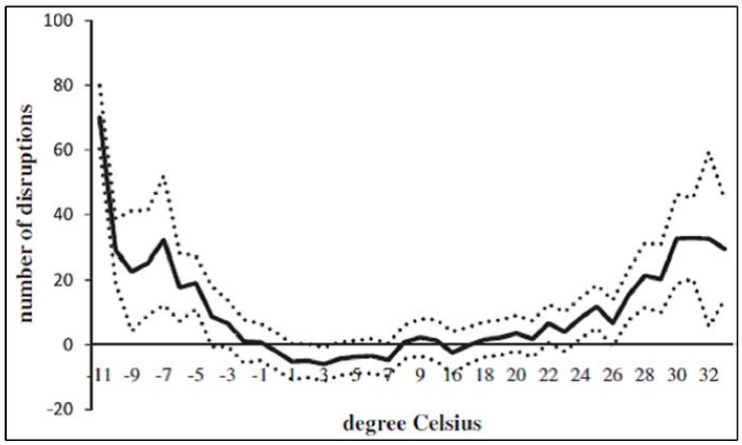
- Environmental Risk

Bad weather conditions, such as cold weather, wind, and fog, can cause significant train delays. The rail infrastructure is exposed to weather-generated risks. For example, tracks can become deformed because of extraordinarily high temperatures, which can cause the uneven expansion of steel. Similarly, the derailment of the rail basement is common in winter because extremely low temperatures lead to brittle tracks and track separation. A study on the Dutch rail network indicates that the

[120] Cf. e.g. (Simchi-Levi, et al., 2009) and (Christopher, 2011)
[121] Cf. (Simchi-Levi, et al., 2009)
[122] Cf. (Jonsson, 2008).
[123] Cf. (Boldt, 2009)
[124] Cf. (Nash, et al., 2008)

number of deformations in the rail network increases with extreme temperature events (temperatures higher than 23 °C or lower than −3 °C) (Figure 15). [125]

Figure 15: Effect of temperature on track disturbances[126]



CT is exposed to environmental influences that are to some degree predictable. The extent of such environmental influences can be estimated in advance. However, this process is difficult. In addition to extreme weather events, disasters, such as earthquakes and volcanic eruptions, can also devastate transportation infrastructures and entire SCs. Natural disasters/accidents (earthquake, floods, excessive snowfall, etc.) are one of the most typical external uncertainty factors. Unforeseeable disruptions, such as natural disasters, strikes, accidents, and terrorism, also occur. Thefts, structural damage, and terrorism are also common external risks that can also increase the likelihood of freight disruption. Regarding the empirical data from international insurance, the damage and spoilage of goods alone account to 3%–4% of inventories.[127]

3.3. Case Studies: Punctuality of Train in Germany

All the risks discussed in the previous subsections are located within a broader theme and examined from an inclusive point of view. The subsections focus on the uncertainties that affect logistic performance, e.g., costs and time. Given that costs will not be discussed in this dissertation, the scope of the case study is restricted to delivery time, i.e., punctuality of transport.

[125] Cf. (Xia, et al., 2012)
[126] Cf. Ibid
[127] Cf. (Ivanov, et al., 2010)

3.3.1. Definition

In the literature punctuality has two definitions. The first definition involves statistical random distribution and considers how much the journey time fluctuates around the mean value over a certain period. This scattering can be analysed based on various statistical variables (e.g., variance and standard variance). The second definition of punctuality considers both the planned (scheduled) and actual arrival times. Punctuality measures the difference between the two types of arrival times. In case the actual arrival time deviates from the planned one, a delay occurs.[128]

The second definition is applied in this dissertation. Punctuality can be expressed as the extent in which the actual arrival time agrees with the planned time of arrival. Despite the available technical tools in scheduling, the meticulous planning of transport is difficult. To achieve meaningful results in the analysis of punctuality in rail freight transport, a tolerance range must be defined for a low scatter of the target numbers. Thus, punctuality in this thesis will be considered as a train arriving at the destination after the pre-agreed arrival time but the time the train is overdue must be within a specified interval of minutes.

It should be explicitly noted the delay includes both early and later incoming shipments, as both directly impact the capacities of the destination/railway station, e.g., overload of the station and consequent blockages in the railway network. The early delivery of a cargo train occurs more seldom than the later ones, thus the case of early shipment is neglected in the dissertation.

Many researchers use the expression “time reliability” for punctuality.[129] In other words, punctuality is treated as an aspect of reliability. Therefore, punctuality is examined as a separate feature in this thesis. Punctuality is emphasised, along with the anticipation of unexpected events during transportation, to enhance the reliability of the railway transport.

3.3.2. Measures of Train Delay

Punctuality requires up-to-date information on the current status of a railway network. The measurements of punctuality fundamentally differ, e.g., the mean versus variance approach, percentiles of the travel time distribution, and scheduling model.

[128] Cf. (SIGNIFICANCE, GOUDAPPEL COFFENG und NEA, 2012)
[129] Cf. e.g. (van Lint,, et al., 2008), (Kaparias, et al., 2008) and (van Loon, et al., 2011)

In the model, only the difference between the is- and should-time is calculated and expressed in minutes. The advantage of this method is its provision of real-time information on the status of a railway that may be accurately communicated to all concerned participants.[130]

For freight transport, only the arrival time of the trains is relevant while generous buffering time must be considered, e.g. personnel change. Those activities can cause massive temporal deviations between the is-time and the scheduled time.

The scheduling model is used by German rail operator DB Netz to report the annual punctuality of trains. The definition of punctuality is closely related to the type of transport. DB Netz identifies two different types of delays: one applies to a passenger train and the other to a freight train.[131]

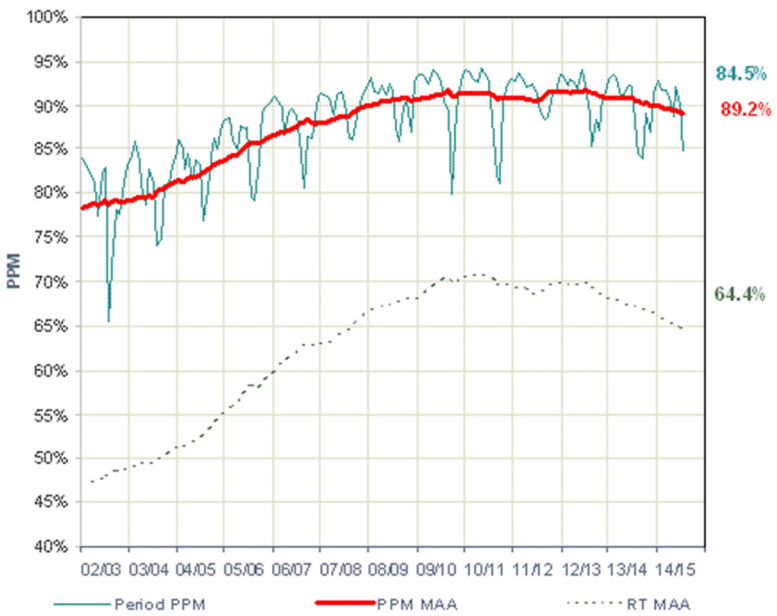
- A passenger train is considered on time if the difference between the actual arrival/departure time and scheduled time is less than 5 minutes and 59 seconds, i.e., the scheduled time plan of trains contains a tolerance of delay (time window).

- A cargo train is considered on time if the difference between the actual arrival/departure time and scheduled time is less than 30 minutes and 59 seconds.

The punctuality of a train is interpreted differently across countries. For example, Network Rail, the British railway operator, established a system of key performance indices to measure the punctuality of trains. As shown in Figure 16, punctuality in the latest period is 84.5%, and its moving annual average (MAA) is 89.2%. The results show that the punctuality is being continuously improved.[132]

[130] Cf. (de Jong, et al., 2004)
[131] Cf. (DB, 2014)
[132] Cf. (Network Rail, 2017)

Figure 16: Punctuality rate of British Rail in 2002-2014[133]



- Public Performance Measure (PPM): measure of train punctuality. Punctuality is defined as a train arriving with an eventual delay within less than 5 minutes for commuter services and less than 10 minutes for long-distance transport.
- Right-time performance (RT): the measure shows the percentage of trains arriving at their terminating station early or within 59 seconds of schedule.

In practice, European railways are typically operating according to a master timetable. The railway traffic is governed by a timetable, in which the running time of a train over a network is matched with others to ensure a conflict-free travel. In addition, time buffers are installed to meet expected delays, such that a slight delay does not directly disturb the original schedule. The timetable ensures the coordination of train paths and slack time to handle train delays. In this dissertation, this kind of delays are neglected because they are already contained in the timetable.

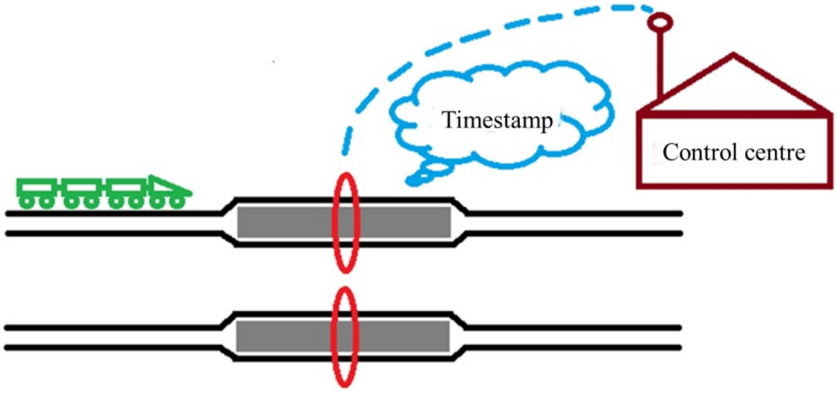
3.3.3. Technical Support for Measuring Punctuality in German Railway Network

All railway stations have control centres to measure the driving time of the trains. The message is sent back to a reception point, which is usually located at the station. As illustrated in Figure 17 every train, including trains arriving and passing through the station, receives a so-called "timestamp," which is the actual arrival time.

[133] Ibid.

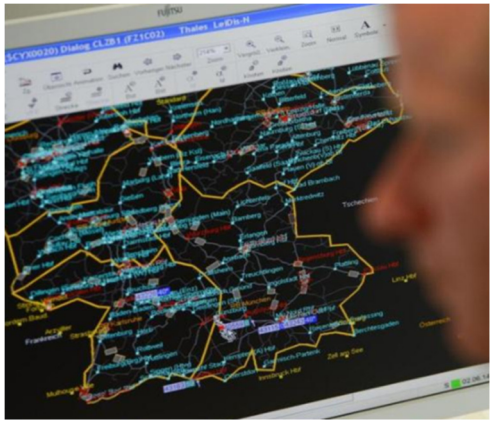
Timestamps are automatically forwarded to the control centre of DB Netz,[134] where the message sent back is compared with the scheduled time. With few exceptions, the technical measure of punctuality is automatically performed by the DB Netz.

Figure 17: Time measurement points



The control centre of cargo trains for DB Schenker is in the European Operations Centre (EOC) in Frankfurt (am Main). About 200 employees are employed to watch the current traffic status on the rails on large screens (see Figure 18). Owing to the great importance of time analysis and sharing it with their partners, the EOC is staffed 24 hours a day, 7 days a week.[135]

Figure 18: Computer work in EOC of DB Schenker[136]



[134] Cf. (Günther, 2010)
[135] Cf. (Frankfurter Allgemeine Zeitung, 2014)
[136] Ibid.

3.3.4. Delay Reasons in Railway Transport

Many reasons can influence the punctuality of trains and cause delays. Generally, delay reasons can be divided into three types: operational, infrastructure, and external causes.

- Operational Causes

Operational factors are related to the organisation and planning of trains.

- Time plan

Time plan involves two types of planning: the planning of timetables (long-term planning) and scheduling of trains (short-term planning). In long-term planning, many factors are considered, such as available rail lines, and legal and political conditions. The planning process often begins a year before it is implemented.[137] By contrast, short-term planning includes the determination of the availability of freight cars, locomotives, train drivers and their working plans, the reservation of the rail lines, etc. From this perspective, a time plan is resource management. All resources, which are needed to produce the time plan, must be coordinated and efficiently used to enhance the utilisation of the resources.

- Route planning

In practice, a train operator applies the traffic principle of dynamic routes. However, dynamic routing requires easy access to track infrastructure via either general slack capacity or dummy slots booked in advance. Lane access plans are currently updated about twice a year. Because of the increasing number of operators, dynamic allocation of slots is complicated. The operation of a cargo train should, therefore, be responsive to disturbances.[138]

- Knock-on delays

Direct delays are a consequence of delays of the train itself and/or the logistics process, e.g., slight delays because of transhipment at a terminal. These delays are independent on the result of other trains on the same line. When the delay of a train is transmitted to other trains, knock-on delays occur. Knock-on delays are caused by the delay of another train/other trains in the system. (The combination of direct and knock-

[137] Cf. (Quintiq, DB Schenker Rail, 2013)
[138] Cf. (Woxenius, et al., 2013)

on delays is called compound delay.) In practice, a maximal tolerant time window of 15 minutes is acceptable.[139]

- Overload of railway network

Plans must constantly adapt to changes, e.g., the available lines are occupied if unscheduled. Another problem in planning is lack of comprehensive consideration of resources and demands in the network. It often leads to peak loads, which limits the capacity of the infrastructure. Thus, a bottleneck or jam occurs, thereby causing delays of rail transport.

- Customer demand fluctuation

The departure time of rail line haulage is determined strictly by time-coordinated transportation, i.e., departure times of cargo trains should match the demand. Timetables are based on efficient time utilisation of rail rolling stock. They would face difficulties if the demand is not high enough for a given filling rate of a train.[140] Those difficulties would further cause transport fluctuation. If the demand for transport is not managed in a holistic and collaborative way, issues such as empty running, delivery delays, and low transport capacity utilisation are likely to arise.[141]

In reality, modern railway logistic service systems provide customised services, e.g., individual shippers can use unit trains. In most cases, such logistic services include long-term contracts, which imply that demand is deterministically known. (Unlike deterministic demand, stochastic demand is characterised in truckload trucking and for-hire ocean shipping.[142]) Therefore, demand uncertainty for railway service is less volatile than as theoretically asserted.

- Other operational causes

Considerable uncertainties exist in loading train and crew handling, e.g., failure by the track switch, lack of staff and late train handover affect train departure from stations. Usually, at a terminal or shunting yard, a train requires enough time to turn, thus the departure of the following train does not compensate for a late arrival.

[139] Cf. (Boldt, 2009)
[140] Ibid.
[141] Cf. (Seebacher, et al., 2015)
[142] Cf. (Crainic, et al., 2007)

Technical issues in locomotives or train cars can cause a delay or absence of the train. For instance, a passenger train would suffer from delay because a door cannot be closed correctly, and the train is not permitted to travel.

- Infrastructure Causes

- Failure of rail connection

Rail connections are parts of a track that serve as junctions and permitting trains to manoeuvre from one line to another. The railway station and railroad yard are typical rail connections. Rail connections fail for various reasons: clogging caused by debris or ice, failure of the drive mechanism, and exceeding the operating tolerances because of extremely hot/cold weather. For instance, on November 11, 2011, a connection failure caused massive delays in London.

- Signal power failure

The electric supply of the railway signal system can fail for various reasons, such as power cut-off or a blown fuse within the circuit. The signal system is a fail-safe mechanism: once the power fails, the signals turn black. When the driver cannot see a green or yellow signal, they must stop the train. Signal power failure can cause delays to all the trains on the same line in the signal system.

- Track circuit failure

A rail network is split into sections, each of which contains an electric circuit which carries out an important function: they permit signallers to “find out” where the train is. The track circuit is designed to ascertain that trains have a safe distance that separates them. Whenever a track circuit fails, the trains must be stopped until alternative signalling plans are introduced, or the issue is fixed. Track circuits can fail for numerous reasons. Track circuit failure can cause massive delays and even accidents.[143]

- Broken lines

The steel rails in the railway track are resilient and strong and can safely carry hundreds of tons of traffic over their lifetime. Rails may have small defects created by the manufacturer or through installation or they are created as trains pass. These small

[143] Cf. (China Real Time, 2011)

defects can grow into serious problems as trains travel over them and they consequently lead to rail interruptions.

Most damages on rails happen during winter when rails could be 5 °C colder than the air temperature, thereby putting the rails under significant tension from trains making the rails susceptible to breaking in defective areas when trains travel over them.

During summer, rails under direct sunlight are often almost 20 °C hotter than the air temperature. As rails are made of steel, they expand when they warm up and are therefore susceptible to strong compression. When a track buckles, the line should be closed until the track is repaired. In such a case, a massive delay occurs. To reduce the risk of buckled rail, local speed restrictions are applied, slower trains impose smaller forces on the rail. However, speed restrictions also cause delays.[144]

- Overhead line problems

Overhead line equipment refers to the cables and supporting infrastructure that carries electricity at 25,000 volts to power electric trains. Generally, two kinds of problems may occur, power supply failures and mechanical failures. Power supply failures - electric trains cannot run (but diesel trains can continue to use the track). Mechanical problems, such as if a wire is lower or parts are displaced from the gantry, no trains can run before the damaged devices are removed. (However, diesel trains can go through.)[145] Sometimes failure is serious, for instance when the wires are lowered because of a falling tree, the repair is much more complicated and takes additional time to fix.

- Breakdown of telecommunications

Railway services progressively depend on complex telecommunication systems. Train motorists and signallers communicate using global system for mobile communications-rail (way) (GSM-R), a high-performance mobile communication network, which is also utilised by the signalling system to bring signals into the train cab. If communication breaks down, signallers and train drivers are unable to ensure the line is free from trains or obstructions, and all affected trains should stop for security purposes.

[144] Cf. (London Evening Standard, 2013)
[145] Cf. (Woodman, 2013)

The GSM-R radios in the train cab may sometimes break down or fail to connect to the network, thus requiring the ratios to be reset. In addition to delaying one train, telecommunication breakdown can have knock-on effects on other trains. Sometimes the failure of the communication system can lead to accidents.[146]

- Construction works

Engineering works are big-scale enhancements on the infrastructure. Examples of engineering work include track and bridge replacements. Some maintenance work, such as daily upkeep of tracks, signals, power supplies, and other infrastructure, require the closure of the associated tracks. During construction, trains cannot run. Even trains on other tracks may face special speed restrictions and thus cause delays and even cancellations.[147]

- External Causes

External causes (i.e., personal, weather, or seasonal factors), which occur outside the railway system, include the following:

- Landslip

Soil and rock falling on the track can derail a train. If the ground becomes saturated, the earth becomes heavier and this can lead to a landslip. Whenever a landslip happens, trains in the affected region are unable to manoeuvre, resulting in rerouting or cancellation of services. A landslip can force a line to be shut down. The repair work can even cause delays or cancellations to the trains in other lines because of the temporary speed restriction in the area.

- Strikes

Machines are subject to failures or breakdown, so do rail-employees. Personnel might make mistakes or even stage strikes. Strikes became common during the Industrial Revolution and are still very popular at the present. Generally, even small-scale warning strikes in the rail may cause massive delays in the affected area, and large-scale strikes lead to large-scale delays, cancellations, and chaos.[148]

[146] Cf. (The Sedney Morning Herald, 2014)
[147] Cf. (George, 2014)
[148] Cf. (The Lokal de, 2014)

- Vandalism and trespassing

If somebody is on the rail or on the rail embankment, all the trains in the vicinity must stop to ensure the safety of the passengers, train crew, and even the trespasser. This may cause delays to related trains. These delays may further have a knock-on effect on other trains. Sometimes the infrastructure of the rail may be damaged by vandalism. Vandalism includes graffiti, litter, fly tipping, and damage to fences, signs, and tracks which make the rail unsafe and forcing trains to stop.[149]

- Bad weather

Although technical measures are taken to predict a natural disaster, its negative influence cannot be avoided. A recent example is the 2014 flood in southwest England, which contributed to week-long failures in rail transport.[150] The effects of an extreme natural event on the transportation chain are not geographically restricted. Owing to the globalisation of the transportation chain, vulnerability to failures in one region can expand into several countries and continents.

- Other external reasons

Fatalities in railways are associated with trespassing, accidents, and rail suicides. From 2008 to 2011 Germany and France continuously have the first and second highest rate of suicides in railways.[151]

A railway network faces a higher likelihood of fires, which normally occurs on warm and sunny days or is caused by cigarettes thrown out of the train. Fires can be caused by an electrical short circuit or even arson. Smoke from the fire can decrease the visibility of the burning area, making it difficult to fight the fire.[152]

Thievery of railway facilities, e.g., tracks and electric wires, is really a huge problem. Thieves target signalling cables, overhead power supply lines, and fences to sell as scrap. Such theft results in extended delays when the damage is identified and repaired.[153]

The three main categories of delay reasons are responsible for almost all train delays in Germany. According to a statistical report, up to 40% of the disturbances to

[149] Cf. (Burn, 2014)
[150] Cf. (Western Morning News, 2014)
[151] Cf. (Chalabi, 2013)
[152] Cf. (Adkins, 2013)
[153] Cf. (Amos, 2014)

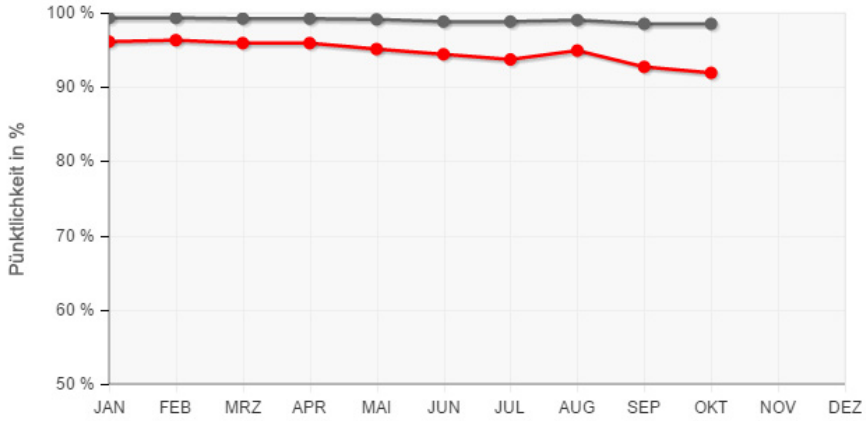
punctuality in the rail system may be traced back to operational causes. By contrast, infrastructural causes account for about 30% of delays, mostly caused by defective signalling systems and repair work on railway tracks and power supply.[154]

A strict categorisation of reasons for delays is, in some cases, not very useful, as they may be a combination of organisational, infrastructural, and other causes.

3.3.5. Status Quo: Punctuality of Railway Transport in Germany

As illustrated in Figure 19, DB Netz categorised punctuality into two categories, 5-minute (min) punctuality, and 15-minutes punctuality. If a train is delayed by less than 6 min, it is still considered punctual in both categories. However, if a train has a delay of 6–16 min, it is considered delayed in the 5-min category but punctual in the 15-min category. The latest numbers on recorded punctualities in the 5-min and 15-min categories are 91.9% and 98.5%, respectively. [155]

Figure 19: Punctuality rate of German Rail from Jan to Oct 2014[156]



	JAN	FEB	MRZ	APR	MAI	JUN	JUL	AUG	SEP	OKT	NOV	DEZ
5 min Pü	96.1	96.3	95.9	95.9	95.1	94.4	93.7	94.9	92.7	91.9		
15 min Pü	99.3	99.3	99.2	99.2	99.1	98.8	98.8	99.0	98.5	98.5		

* Pü: Punctuality

The Stiftung Warentest, a German consumer organisation has calculated punctuality in a different way and has generated different results of punctuality.[157] The Stiftung Warentest recorded punctual and delayed trains in Germany, and delays caused by labour strikes are not included.

Figure 20 is based on the data of 496,129 actual arrival times of long-distance trains (IC, EC, ICE, and City Night Line) in 20 train stations. Trains belonging to the

[154] Cf. (BSL Management Consultants of the Lloyd's Register Group, 2008)
[155] Cf. (DB, 2014)
[156] Ibid.
[157] Cf. (Stiftung Warentest, 2011)

5-min punctuality category account for 67%, which is lower than the records of DB Netz show. About 11% of the delays are more than 20 min, thus trains belonging to the 15-min punctuality category are less than 89%.

Figure 20: Statistic of long-distance trains from Stiftung Warentest[158]

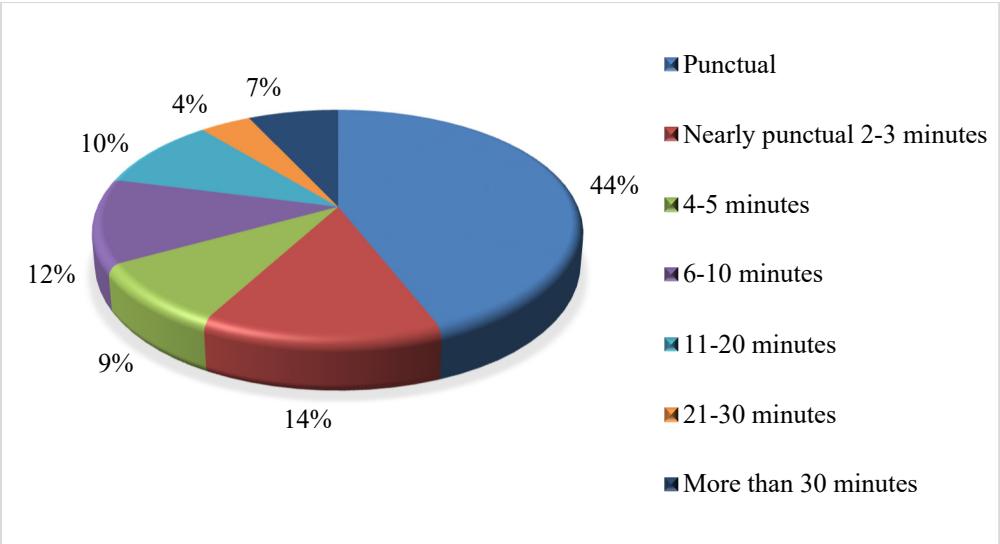
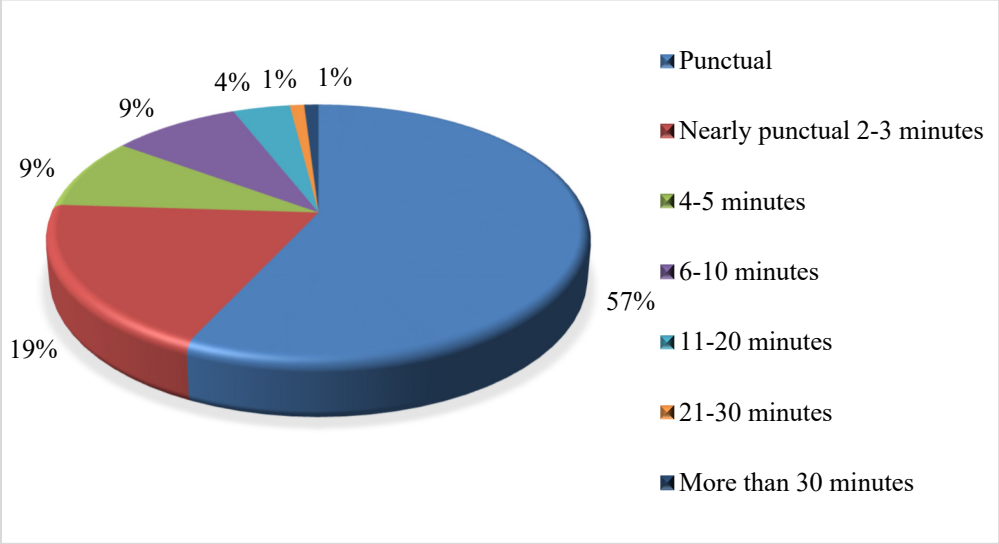


Figure 21 is based on the data of 580,977 actual arrival times of long-distance trains (IRE, RE, and RB) in 20 train stations. The trains recorded under 5-min punctuality reach 85%. Only 5% of the delays are more than 10 min.

[158] Cf. (Stiftung Warentest, 2011)

Figure 21: Statistic of local trains from Stiftung Warentest[159]



According to statistics from Stiftung Warentest, delays happen more often than those provided by DB Netz. German rail transport has assessed its punctuality over-optimistically.

3.4. Intermediate Conclusion

A large body of literature has analysed the different sources of risks and their impacts on CT performance. All the risks explained in the previous sections are summarised in the followed table:

[159] Ibid.

Table 3: Risk classification

Risk origins	Classification	Risks
Operational Risk	Risk related to consigner	• Fluctuation in value-added activities • Production strategy • Characteristics of specific products
	Risk related to carrier	• Insufficient coordination of transportation • Lack of flexibility of route planning and scheduling • Inefficient fleet management • Technical faults on locomotives, trucks and railway infrastructure
	Risk related to consignee	• Fluctuation of demand of the customer • Mismatch between the forecasts and actual demand • Bullwhip effect
Organisational risks	Multi-agent system	• Multi-criteria and multi-goal conflict • Partnership quality • Limited information sharing
	Transport network management	• Inefficient information communication • Interaction between cooperating partners • Vulnerability to the risks of other partners • Behaviour of management
	IT	• Dependency on IT • Barriers to information sharing • Security of data
External risks	• Technological Change and Macroeconomic Fluctuation • Political policies • Environmental Risk	

Examining the literature review, many challenging and long-standing problems are closely related to the risks. Some types of risks include elements that are predominantly operational in nature (e.g., demand variability, lead-time variability, supply delays, order cancellations). Hence, such risks can usually be estimated. By contrast, some types of risks are beyond control and difficult to anticipate, e.g. natural disaster.[160] Such risks are considered unexpected changes affecting the transport process.

[160] Cf. (Srinivasan, et al., 2011)

Risks are impossible to avoid as they are the inherent feature of a system.[161] Given the endogenous characteristics of railway transport, its scheduling suffers from the vulnerability of the transport process; thus, the delivery time of the cargo train is always out of control.[162] Such vulnerability result out of the inefficiency of processes and non-value-adding activities (e.g. double handling). Furthermore, railway transport is combined with cargo trucks for pre- and post-haulage. This increases the complexity of the logistic system,[163] which discourages decision-makers to chose cargo train for goods transportation.

Thus, to enhance the competitiveness of CT in the logistics market, the decision-making process should be simplified. Scholars have proposed many theories and models to assist decision-makers to explore solutions effectively and efficiently. For example, decision-makers can access accurate information in a short period using a decision support system. In the next chapter, a decision support system is introduced. With this system, the complexity of the decision-making process for CT operations can be reduced.

[161] Cf. (Verbano, et al., 2013)
[162] Cf. (Schöbel, 2006)
[163] Cf. (Christopher, 2011)

4. Decision Support System for Combined Transport

As discussed in the previous chapters, uncertainties and risks in CT arise more frequently in CT than that in mono-transport. As a result, CT is losing its competitiveness with mono-transport. Therefore, forecasting of risks and estimating the influence is an effective tool to enhance the service of CT. However, given that CT is a complex system, participants should consider various decision-making aspects (e.g., goal conflicts due to multi-agents and information sharing in multi-agents). Predicting risks alone is insufficient in enhancing the effectiveness of the decision making of CT. The decision support system (DSS) is introduced as the framework in this chapter to explain the principles of the decision-maker support system in CT as a whole. As a fundamental component that supports decision making in CT, risk prediction is separately explained in Chapter 5 and Chapter 6.

In this chapter, the background of DSS is first introduced to understand and adapt to uncertainties in CT. Second, fundamentals and the working processes of DSS are explained. In this subsection, the feature of dynamic decision-making is emphasised as well. Finally, an example of DSS, Transport-Suite, is presented to explain specifically functionalities of DSS.

4.1. Application of Decision Making System in Combined Transport

4.1.1. Background of Decision Support System

Due to the high uncertainties of CT, a decision-maker is used in certain situations: Solutions to some problems in CT are vague or the priorities of the solutions are too complex to be identified. Such problems are defined as less-structured problems. (In contrast, the well-structured problems have definitive solutions.)[164] Optimal or satisfactory solutions to less-structured problems are either rarely available or a procedure to obtain them is unknown.

The less-structured problems are a direct result of uncertainties in CT. To cope with the less-structured problems, Gorry and Scott-Morton first proposed DSS in the early 1970s. They interpreted DSS as a correlated computer-based system that

[164] Cf. (Turban, et al., 2011)

provided solutions through data and models that allow decision-maker to solve less-structured problems.[165] Nowadays, DSS is widely applied for diverse aspects of supply chain (SC) management for inter-organisational operations, such as production planning and scheduling, [166] and intra-organisational management, such as manufacturer-customer relationship management[167].

Although there is no present consensus on the definition of DSS, two concepts highlight its objectives: Decision-makers can solve managerially or organisationally less-constructed problems more effectively and efficiently than without the DSS.[168] DSS enhances the flexibility of CT because the users can promptly adapt to uncertainties. Along with this objective, in this dissertation, DSS is defined as a computational assistant of decision- makers for less-structured problems.

4.1.2. Literature Review of Decision Support System

The DSS presented in this dissertation is generally a simulation-based tool. Hence, the literature review in this section focuses on DSS for intra-organisational management of SC/CT in the last decade.

Researchers desinged two agent-based DSSs for a manufacturing SC and a service SC. By comparing the results of DSSs, decision-makers in the SC benefit in several respects by using DSSs, such as conducting a what-if analysis and improving communication within and between participants in SC.[169] It was demonstrated that a web-based DSS can provide agile and flexible support for the operation in SC management.[170] Through a case study of a Brazilian manufacturer in the oil industry, it was proven that DSS meets the coordination requirements of SC partners along with constraints imposed by a given collaboration problem.[171] The export flows of freights between a dry port and a seaport were tested and analysed on the basis of discrete-event simulation and optimisation modules in a DSS. Simulation results demonstrated that the DSS has a considerable potential for freight transport efficiency and real-time management.[172] A model is established by imitating the process of a target system. By

[165] Cf. (Gorry, et al., 1971)
[166] Cf. e.g. (Hernández, et al., 2013) and (Vinodh, et al., 2014)
[167] Cf. (Carvalho, et al., 2014)
[168] Cf. e.g. (Turban, et al., 2011) and (Ngai, et al., 2014)
[169] Cf. (Hilletofth, et al., 2012)
[170] Cf. (Carvalho, et al., 2014)
[171] Cf. (Küpper, et al., 2015)
[172] Cf. (Fanti, et al., 2015)

inputting stimuli, the model yields different simulation results, which are used for the analysis to estimate the target system.[173]

Risks in freight transport were specifically studied. A DSS was described to study the effects of uncertainties on several global SC aspects.[174] The researchers applied two mixed integer programs along with a simulation model. A DSS was specified to manage intermodal logistics operations by countering delay and delay propagation. A dispatching control model was established to determine if each ready outbound vehicle should be dispatched immediately or held-back to wait for some late incoming vehicles.[175] A DSS was focused to assess risks in multimodal green logistics. The DSS quantitatively evaluates the risk of the unexpected events, e.g. accidents, freight damages, and logistic political changes. In the DSS, models of failure mode and effect analysis, analytic hierarchy process, and data envelopment analysis were applied.[176] In addition, a DSS was designed for transporting hazardous materials. To prevent accidents during transportation and mitigate their effects, risks of transporting hazardous materials were estimated in the DSS. Their study proved that the DSS could assist decision-makers to identify solutions to prevent/manage accidents.[177]

Application of DSS in diverse SC areas has been studied by academic researchers. Various mathematical models were presented and simulated. Risks in IMT/CT have been seldom considered and discussed. Furthermore, the studies were too complex for quick understanding. For non-expert DSS users, studies which provide a quick understanding of sophisticated circumstances in freight transportation with risks (e.g. train delay) are lacking. In the dissertation, a DSS is designed to provide decision-makers with solutions in the area of freight transport.

4.2. Conceptual Framework of Decision Support System

In principle, DSS aims to accelerate decision making under hazards circumstances in CT. To facilitate DSS as an effective system for less-structured problems, the fundamentals of DSS are defined in this subsection.

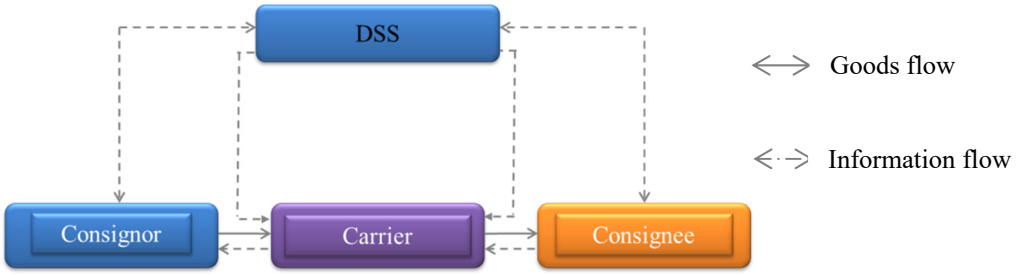
[173] Cf. (Rai, 2016)
[174] Cf. (Acar, et al., 2010)
[175] Cf. (Chen, et al., 2016)
[176] Cf. (Kengpol, et al., 2016)
[177] Cf. (Torretta, et al., 2017)

4.2.1. Integration of users in Decision Support System

Arranging a transporting task in CT is identified as a complex problem that involves multiple objectives and multiple agents to be satisfied simultaneously, e.g., maximisation of transhipment, device utilisation, and minimisation of waiting time.[178] After stripping away the physical movement of goods in CT, only one element is left, information.

From this viewpoint, the DSS in the dissertation concentrates on the role of information along the transport chain. As illustrated in Figure 22, users are integrated and supported through DSS in their operational tasks.

Figure 22: Integrated transport chain[179]

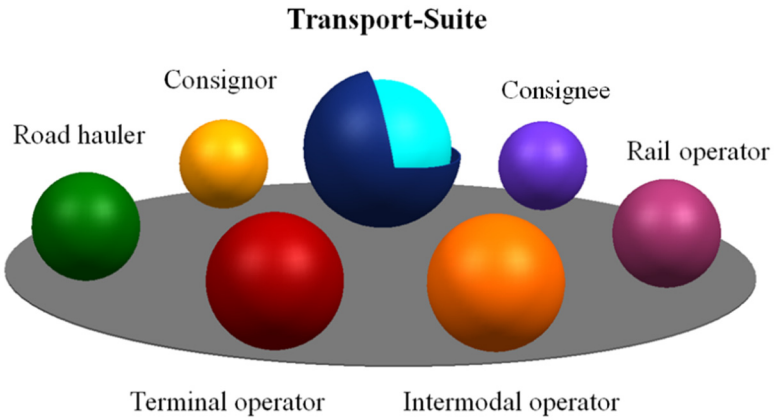


Traditionally, an organisation only engages in its own business and operates its deliveries according to orders, such as order and goods information, transport routes and timetable data.[180] Information is often asymmetric between consignor, carrier, consignee, and other participants of the transport chain.[181] In contrast, DSS allows all partners to jointly gain a clear understanding of the transport processes and develop efficient and effective plans. Empirical studies have shown that collaboration crucially contributes to the reduction of transport chain cost, as well as performance optimisation.[182] Thus, the decision space is extended, ranging from an analysis to an expert system for possible alternatives.

Users with the same function are treated as an echelon in DSS, i.e., a horizontal association. Figure 23 shows an example of the main users in Transport-Suite (Transport-Suite is a DSS, which is introduced in Chapter 4.3).

[178] Cf. (van Donk, et al., 2005)
[179] Cf. (Rodrigues, et al., 2008)
[180] Cf. (Márquez, 2010)
[181] Cf. (Küpper, et al., 2015)
[182] Cf. (Smith, et al., 2007)

Figure 23: Users in Transport-Suite



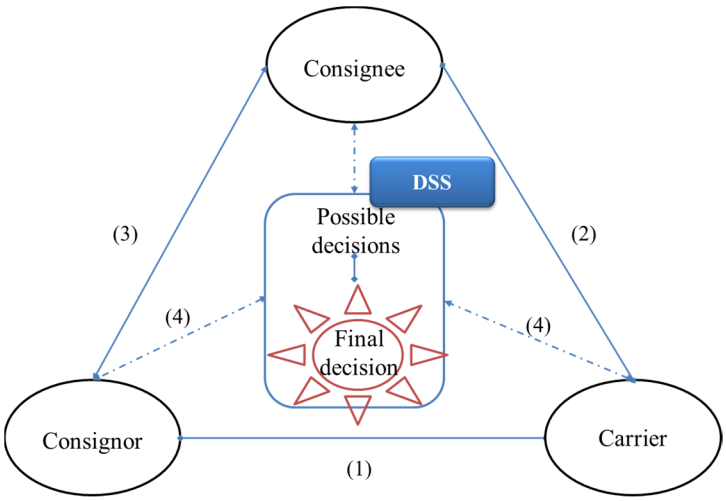
As illustrated in Figure 23, users are integrated and supported through Transport-Suite in operational level of tasks. (From a logistic practical viewpoint, smoothing a large amount of material and information follows the strategic (e.g., network design), tactical (e.g., the assignment of products to facilities), and operational (e.g., day-to-day scheduling) levels in an integrated transport chain.) [183] The information used in the process of transportation is symmetrised for all users in the DSS, so that the risks in CT could be reduced.

4.2.2. Decision Cycle of Decision Support System

Day-to-day tasks require participants to perform immediate decisions to spontaneous changes in CT, e.g. revisions of already established routes and schedules. [184] To fulfil the requirement, DSS is designed as a dynamic system to encounter the challenges in the operational management. Figure 24 shows the dynamic decision cycle of DSS. As an intelligent system, the system starts with the data where the information of transported items is accurately collected, at the consignor (1). In DSS, the information is analysed and possible options are provided (2). As soon as the consignor chooses the final decision (3), the collected data is then sent to the carrier and consignee (4). After the transport order is created, the goods will be delivered from consignor via carrier to the consignee.

[183] Cf. (Stadtler, 2011)
[184] Cf. (Kelleher, et al., 2003)

Figure 24: The decision cycle of DSS[185]



To plan and schedule ongoing processes and a response to unexpected and evolving circumstances, the latest transport data should be available for the actors in CT.[186] By an accurate data exchange in real-time, the planning of the transport process can be optimised.[187] In other words, intelligently managing information with less latency can be concluded as a core competence for market entities.[188] Therefore, information sharing plays a key role in real-time decision making to reduce the influence of uncertainties in CT. In the following section, information sharing in DSS is explained.

4.2.3. Information Sharing in Decision Support System

Generally, DSS is based on a large amount of data and information to support the decision-making process.[189] In the context of CT, there are many less-structured problems related to information sharing. For example, it is difficult to access information on a higher level of confidential, or to retrieve data in the database in practice.[190] In order to effectively control the risks in CT, the role of data/information is discussed in this section.

- Data and Information in DSS

Three components, data, information, and knowledge, play important roles in information sharing. Data have no context, whereas information is data but has given

[185] Cf. (Turban, et al., 2011)
[186] Cf. (Kang, et al., 2010)
[187] Cf. (Qrunfleh, et al., 2014)
[188] Cf. (Dullaert, et al., 2009)
[189] Cf. (Torretta, et al., 2017)
[190] Cf. (Hilletofth, et al., 2012)

a meaning through a relational connection; information is data in a certain context. In contrast to information or data, knowledge requires the presence of context, semantics, and purpose. Knowledge is defined as:

> *"Knowledge is the accumulation and synergy of information, which facilitates choice or improves decisions. Knowledge which is required for a specific decision is not necessarily based upon dedicated information related to it. It is also based on tacit knowledge, the use of intuition and the experience of the decision-maker."*[191]

This concept implies that knowledge can be divided into two parts: the results of communication (information sharing) with knowledge source and the personal background of the decision-maker, such as experience. (The behavioural influence of the decision-maker is not observed in this thesis.) Therefore, the database in DSS is referred to as the database of "knowledge".

Given that the database of the DSS is a collection of a substantial amount of data and information, in the dissertation, data and information can be used interchangeably. A diverse range of data is handled in the knowledge base.

- Full Integration of Information in DSS

Decision makers collect ample information and data to make an appropriate decision to satisfy the requirement of the knowledge base. Meanwhile, alternative solutions to less-structured problems are efficiently evaluated.[192] To provide users with accurate, timely, and consistent system-wide data, knowledge is required to be integrated into the DSS. The knowledge integration would provide a rich pipeline of the interaction between partners.

The information integration consists of two aspects: full information sharing and confidential data. The full information sharing in this study is defined as information that is available on a database level. From this point of view, the full integration of information requires DSS as a platform, so users can exchange real-time information to eliminate information asymmetries.[193]

[191] Cf. (Cohen, et al., 2002)
[192] Cf. (Closs, et al., 2003)
[193] Cf. (Inderfurth, et al., 2012)

In parallel, different users are facilitated with different information and data. Some information and data are accessible only to a limited number of users. Such data are defined as confidential data, which are exchanged with other partners or to be published with the permission of the data owner. This partial sharing of information implies sharing the information between certain users/groups of users.[194] In this way, the data privacy of users is protected.

In brief, DSS is a quick-response system that provides decision-makers with dynamic solutions to less-structured problems, especially on the operational level. CT may encounter a situation where all entities gain total access to information, which they could not access before the integration of the information flow. They use this information in their planning process instead of using local data.[195] In the next section, an example of DSS is explained.

4.3. Transport-Suite: an Example of Decision Support System

As mentioned in section 1.1, the DSS in DynKo is addressed as Transport-Suite. In Transport-Suite, a tactical and/or operational perspective is applied. (A plan with a planning horizon between 3 and 12 months is commonly considered a tactical plan, whereas an operational plan concerns day-to-day operations.) The database design and basic functionalities of Transport-Suite are explained in details in the followed sections.

4.3.1 Architecture of Transport-Suite

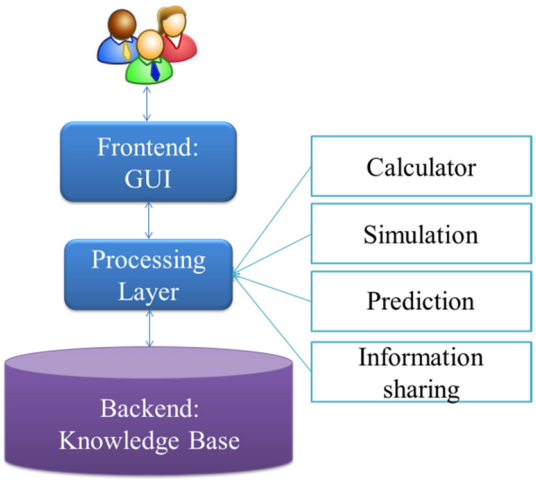
Technically, Transport-Suite consists of three tiers: presentation, functional processing, and database tier. The functional processing tier and the database tier are invisible on the user side. Correspondingly, data processing in Transport-Suite is presented in three layers (as illustrated in Figure 25):

- Fronted (the presentation tier): Fronted is based on a Java-enabled browser- and an APP-user interface, e.g. graphic-user interface (GUI). Through Fronted, users are correlated with Transport-Suite.
- Backend (the database tier): Backend is database layer in Transport-Suite. The database includes all information required to realise the functions of Transport-Suite.

[194] Cf. (Stadtler, 2011)
[195] Cf. (Smirnov, et al., 2006)

- Processing layer: The communication between the presentation and database layer is managed by using the processing layer, which connects the frontend and backend. The processing layer is responsible for business logic, optimisation and simulation, calculation, document generator, and data management.

Figure 25: Architecture of DSS



In the knowledge base, the data are divided into two categories: master data and specific data. The master data are those that are obtained through public channels, e.g., infrastructure data (railway stations, terminals, costs, and schedules). This information can also be captured by collecting the surveys of logistics experts and logistical service providers. By exploring the historical data in the knowledge base, master data are generated which are standardised and is available for all users. By contrast, specific data are the data with a privacy level, involving the disclosure of explicit information about the companies involved, is defined as confidential.

As a data centre, an MS-SQL server express R2 is implemented for direct links to common relational databases that are regularly updated to store current knowledge than a stand-alone database has.[196] To avoid the incompatibility of information systems, the data exchange between applications is possible using standardised formats for information sharing, such as the Extensible Markup Language format. A processing unit will communicate with the knowledge base that is installed on the same server of Transport-Suite.

[196] Cf. (Noche, et al., 2014)

Transport-Suite provides a web-based application programming interface that allows users to access the simulation results in Transport-Suite and to integrate the results into their system. In other words, the frontend is based on the user interface through which the user interacts with others of the Transport-Suite. Based on the data in the knowledge base, the outcomes of Transport-Suite are processed in the processing layer to satisfy the requirements of users.

(According to the discussion in the previous section, master data and the results of simulation in Transport-Suite are knowledge as well. However, the software is user-oriented and many of the users are not experts in the academic area. To avoid confusion of the data, information, and knowledge, the knowledge in Transport-Suite is only related to the knowledge base.)

4.3.2 Main Functionalities in Transport-Suite

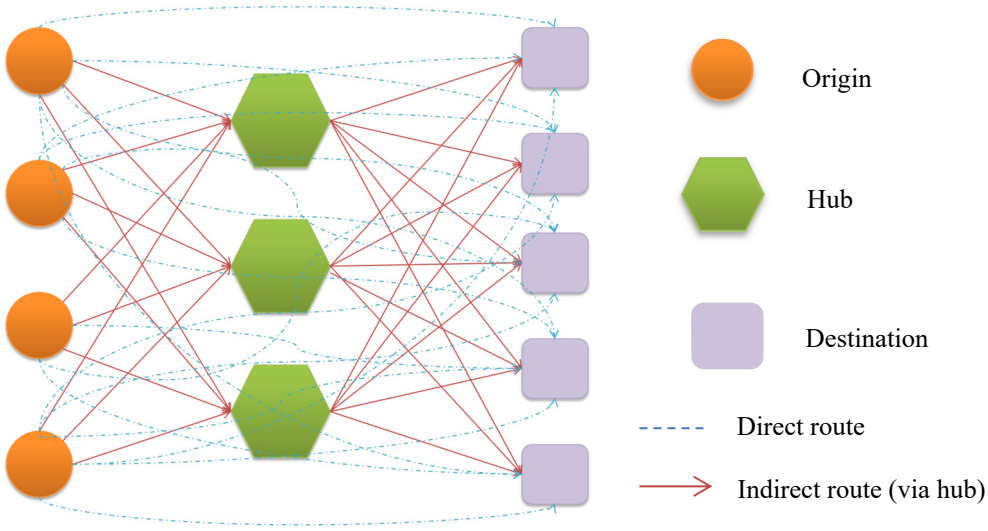
To realise the functionalities in the modules, three functions are implemented in Transport-Suite, namely, calculator, simulation, and prediction. As an information platform for decision-makers, real-time information sharing is also an important function of Transport-Suite.

- Calculator

Specifically, for route and time planning genetic algorithm (GA) is applied in Transport-Suite. GA is particularly suitable of optimisation.[197] Following the arguments of Bozorgirad et al. (2012),[198] transportation is classified into two types in Transport-Suite: normal delivery and direct delivery. As shown in Figure 26, the normal delivery starts from the source through a consolidation point to the destination. In a direct delivery, commodities are shipped directly from the source according to the corresponding destination.

[197] Cf. (Ngai, et al., 2014)
[198] Cf. (Bozorgirad, et al., 2012)

Figure 26: Structure of a dynamic hybrid network



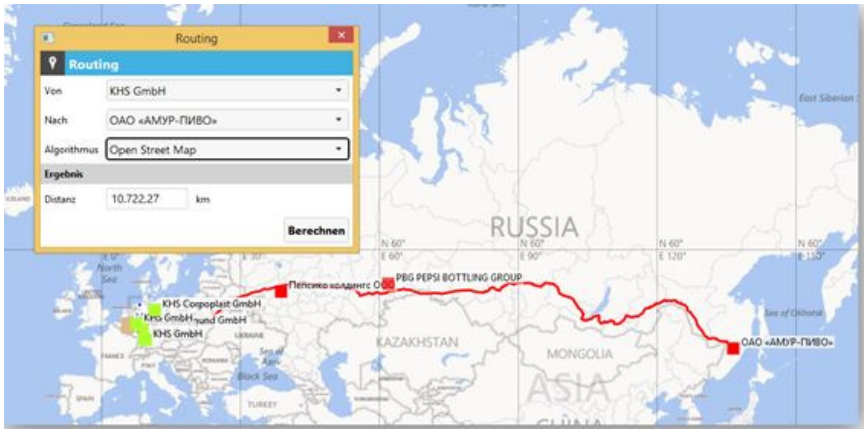
A node in the network represents a location (origin, destination, or terminal). An arc denotes a segment of a lane connecting two nodes. It is also a route is a set of service links forming a connected path from one node to another. Thus, a service network is a graph of all feasible directed arcs defined between nodes.[199]

The network design is modified using the specific provisions of the transportation order. Nevertheless, the route segment provides an explicit overview of routes for decision makers because master data can be applied for the generalised description of the transportation order.[200] The user enters the project-specific details of a transport task, e.g., origin and destination, number of commodities (usually packed in the container), and preferred transport mode. Speed and capacity utilisation of each transport mode is embedded into the model. Transport costs basically consist of transport and packaging costs. The possible routes are simulated in a map, such as OpenStreetMap.

Once the user defines the order-specific data, e.g., origin and destination, a routing/time plan is interpreted by Transport-Suite. Correspondingly, transport orders are established and expressed in terms of transportation volumes to be moved between source and destination. Figure 27 shows a geographical representation of transport routes and transport nodes.

[199] Cf. (Jeong, et al., 2007)
[200] Cf. (Stadtler, 2011)

Figure 27: Presentation of route in Transport-Suite[201]



Once the route is set, the corresponding delivery time and costs are estimated via simulation. The transport costs are calculated based on the real market price for each transport mode associated with CT-processes.

- Simulation

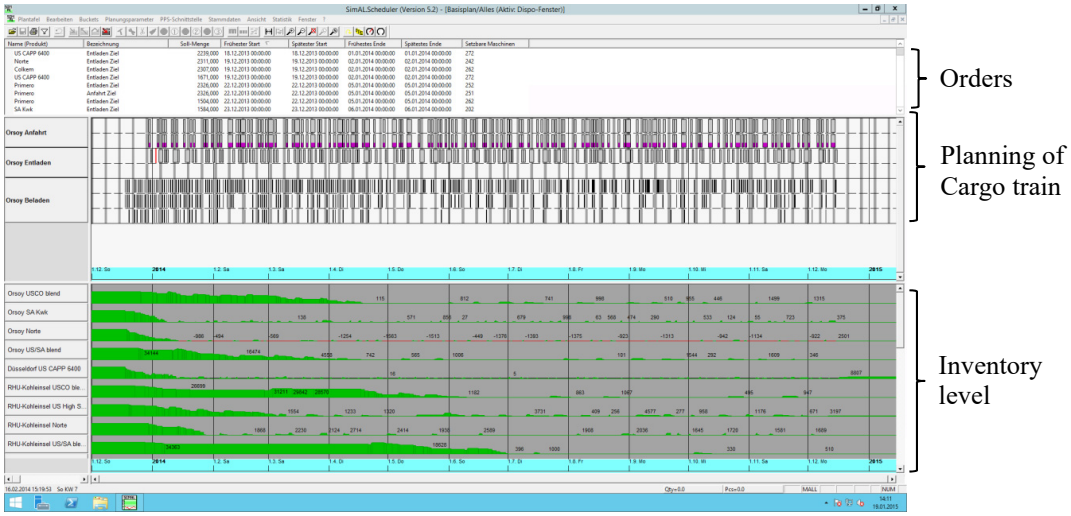
Randomness or stochasticity is an inherent attribute of management systems.[202] To ensure an effective support for decision-making at the operational level, simulations are conducted in Transport-Suite to generate scenarios to analyse the reality accurately and completely. In a simulation-based DSS, the system of a CT is modelled and implemented based on real data. Then the simulation model is then used to support the decision-making through repeated simulations.[203]

In Transport-Suite, users specify the attributes, origin and destination, the number of containers and transport mode through simulation. Statistical data (e.g., transhipment points and unit transport cost) in the knowledge base are first analysed. The routes are then selected based on the analysis results.

The delivery times and costs presented in Figure 28 are the results of a simulation process. Figure 28 shows the simulation results that concentrate on the design of the CT timetable. For instance, Port XY is a transhipment point for coal transport. The coal per inland ship from Amsterdam is unloaded and further loaded in cargo trains to different power plants (customers). Considering the storage of coal, the time plan of cargo trains is designed according to customer orders.

[201] Cf. (Noche, et al., 2014)
[202] Cf. (SteadieSeif, et al., 2014)
[203] Cf. (Hilletofth, et al., 2016)

Figure 28: Scheduling of cargo train in Transport-Suite



- Prediction

In the case of risk management, the "Resilient of SC" or resistance-capable SC is often discussed in the literature. In the context of transport, resilience is the ability of a system to maintain its original state or change to a new or more desirable state.[204] For instance, with real-time information on the delay, the load plan has a good possibility of being preserved. Freight forwarders and operators are therefore required to be highly adaptable to unforeseen changes, to identify and produce well-crafted solutions to organisational problems, and to reduce monitoring costs. To achieve this objective, prediction of the risks is an important tool.

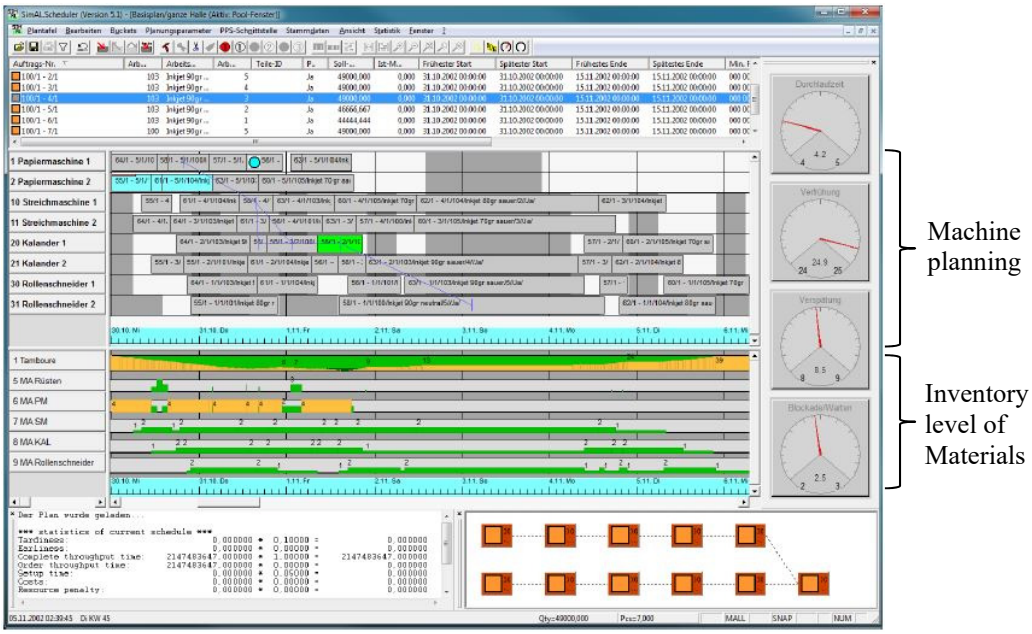
To facilitate the proper reaction to unexpected events, propagation of event messages should be automated. This method requires that risk-management in DSS includes a feedback loop of gaps between foreseen and actual processes. In the freight railway transportation, for example, simulation techniques can be used to study train delays from conflicts at complex junctions, terminals, railroad crossings, network topologies, and traffic parameters.[205] Specifically, an artificial neural network (see Chapters 5 and 6 for details) is applied to accomplish the task of prediction.

The methods can be applied for many different application areas (the applicability has been proved in many cases well documented in literature), but as a general application that enables the analysis of various data because systems that are

[204] Cf. (Christopher, et al., 2004)
[205] Cf. (Murali, et al., 2010)

tailored to a specific problem are more expensive.[206] For example, SimAL.Scheduler® (SimAL®) is originally applied for operational production planning (see Figure 29). This scheduler aims to optimise the occupancy of machines while considering the real-time adjustment of resources, such as materials.

Figure 29: An example of production planning in SimAL®



- Information Sharing in Transport-Suite

Obtaining the correct information within a short period of time often remains a complex issue. In the practice, information is largely available in digital form, but conventional means of communication, such as telephone, marine telephone, fax, and e-mail, are often used.

In Transport-Suite, the communication between user and server is through TCP/IP in most cases. Thus, information is collected and access with high speed. The server and the database are located on the same host. For the input data, the system provides alternative routes, transport costs, transport times, and the required documentation needed to handle transportation and scheduling. A processing unit will communicate with the knowledge base in Transport-Suite. To realise the functionality of information sharing, Information Communication Technology (ICT) is applied in Transport-Suite.

[206] Cf. (Simchi-Levi, et al., 2009)

From the viewpoint of information integration, Transport-Suite is applied not only to check the availability of resources (e.g., carrying capacity of a cargo train and possible lane changes), but also to inform users immediately of any updated information through messages (e.g., in case a new load or transport order has been submitted to the system). For instance, the information of the current status of shipment can be obtained in Transport-Suite from the logistics service provider. Not only obtaining data from the external systems, but Transport-Suite also sends data and information from external systems back to the knowledge base. Communications arise between the user and the software as well between one user and another user through the software.

4.4 Intermediate Summary

In practice, a major concern related to CT is that it is more complicated than mono-modal transport. A distinguished feature of CT is the variety of risks encountered by participants in CT. Under the conditions of high uncertainties, decision-makers often encounter less-structured problems, which depresses the decision-makers to choose CT.

In order to reduce the effects of uncertainties in CT, DSS provides a tool for decision-makers to implement their own analysis of the less-structured problems and accelerate the process of decision-making. Most of the management tasks are performed through configuration and collaboration in DSS. The specification and operation, such as information-sharing and feedback mechanisms, are used in the business of CT to support the decision making of the partners in productive ways.[207]

In this chapter, a Transport-Suite was introduced to illustrate DSS in particular in the field of information sharing and software design. Decision-makers benefit from DSS in two main aspects. On one hand, unexpected events are promptly shared with the participants of CT, so that users have more time for decision-making than without the system. On the other hand, the influence of unexpected events is estimated to reduce the decision-process in less-structured problems.

To cope with the uncertainties and risks in CT, the prediction as a substantial functionality of DSS will be specifically introduced and explained in the next chapters using a different analysis technique, Artificial Neural Network. Based on this

[207] Cf. (Gulati, et al., 2012)

technique, a delay propagation model is in detail described in the next chapters. By means of this detailed example, the mechanism of the risks prediction in DSS is explained.

5. Application of Multilayer Perceptron for Prediction in Transport-Suite

As mentioned in the previous chapters, several factors affect the stability of the transport chain. As a result, less-structured problems often arise in CT. DSS provides decision-makers solutions to these problems by facilitating various functionalities. The functionality of risk propagation is emphasised in the dissertation because less-structured problems are direct results of uncertainties and risks.

Numerous models have attempted to describe less-structured problems and estimate their influence. This dissertation does not discuss the entire prediction toolbox but rather focuses on one component, multilayer perceptron (MLP). MLP is a type of artificial neural network (ANN) that can forecast the influence of important risk factors that often cause delay.

The background and fundamentals of ANN are first introduced. Then, MLP is demonstrated to be an efficient prediction tool. Given the endogen disadvantages of MLP, a genetic algorithm is proposed as a performance-improvement method for MLP in the last subsection.

5.1 Introduction to Artificial Neural Network

5.1.1 Brief History

In 1943, McCulloch and Pitts presented a formal mathematical model describing the workings of the human brain. Their work pioneered the modern research of ANN. Hebb (1949) introduced the neuron assembly theory.[208] Human behaviour is the result of a series of neuron actions. Hebb's theory has provided a biological basis for automated learning. Although his study was rotted in the field of psychology, it provided insight into the development of training algorithms for ANN. He stated in his book that the weight between two neurons in neighboured layers increases if these neurons simultaneously activated. The weight decreases if the neurons activate separately. This concept is also known as *Hebb's rule*.

In the 1950s, Rosenblatt designed the perceptron, which is an ANN model that was proven capable of learning from examples. Around the same time as Rosenblatt's

[208] Cf. (Hebb, 1949)

work, Widrow and Hoff developed the ADELINE model with delta algorithm for adaptive learning. Rosenblatt is one of the pioneers of applying the ANN theory. In their book published in 1969, Minsky and Papert proved that single-layer neural networks have limited power, and that solving complex problems requires multilayer networks.[209] However, the study of ANN at that time did not progress because no suitable methods were available for the effective adjustment of connection weights. Until the mid-1980s, the back-propagation algorithm (BP) was widely applied in multilayer networks and gained worldwide recognition.

At present, ANNs are data-mining analytical tools that have been widely employed in many areas ranging from manufacturing and engineering to finance and marketing. ANNs have been demonstrated effective for providing solutions to the following:

- capturing associations or discovering regularities within a set of patterns, where the volume, number of variables, or diversity of the data is large;
- identifying the relationships between vaguely understood variables; and
- determining relationships that cannot be adequately described with conventional approaches.

The preceding statements imply that ANN is widely applied for pattern recognition and pattern classification, which are two active fields in statistics and engineering. Researchers have demonstrated the excellent contributions of ANN in those fields.[210]

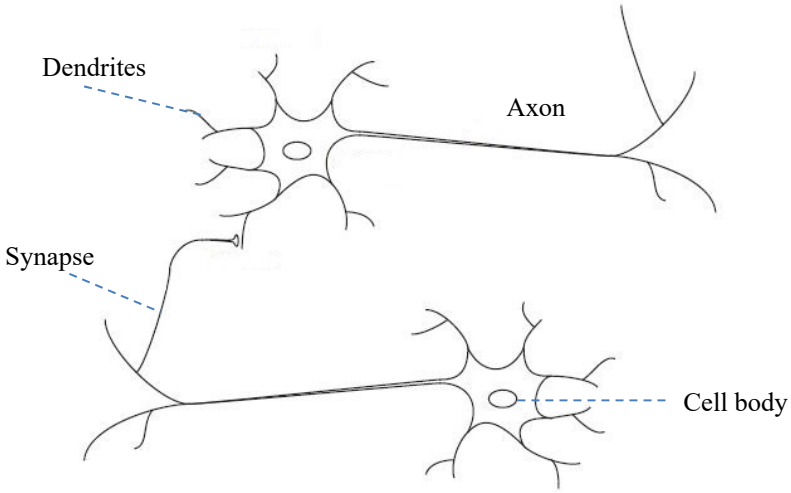
5.1.2 Systems of Artificial Neural Network

ANNs have been inspired by biological neural connections in the human brain. Figure 30 shows a classic structure of neurons in the human brain. Dendrites are treelike receptive networks of nerve fibres that carry electrical signals into the cell body. The cell body effectively calculate these electrical signals, which are transferred further if they are larger than the threshold. The axon is a single long fibre that carries the signal from the cell body to other neurons. The point of connection between an axon of one cell and a dendrite of another cell is called a synapse. Biological neurons

[209] Cf. (Palit, et al., 2006)
[210] Cf. (Webb, et al., 2011)

have different synapses and synaptic strength. Thus, some neurons have a stronger influence than others do.

Figure 30: Simplified biological neurons[211]



To provide a convenient tool for the simulation of the biological decision system, an ANN is designed to describe the main aspect of the biological neural network while ignoring the aspects that are insignificant to the simulation.

An ANN consists of the following main components: neurons, connection weights, and outputs. The inputs of a neuron (electric signals) arrive from the environment or from other neurons (dendrites). In the neuron (cell body), the inputs are processed (calculated) by applying an activation mode. Then, an output is generated (axon) and further transmitted. The output of an ANN is the decision that is made by the ANN. A collection of neurons/units works in ANN. The neurons are highly interconnected but their influence on the others is numerous. Setting w is the connection weight (synapse) between two neurons in an ANN, which is an indicator of the strength and transferability of the connection between two neurons. Connections between neurons are generally of three types:

(1) When neurons have positive weights ($w > 0$), they tend to be both positive and negative at the same time.

(2) When neurons have negative weights ($w < 0$), they tend to be opposite; that is, one is positive, and the other is negative.

[211] Cf. (Hagan, et al., 2014)

(3) When w is zero, the two neurons have no connection in the two layers.

The relationships imply that precise learning can be attained by altering the weights between neurons. Their internal structure is also modified in the learning process.

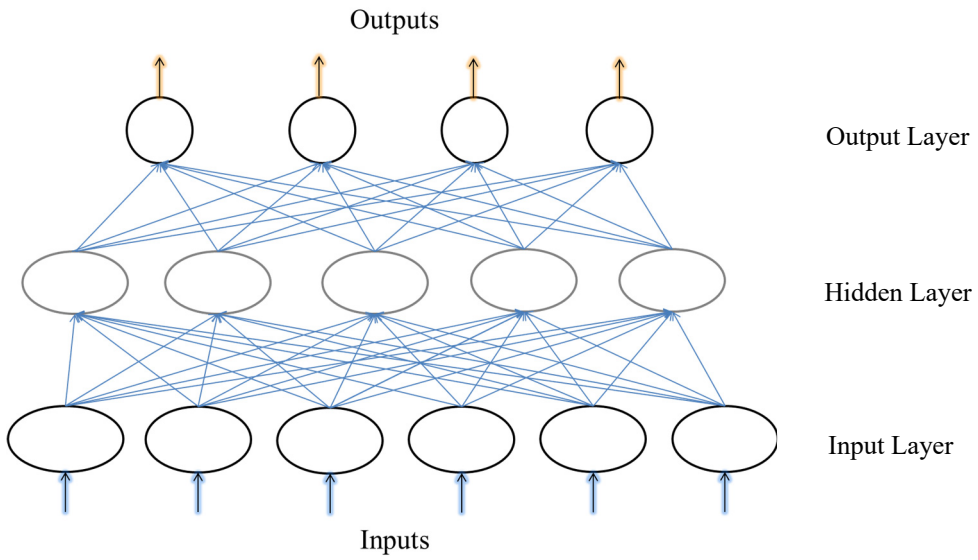
5.1.3 Topology of Artificial Neural Network

Various criteria have been established to categorise ANNs. According to the information direction, ANN has two kinds: feed-forward and back-propagation. These two types of ANN are explicitly introduced in the following subsection.

- Feed-forward Neural Network

The architecture of a feed-forward neural network is composed of one input layer, one output layer, and at least one hidden layer. The most typical feed-forward neural network is a perceptron. Figure 31 shows the architecture of a three-layer perceptron. It consists of an input layer, an intermediate layer (i.e., the hidden layer), and an output layer. Each layer further consists of more than one neuron. In the system, the input and output always remain stable, whereas the hidden layer can be changed according to specific functions of the ANN. The hidden layer enhances adaptive learning in ANN, which is the ability to learn how to accomplish tasks on the basis of the data given for training. All layers play a different role in the network and are consequently connected. Neurons in the same layer are not connected. Every node in the same layer is directly connected to one other node in the next layer. But nodes in the same layer have no direct connections with each other.

Figure 31: Hierarchical ANN: MLP



Let x_r represent the input values in a three-layer perceptron. The output of the hidden layer y_c and that of the output layer y_d are respectively expressed as follows:

$$y_c = G_c\{[\sum_{r=1}^{R} w_r^c x_r] + b_c\}, r \in R, c \in C \quad (5\text{-}1)$$

$$y_d = G_d\{[\sum_{c=1}^{C} w_c^d y_c] + b_d\}, d \in D \quad (5\text{-}2)$$

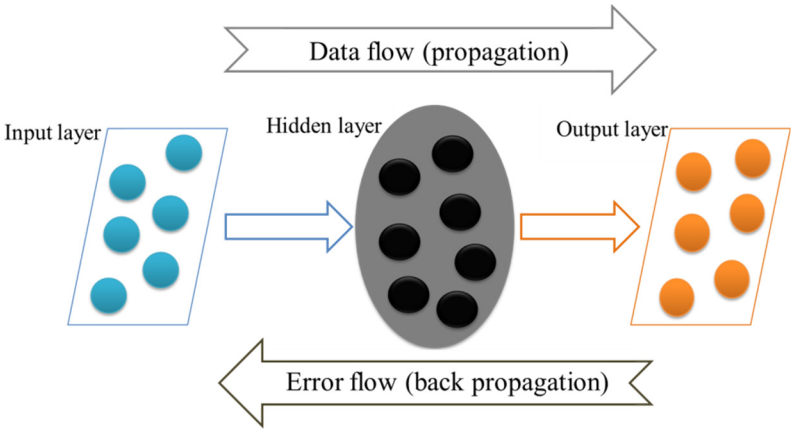
where w_r^c is the connection weights between the input and hidden layer, b_c is the bias of the hidden layer, G_c is the activation function of the hidden layer, w_c^d is the connection weights between the hidden and output layer. In addition, b_d is the bias of the output layer, and G_d is the activation function of the output layer. *R, C and D* present, the input data, data in hidden layer and output data.

- BP in Perceptron

As the name implies, the training scheme of BP is activated by back–forward spreading error signals. The data set to train the network consists of a series of input-output pairs also referred to as patterns. Weights are modified when all the training data passed through the neural network, namely, learning by epoch. Every presentation of the entire data set is called an epoch; that is, an epoch is defined as one full pass through the training set. Based on the relationships it has learned, a trained ANN is expected to produce an output whenever a new pattern is introduced into the network. The difference between the actual and target outputs is considered an error, i.e., training error.

In other words, BP is a trial-and-error approach that consists mainly of two phases (see Figure 32). In the first phase, the inputs of the training patterns are fed into the network. Its output is calculated feed-forward and compared with the desired output of the training patterns, i.e., the output contains errors. In the second phase, the errors from the first phase are sent back through the hidden layer to the input layer, and the initial weights in the first phase are adjusted according to the error signals. As a result, the weights are automatically changed until their optimal values are determined.[212]

Figure 32: Information delivery in a BP-based MLP



According to the trial-and-error approach, the input information should be divided into two groups: (1) a subset of training data that contains function values; and (2) a subset of comparison data that contains prior information, e.g., properties of the data.[213]

Given that this dissertation aims to demonstrate the forecasting function of MLP in freight train transportation, the MLP adopts this architecture.

5.1.4 Learning Rules of Artificial Neural Network

Initially, an ANN has no memory. ANN obtains its knowledge by interacting with the environment (learned information) and its own process.[214] That is, the knowledge and data-processing of ANN depends substantially on learning. A well-learned ANN can solve the given tasks or a similar process efficiently and/or effectively.

[212] Cf. (韩 (Han), 2006)
[213] Cf. (Enăchescu, et al., 2005)
[214] Cf. (Russell, et al., 2003)

The learning process of ANN is the procedure of continual connection-weight modification, which is also known as the learning rule or learning law of an ANN. Learning has three main categories: supervised, unsupervised, and reinforcement.

- Supervised learning

In supervised learning, the learned information of a system is predefined. The information is divided into two subsets: inputs and target outputs. The learning rule is provided with a set of patterns (the training set):

$$(x_1, d_1), (x_2, d_2), \dots, (x_r, d_r)$$

where x_r is the series of inputs to the network and d_r is the corresponding correct (desired/targeted) outputs. The proper network behaviour has been embossed into the data via component d_r.

In supervised learning, an ANN can evaluate the effect of its own reaction to the environment. The outputs are compared with the target ones as the patterns are fed into the network. Then, the supervised learning rule is used to adjust the connection weights and biases of the network, such that the network outputs can move closer to the targeted values. Thus, the quality of the output is enhanced.

- Reinforcement learning

Reinforcement learning is like supervised learning, except that no explicit outputs are given for comparison. Instead, a grade (or score) is specified for every state of ANN. The learning process consists of a series of sequential states. For example, in the first step, the ANN is in an initial state st_0. As the input is fed, the network adjusts itself to a new state st_1. At the same time, it obtains a reward. According to the reward, the network takes the next step of adjustment, and its state will change to st_2. The grade (or score) is a measure of the network performance over a sequence of inputs.[215] Reinforcement learning is most suited for control-system applications, e.g., computer-guided electromechanical machines.

- Unsupervised learning

In unsupervised learning, weights and bias are modified in response to network inputs only. No target outputs are available. Pure "unsupervised learning" does not

[215] Cf. (Russell, et al., 2003)

exist. An ANN learns nothing under these conditions because no correct knowledge or desired state is provided for an ANN to learn from. Unsupervised learning is performed mostly in the context of clustering operation, e.g., self-organising maps. [216]

5.2 Theoretical Properties of Multilayer Perceptron

A Perceptron is a typical type of feed-forward ANN. A perceptron can be divided into single-layer perceptron and MLP according to the number of layers. This dissertation focuses on the MLP because of the limited ability of single-layer perceptron.

5.2.1 Training and Generalisation Ability of Multilayer Perceptron

The learning ability of an MLP depends substantially on its training and generalisation ability. Training ability indicates how well the given data (training data) can be mapped in a neural network. Meanwhile, generalisation ability describes how well new and unseen data are processed in the trained neural network. Given these two attributes, MLP can certainly be trained for the purpose of prediction.

- Universal Approximation Capability

The ability to map a given behaviour is one of the substantial tasks of an MLP, that is, to represent the input information. Approximation capability facilitates the ability of an MLP to recognise, handle, and reproduce information.

In 1957, Kolmogorov suggested that a two-layer neural network with arbitrary multivariate function could complete complex nonlinear mapping from input to output at any degree of accuracy (Kolmogorov extension theorem).[217] Kolmogorov's theorem states the universality of a layered feed-forward neural network as a multivariate function approximation in a compact space. Other researchers have also confirmed Kolmogorov's report.[218]

Scholars in 1989 proposed that a feed-forward neural network with one hidden layer and enough hidden nodes could uniformly approach a nonlinear function to any desired degree of accuracy when a continuous function is applied to the hidden layer.[219] Academic researchers proved the approximation capability of a multilayer

[216] Cf. (Hagan, et al., 2014)
[217] Cf. (Kolmogorov, 1957)
[218] Cf. e.g. (Lippmann, 1987), (Hecht-Nielsen, 1991) and (Sprecher, 1993)
[219] Cf. (Satin, et al., 2004)

feed-forward neural network with a sigmoid activation function in the hidden layer later. Their studies further indicated that the network can approximate not only an unknown function but also its derivative.[220] Pinkus (1999) explicitly stated that an MLP can approximate any function in a compact space if its activation function is continuously differentiable in the space and is not polynomial.[221]

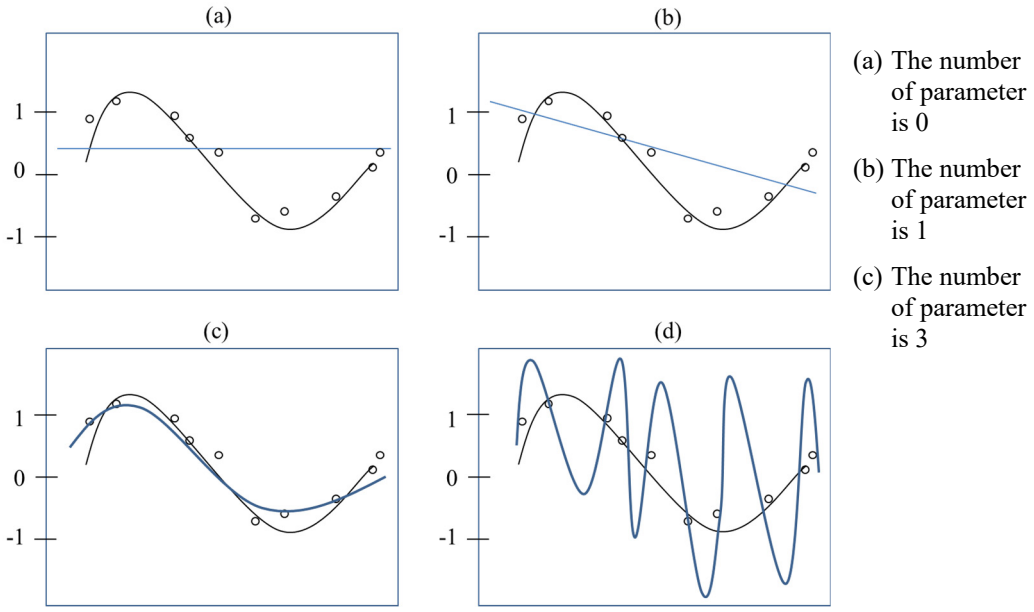
- Generalisation Ability of MLP

Like the memory of a human brain, the memory of an ANN is limited. Thus, generalisation substantially determines ANN quality. This generalisation allows the network to classify new examples to the correct category by referring to a limited set of examples.[222] Generalisation can be obtained in different ways. For instance, an MLP can learn from a large size of the qualified data set.

Nevertheless, like all statistical models, MLP is subject to poor generalisation or over-fitting (overtraining), particularly when it contains too many parameters (depending on the problem complexity) in the model. In other words, too many parameters in a model could result in highly qualified predictions from known data, but low-qualified predictions from unknown data.[223] Figure 33 illustrates that the generalisation of the given polynomial decreases, whereas the number of variables in the function increases. An over-fitting MLP learns the details of the samples but not its contents. This concept implies that the peculiarities of the individual samples are accurately modelled in the network, instead of the common individualities of the data set.

[220] Cf. (Hassoun, 1995)
[221] Cf. (Pinkus, 1999)
[222] Cf. (Anderson, 1995)
[223] Cf. (Russell, et al., 2003)

Figure 33: A polynomial with different parameter [224]



In theory, the training and the prediction abilities of an MLP have a positive relation: when training ability is improved, prediction ability is enhanced correspondingly. However, this trend has a limit.[225] When this limit is reached, over-fitting occurs. In the case of over-fitting, the improved ability of the training leads to decreased ability to predict.

Several factors often cause a system over-fitting. A poor generalisation is frequently observed in the case in which a network is over-trained or if problem complexity is relatively higher than in the training data.[226] Other factors can also lead to overfittings, such as the low quality of training examples, too many nodes in the hidden layer, inappropriate initial weights, and inaccurate application of algorithms to the network. Statistical methods can improve MLP generalisation, e.g., optimal brain damage algorithm and the tiling algorithm.

In practice, several measures can also be implemented to avoid over-fitting. For example, the size of the training data should be considerably large, that is, 5 to 10 times the estimated complexity. Moreover, the learning process should stop before the minimum error of the training set is reached (premature).[227] This dissertation mainly

[224] Cf. (Bishop, 2006)
[225] Cf. (李(Li), 2012)
[226] Cf. (Hassoun, 1995)
[227] Cf. (Kroll, 2012)

considers the effective improvement of the generalisation ability in network structure. From this viewpoint, the generalisation ability of the network is affected by the connection weights.

5.2.2 Learning Rule in Multilayer Perceptron: Back-propagation Algorithm

- Background and Foundation

The theorems in the preceding section demonstrate the approximation capability of a feed-forward MLP if continuous functions are employed in the network. However, initially, an MLP has no function. Some function must be applied to train the MLP.

Based on Hebb's principle, Widrow et al. in 1960 introduced the *delta rule* in their report.[228] Delta-rule (also called Widrow-Hoff-rule or least mean square) algorithm implies that the weights of an MLP can be optimised by minimising the difference between the actual and the target outputs. The delta rule is applied to the MLP to perform weight-factor modifications so that an input is associated with the desired output. However, the desired output is defined only for a two-layer network, i.e., the desired output of a unit is described only in the output layer but not for the hidden units.

Rumelhart et al. (1986) proposed a back-propagation algorithm by expending the application area of the delta rule. This algorithm is a special form of delta rule but also suitable for multilayer MLP with continuous and nonlinear function.[229] Then, a larg amound of literature studied on BP and its improvements were conducted. Haykin (1994) developed a complete system of BP technique.[230] BP being explained in the following section is also based on the Haykin (1994) study.

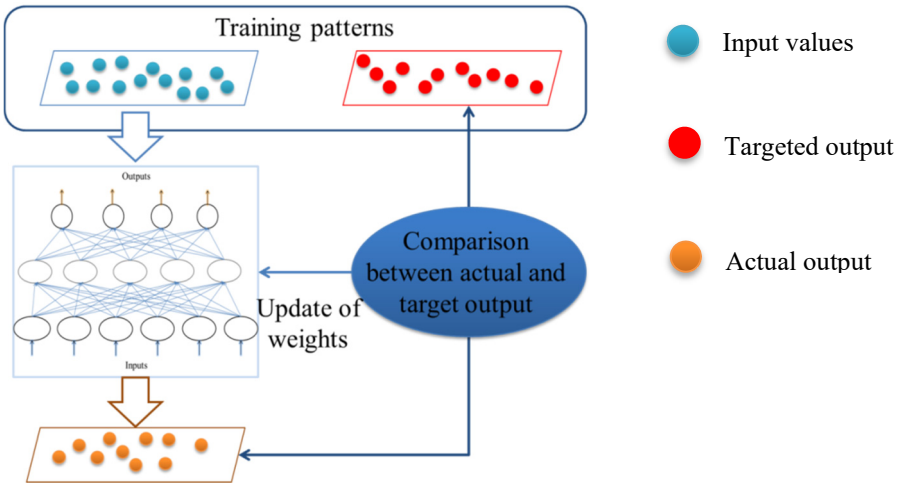
- Back-propagation of Errors

The errors in the hidden layer are corrected and updated by calculating the errors in the output layer. Similar to the delta rule, BP also aims to minimise the errors between network output and desired output. BP is particularly suitable for nonlinear functions.[231] The neural network is considered trained when the training error between

[228] Cf. (Widrow, et al., 1960)
[229] Cf. (Rumelhart, et al., 1986)
[230] Cf. (Palit, et al., 2006)
[231] Cf. (韩 (Han), 2006)

the desired outputs and the actual outputs are minimised. During the training process, the patterns are sequentially presented to the network in an iterative manner. The trial-and-error iteration continues until the errors lie in the acceptable range.[232] Thus, appropriate weight corrections are obtained during this process. The training process of MLP through BP is illustrated in Figure 34.

Figure 34: Training principle in MLP



The comparison of the desired and actual outputs obviously plays a substantial role in BP. Let (x_d, y_d) be a training pair in training data D. Then, for arbitrary hidden layer neuron, error E in the weight space can be interpreted as follows:

$$E = \frac{1}{2}\sum_{d \in D}(t_d - y_d)^2 \qquad (5\text{-}3)$$

where t_d is the targeted (desired) output of the MLP, y_d is the actual (calculated) output of the MLP, d is the dth input for the MLP, and D is the training data set of the MLP.

Many definitions in the literature explain the error in an MLP. In this dissertation, the definition of error is widely used in practice at this time. The errors of an MLP are half squared the differences between the desired and actual outputs. The pre-factor 1/2 is not necessary but leads to a compacted result.[233]

At the beginning of training, this system is initially using default values (i.e., random values), and all outputs (possible answers of the system) have the same

[232] Cf. (Moreira, et al., 1995)
[233] Cf. (Haykin, 2009)

probability. In the training process, the connection weights are modified through consistent comparisons of the desired and calculated output. The structure of the MLP is also adjusted correspondingly. In other words, an MLP can be trained by modifying its weights. The gradual adjustments in the training period finally obtain an acceptable weight distribution.[234] From this viewpoint, error E implicitly contains prior knowledge about the problem domain. Furthermore, it indicates that MLP belongs to the supervised neural networks.

- Gradient Descent

Gradient descent is applied to determine the optimum of weights by minimising the error, particularly in a high-dimensional space.[235] In detail, connection weights are adjusted by gradient descent, which includes the current weight update in the sequence of past iterations:

$$w_{k+1} = w_k + \Delta w_k \tag{5-4}$$

where k presents the iteration in an MLP, w_{k+1} represents the weights in the current iteration, w_k is the weights in the previous iteration, and Δw_k is the adjustment of the weights in the previous iteration.

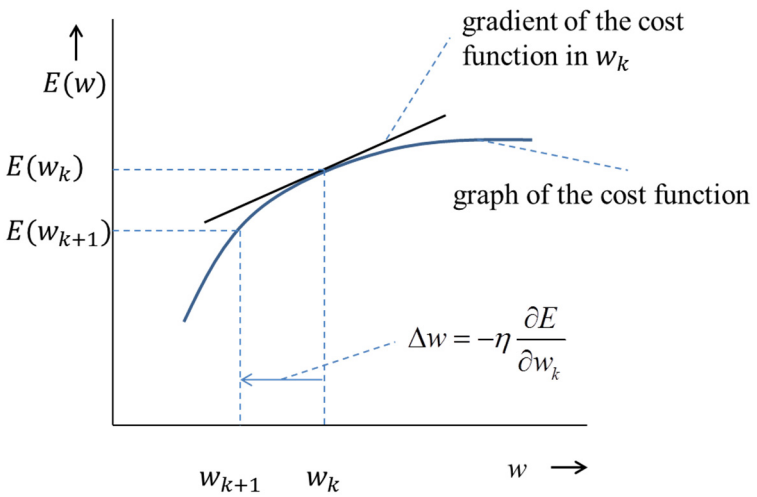
A simplified gradient-descent algorithm is known as follows:

$$\Delta w = -\eta \frac{\partial E}{\partial w} \tag{5-5}$$

The parameter η denotes learning rate, which is a step-size parameter, to evaluate the speed of MLP to the final solution. The learning rate is usually fixed. The fraction $\partial E / \partial w$ is used to determine the optimal value of w through calculation, i.e., the steepest descent in the weight space (see Annex b). To minimise errors, the downhill direction of the corresponding gradient is used to modify Δw (see Figure 35). BP is performed with a gradient descent technique in a retrospective procedure. Based on the gradient descent, BP determines the weight adjustment.

[234] Cf. (Senties, et al., 2009)
[235] Cf. (Haykin, 2009)

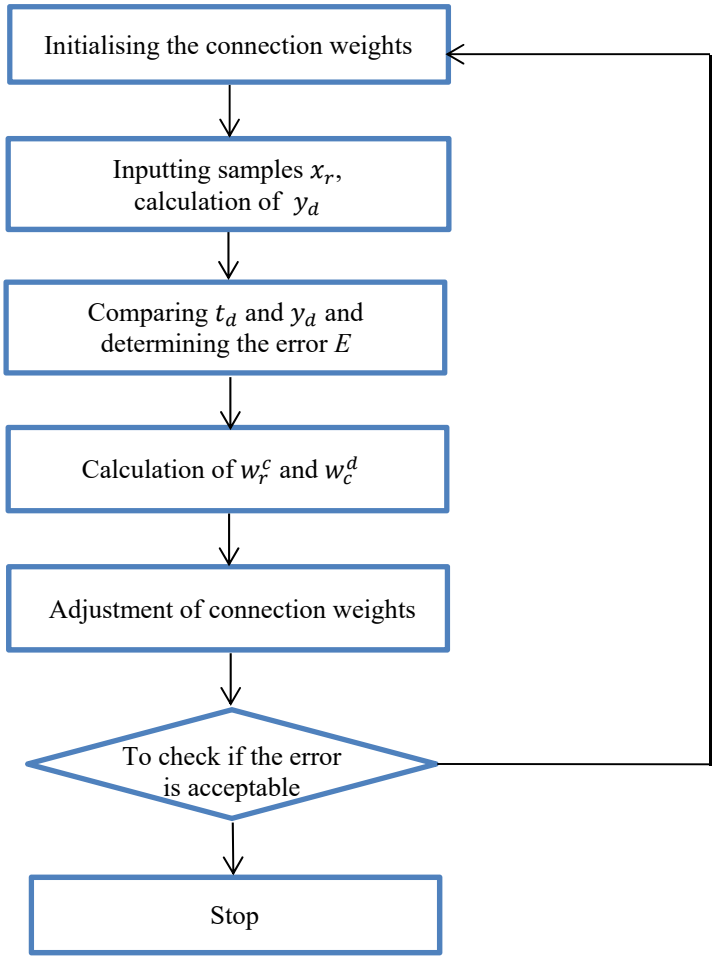
Figure 35: Principle of gradient descent[236]



In brief, the learning process of an MLP depends on both the current weight factors and the previous weight tuning. It implies that the error values do not depend on the size of the pattern set or output neurons of the specific network. However, a low learning rate can slow down the convergence speed of the network.[237] Setting the learning rate too high can cause the loss of the correct solution. The above-mentioned process is presented as a flowchart in Figure 36.

[236]Cf. (Kroll, 2012)
[237] Cf. (Murali, et al., 2010)

Figure 36: Chart flow of MLP



5.2.3 Drawbacks of Multilayer Perceptron

MLP has typical limitations, e.g. convergence unsteadiness in its training procedure.[238] Gradient descent is commonly applied to find solutions to optimal weights. However, MLP is prone to be trapped at local minimum given that the gradient algorithm is a local search.

MLP with BP converges slowly because its parameters (including connection weights, learning rate, and momentum parameter) are very sensitive to small changes in the oscillation.[239] This attribute further causes not only complicated calculations, but also overtraining.

Moreover, no samples in the training set are representative for the characteristics of the data set, thereby affecting the generalisation capability of the network and limiting the practical application of forecasting. BP has been criticised

[238] Cf. (Turban, et al., 2011)
[239] Cf. (Haykin, 2009)

for its poor interpretability, given that humans cannot easily interpret the symbolic meaning behind the learned weights.

Other drawbacks of MLP restrict the wide application of MLP as well, e.g., fixed learning rate and the difficulty of choosing a suitable activation function. Thus, an enormous effort is proposed to improve the performance of BP. In this dissertation, several improvement techniques are introduced and detailed in the next chapter.

5.3 Improvement of the Performance of Multilayer Perceptron

The quality of an ANN depends directly on two perspectives: the design of the hidden layers and the calculation of connection weights. In this dissertation, the design of the hidden layer is not modified. Thus, the interest here lies only in the calculation of the system weights. The main reason lies in the significance of the weights in information processing: the overall distribution of the connection weights that contain all the knowledge of an MPL. Many methods are applied to improve the efficiency of BP. The methods introduced in this section are also used in MATLAB®.

5.3.1 Momentum

Given the low speed of the learning scheme, "momentum" has been introduced in BP to enhance its efficiency. As shown in subsection 5.2.2, the updated weights can be expressed by the gradient descent Eq. (5-4). Considering the improving parameter momentum θ, the function is updated as followed:

$$\Delta w_{k+1} = \Delta w_k + \theta \Delta w_k \tag{5-6}$$

Momentum is the weight vector that is updated at both the current and previous steps. If the momentum is too high, then the system can become unstable because the risk of overshooting the minimum increases. However, if the momentum is too low, then the local minimum cannot be reliably avoided. [240]

Momentum is the parameter that is frequently used for weight updates and for controlling oscillations.[241] Moreover, this parameter avoids the negative result caused by the local minimum and slow convergence.

[240] Cf. (Qian, 1999)
[241] Cf. (Zweiri, et al., 2005)

5.3.2 Variable Learning Rate

Through the variable learning-rate back-propagation (VLBP), the learning rate is modified in iterations rather than held constant as in the traditional setting. The performance of BP is very sensitive to the proper setting of the learning rate. Determining the optimal setting for the learning rate before training would be impractical.[242] In VLBP, both parameters, the momentum and learning rate, are applied to enhance the quality of the results in MLP. The details of the method are explained as follows:[243]

a) If error E increases such that it is greater than ξ (typically 1 to 5 percent) after an iteration of weight update, then the weight update is discarded and the learning rate η is multiplied by ρ_1 ($0 < \rho_1 < 1$), and the momentum coefficient θ (if it is used) will be set to 0.
b) If error E increases such that it is less than ξ, then the weight update is accepted, but η is not changed. If θ has been previously set to zero, it is reset to its original value θ_0.
c) If error E decreases after an iteration of weight update, then the weight update is accepted, and η is multiplied by ρ_2 ($\rho_2 > 1$). If θ has been formerly set to 0, it is reset to its original value θ_0.

In this manner, the weights are updated in the iteration. Correspondingly, the process is mathematically expressed as:

$$\eta = \begin{cases} \rho_1\eta, \theta = 0, \ if \ E > (1+\xi)E \\ \eta, \theta = \theta_0, \ if \ E < (1+\xi)E \\ \rho_2\eta, \theta = \theta_0, \ if \ E < E_{previous} \end{cases} \tag{5-7}$$

With VLBP the learning rate changes during the training process until it reaches the optimal value.

5.3.3 Levenberg-Marquardt Back-propagation Algorithm

As defined in Eq. (5-3), the error of the desired and actual output of an MLP is equal to half of the sum of the squared errors. Thus, minimising the squared errors is the core problem of the error function. The Levenberg-Marquardt back-propagation algorithm (LMBP), also known as the damped least-squares method, is a widely used

[242] Cf. (Magoulas, et al., 1999)
[243] Cf. (Hagan, et al., 2014)

algorithm that minimises nonlinear least-squares problems. By applying LMBP in MLP, the convergence of MLP can be accelerated as the algorithm moves across the error surface.[244]

LMBP was initially proposed by Levenberg (1944) and later rediscovered by Marquardt (1963).[245] LMBP was designed to support second-order training speed without computing for the Hessian matrix. It updates the weight using the Jacobian matrix, which can be computed using the standard BP. LMBP is being less complex than computing the Hessian matrix.[246]

According to LMBP, connection weights are modified in the iteration as following (see Annex c and d):

$$w_{k+1} = w_k + \Delta w_k, \Delta w = -(J^T(w)J(w) + \varphi I)^{-1} J^T(w)e \qquad (5\text{-}8)$$

where:

- *J(w)*: Jacobian matrix, which contains the first derivatives of the network errors with respect to the weights
- *I*: Identify matrix of the same dimension as *w*
- *φ*: regularising parameter, if the parameter has a large value, then the LMBP results in a gradient descent update. If *φ* is small, then the LMBP approaches the Gauss-Newton method, which converges rapidly, but to the local minimum.[247]
- *e*: vector of the network errors

Therefore, the errors of MLP are reduced after iteration by decreasing *φ* after each step and are increased only when a tentative step increases the error.[248]

5.3.4 Improvement of Performance of Multilayer Perceptron through Genetic Algorithm

- Fundamentals of GA

GA belongs to an evolutionary algorithm. It is an adaptive search technique based on the principles and mechanisms of natural selection and "survival of the fittest"

[244] Cf. (Hagan, et al., 2014)
[245] Cf. (MathWorks)
[246] Cf. (Roy, et al., 2013)
[247] Cf. (Haykin, 2009)
[248] Cf. (Pradeep, et al., 2011)

from natural evolution. A candidate represents an encoding of the solution into a form that is analogous to a chromosome, i.e., the individuals in the genetic spaces are called chromosome. With the fitness function, each chromosome is evaluated. The fitness value (results of a fitness function) is the fitness of a chromosome that determines its ability to survive and produce an offspring.

GA performs a global search to find the most suitable network connection weights, whereas the traditional method relies on gradient information to adjust the weight factors.[249] Given an initial set of weights, the connection weights of the network are updated through global searches instead through the traditional gradient descent. Thus, the quality of output of MLP is improved.[250] From this perspective, a hybrid model was proposed to decrease the possibility of trapping at local minimums by combining the advantages of global searches into the solution space of the BP algorithm.

The GA process is introduced as followed:

i. Encoding

The key benefit of GA is the wide spectrum of individuals that are represented by chromosomes.[251] Thus, representing chromosome (encoding) is the foremost step in GA. As mentioned in Chapter 5, r nodes exist in the input layer, c nodes exist in the hidden layer, and d nodes exist in the output layer. The number of weights to be computed is presented with $(r + c) * d$, i.e. each chromosome contains also $(r + c) * d$ gens. Gens are encoded with a real number encoding method. The original population is a set of chromosomes, which are generated randomly. Each chromosome represents a potential solution, i.e., a series of weights for BP. Weight values can be coded using a binary code, Prüfer code, and real-valued code.

ii. Selection (Roulette-wheel Selection)

The most common methods for selections are tournament selections, ranking selections, and roulette wheel selections. In this dissertation, a roulette wheel selection is applied. The nth candidate in the original population is selected for the mating pool

[249] Cf. (Dündar, et al., 2013)
[250] Cf. (Whitley , et al., 1990)
[251] Cf. (Noorul Haq, et al., 2010)

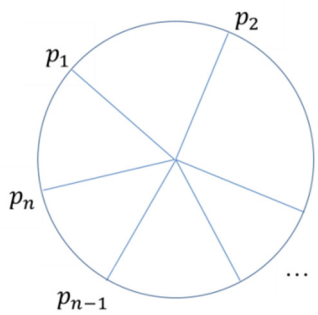
with a probability proportional to its fitness value f_n. By using the fitness value, the probability p_n of selecting the n^{th}individual can be calculated: [252]

$$p_n = \frac{f_n}{\sum_{n \in N} f_n} \tag{5-9}$$

where n is the candidate in the mating pool and f_n is defined as the fitness value of individual n.

Once the fitness of all candidates is computed, the cumulative probability p_i of each selected candidate can be calculated by adding the individual probabilities from $p_1$to p_n. Thus, the fitness values of candidates mark the circumference of the wheel (Figure 37). A candidate with a high fitness value means a larger range of cumulative probability. The candidates that have high fitness values are favourable in the fitness function and will be reproduced and survive in the next generations, whereas weak ones disappear. [253]

Figure 37: Dividing the Roulette wheel with cumulative probability



iii. Crossover

In the crossover phase, the selected chromosomes are stochastically grouped into pairs. A subset of gens (randomly chosen) of a chromosome is exchanged with gens of the other chromosome in the pair. Various methods for crossing exist, e.g., single-point crossover, two-point crossover, and multipoint crossover. Crossover probability p_c plays a key role in generating new individuals. If the crossover probability is too high, the individuals with good traits will be lost. If p_c is too small,

[252] Cf. (Deb, 2009)
[253] Cf. (Sexton, et al., 1998)

the new generation will be produced too slowly because the parents tend to generate the same offspring. In practice, p_c lies usually between [0.6, 0.9].[254]

iv. Mutation

Mutation controls candidate diversity. The chromosomes of the offspring are randomly changed through the mutation operator. A high probability of mutation would destroy the robustness of the population. The necessary features of the individuals will be lost. In contrast, if a mutation occurs too seldom in a generation, possible new "good" individual will be eliminated or reproduce too slowly. In this case, solutions can be trapped in the local "best".[255] In practice, a mutation typically takes place in only 1 bit per chromosome, so that good genes are not deeply disturbed, i.e.

$$p_m = \frac{1}{\text{bits in chromosome}}$$

where p_m represents mutation probability.

v. New generation

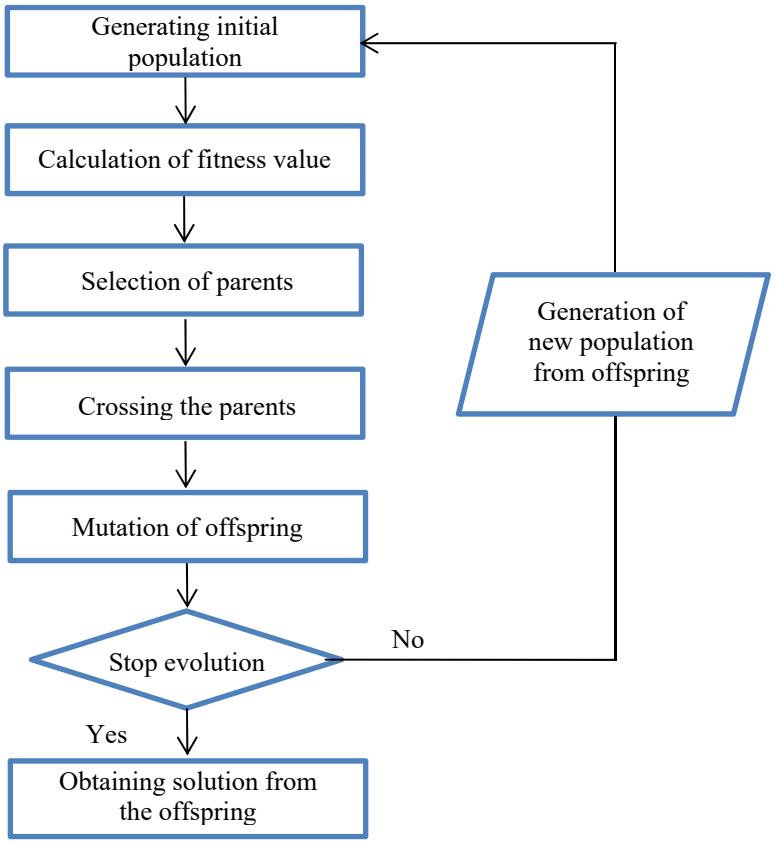
After the mutation operation, individuals with the best fitness value are introduced to the new generation. The genetic operators, selection, crossover, and mutations are repeated for the new population. The process is repeated until all the chromosomes nearly converge to the same fitness value. The weights represented by the chromosome in the final converged population are the optimised connection weights of MLP.

vi. Termination condition (criterion)

At each step in the iteration, the chromosomes are probabilistically selected from the population for reproduction. The off-springs are then returned in the pool. The working flowchart of GA is illustrated in Figure 38. The algorithm stops as soon as the termination condition is satisfied. After termination, the optimised connection weights are applied in the MLP model for testing, whether the model is suitable for prediction or not.

[254] Cf. (Kroll, 2012)
[255] Cf. (Mitchell, 1997)

Figure 38: Flowchart of GA



- Fitness Function in GA

Fitness function influences on the network weights by controlling chromosome quality. The fitness function is a measure used to indicate how well the chosen individual can fit the current network. The lower the fitness value of the chosen individual is, the better this value can fit the established MLP. Thus, the function is a novel and general rule of supervised learning for MLP.[256]

Despite its acknowledged benefits, this kind of approach often reaches its limits. For instance, slow convergence pace is inevitable because of the characteristics of global searches. GA converges is much slower than BP alone.

5.4 Interim Conclusion

MLP is one of the typical feed-forward ANN in which signals are delivered forward from one layer to the next. The flow of information is received as signals by neurons in the input layer, further processed in the hidden layer, and then shown as an output value in the output layer. Thus, knowledge and experiences are documented in

[256]Cf. (Schöneburg, et al., 1994)

the system. Training with a large amount of input-output pattern results in the learning of MLP to understand the relationship between input and output.

Although MLP provides valuable insights to improve prediction in transportation, its low level of generalisation implies that the network loses its practical value. To break the local optimum, in the dissertation, the parameters of the algorithm are adjusted by several methods, that is, momentum, VLBP and LMBP. Moreover, GA is applied to affect the inherent search method of BP. The main reason lies in that the search space of GA is enlarged.[257]

In the next chapter, a case of train transportation is presented. The scenario illustrates the application of MLP in DSS to solve less-structured problems. An MLP is designed to analyse the impact of reasons for delays in train transportation. In the system, the delay reasons are input data and the delay time of the freight trains are an output of the MLP. The MLP is modified and trained in MATLAB® to find a relationship between the delay reasons and the delay times. Thus, the impact of unforeseen events is not an uncontrollable factor in the transport chain for decision-maker any more.

[257] Cf. (Noorul Haq, et al., 2010)

6 Application of the Delay-prediction Model to Freight Train

This chapter details the application of a suitable tool in Transport-Suite to assist decision-makers in identifying risks. Train delays are an example of these risks. First, literature is presented that concentrates on the development of simulation models for train delays. Then, the problem characteristics of train delays are described. Based on this description, an experiment is designed as an example of the prediction function in Transport-Suite. Finally, the results of the experiments are compared in terms of different experimental factors and their implications. Appropriate settings for prediction are established according to this comparison.

6.1. Recent Developments in Train-Delay Research

Many researchers have investigated the train-delay problem and have presented numerous models and algorithms, e.g., the mixed integer program, constraint satisfaction problem, iterative optimisation, and hybrid neighbourhood search algorithms.[258] Nonetheless, the effects of the interactions cannot be effectively captured in an analytical delay model.[259] By contrast, simulation models can develop simple and accurate mathematical relationships that effectively reflect the stochastic feature of the interactions of numerous traffic parameters, as well as their influence on delays in railway networks.[260] Rail networks have been simulated extensively since Minger et al. (1969) introduced a simulation model in 1969 for design and implementation given by the problem of the rail network of the United States.[261]

A discrete-event simulation model was developed to estimate the transit time of train-truck combined transport (CT) in inland intermodal terminals. The simulation focused on the flow of intermodal terminals, e.g. the performance of the terminal equipment and the time the train is parked in the terminal.[262] A deadlock-free simulation methodology was proposed by researchers to analyse the train delay and the capacity of the rail network by considering track configurations and speed limits. Through inputting the data from Log Angeles County, simulation results were

[258] Cf. (Lin, et al., 2014)
[259] Cf. (Murali, et al., 2010)
[260] Cf. (Rai, 2016)
[261] Cf. (Wilson, et al., 1995)
[262] Cf. (Rizzoli, et al., 2002)

generated to approximate the relationship between train delays and network capacity adequately.[263] A model was formulated with a linear system in max-plus algebra to simulate the train delays within a timetable period. Through the simulations in the paper, it is demonstrated that the linear model can be applied to large-scale scheduled railway networks in real-time.[264] A Markov-chain based model was presented in order to forecast freight train delays as trains visit successive terminals. Terminals were classified according to their ability either to absorb or to cause delays. A large set of historical data were simulated. The model is also applied to support dispatchers by dispatching trains in a terminal.[265] A Fuzzy Petri Net model was proposed for estimating train delays to create timetables, to dispatch trains, and to plan infrastructures. Compared with statistical methods, a delay is calculated for each train in the fuzzy model. The precise delay propagation is thus enhanced.[266] Alternative pathways in the railway network were developed by studying unsuccessful transfers between trains. The problem was simulated in a model of Markov decision process in which the historic solution is also included. The study aimed to find not only an optimal policy for traveling from a given origin to a given destination but also reconsidering the remaining path to the destination.[267]

In brief, various simulation methods are applied to anticipate train delays. In the present problem, the set of the feasible solutions is complex because of the number of constraints. For instance, the possibility of train delays is one of the most frequently considered. Therefore, the accuracy of the simulation results is highly sensitive to this scenario. However, an appropriate value for the possibility of train delay is difficult to set. This task requires not only a mature theory for support but also adequate experience in its practical application.

Most previous works on delay estimations for railway networks concentrated on the network and operational parameters (e.g., available resources, capacity, and timing), as well as their complex interactions. The algorithms used to solve a system of equations may not be easy to understand and accurate delay propagation.

[263] Cf. (Lu, et al., 2004) and (Murali, et al., 2009)
[264] Cf. (Goverde, 2010)
[265] Cf. (Barta, et al., 2012)
[266] Cf. (Milinković, et al., 2013)
[267] Cf. (Häme, et al., 2013)

From the practical point of view for decision-makers, these models are difficult to implement because the models and systems are complicated. The implementation requires not only extensive practical experience with transportation planning but also a staff with a high level of education and training.[268] A few prerequisites in these models restrict the application area especially on an operational level because additional unexpected events can cause delays on the operation level than on the strategic and tactical levels.

In this dissertation, the different kinds of delay are disregarded because multilayer perceptron (MLP) focuses on the outputs (the influence of reasons) and their classification rather than on the reasons themselves. The structure of MLP is adapted to deliver accurate output according to the data collected. Theoretical and practical experience and knowledge are embedded in the data. Once MLP is configured, this algorithm is simplified for application by a decision-maker. In the following chapter, an experiment is presented that demonstrates how MLP supports decision-making.

6.2 Research Methodology

6.2.1 Problem Formulation

As explained in Chapter 3, freight trains for long-distance transportation are prone to delays. Furthermore, punctuality is an important performance indicator that is related to travel time minimisation, utility maximisation, and resource allocation in the railway network. To meet this objective, train delays should be quantified as accurately as possible and communicated to related users to minimise the influence of disturbances. To realise this objective, the risk of delays and their propagation on railroads are predicted in Transport-Suite.

To enhance the effectiveness of solution mechanisms, several specified operational constraints are considered. In this dissertation, the railroad network is a hub-and-spoke network where

- each rail station is a potential hub with consolidation capability that aims to minimise total cost, and the locations of facilities are fixed;
- train speed is dependent on the traffic situation, and the use of maximum speed

[268] Cf. (Hasan, 2010)

is limited;

- the headways of two trains are adequate for the schedule; and
- multiple periods are considered.

In this study, the delays of pre- and post-haulage (trucks) is neglected because customers presumably deliver and pick up their commodities using terminal-to-terminal transportation.

Railway network scheduling is featured as a discrete-event dynamic system; therefore, linear regression is generally unsuitable for defining a dependent variable in relation to delays in train transportation. Studies conducted with disaggregate data report that the relationship between delay cause and delay time is often nonlinear, time-variable, and S-shaped. In addition, train delays may exceed 100%. As a result, the study results are meaningless if a linear regression is applied.[269]

6.2.2 Configuration of the Back-propagation Neural Network in MATLAB®

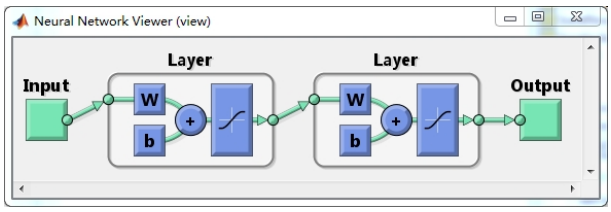
In this dissertation, the delay-prediction model is realised by the MATLAB® program. In this chapter, MLP is labeled as a back-propagation neural network (BPNN) to maintain its accordance with MATLAB®. In MATLAB®, a BPNN can contain several hidden layers. A BPNN with one hidden layer is a two-layer neural network with a back-propagation algorithm. A BPNN with two hidden layers is a three-layer BPNN and so on.

- Architecture of BPNN in MATLAB®

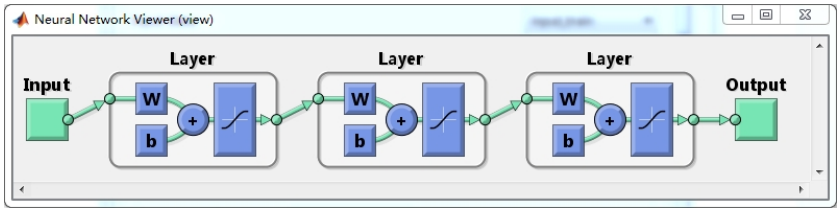
Figure 39 illustrates a presentation of the topology of the BPNN in this software.

[269] Cf. (Ludvigsen, et al., 2014)

Figure 39: Topology of the BPNN in MATLAB®



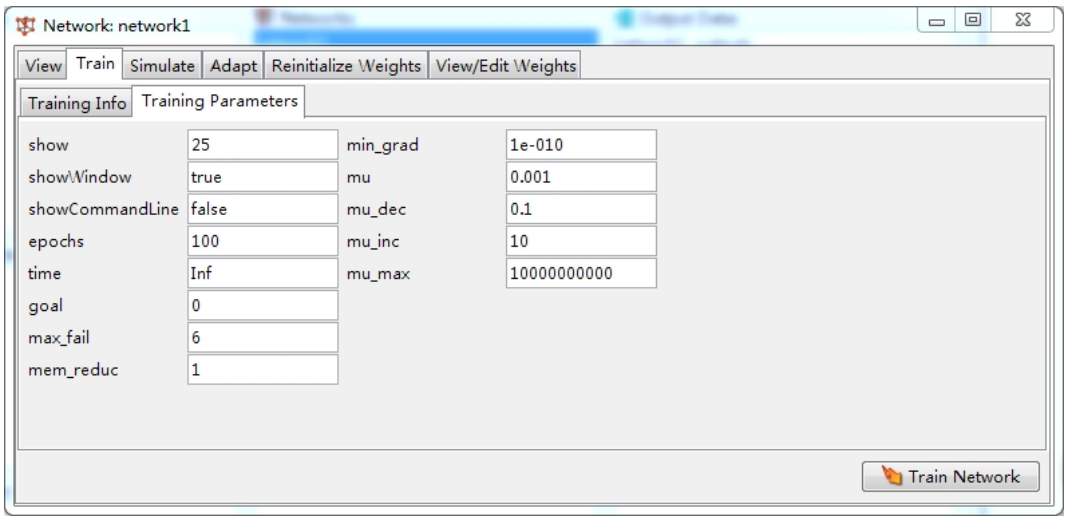
A four-layer BPNN



A five-layer BPNN

Parameters are set to fix the topology of BPNN in MATLAB®, including training function, learning function, activation function, and a number of layers, as illustrated in Figure 40.

Figure 40: Sample of setting training parameters



The number of nodes in the hidden layer depends on the nodes in the input layer. A large number of neurons in the hidden layer may result in over-fitting. This over-fitting may eliminate the generalisation capability of the network. An insufficient number of hidden neurons reduces network accuracy because the network is too constrained to learn sufficiently from the training data. [270]

The precise, actual size of the hidden layer remains an open issue.[271] In this dissertation, the number of nodes in the hidden layer is set according to previous

[270] Cf. (Zhang, et al., 2000)
[271] Cf. (Kroll, 2012)

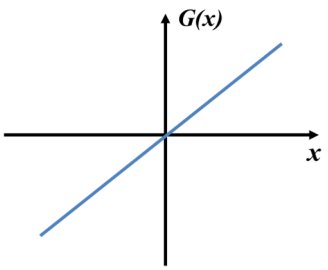
experience, that is, the number of hidden neurons is usually established at approximately 1.2 to 1.5 times that in the input layer.

- Activation Functions of BPNN

The activation function affects the signal transformation from the current layer to the next layer. Many activation functions can be applied to BPNN. Figure 41 illustrates three types of activation functions, namely: linear, log-sigmoid, and tangent functions.

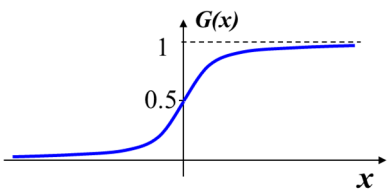
Figure 41: Three types of activation function for BPNN

$$G(x) = x$$



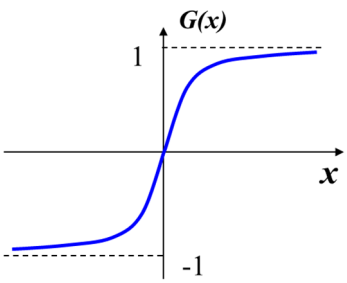
Linear activation function

$$G(x) = \frac{1}{1+e^{-x}}$$



Log-Sigmoid activation function

$$G(x) = \frac{1-e^{-x}}{1+e^{-x}}$$



Tangent activation function

Due to its nonlinearity, the log-sigmoid function is often used as the activation function. That is, the function is monotonically and continuously increasing. This

function is also universally differentiable. These properties facilitate the smooth application of the derivative-based learning method.[272]

Various activation functions can be applied between layers to map variables in MATLAB®. For instance, the log-sigmoid function is used to activate the connection between the input and the hidden layers and the linear function is employed to connect the hidden and the output layers. The relationships between the variables in BPNN can be expressed as follows:

$$y_d = \sum_{c \in C} w_c^d \cdot G_c[\sum_{r \in R} w_r^c \cdot x_r + b_c] + b_d \tag{6-1}$$

Where:

- y_d: outcome of the output layer
- r: node in the input layer
- c: node in the hidden layer
- d: node in the output layer
- w_r^c: connection weights of the input and hidden layer
- w_c^d: connection weights of hidden and output layer
- b_c: bias of the input layer
- b_d: bias of the output layer

Correspondingly, the pseudo code of the BPNN model is depicted in Table 4:

[272] Cf. (Kroll, 2012)

Table 4: Pseudo code of the BPNN model

Initialise network weights

do

For each training sample

Desired output = output of pattern

Actual output = calculated output

compute error (difference between desired and actual output) at the output units

compute Δw_c^d *for all weights from the hidden to the output layer*

compute Δw_r^c *for all weights from the input to the hidden layer*

update network weights

until all samples are classified correctly or another stopping criterion is satisfied

return the network

- Network Creation Function (newff)

newff is a function of Neural Network Toolbox™ in MATLAB®. Using the newff function facilitates the customisation of the BPNN with the settings. The syntax of newff is as follows:

net = newff (P, T, [S1 S2...S(N-l)], {TF1 TF2...TFNl}, BTF, BLF, PF, IPF, OPF, DDF)

where P is the input matrix and T is the expected output matrix. The processing functions transform the provided data (input-output patterns) into a network appropriate form (IPF). After the training, the processing functions restore the data to their original forms (OPF). Other arguments can be explained by the following example, which demonstrate the use of the newff function.

```
%% BPNN Parameters
input_trainum=7;  % Number of the nodes in the input layer
hiddennum1=2;     % Number of the nodes in the first hidden layer
hiddennum2=2;     % Number of the nodes in the second hidden layer
output_trainum=1; % Number of the nodes in the output layer
                  TF1='logsig';     % Activation function from the
                  input layer to the first hidden layer
                  TF2='logsig';     % Activation function from the
                  first hidden layer to the second hidden layer
TF3='tansig';     % Activation function from the second hidden layer
                  to the output layer
BTF='trainlm';    % Network training function
BLF='learngdm';   % Weight/bias learning function
PF='mse';         % Performance function
IPF='mapstd';     % Input processing functions
IPF='mapstd';     % Output processing functions

%% Network creation
net=newff(input_train, output_train, [hiddennum1,hiddennum2], {TF1
TF2 TF3},BTF,BLF,PF,{IPF},{OPF},{DDF});
net.divideFcn = '' ;
net.trainParam.min_grad=1e-20;
```

As discussed in section 5.2.2, several modified versions of the original BPNN have been developed to improve the performance of BPNN. These versions include the Levenberg–Marquardt BP (LMBP) algorithm, the variable learning rate BP (VLBP), and the genetic algorithm (GA). The LMBP and VLBP attempt to adjust the parameters of the BPNN to enhance the quality of the results in the network. Given that GA is a complete and independent heuristic method, the incorporation of BPNN and GA is a complex process. In the succeeding section, the integration of GA into BPNN is explained in detail.

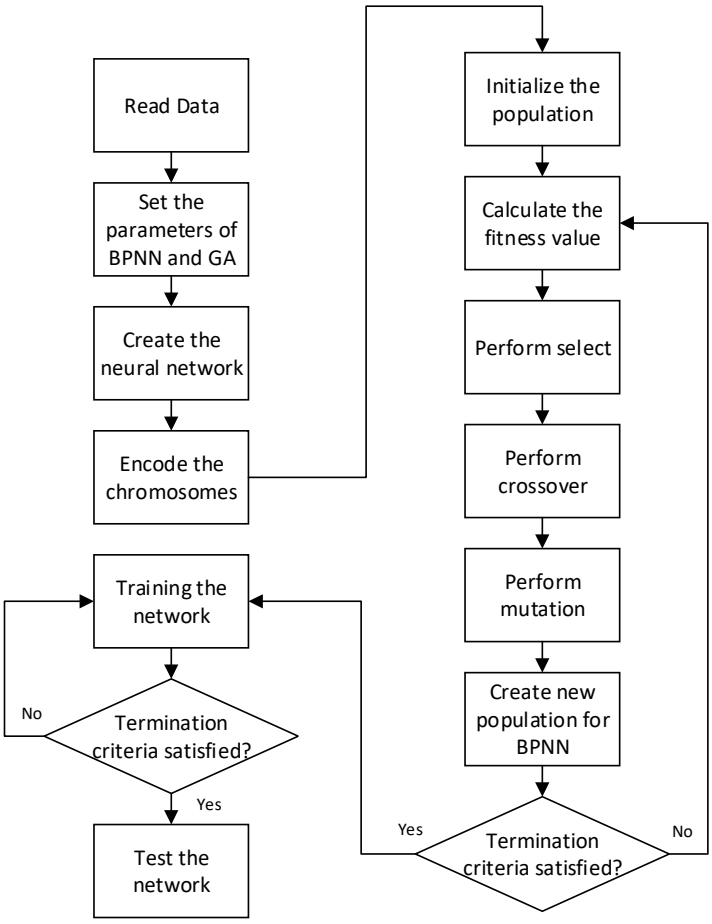
- Integration of GA in BPNN

A new population is generated through genetic operation. This population is fed into the BPNN model for qualified prediction. GA initially calculates the fitness value. The fitness function calculates the sum of the errors between the outputs and the targets:

$$fitness = \sum_{d \in D} \left| y_d - t_d \right| \tag{6-2}$$

In the succeeding generations, superior individuals are maintained, and inferior ones are eliminated. This algorithm is then reiterated ten times in the experiment to optimise the initial value of the weight and the bias for the network. Figure 42 depicts a flowchart of this model.

Figure 42: Flowchart of the GA-BPNN model



The BPNN model framework is established. In the next step, the inputs are fed into the model for training and testing. The details of the process are discussed in the following section.

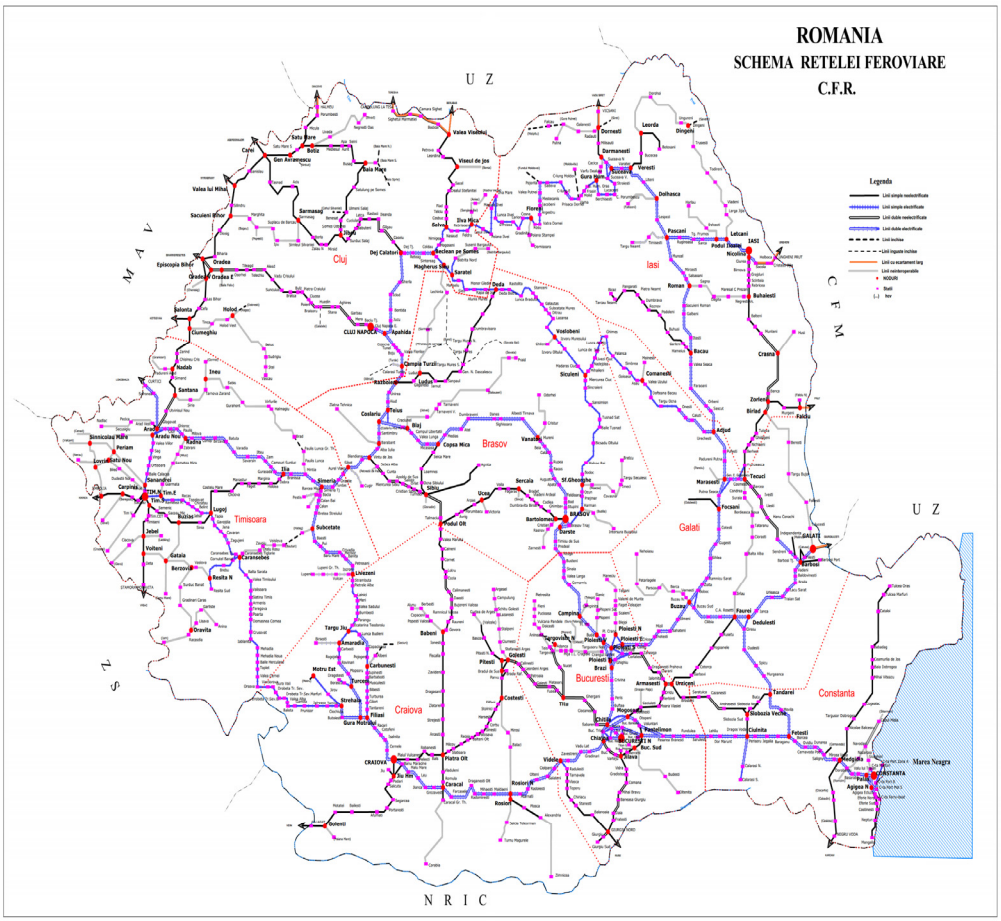
6.3 Experiment on the Delay-prediction Model

The delay-prediction model aims to maximise the reliability of a traffic journey. The methodology consists of three steps: first, the relevant variables, namely, the inputs, are identified and quantified. These inputs determine the configuration of the freight network, infrastructure, locations of facilities and depots, and order timing. Second, these variables are simulated in the model. Meanwhile, the model is configured. Finally, the results of the simulation are analysed. Delay samples are collected from data sets from Romania. The source is used to train and test the prediction model.

6.3.1 Background

The Romanian railway network is operated by Căile Ferate Române (CFR, meaning "Romanian Railways"). This network has a line length of 20,077 kilometer (km).[273] Romania offers outstanding train coverage and various services to satisfy the passengers on its railway network. The network is connected to the major cities of Europe as well, including Budapest, Prague, Vienna, Warsaw, and Venice. This network serves Pan-European passenger and freight trains via several passes. Figure 43 provides an overview of the Romanian railway network.

Figure 43: Romanian railway network[274]



The CFR railway network applies the European (standard) gauge of 1435 mm. Nevertheless, at the railway borders of the Ukraine and the Republic of Moldavia, the lines with the usual standard gauge are doubled by a line with gauge of 1520 mm for the distance from the CFR border station to the neighbouring railway network.

[273] Cf. (The National Railway Company „CFR" - S.A., 2013)
[274] Ibid.

Commuting personal trains in this country link rural villages and run at an average speed of approximately 34 km/h. The fast InterCity trains travel at 87 km/h. The CFR railway network reports a maximum operating speed of 160 km/h.[275] However, Romania has no high-speed rail lines.

6.3.2 Preliminary Statistical Analysis of the Data

The data set includes the delay records of the trains in the period from January 2014 to April 2014, as well as a single day record for May 15, 2014. A total of 115,621 records are obtained and divided into two sets 114,532 records (from January 2014 to April 2014) were used in the training data set, and 1,089 records (May 15, 2014) were also applied as the test data set.

The CFR employs a delay code to identify the causes of the delays. The staff members of a station record a delay along with its cause. Moreover, the data set provides the name of the station at which the delay was recorded. Table 5 shows a sample of the data set. (Traction denotes the power supply on the locomotives: A for auto motor, D for diesel, E for electric, and H for hydraulic.) The delay code indicates the main cause of the delay.

Table 5: Sample of the data set from CFR

Train Id. No.	Traction	Date	Delay code	Delay time	Station	Region
#14092#14092-1	E	2014/1/1	Irv	3	Galateni	R1
#14364	D	2014/1/1	D	7	Periam	R1
#14439	D	2014/1/1	D	4	Arad	R3
#15203	D	2014/1/1	Iii	3	Piatra Craiului	R8
#15208	D	2014/1/1	Irv	1	Poieni	R5
#15208	D	2014/1/1	Iii	6	Alesd	R4
#15208	D	2014/1/1	Otd	6	Piatra Craiului	R8
#1521	D	2014/1/1	Irv	3	Galateni	R1
#1552#1552-1	E	2014/1/1	Irv	2	Brazi	R1
#1580-1#1580	E	2014/1/1	F	9	Sarulesti	R8

As presented in Table 6, the delay code indicates the main reason for the delay of a freight train.

[275] Ibid.

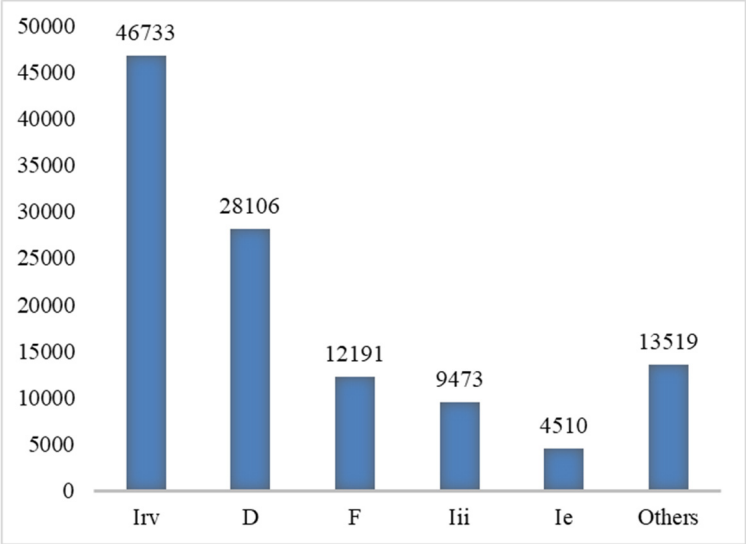
Table 6: Original delay reasons

Delay code	The meaning of code
B	Incidents
CFS	Border police formalities
D	Other entities (different by Infrastructure and RU)
F	Force majeure (vandalism, bad weather, etc.)
G	Strike
H	Other railways entities (neighbour network)
I	In departure station
Iai	Infrastructure signalling staff mistake
Ial	Infrastructure track staff mistake
Iam	Infrastructure traffic staff mistake
Ie	Infrastructure, other cause
Iii	Infrastructure, secondary cause
IM	Infrastructure Manager
Imd	Infrastructure, turnout (shift) defective
Irv	Tempo restriction
Isd	Infrastructure, signalling installation defective
O	Orders given by Transport Minister
Oca	Passenger or freight train, commercial staff mistake
Oe	Passenger or freight RU, other cause
Oii	Passenger or freight RU, secondary cause
Oma	Passenger or freight RU, shunting staff mistake
Ota	Passenger or freight RU, engine driver mistake
Otd	Passenger or freight RU, engine driver defective
Ova	Passenger or freight RU, wagons staff mistake
Ovd	Passenger or freight RU, wagons defective
P	In other station (not in departure station)
R	recovery time
RU	Railway Undertaking, the company who run the train

As per the 114,532 records of the training set, the top 5 delay causes account for approximately 88.2% of the records. Figure 44 depicts these five delay causes. Tempo restriction (Irv) caused the most delays and accounted for nearly 40.8% of the

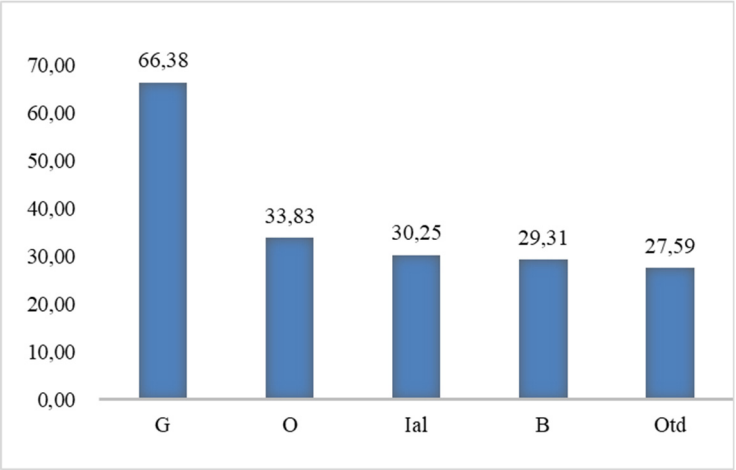
total. This finding is attributed to the fact that as mentioned previously, Romania has no high-speed rail lines, and the maximum operating speed is only 160 km/h.[276]

Figure 44: Top 5 causes for the delay



The average delay is 6.77 minute (min.), as per the 114,532 records and as illustrated in Figure 45. The top five delay causes of this average delay are listed below. Strike (G) caused 430 delays, and the largest mean value in the data set is 66.38 min.

Figure 45: Top five causes of average delay (in min.)



The delay records are analysed and displayed in Table 7 according to the delay reasons. The longest recorded delay was by train #4133 and lasted 1,105 min. on

[276] Cf. (CFR, 2013)

January 27, 2014. It was caused by force majeure (F). Furthermore, engine driver defects (Otd) caused a 364-min. delay on January 30, 2014.

Table 7: Basis analysis of delays data

No.	Delay code	Count	Max	Mean	SD
1	Irv	46733	147	3.54	2.69
2	Ota	934	203	4.61	9.44
3	Ie	4510	105	5.39	5.44
4	D	28106	295	5.85	7.47
5	Isd	2238	65	6.85	6.22
6	Ova	1	7	7.00	
7	Oca	35	18	7.06	4.12
8	Iii	9473	151	7.22	7.90
9	Iam	5	17	8.60	6.02
10	Oe	2958	781	8.69	19.24
11	Imd	117	50	10.69	9.25
12	H	807	178	12.05	16.47
13	F	12191	1105	12.29	30.26
14	Cfs	314	89	13.54	11.12
15	Oii	3333	293	14.31	19.13
16	Ovd	42	92	18.69	18.18
17	Oma	15	87	20.20	22.59
18	Iai	1	22	22.00	
19	Otd	2069	364	27.59	35.06
20	B	83	247	29.31	47.11
21	Ial	12	78	30.25	19.58
22	O	125	62	33.83	23.24
23	G	430	133	66.38	42.06

The data are summarised by region in Table 8. Region R5 reported the most delays with 21,760, whereas region R8 had the least at 5,817 delays. The 1,105-min. delay (the longest delay) occurred in region R2. This region also had the largest mean delay value at 18.50 min.

Table 8: Delay summary according to regions

No.	Region	Count	Max	Mean	SD	%
1	R1	16624	571	10.64	6.22	0.15
2	R8	5817	162	11.94	7.10	0.05
3	R3	16303	341	12.63	6.90	0.14
4	R4	14798	609	13.01	6.35	0.13
5	R5	21760	891	13.67	5.45	0.19
6	R7	9104	443	14.25	7.13	0.08
7	R6	16011	395	17.98	7.61	0.14
8	R2	14115	1105	18.50	8.41	0.12

No significant difference in delay count is observed among the different weekdays, as per Table 9. However, the mean delay value on Tuesdays is the lowest among all obtained values at 9.37 min. Furthermore, Sunday has the largest mean delay value at 19.34 min.

Table 9: Delay summary of weekdays

No.	Weekday	Count	Max	Mean	SD	%
1	Tue	15412	371	9.37	5.94	0.13
4	Sat	15738	781	14.44	7.01	0.14
3	Thu	15771	443	11.97	6.27	0.14
7	Sun	16626	609	19.34	7.64	0.15
6	Mon	16696	1105	17.09	6.70	0.15
2	Fri	16834	261	11.08	6.35	0.15
5	Wed	17455	295	14.64	7.35	0.15

6.3.3 Pre-processing of Data

The data set must be specified for suitability for programming. Given the structure of the data set, input and output, signals are indicated as the elements in Table 10:

Table 10: Input and output in BPNN

Input	Output
Train Id. (Train No.)	Delay time
Traction	
Weekday	
Delay code	
Station	
Region, where the train operates	

All the inputs are initially sorted in ascending order and then normalised applying the mean value of delay time. If the input is derived from a “weekday” during a national holiday, then its weekday number is like that of a Sunday. The date is normalised using an Excel 1900 Date System. In this system, the first day supported is January 1, 1900. This date is converted into a serial number that represents the number of days elapsed since January 1, 1900. For example, Excel converts the date July 5, 1998, to the serial number “35981”. Table 11 shows the data after the pre-processing procedure.

Table 11: Examples of pre-processed data

Original format in the data set:

Train Id.	Traction	WEEKDAY	Delay code	Station	Region	Date	Delay time
#10163	E	Sun	F	Gura Vaii	R7	2014/2/2	6

Converted to MATLAB®-format:

Train Id.	Traction	WEEKDAY	Delay code	Station	Region	Date	Delay time
303	1	7	13	306	6	41672	6

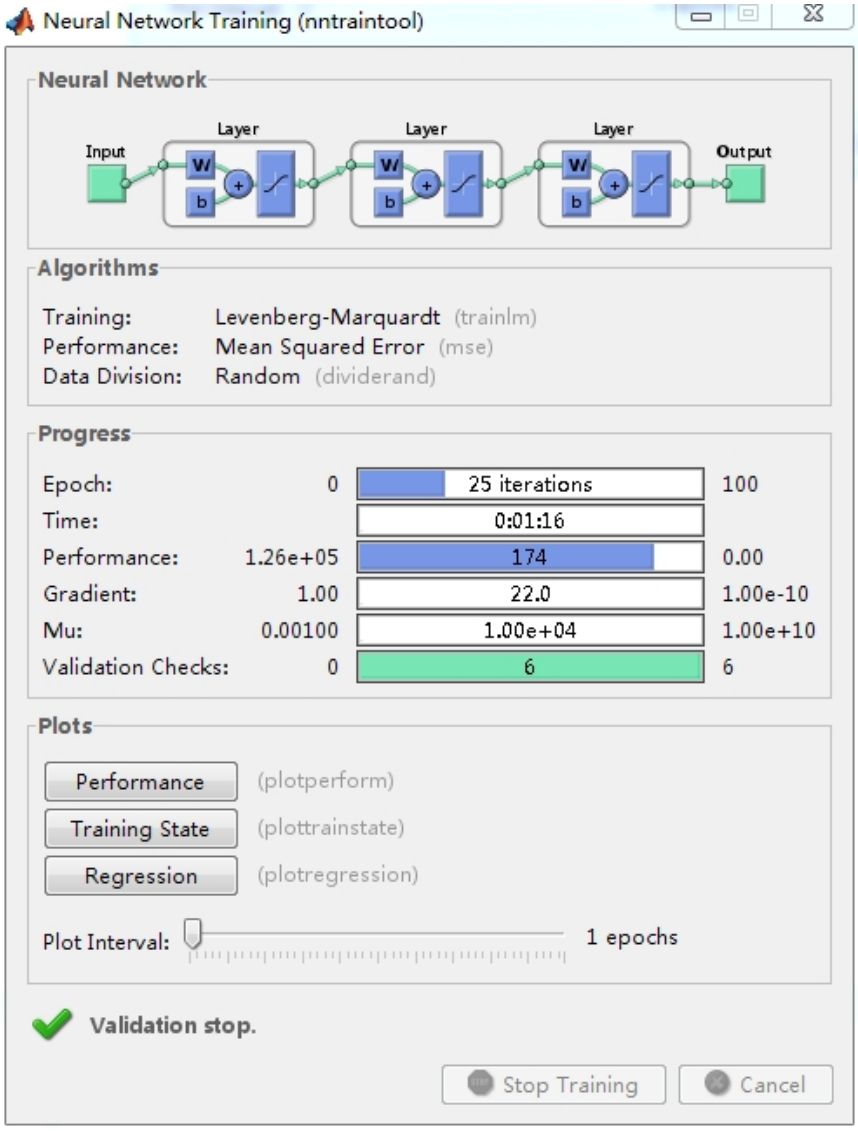
The samples deployed in the model mainly consist of two subsets, namely, training and test samples. The number of samples in one subset defines the sample size. The training subset data are used to recognise and analyse the potential structure of the connection weights by gradient descent in training phases. Meanwhile, the samples in the test subset are not used during training but are employed to verify these weights.

The input data are further divided into three groups in MATLAB® with the "early-stop" method to improve BPNN generalisation. As discussed in section 5.2, the weights of BPNN are optimised by gradient descent. Nonetheless, the appropriate point at which to stop the training process is difficult to determine. When BPNN training cannot stop at the optimal point, over-training can occur. Thus, "crossover-validation" is conducted to avoid BPNN over-fitting. The test samples are further split into two subsets, namely, the validation and the test subsets. The training phase is periodically stopped. Following each training phase, the BPNN is tested on the validation subset. Once the validation session is completed, the training continues.

To avoid overfitting, a validation data set is applied to check for error within the acceptable range. If the errors in the training data set decrease, but the errors of the validation data set stay the same or increase, BPNN is overfitting. The training process should stop (early-stop) and the weights of the iteration, which yields the minimal errors of the validation, are applied to the BPNN.

Figure 46 depicts a sample of the early stopping of the "Validation Stop," which is caused by increased validation errors.

Figure 46: Sample of early stopping during neural network training



In the experiment conducted for this dissertation, the functionality of the early stop is disabled to examine the performance of BPNN only. Through the experiment, this dissertation verifies whether BPNN and its improved versions have the ability to predict actual train delay and enhance the quality of the prediction results.

6.3.4 Integration of Back-propagation Neural Network and Genetic Algorithm

The GA-BPNN model is principally designed in the following steps:

- The Train ID. No., Traction, Weekday, Delay code, Station, and Region of the training set are the input elements, and the Delay time is the target.

- The network is trained by applying different modification methods.
- The network is validated with the test data set, which contains 1,089 records.

The GA-BPNN model consists of several sub-functions: GAxxBPxx.m is the main function; GA00BPxx.m is the BPNN model; and GA01BPxx.m is the integrated GA-BPNN model. fun.m, funh2.m, select.m, code.m, cross.m, and mutation.m are sub-functions used to implement GA optimisation. The parameters of BPNN model in MATLAB® are summarised in Table 12:

Table 12: Settings in BPNN

Parameters	Settings
Number of hidden layer	1 or 2
Number of nodes in hidden layer(s)	For 1 hidden layer networks, Fibonacci numbers are used from 1 to 144. For 2 hidden layers networks, the number of elements in each layer is from set {2, 3, 5, 10, 20}.
Transfer functions of each layer	purelin, logsig or tansig
Neural network training function	traingdx or trainlm
Weight/bias learning function	learngd or learngdm
Error function (Performance function)	mse or msereg
Input and output processing functions	mapminmax or mapstd
Learning rate	0.1 or 0.01
Epochs of training	100, except BP60 to BP62 are 10, 20 and 50

The GA part has four parameters, whose values are presented in Table 13:

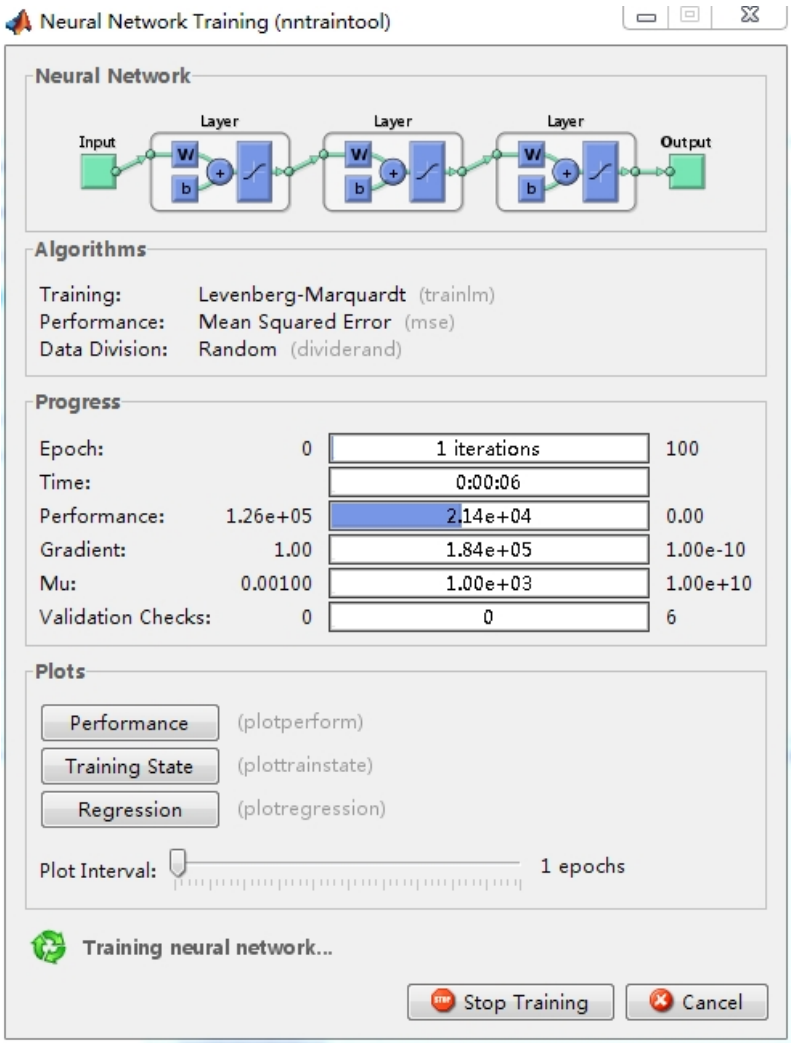
Table 13: GA settings

Parameters	Settings
Maximum number of generations	7 or 15
Size of population	10, 20 or 100
Crossover rate	0.1, 0.3, 0.5, 0.7 or 0.9
Mutation rate	0.1, 0.3, 0.5, 0.7 or 0.9

Principally, the model examined in this dissertation is the GA-BPNN model. Nonetheless, several experiments are conducted without GA testing the performance of different parameters provided by Neural Network Toolbox™ in the MATLAB®.

Once the input-output patterns are loaded and the training parameters are set up as indicated in Figure 47, the process of the model training begins.

Figure 47: Sample of training a network



The results are explained in the following section.

6.3.5 Results analysis

Several key factors are manipulated to determine the ideal configuration for the BPNN during the MATLAB® training phase. These factors include the number of hidden layers, optimised techniques, and activation function. Furthermore, GA is integrated into BPNN. Correspondingly, the experiments are composed of four cases:

- number of hidden layer (case 1),
- different activation functions (case 2),
- different parameters facilitated in MATLAB® (case 3), and
- GA (case 4).

The case comparisons focus on the four key performance indexes (KPI):

- Mean error on test sets
- Standard deviation (SD) of the errors on test sets
- Mean error on training sets
- SD of the error on training sets

Failures in function mapping by a BPNN can arise from an inadequate choice of parameters, e.g., poor selection of weight factors and/or an insufficient number of neurons in the hidden layer.[277] Therefore, the different parameters of BPNN are tested. Although certain rules must be followed when setting BPNN values, a standard to which a researcher can refer to derive the optimum configurations for BPNN training has not been established.[278] Parameters are tested in different cases to determine the ideal setting for BPNN. The simulation is confirmed to approximate current system performance adequately. The settings are detailed in Annex f. The results are sorted in the order of the codes recorded in Annex g.

- Comparison of BPNNs with one Hidden-layer and two Hidden-layers

To improve BPNN performance, an important parameter is modified, namely, the number of hidden layers. Except for the number of hidden layers, the other settings are similar in both experiments. To compare the influence of parameters on BPNN performance, the experiments are divided into four groups as shown in Table 14:

Table 14: Experiment groups with one hidden layer and two hidden layers

Function No.	Type of BPNN	Number of hidden-layer in BPNN
GA00BP49 to GA00BP59	BPNN	one hidden-layer
GA00BP10, GA00BP24 to GA00BP47	BPNN	two hidden-layer
GA01BP49 to GA01BP59	GA-BPNN	one hidden-layer
GA01BP01 to GA01BP47	GA-BPNN	two hidden-layer

[277] Cf. (Rehman, et al., 2012)
[278] Cf. (Sexton, et al., 1998)

The values of the four KPI are presented in Table 15 along with their sources. The performance levels of the two groups differ significantly. Based on the mean errors on both training and test sets, the BPNN with the two hidden layers performs better than the BPNN with one hidden layer. The comparison of the performance of the GA-BPNN model with one hidden layer with that with two hidden layers suggests that the GA optimised search space exploration.

As the number of elements in the hidden layer increases, the mean errors on the training set decrease. By contrast, the mean errors on the test set initially decrease and then increase. The average and minimum values of the KPI and their sources are as follows.

Table 15: Results for BPNNs with one and with two hidden layers

	KPI	Average value	Minimum value	Code of record file	Type of model	Number of nodes in hidden-layer
One hidden-layer BPNN	Mean error on test sets	5.11	4.97	GA00BP55A	BPNN	21
	SD of the errors on test sets	8.39	8.07	GA01BP54B	GA-BPNN	13
	Mean error on training sets	5.41	5.22	GA01BP59B	GA-BPNN	144
	SD of the errors on training sets	12.15	11.96	GA01BP59C	GA-BPNN	144
Two hidden-layers BPNN	Mean error on test sets	3.62	3.51	GA01BP46B	GA-BPNN	10-20
	SD of the errors on test sets	8.55	8.42	GA00BP25A	BPNN	10-20
	Mean error on training sets	4.26	4.07	GA00BP47A	BPNN	20-20
	SD of the errors on training sets	12.33	12.26	GA00BP47A	BPNN	20-20

- Comparison of Various Activation Functions in BPNN

The option for activation functions is crucial to the BPNN performance. In the experiments, GA00BP01 to GA00BP09 and GA01BP01 to GA01BP09 used networks with two hidden layers and various activation functions. A total of 36 records are examined.

Ten of the best records in this experiment are represented in Table 16. These records are sorted in ascending order according to the mean error on the test sets. Three types of activation functions are considered for the test, namely, linear (purelin, P), log-sigmoid (logsig, L), and hyperbolic tangent sigmoid activation functions (tansig, T). For instance, the "TTP" presents that tansig is the activation function for the first and second hidden layers, and purelin is the activation function for the output layer. Similarly, the "LLT" indicates that logsig is applied to the first and second hidden layer, whereas tansig is applied for the second hidden layer and output layer. The best records (lowest mean and SD values) show that TTP and LLT are satisfactory activation function combinations.

Table 16: Top 10 records with minimal mean errors on test sets

Code of Record File	Mean of the errors on training sets	SD of the errors on training sets	Mean error on test sets	SD of the error on test sets	Model	Activation function
GA00BP09A	4.09	9.98	3.63	8.19	BPNN	TTP
GA01BP09A	4.25	10.14	3.67	8.48	GA-BPNN	TTP
GA01BP09B	4.25	10.14	3.67	8.48	GA-BPNN	TTP
GA01BP09C	4.25	10.14	3.67	8.48	GA-BPNN	TTP
GA00BP03A	7.76	14.43	3.77	8.44	BPNN	LLP
GA00BP04A	7.09	14.43	3.77	8.27	BPNN	TTT
GA01BP01A	7.76	14.43	3.78	8.26	GA-BPNN	LLT
GA01BP01B	7.76	14.43	3.78	8.26	GA-BPNN	LLT
GA00BP01A	7.76	14.43	3.83	8.69	BPNN	LLT
GA01BP01C	6.82	14.43	4.03	8.22	GA-BPNN	LLT

- Comparison of Parameters: VLBP and LMBP

VLBP and LMBP are popular BPNN optimisation techniques introduced in section 5.3. In this subsection, their influence on BPNN is tested. Various settings in both BPNN and GA-BPNN models are applied to investigate both VLBP and LMBP sub-models. These settings affected the results. Moreover, their performance levels are compared. Table 17 displays the different settings for both models.

Table 17: Various settings of VLBP and LMBP models

Main Function	BPNN	Error Function	Input and Output Processing Function	Learning Rate	Activation Function
GA00/GA01 BP13	VLBP	mse	mapminmax	0.01	LLT
GA00/GA01 BP14	VLBP	mse	mapstd	0.01	LLT
GA00/GA01 BP15	VLBP	msereg	mapminmax	0.01	LLT
GA00/GA01 BP16	VLBP	msereg	mapstd	0.01	LLT
GA00/GA01 BP20	VLBP	mse	mapminmax	0.01	TTP
GA00/GA01 BP21	VLBP	mse	mapstd	0.01	TTP
GA00/GA01 BP22	VLBP	msereg	mapminmax	0.01	TTP
GA00/GA01 BP23	VLBP	msereg	mapstd	0.01	TTP
GA00/GA01 BP01	LMBP	mse	mapminmax	0.10	LLT
GA00/GA01 BP09	LMBP	mse	mapminmax	0.10	TTP
GA00/GA01 BP10	LMBP	mse	mapstd	0.10	LLT
GA00/GA01 BP11	LMBP	msereg	mapminmax	0.10	LLT
GA00/GA01 BP12	LMBP	msereg	mapstd	0.10	LLT
GA00/GA01 BP17	LMBP	mse	mapstd	0.10	TTP
GA00/GA01 BP18	LMBP	msereg	mapminmax	0.10	TTP
GA00/GA01 BP19	LMBP	msereg	mapstd	0.10	TTP

The LMBP model performed better than the VLBP according to Table 18. All LMBP indices are smaller than those of VLBP. Moreover, the LMBP networks can fit both test and training sets better than the VLBP networks can. However, LMBP requires much hardware capacity given the Jacobian matrix in the calculation.[279]

[279] Cf. (Hagan, et al., 2014)

Table 18: Analysis of VLBP and LMBP result

	KPI	Minimum	Maximum	Average	Median
VLBP	Mean error on test sets	3.90	100.85	11.44	4.81
	SD of the errors on test sets	8.21	94.51	16.11	8.89
	Mean error on training sets	4.50	45.17	9.01	5.07
	SD of the errors on training sets	11.88	46.80	17.93	12.69
LMBP	Mean error on test sets	3.53	4.24	3.75	3.70
	SD of the errors on test sets	7.95	11.00	8.55	8.53
	Mean error on training sets	4.09	7.76	4.65	4.26
	SD of the errors on training sets	9.98	14.43	11.38	10.48

- Comparison of BPNN and GA-BPNN

The results provided in Table 19 are based on the records of GA00BPxx and GA01BPxx (main functions).

Table 19: Analysis of BPNN model results

	KPI	Minimum	Maximum	Average	Median
BPNN	Mean of Error on Test Sets	3.53	547.19	32.88	3.82
	SD of Error on Test Sets	7.95	94.51	10.83	8.52
	Mean of Error on Training Sets	4.07	45.17	6.28	4.39
	SD of Error on Training Sets	9.98	45.06	13.43	12.32
GA-BPNN	Mean of Error on Test Sets	3.49	547.19	31.30	3.74
	SD of Error on Test Sets	8.07	39.86	9.29	8.54
	Mean of Error on Training Sets	4.07	28.64	5.65	4.37
	SD of Error on Training Sets	10.14	46.80	13.03	12.34

During the evaluation, a neural network is established in MATLAB®, and 20 epochs are considered for each run. The setting of these epochs is written in fun.m and fun2.m. The number of created neural networks is like the size of the population.

Furthermore, the initial part is incorporated into the GA. The number of neural networks created is equal to the size of the population multiple (number generated + 1), which is 160 in the GA01BPxx series and can reach 1,100 in GA76BP10. For example, the GA76BP10 created 1,101 neural networks (1,000 for the GA part and 1 for the BPNN component), whereas the GA00BP10 created only one network. During

GA parameter tuning (GA01BP10 to GA76BP10), the runtime of some experiments exceeds 24 hours. Without GA optimisation, the runtime is only a few minutes long. Thus, GA optimisation is unnecessary under time constraints.

The GA-BPNN model usually performs better than the pure BPNN model. The best overall result of the experiments is generated in the GA01BP62A.mat program. Table 20 highlights the best overall results from all of the simulation experiments. All of these tests applied the GA-BPNN model. Thus, GA optimisation can be sensibly incorporated into simulations although the run time is long.

Table 20: Best values on each KPI

Key Performance Index	Best Value	Record File Name	Model
Mean error on test sets	3.47	GA61BP10A	GA-BPNN
SD of the errors on test sets	7.15	GA09BP10A	GA-BPNN
Mean error on training sets	4.07	GA01BP47A	GA-BPNN
SD of the errors on training sets	9.98	GA01BP09A	GA-BPNN

Implementing GA in BPNN improves prediction performance. Specifically, disadvantages of the pure BPNN are overcome, including too-rapid convergence. The use of a GA-BPNN model is preferred over the direct application of a classical ANN procedure in the modelling of train delays for response time reasons. Therefore, the GA-based BPNN is an effective simulation method with which to estimate delays.

Although the GA-BPNN performed better than the pure BPNN model, the GA-BPNN required considerably more time. The runtime of the GA-BPNN is usually 3 hours to 10 hours. The reason for this long runtime is that the GA performs a global search of the solution space.

6.4 Interim Conclusion

The prediction model in Transport-Suite imitates the decision-making behaviour of a human being by considering factors similar to those used by a person when making a decision. The BPNN model evolves automatically through the interrelations of signals. Given this capability, this network is highly suitable for problems in which no relationship is determined between the output and the inputs.[280]

[280] Cf. (Turban, et al., 2011)

As the discussion in section 5.2.3, BPNN has some drawbacks. In order to overcome the drawbacks, modification and optimisation techniques are applied. Neural Network Toolbox™ in MATLAB® is facilitated by several methods. A BPNN is established and tested in MATLAB® to predict train delay at the operational level.

Various elements become decisive through the establishment of an ANN, network topology, learning rule, initial weights and biases, activation function, and learning rule. In this thesis, different results can be compared by tuning the model parameters. It is attempted to compare the possible solution approaches, considering the varying set of the parameter in MATLAB®. The GA-BPNN is demonstrated as a well-performance prediction model in comparison with other parameters of performance improvement, which are mentioned in the dissertation.

7 Conclusions and discussions

7.1 Conclusions

Combined transport (CT) is characterised by highly environment-friendly traffic modes and minimal congestion, as well as improved accessibility of connections, e.g., transhipment terminals. The operator of CT offers a full range of services in the transportation of rail/road, particularly in journeys between different terminals. Such services cover the organisation and supervision of the whole journey of the CT, including the handling of transhipment and setting wagon for traction.

Owing to environmental considerations, an environment-friendly transport mode is generally the focus of transportation policies. The government (regulator) constructs transport infrastructures to meet the demands of both customers and carriers and to impose fare (toll) regulations that alter the behaviour of users and carriers of CT. These regulations facilitate the achievement of sustainability objectives.[281] As an environment-friendly transport module, CT is frequently requested to be widely used in the practice. To courage market entities to choose CT for freight transportation, CT is politically supported. For example, the European Commission (EC) and its member governments have released a series of policies to support CT in the last twenty years.[282]

- Risk analysis in CT (Railway as the main haulage)

However, in the context of the industrial reality, operators are not in favour of CT because of its high complexity. Too many factors influence the quality of CT for a decision-maker to find a solution in a short time. Scholars proposed many reasons that contribute to inefficient CT management. Risk management plays a vital role in CT. Risks in CT are generally divided into four categories: operations, system, information technology, and external risks. The first three categories are divided further into several risk groups. Risks result in instability of CT performance.

Hence, less-structured problems are common for CT participants. Less-structured problems are problems without available solutions. Such problems create a burden of work in CT, in contrast with mono-modal transportation. To provide

[281] Cf. (Chiou, et al., 2013)
[282] Cf. (Janic, 2008)

decision-makers with solutions to less-structured problems in CT, risk prediction and analysis of the results is a fundament to support the decision-makers. Furthermore, other functionalities, e.g. simulation of alternatives transport routes, are necessary as well. To fulfill the requirements in the CT as a complete system, DSS is established to run the process of CT smoothly.

- DSS as a framework of solutions to less-structured problems

As the framework of solutions to less-structured problems, DSS provides an integrated view of different CT phases, from defining the transportation task to route designing and time planning. Entities in CT can rely on modern information technology to achieve efficient decision-making because efficient and effective information sharing is essential to a successful transport chain. By providing relevant and timely information in the DSS, decision-makers could explore data, capture information, and evaluate alternatives, particularly on an operational level. In other words, DSS is found to influence the nature of intra-organisational information sharing in specific transportation network designs.[283]

In this context, Transport-Suite is proposed as the deliverable of research project Dynamische Konsoliderung (DynKo) and as a DSS to enhance the work efficiency of the decision-makers involved in CT. The modules in Transport-Suite are modified according to the specific requirements of partners. Through the employment of heuristics in the system, the process of generating plans involves determining what should be provided, when, how much, and what kind of logistic service. By integrating with the information-sharing platform, Transport-Suite evolves through coordination of stakeholders for management decisions. The techniques applied in Transport-Suite directly determine the average outcome and variability of the outcome.[284]

- Train-delay prediction with help of artificial neural network

Models that predominantly apply three performance indicators, namely, cost, delivery time and environment performance measure the function-oriented performance of CT. The factors costs and environment performance are not discussed in the thesis. In CT, accurately estimating delivery time is difficult. Delay in CT is not rare in practice. In the dissertation, risks in CT have been concluded as a major reason

[283] Cf. (Datta, et al., 2011)
[284] Cf. (Turban, et al., 2011)

for CT delays. Risk prediction is discussed intensively in the dissertation as an important functionality of DSS. Risk forecasting and evaluation are complex problems in the real world. Given its remarkable ability to derive meaning from complicated and/or imprecise data, a type of artificial neural network, namely, back-propagation multi-layer perceptron (MLP) can be used to extract patterns and detect trends that are too complex to be noticed by humans or other computer techniques. The back-propagation MLP has distinguished advantages over traditional methodologies (e.g., regression analysis, logistic regression, etc.) because it provides solutions to highly complex functions for nonlinear variables.[285]

After training a large amount of historical data, MLP learns the structure of the trained data. Based on the learning results, MLP can automatically identify the features of data. To optimise the weights in an MLP, gradient descent is applied, which cause local minimum and convergence unsteadiness of the network. However, endogen disadvantages limit the ability of MLP. In the research, four improvements are applied: momentum, variable learning-rate, Levenberg–Marquardt back-propagation, and genetic algorithm (GA). All four improvements aim to avoid the local convergence of MLP.

A model of MLP (BPNN) was trained in MATLAB® in the dissertation. By tuning the diverse parameters of BPNN in MATLAB®, that is, by applying improvements of BPNN, the system will yield different simulation results. BNPP with GA has the best result compared with simulation results. GA was thus proved well suited to the quick global exploration of a large search space and for determining possible solutions of satisfactory qualities. The BPNN designed and presented in the dissertation was demonstrated to reliably predict train delays and accelerate the process of decision-making.

In conclusion, uncertainties and risks explain the complexity in CT, which is also the focus of the dissertation. From this viewpoint, estimating the risks is necessary to support decision makers. However, risk prediction alone could not answer all the problems in CT, especially less-structured ones. Therefore, DSS is introduced in the dissertation to provide decision makers with comprehensive solutions to problems in CT. DSS aims to enhance the efficiency and effectiveness of finding solutions to less-

[285] Cf. (Rumelhart, et al., 2002)

structured problems in CT. As a substantial function of the DSS, risk prediction in CT is explained in detail. The MLP is applied to support decision-makers in solving less-structured problems in daily business. This algorithm simplifies the process of decision-making by imitating human decision-making behaviour. It is demonstrated as well that CT competitiveness with mono-transport can be improved.

7.2 Discussions

7.2.1 Limitations

Three main limitations in the DSS are presented in the dissertation: one limitation relates to the DSS system; one relates to partners in the DSS; and the last relates to the technique used in the DSS.

First, the design of the DSS in the research is rather simple compared with the real system. Not all the contributing factors for the given output are identified. These unidentified variables can lead to further noise or error in the model. For example, the BPNN did not consider the effects of delay between trains (i.e. compound delay). Given the limited capacity of a railway network, a delayed train could lead to further train delays on the same path. This might decrease or distort the applicability of the BPNN for delay prediction. Consequently, the experiment in the dissertation may be extended, and an error term may be added to the training output terms for the stated problems. Other prediction functions can be added to the prediction model if future analyses are necessary.

Second, to enhance the ability of data exploring in DSS, the perfect sharing of information is required. All CT-members have access to full information, eliminating information asymmetries. However, some members may have a vested interest in masking information. Thus, the perfect sharing of information is implausible.[286] Privacy considerations form awkward obstacles because the success of information sharing depends highly on the willingness of the participants to share all useful information. The barrier of information sharing is an endogen disadvantage of CT.

Third, CT is operated in a complicated environment. Comprehensive variables should be investigated through simulation. Meanwhile, the interactions of several risk factors are too complex for description and require much study in their specific

[286] Cf. (Rodrigues, et al., 2008)

contexts. For instance, train delays are categorised into three types as mentioned in Chapter 3.3.4: direct, knock-on, and compound delays. A model that accurately describes the influence of knock-on and compound delays is difficult to establish because the boundary of the definitions is vague in practice.

Finally, the mathematical model has its own drawbacks, which results in a limitation of the DSS. Theoretically, the size of a solution space can increase exponentially. For example, a search space can have 2^n solutions when a problem is described with n binary variables. As a result, the most optimal solution in the large space is difficult to find. Heuristics is applied to provide "good" but not (necessarily) "optimal" solutions to problems.[287] Although the model can provide efficient solutions, this result does not mean that the models can replace human decision-makers. By contrast, such tools can and should only support the decisions of train dispatchers on duty. The tools provide decisions that are usually "good enough" given the complex nature of the conflict-resolution problem. Any specific circumstances may also be left unnoticed in the BPNN model in the data extracted for BPNN training and testing.

7.2.2 Future Research Agenda

The limitations of the DSS in the dissertation also open new research agendas for further research.

The vast amounts of data and information in DSS is linked to big data, which can be realised by cloud computing to flexibly perform massive-scale and complex computing.[288] Available over the past several years, cloud services store, process, and analyse data. Additionally, cloud computing can improve the dynamics of the DSS by promptly processing various degrees of information needs.[289] Investigation of the role of big data and cloud computing may be a promising area for future research in DSS areas.

In the dissertation, several risk factors are not studied, such as the capacity of the railway network, network topology (single- or double-track) and policies changes. The interactions of the risks are complex and require further studies in their specific context. Interactions of several risk factors are not studied in the dissertation. Interactions are complex and require further studies in their respective contexts. In-

[287] Cf. (Simchi-Levi, et al., 2009)
[288] Cf. (Giannakis, et al., 2016)
[289] Cf. (Wu, et al., 2013)

depth investigation of the logistic decision-maker should be conducted to examine possible measures that may have been overlooked and to identify means of improving and optimising decisions. For example, game theory can be applied to study the behaviour of decision-makers (actors) and interoperable relationships (actions) between them by decision-making.

The MLP used in the dissertation belongs to shallow learning, which consists of a few stages in the perceptron and is designed by a human being. By contrast, layers of perceptron in deep learning evolve from data in a general-purpose learning procedure.[290] Deep learning is suitable to discover complex structures of high-dimensional data.[291] Deep learning provides insights on how to possibly develop and apply MLP in the context of risk prediction in an intricate system. Further investigation is required for these issues.

[290] Cf. (Schmidhuber, 2015)
[291] Cf. (LeCun, et al., 2015)

Annex

a. Mathematical Expression of a Three-Layer Perceptron

(The mathematical derivation of the equation in this subsection and the succeeding section adhere to the arguments of Han, 2006.[292])

Let x_r represent the input that the neuron c in the hidden layer receives, and the output of the neuron c y_c is defined as:

$$y_c = G_c\left\{\left[\sum_{r=1}^{R} W_r^c x_r\right] + b_c\right\} \tag{a-1}$$

where:

- W_r^c is the matrix of the connection weight between the input and hidden layer,

$$W_r^c = \begin{pmatrix} w_1^1 & w_2^1 & \dots & w_r^1 \\ w_1^2 & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ w_1^c & \cdots & \cdots & w_r^c \end{pmatrix}, X = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_r \end{pmatrix}$$

- b_c is the threshold of the hidden layer, and

$$b_c = \begin{pmatrix} b_1 \\ b_2 \\ \vdots \\ b_c \end{pmatrix}$$

- G_c is the activation function of the input and hidden layer.

Set $w_0^c = 1, b_c = 1$, then $w_0^c x_0 = 1 * b_c = b_c$, $\because b_c = w_0^c x_0$. Substituting this outcome in Eq. (a-1):

[292] Cf. (韩 (Han), 2006)

$$G_c\left\{\left[\sum_{r=1}^{R} W_r^c x_r\right] + b_c\right\}$$

$$= G_c\left\{\sum_{r=1}^{R} W_r^c x_r + (w_0^c x_0)\right\}.$$

$$= G_c\left[\sum_{r=0}^{R} W_r^c x_r\right]$$

If $net_c := \left[\sum_{R=0}^{R} W_r^c x_r\right]$, then

$$y_c = G_c(net_c) \tag{a-2}$$

Similarly, the output of the neuron in the output layer, y_d, is defined as:

$$y_d = G_d(net_d) \tag{a-3}$$

where:

- $net_d = \left[\sum_{c=0}^{C} W_c^d y_c\right]$
- $W_c^d = \begin{pmatrix} w_0^1 & w_1^1 & \dots & w_c^1 \\ w_0^2 & w_1^2 & & \vdots \\ \vdots & & \ddots & \vdots \\ w_0^d & w_1^d & \cdots & w_c^d \end{pmatrix}$

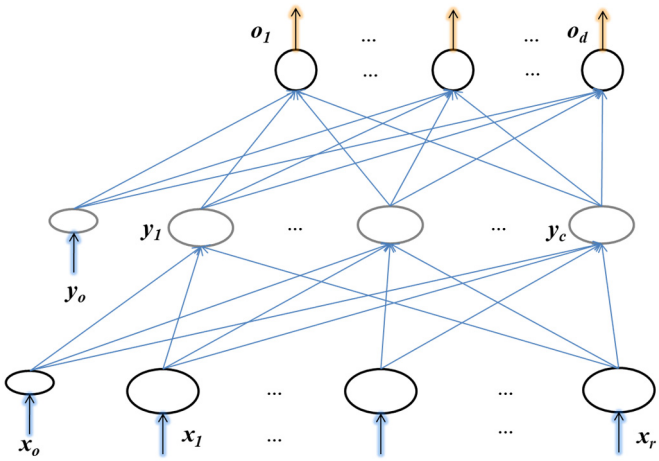
Equation (a-2) and (a-3) imply that both connection weights and bias can be updated at the same time in the learning process.

b. Steepest Descent Algorithm

(The mathematical derivation of the equation in this subsection and the succeeding section adhere to the arguments of Han, 2006.[293])

A three-layer multi-layer perceptron (MLP) is presented Figure 48:

Figure 48: Three-layer MLP



As demonstrated in Appendix a, the hidden layer in a three-layer MLP with *r* input signals can be expressed as:

$$y_c = G(net_c), c \in C \tag{b-1}$$

$$net_c = \sum_{r \in R, c \in C} W_r^c y_c \tag{b-2}$$

The output layer with *d* neurons is expressed as:

$$y_d = G(net_d), d \in D \tag{b-3}$$

$$net_d = \sum_{d \in D, c \in C} W_c^d y_c \tag{b-4}$$

The log-sigmoid function is chosen for the activation function:

$$G(\zeta) = \frac{1}{1 + e^{-\zeta}}$$

[293] Cf. (韩 (Han), 2006)

The error E is expressed as:

$$E = \frac{1}{2}\sum_{d\in D}(t_d - y_d)^2$$

$$= \frac{1}{2}\sum_{d\in D}[t_d - G_d(net_d)]^2 \quad \text{(b-5)}$$

$$= \frac{1}{2}\sum_{d\in D}[t_d - G_d(\sum_{c\in C} W_c^d y_c)]^2 \quad \text{(b-6)}$$

$$= \frac{1}{2}\sum_{d\in D}\{t_d - G_d[\sum_{c\in C} W_c^d G_c(net_c)\}^2$$

$$= \frac{1}{2}\sum_{d\in D}\{t_d - G_d[\sum_{c\in C} W_c^d G_c(\sum_{r\in R} W_r^c x_r)\}^2$$

As Eq. (b-5) and (b-6) show, the error in an MLP depends on the connection weights, w_c^d and w_r^c. In other words, the error E can be minimised by the update of the connection weights. As defined in Chapter 5, the update of the weights is expressed as:

$$w_{k+1} = w_k + \Delta w,\ \Delta w = -\eta\frac{\partial E}{\partial w}, \eta \in (0,1) \quad \text{(b-7)}$$

where η is the learning rate in the process of training. To find a local minimum of the function, a gradient descent is used. A step proportional to the negative of the gradient of the function at the current point is taken. In detail, the update of the weights in the hidden and output layers and that in the hidden and input layers are represented respectively as:

$$\Delta w_c^d = -\eta\frac{\partial E}{\partial w_c^d}, c \in C; d \in D \quad \text{(b-8)}$$

$$\Delta w_r^c = -\eta\frac{\partial E}{\partial w_r^c}, r \in R; c \in C \quad \text{(b-9)}$$

Taking Eq. (b-1), (b-2), (b-3) and (b-4) into account for the output layer, Eq. (b-8) and (b-9) can be further modified as follows:

$$\Delta w_c^d = -\eta\frac{\partial E}{\partial w_c^d} = -\eta\frac{\partial E}{\partial net_d}\frac{\partial net_d}{\partial w_c^d} = -\eta\frac{\partial E}{\partial net_d}y_d$$

$$\Delta w_r^c = -\eta\frac{\partial E}{\partial w_r^c} = -\eta\frac{\partial E}{\partial net_c}\frac{\partial net_c}{\partial w_r^c} = -\eta\frac{\partial E}{\partial net_c}y_c$$

The deviation process currently concentrates on $\frac{\partial E}{\partial net_d}$ and $\frac{\partial E}{\partial net_c}$.

$$\frac{\partial E}{\partial net_d} =: \delta_c^d \tag{b-11}$$

$$\frac{\partial E}{\partial net_c} =: \delta_r^c \tag{b-10}$$

Equation (b-11) and (b-10) are further modified as:

$$\delta_c^d = -\frac{\partial E}{\partial net_d} = -\frac{\partial E}{\partial y_d}\frac{\partial y_d}{\partial net_d} = -\frac{\partial E}{\partial y_d} G'(net_d) \tag{b-12}$$

$$\delta_r^c = -\frac{\partial E}{\partial net_c} = -\frac{\partial E}{\partial y_c}\frac{\partial y_c}{\partial net_c} = -\frac{\partial E}{\partial y_c} G'(net_c) \tag{b-13}$$

The deviation process consequently solves the two equations $\frac{\partial E}{\partial y_d}$ and $\frac{\partial E}{\partial y_c}$:

$$\frac{\partial E}{\partial y_d} = \frac{1}{2} 2\sum_{k=1}^{l}(t_d - y_d) * \frac{\partial (t_d - y_d)}{\partial y_d} = \sum_{k=1}^{l}(t_d - y_d) * (-1) = -\sum_{k=1}^{l}(t_d - y_d) \tag{b-14}$$

$$\begin{aligned}
\frac{\partial E}{\partial y_c} &= \frac{\partial\{\frac{1}{2}\sum_{d\in D}[\mathrm{t}_d - G_d(net_d)]^2\}}{\partial y_c} * \frac{\partial[y_d - G(net_d)]}{\partial y_c} * \frac{\partial G(net_d)}{\partial y_c} \\
&= \frac{1}{2}\sum_{d\in D} 2[t_d - G_d(net_d)] * (-1)[\frac{\partial G_d(net_d)}{\partial y_c}] * \frac{\partial w_c^d y_c}{\partial y_c} \\
&= -\sum_{d\in D}[t_d - G(net_d)] * G'(net_d) * w_c^d \\
&= -\sum_{d\in D}(t_d - y_d) G'(net_d) w_c^d
\end{aligned} \tag{b-15}$$

The first-order derivative of the activation function:

$$\begin{aligned}
G'(\zeta) &= (\frac{1}{1+e^{-\zeta}})' \\
&= -(1+e^{-\zeta})^{-2} * (-e^{-\zeta}) \\
&= \frac{e^{-\zeta}}{(1+e^{-\zeta})^2} = \frac{1}{1+e^{-\zeta}} * \frac{e^{-\zeta}}{1+e^{-\zeta}} \\
&= G(\zeta) * \frac{1+e^{-\zeta}-1}{1+e^{-\zeta}} \\
&= G(\zeta) * (1 - \frac{1}{1+e^{-\zeta}}) \\
&= G(\zeta)[1 - G(\zeta)]
\end{aligned} \tag{b-16}$$

Substituting Eq. (b-16) to Eq. (b-14) and (b-15):

$$\delta_c^d = -\frac{\partial E}{\partial y_d} G'(net_d) = -[-\sum_{d \in D} (\mathrm{t}_d - y_d)]*\mathrm{y}_d(1-y_d) = \sum_{d \in D} (\mathrm{t}_d - y_d) y_d (1-y_d) \qquad \text{(b-17)}$$

$$\delta_r^c = -\frac{\partial E}{\partial y_c} G'(net_c)$$

$$= [\sum_{d \in D} (t_d - y_d) G? net_d) \mathrm{w}_c^d]*y_c(1\text{-}y_c)$$

$$= [\sum_{d \in D} (t_d - y_d) y_d (1-y_d)] \mathrm{w}_c^d * y_c(1\text{-}y_c)$$

$$= (\delta_c^d w_c^d) y_c (1\text{-}y_c) \qquad \text{(b-18)}$$

Substituting Eq. (b-17) and (b-18) into (b-12) and (b-13), Eq. (b-8) and (b-9) are modified as:

$$\begin{cases} \Delta w_c^d = \eta \delta_c^d y_d = \eta (t_d - y_d) y_d (1-y_d) y_d \\ \Delta w_r^c = \eta \delta_r^c y_c = \eta (\delta_c^d w_c^d) y_c (1-y_c) x_r \end{cases}$$

The given results indicate that the adjustment of weights in an MLP is determined by three factors: the learning rate η, the training error of the output layer $(t_d - y_d)$, and the input signal from the previous layer (i.e., y_c or x_r in the case of the example).

c. Gauss-Newton Algorithm

(The mathematical description presented in this section and the succeeding section is drawn from Haykin et al. (2009) and Yu et al. (2011).[294])

As mentioned in Chapter 5.3, one of the most distinct disadvantages of the BP is its slow convergence because the steepest descent method does not provide the correct step size and correct downhill direction.

As Eq. (b-7) shows, $\frac{\partial E}{\partial w}$ is also called gradient, which is the first-order of derivative of the error matrix. If the weights between the hidden and output layer are observed, the gradient is expressed as:

$$\nabla E = \frac{\partial E}{\partial w} = \begin{bmatrix} \frac{\partial E(w_0^1)}{\partial w_0^1}, \frac{\partial E(w_1^1)}{\partial w_1^1}, \frac{\partial E(w_2^1)}{\partial w_2^1}, \ldots \frac{\partial E(w_c^1)}{\partial w_c^1} \\ \frac{\partial E(w_0^2)}{\partial w_0^2}, \frac{\partial E(w_1^2)}{\partial w_1^2}, \frac{\partial E(w_2^2)}{\partial w_2^2}, \ldots \frac{\partial E(w_c^2)}{\partial w_c^2} \\ \vdots \\ \frac{\partial E(w_0^d)}{\partial w_0^d}, \frac{\partial E(w_1^d)}{\partial w_1^d}, \frac{\partial E(w_2^d)}{\partial w_2^d}, \ldots \frac{\partial E(w_c^d)}{\partial w_c^d} \end{bmatrix} \tag{c-1}$$

As Eq. (c-1) shows, the gradient is consisted of *c+1* vetors. Let g_d be the gradient of a vector, then

$$g_d = \begin{bmatrix} \frac{\partial E(w_0^1)}{\partial w_0^1}, \frac{\partial E(w_1^1)}{\partial w_1^1}, \frac{\partial E(w_2^1)}{\partial w_2^1}, \ldots \frac{\partial E(w_c^1)}{\partial w_c^1} \\ \frac{\partial E(w_0^2)}{\partial w_0^2}, \frac{\partial E(w_1^2)}{\partial w_1^2}, \frac{\partial E(w_2^2)}{\partial w_2^2}, \ldots \frac{\partial E(w_c^2)}{\partial w_c^2} \\ \vdots \\ \frac{\partial E(w_0^d)}{\partial w_0^d}, \frac{\partial E(w_1^d)}{\partial w_1^d}, \frac{\partial E(w_2^d)}{\partial w_2^d}, \ldots \frac{\partial E(w_c^d)}{\partial w_c^d} \end{bmatrix} = \begin{bmatrix} g_0 \\ g_1 \\ \vdots \\ g_d \end{bmatrix} \tag{c-2}$$

Using the Taylor series, Eq. (c-2) is transformed to:

[294] Cf. (Haykin, 2009) and (Yu, et al., 2011)

$$\begin{bmatrix} g_0 \\ g_1 \\ \vdots \\ g_d \end{bmatrix} = \begin{bmatrix} g_{0,0} + \frac{\partial g_1}{\partial w_0^1}\partial w_0^1 + \frac{\partial g_1}{\partial w_1^1}\partial w_1^1 + \frac{\partial g_1}{\partial w_2^1}\partial w_2^1 + \ldots + \frac{\partial g_1}{\partial w_c^1}\partial w_c^1 \\ g_{1,0} + \frac{\partial g_2}{\partial w_0^2}\partial w_0^2 + \frac{\partial g_2}{\partial w_1^2}\partial w_1^2 + \frac{\partial g_2}{\partial w_2^2}\partial w_2^2 + \ldots + \frac{\partial E g_2}{\partial w_c^2}\partial w_c^2 \\ \vdots \\ g_{d,0} + \frac{\partial g_c}{\partial w_0^d}\partial w_0^d + \frac{\partial g_c}{\partial w_1^d}\partial w_1^d + \frac{\partial g_c}{\partial w_2^d}\partial w_2^d + \ldots + \frac{\partial g_c}{\partial w_c^d}\partial w_c^d \end{bmatrix} \quad \text{(c-3)}$$

Eq. (c-2) further indicates that $\frac{\partial g_d}{\partial w_c^d} = \frac{\partial\left(\frac{\partial E}{\partial w_{c1}^d}\right)}{\partial w_{c2}^d} = \frac{\partial^2 E}{\partial w_{c1}^d * \partial w_{c2}^d}$. Applying this equation to Eq. (c-3):

$$\begin{bmatrix} g_0 \\ g_1 \\ \vdots \\ g_d \end{bmatrix} \approx \begin{bmatrix} g_{0,0} + \frac{\partial^2 E}{\partial (w_0^1)^2}\partial w_0^1 + \frac{\partial^2 E}{\partial w_1^1 w_0^1}\partial w_1^1 + \frac{\partial^2 E}{\partial w_2^1 w_0^1}\partial w_2^1 + \ldots + \frac{\partial^2 E}{\partial w_c^1 w_0^1}\partial w_c^1 \\ g_{1,0} + \frac{\partial^2 E}{\partial w_0^2 w_1^2}\partial w_0^2 + \frac{\partial^2 E}{\partial (w_1^2)^2}\partial w_1^2 + \frac{\partial^2 E}{\partial w_2^2 w_1^2}\partial w_2^2 + \ldots + \frac{\partial^2 E}{\partial w_c^2}\partial w_c^2 \\ \vdots \\ g_{d,0} + \frac{\partial^2 E}{\partial w_0^d w_c^d}\partial w_0^d + \frac{\partial^2 E}{\partial w_1^d w_c^d}\partial w_1^d + \frac{\partial^2 E}{\partial w_2^d w_c^d}\partial w_2^d + \ldots + \frac{\partial^2 E}{\partial (w_c^d)^2}\partial w_c^d \end{bmatrix}$$

(c-4)

Eq. (c-4) implies that the second-order derivatives of the total error must be calculated to obtain the minimal value. Eq. (c-4) is therefore transformed into:

$$\begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \approx \begin{bmatrix} g_{0,0} + \frac{\partial^2 E}{\partial (w_0^1)^2}\partial w_0^1 + \frac{\partial^2 E}{\partial w_1^1 w_0^1}\partial w_1^1 + \frac{\partial^2 E}{\partial w_2^1 w_0^1}\partial w_2^1 + \ldots + \frac{\partial^2 E}{\partial w_c^1 w_0^1}\partial w_c^1 \\ g_{1,0} + \frac{\partial^2 E}{\partial w_0^2 w_1^2}\partial w_0^2 + \frac{\partial^2 E}{\partial (w_1^2)^2}\partial w_1^2 + \frac{\partial^2 E}{\partial w_2^2 w_1^2}\partial w_2^2 + \ldots + \frac{\partial^2 E}{\partial w_c^2}\partial w_c^2 \\ \vdots \\ g_{d,0} + \frac{\partial^2 E}{\partial w_0^d w_c^d}\partial w_0^d + \frac{\partial^2 E}{\partial w_1^d w_c^d}\partial w_1^d + \frac{\partial^2 E}{\partial w_2^d w_c^d}\partial w_2^d + \ldots + \frac{\partial^2 E}{\partial (w_c^d)^2}\partial w_c^d \end{bmatrix} \quad \text{(c-5)}$$

Eq. (c-2) indicates that $g = \frac{\partial E}{\partial w}$. Thus, Eq. (c-5) can be further modified as:

$$\begin{bmatrix} -\frac{\partial E}{\partial w_0^1} \\ -\frac{\partial E}{\partial w_1^2} \\ \vdots \\ -\frac{\partial E}{\partial w_c^d} \end{bmatrix} \approx \begin{bmatrix} \frac{\partial^2 E}{\partial (w_0^1)^2}, \frac{\partial^2 E}{\partial w_1^1 w_0^1}, \frac{\partial^2 E}{\partial w_2^1 w_0^1}, \ldots, \frac{\partial^2 E}{\partial w_c^1 w_0^1} \\ \frac{\partial^2 E}{\partial w_0^2 w_1^2}, \frac{\partial^2 E}{\partial (w_1^2)^2}, \frac{\partial^2 E}{\partial w_2^2 w_1^2}, \ldots, \frac{\partial^2 E}{\partial w_c^2} \\ \vdots \\ \frac{\partial^2 E}{\partial w_0^d w_c^d}, \frac{\partial^2 E}{\partial w_1^d w_c^d}, \frac{\partial^2 E}{\partial w_2^d w_c^d}, \ldots, \frac{\partial^2 E}{\partial (w_c^d)^2} \end{bmatrix} * \begin{bmatrix} \Delta w_0^1 \\ \Delta w_1^2 \\ \vdots \\ \Delta w_c^d \end{bmatrix} \tag{c-6}$$

In Eq. (c-6), the square matrix is the Hessian matrix:

$$H = \begin{bmatrix} \frac{\partial^2 E}{\partial (w_0^1)^2}, \frac{\partial^2 E}{\partial w_1^1 w_0^1}, \frac{\partial^2 E}{\partial w_2^1 w_0^1}, \ldots, \frac{\partial^2 E}{\partial w_c^1 w_0^1} \\ \frac{\partial^2 E}{\partial w_0^2 w_1^2}, \frac{\partial^2 E}{\partial (w_1^2)^2}, \frac{\partial^2 E}{\partial w_2^2 w_1^2}, \ldots, \frac{\partial^2 E}{\partial w_c^2} \\ \vdots \\ \frac{\partial^2 E}{\partial w_0^d w_c^d}, \frac{\partial^2 E}{\partial w_1^d w_c^d}, \frac{\partial^2 E}{\partial w_2^d w_c^d}, \ldots, \frac{\partial^2 E}{\partial (w_c^d)^2} \end{bmatrix} \tag{c-7}$$

The Hessian matrix H consists of the second-order derivatives of error function E. Substituting Eq. (c-7) into Eq. (c-6),

$$\begin{bmatrix} -\frac{\partial E}{\partial w_0^1} \\ -\frac{\partial E}{\partial w_1^2} \\ \vdots \\ -\frac{\partial E}{\partial w_c^d} \end{bmatrix} \approx H * \begin{bmatrix} \Delta w_0^1 \\ \Delta w_1^2 \\ \vdots \\ \Delta w_c^d \end{bmatrix} \tag{c-8}$$

As mentioned above $g = \frac{\partial E}{\partial w}$; thus, the vector g can be further modified as:

$$\begin{bmatrix} -\frac{\partial E}{\partial w_0^1} \\ -\frac{\partial E}{\partial w_1^2} \\ \vdots \\ -\frac{\partial E}{\partial w_c^d} \end{bmatrix} = \begin{bmatrix} -g_0 \\ -g_1 \\ \vdots \\ -g_d \end{bmatrix} = -g \qquad \text{(c-9)}$$

Substituting (c-9) into (c-8), Eq. (c-8) is furhter modified:

$$-g = H\Delta w$$

$$-gH^{-1} = \Delta w \qquad \text{(c-10)}$$

Therefore, the update rule of the weights in Eq. (b-7) is expressed as:

$$w_{k+1} = w_k - H^{-1}g \qquad \text{(c-11)}$$

This update rule is called Newton's method. Given the complexity of the calculation of the Hessian Matrix, the Jacobian matrix *J(w)* is introduced to simplify Newton's method.

The error vector *e* is expressed as

$$e = \begin{pmatrix} e_1 \\ e_2 \\ \vdots \\ e_d \end{pmatrix} \qquad \text{(c-12)}$$

From the viewpoint of vector *e*, the error function *E* in Eq. (5-3) can be expressed as

$$g = \frac{\partial E}{\partial w_c^d} = \frac{\partial(\frac{1}{2}\sum_{d \in D} e_d{}^2)}{\partial w_c^d} \qquad \text{(c-13)}$$

The second-order of deviation of the Hessian Matrix *H* is modified as

$$h = \frac{\partial^2 E}{\partial w_{c1}^d \partial w_{c2}^d} = \frac{\partial^2 (\frac{1}{2}\sum_{d\in D} e_d{}^2)}{\partial w_{c1}^d \partial w_{c2}^d} = \sum_{d\in D} \frac{\partial e_d}{\partial w_{c1}^d} \frac{\partial e_d}{\partial w_{c2}^d} + S_d \tag{c-14}$$

Where S_d is called sensitivity factor of the d^{th}ouput:

$$S_d = \sum_{d\in D} \frac{\partial^2 e_d}{\partial w_{c1}^d \partial w_{c2}^d} e_d \tag{c-15}$$

Based on the basic assumption of Newton's method, which holds that S_d is closed to zero,[295] the Hessian matrix H can be approximated by Jacobian matrix $J(w)$:

$$H \approx J(w)^T J(w) \tag{c-16}$$

Jacobian matrix $J(w)$ has the form:

$$J(w) = \begin{bmatrix} \frac{\partial e_0}{\partial w_0^1}, \frac{\partial e_0}{\partial w_1^1}, \frac{\partial e_0}{\partial w_2^1}, \ldots, \frac{\partial e_0}{\partial w_c^1} \\ \frac{\partial e_1}{\partial w_0^2}, \frac{\partial e_1}{\partial w_1^1}, \frac{\partial e_1}{\partial w_1^2}, \ldots, \frac{\partial e_1}{\partial w_c^2} \\ \vdots \\ \frac{\partial e_d}{\partial w_0^d}, \frac{\partial e_d}{\partial w_1^d}, \frac{\partial e_d}{\partial w_2^d}, \ldots, \frac{\partial e_d}{\partial w_c^d} \end{bmatrix} \tag{c-17}$$

Substituting (c-16) and Eq. (c-11), Eq. (c-11) is therefore transformed to:

$$w_{k+1} = w_k - \left(J(w)^T J(w)\right)^{-1} J(w) e \tag{c-18}$$

This method of updating weights is called Gauss–Newton method. Eq. (c-18) implies that the second-order derivatives of the error function are not required by the Gauss–Newton method. Comparing with Newton's method the Gauss–Newton method simplifies the calculation.

[295] Cf. (Hagan, et al., 2014)

d. Levenberg-Marquardt Algorithm

(The mathematical description presented in this section and the succeeding section is drawn from Haykin et al. (2009) and Yu et al. (2011).[296])

The Gauss–Newton algorithm can find proper step sizes for each direction and therefore converges very fast. However, the Gauss–Newton method becomes unstable when the quadratic approximation of the error function is unreasonable. Moreover, this algorithm does not solve the inherent disadvantage of MLP, that is, the convergent problem. Mathematically, the problem, which can be interpreted as matrix $J(w)^T J(w)$ may not be invertible. To ensure that matrix $J(w)^T J(w)$ is invertible, the Levenberg–Marquardt algorithm (LMBP) approximates Hessian matrix H:

$$H \approx J(w)^T J(w) + \varphi I \qquad \text{(d-1)}$$

where φ is regulation parameter and I is identifying matrix. This equation implies that matrix H is always invertible because the elements on the main diagonal of the approximated Hessian matrix are larger than one.

Substituting Eq. (d-1) into Eq. (c-11), the LMBP is modified as

$$w_{k+1} = w_k - (J(w)^T J(w) + \varphi I)^{-1} J(w) e \qquad \text{(d-2)}$$

[296] Cf. (Haykin, 2009) and (Yu, et al., 2011)

e. Programming Codes

e.1 MATLAB® Program GA01BP10.m

```
clc
clear all

%
%% Establish Network structure established
% Read data
load data input output

%% Parameters of GA
maxgen=7;            %Max generations
sizepop=20;          %Size of population
pcross=[0.2];        %Crossover probability
pmutation=[0.1];     %Mution probability

%% Parameters of BP
input_trainum=7;     % Number of the nodes in the first hidden layer
hiddennum1=10;   % Number of the nodes in the first hidden layer
hiddennum2=10;   % Number of the nodes in the second hidden layer
output_trainum=1;    % Number of the nodes in the first hidden layer
TF1='logsig';    % Activation function from input layer to the frist
hidden layer
TF2='logsig';    % Activation function from input layer to the frist
hidden layer
TF3='tansig';    % Activation function from input layer to the frist
hidden layer
BTF='trainlm';   % Network training function
BLF='learngdm'; % Weight/bias learning function
PF='mse';        % Performance function
IOPF='mapstd';   % Input and output processing functions

%Split data into 2 sets
input_train=input(1:114532,:)';
input_test=input(114533:115621,:)';
output_train=output(1:114532)';
output_test=output(114533:115621)';

%% Network creation
net=newff(input_train,output_train,[hiddennum1,hiddennum2], {TF1 TF2
TF3},BTF,BLF,PF,{IOPF},{IOPF});
net.divideFcn = '' ;
net.trainParam.min_grad=1e-20;


%-------------------------------------------GA PART---------------
--------------------------------------
numsum=input_trainum*hiddennum1+hiddennum1+hiddennum1*hiddennum2+hid
dennum2+hiddennum2*output_trainum+output_trainum;
lenchrom=ones(1,numsum);
bound=[-3*ones(numsum,1) 3*ones(numsum,1)];
```

```
individuals=struct('fitness',zeros(1,sizepop), 'chrom',[]);
avgfitness=[];
bestfitness=[];
bestchrom=[];

for i=1:sizepop
    individuals.chrom(i,:)=Code(lenchrom,bound);
    x=individuals.chrom(i,:);

individuals.fitness(i)=funh2(x,input_trainum,hiddennum1,hiddennum2,o
utput_trainum,net,input_train,output_train);
end
FitRecord=[];
[bestfitness bestindex]=min(individuals.fitness);
bestchrom=individuals.chrom(bestindex,:);
avgfitness=sum(individuals.fitness)/sizepop;
trace=[avgfitness bestfitness];


for i=1:maxgen
    i
    % Selection
    individuals=Select(individuals,sizepop);
    avgfitness=sum(individuals.fitness)/sizepop;
    % Crossover

individuals.chrom=Cross(pcross,lenchrom,individuals.chrom,sizepop,bo
und);
    % Mutation

individuals.chrom=Mutation(pmutation,lenchrom,individuals.chrom,size
pop,i,maxgen,bound);
    for j=1:sizepop
        x=individuals.chrom(j,:);

individuals.fitness(j)=funh2(x,input_trainum,hiddennum1,hiddennum2,o
utput_trainum,net,input_train,output_train);
    end


    [newbestfitness,newbestindex]=min(individuals.fitness);
    [worestfitness,worestindex]=max(individuals.fitness);

    if bestfitness>newbestfitness
        bestfitness=newbestfitness;
        bestchrom=individuals.chrom(newbestindex,:);
    end
    individuals.chrom(worestindex,:)=bestchrom;
    individuals.fitness(worestindex)=bestfitness;

    avgfitness=sum(individuals.fitness)/sizepop;

    trace=[trace;avgfitness bestfitness];
    FitRecord=[FitRecord;individuals.fitness];
end




w1=x(1:input_trainum*hiddennum1);
```

```
B1=x(input_trainum*hiddennum1+1:input_trainum*hiddennum1+hiddennum1)
;
w2=x(input_trainum*hiddennum1+hiddennum1+1:input_trainum*hiddennum1+
hiddennum1+hiddennum1*hiddennum2);
B2=x(input_trainum*hiddennum1+hiddennum1+hiddennum1*hiddennum2+1:inp
ut_trainum*hiddennum1+hiddennum1+hiddennum1*hiddennum2+hiddennum2);
w3=x(input_trainum*hiddennum1+hiddennum1+hiddennum1*hiddennum2+hidde
nnum2+1:input_trainum*hiddennum1+hiddennum1+hiddennum1*hiddennum2+hi
ddennum2+hiddennum2*output_trainum);
B3=x(input_trainum*hiddennum1+hiddennum1+hiddennum1*hiddennum2+hidde
nnum2+hiddennum2*output_trainum+1:input_trainum*hiddennum1+hiddennum
1+hiddennum1*hiddennum2+hiddennum2+hiddennum2*output_trainum+output_
trainum);

net.iw{1,1}=reshape(w1,hiddennum1,input_trainum);
net.lw{2,1}=reshape(w2,hiddennum2,hiddennum1);
net.lw{3,2}=reshape(w3,output_trainum,hiddennum2);
net.b{1}=reshape(B1,hiddennum1,1);
net.b{2}=reshape(B2,hiddennum2,1);
net.b{3}=B3;

%---------------------------------------------GA PART----------------
--------------------------------------

%---------------------------------------------BPNN PART--------------
--------------------------------------

net.trainParam.epochs=100;
net.trainParam.lr=0.1;
[net,per2]=train(net,input_train,output_train);
test_simu=sim(net,input_test);
error=test_simu-output_test;
```

e.2 MATLAB® Program Select.m

```
function ret=select(individuals,sizepop)
% Perform Select
% individuals input  : Information of population
% sizepop     input  : Size of population
% ret         output : New population

fitness1=10./individuals.fitness;

sumfitness=sum(fitness1);
sumf=fitness1./sumfitness;
index=[];
for i=1:sizepop
    pick=rand;
    while pick==0
        pick=rand;
    end
    for i=1:sizepop
        pick=pick-sumf(i);
        if pick<0
            index=[index i];
            break;
        end
    end
end
individuals.chrom=individuals.chrom(index,:);
individuals.fitness=individuals.fitness(index);
ret=individuals;
```

e.3 MATLAB® Program Cross.m

```
function ret=Cross(pcross,lenchrom,chrom,sizepop,bound)
%The function completed crossover
% pcorss                 input  : Crossover probability
% lenchrom               input  : Length of the chromosome
% chrom                  input  : Chromosome group
% sizepop                input  : Population size
% ret                    output : The chromosome after crossover
 for i=1:sizepop
     pick=rand(1,2);
     while prod(pick)==0
         pick=rand(1,2);
     end
     index=ceil(pick.*sizepop);

     pick=rand;
     while pick==0
         pick=rand;
     end
     if pick>pcross
         continue;
     end
     flag=0;
     while flag==0

         pick=rand;
         while pick==0
             pick=rand;
         end
         pos=ceil(pick.*sum(lenchrom));
         pick=rand;
         v1=chrom(index(1),pos);
         v2=chrom(index(2),pos);
         chrom(index(1),pos)=pick*v2+(1-pick)*v1;
         chrom(index(2),pos)=pick*v1+(1-pick)*v2;
         flag1=test(lenchrom,bound,chrom(index(1),:));
         flag2=test(lenchrom,bound,chrom(index(2),:));
         if   flag1*flag2==0
             flag=0;
         else flag=1;
         end
     end
 end
ret=chrom;
```

e.4 MATLAB® Program Mutation.m

```
      function
ret=Mutation(pmutation,lenchrom,chrom,sizepop,num,maxgen,bound)
      % This function mutation operation completed
      % Pcorss        input: mutation probability
      % Lenchrom      input: chromosome length
      % Chrom         input: chromosome group
      % Sizepop       input: population size
      % Opts          input: Select the method of variation
      % Pop           input: current evolution generation and
population information
      % Bound         input: individual's bound
      % Maxgen        input: maximum number of iterations
      % Num           input: current iteration
      % Ret           output: chromosome after mutation

      for i=1:sizepop
          pick=rand;
          while pick==0
              pick=rand;
          end
          index=ceil(pick*sizepop);
          pick=rand;
          if pick>pmutation
              continue;
          end
          flag=0;
          while flag==0
              pick=rand;
              while pick==0
                  pick=rand;
              end
              pos=ceil(pick*sum(lenchrom));

              pick=rand;
              fg=(rand*(1-num/maxgen))^2;
              if pick>0.5
                  chrom(i,pos)=chrom(i,pos)+(bound(pos,2)-
chrom(i,pos))*fg;
              else
                  chrom(i,pos)=chrom(i,pos)-(chrom(i,pos)-
bound(pos,1))*fg;
              end
              flag=test(lenchrom,bound,chrom(i,:));
          end
      end
      ret=chrom;
```

e.5 MATLAB® Program fun2.m

```
function error =
funh2(x,inputnum,hiddennum1,hiddennum2,outputnum,net,inputn,outputn)
%This function is used to calculate the fitness value
%x          input     Individual
%inputnum   input     Input layer nodes
%outputnum  input     Hidden layer nodes
%net        input     Network
%inputn     input     Training input data
%outputn    input     Training output data

%error      output    Individual fitness value

w1=x(1:inputnum*hiddennum1);
B1=x(inputnum*hiddennum1+1:inputnum*hiddennum1+hiddennum1);
w2=x(inputnum*hiddennum1+hiddennum1+1:inputnum*hiddennum1+hiddennum1
+hiddennum1*hiddennum2);
B2=x(inputnum*hiddennum1+hiddennum1+hiddennum1*hiddennum2+1:inputnum
*hiddennum1+hiddennum1+hiddennum1*hiddennum2+hiddennum2);
w3=x(inputnum*hiddennum1+hiddennum1+hiddennum1*hiddennum2+hiddennum2
+1:inputnum*hiddennum1+hiddennum1+hiddennum1*hiddennum2+hiddennum2+h
iddennum2*outputnum);
B3=x(inputnum*hiddennum1+hiddennum1+hiddennum1*hiddennum2+hiddennum2
+hiddennum2*outputnum+1:inputnum*hiddennum1+hiddennum1+hiddennum1*hi
ddennum2+hiddennum2+hiddennum2*outputnum+outputnum);

net.trainParam.epochs=20;
net.trainParam.lr=0.1;
net.trainParam.goal=1e-3;
net.trainParam.show=100;
net.trainParam.showWindow=0;

net.iw{1,1}=reshape(w1,hiddennum1,inputnum);
net.lw{2,1}=reshape(w2,hiddennum2,hiddennum1);
net.lw{3,2}=reshape(w3,outputnum,hiddennum2);
net.b{1}=reshape(B1,hiddennum1,1);
net.b{2}=reshape(B2,hiddennum2,1);
net.b{3}=B3;

net=train(net,inputn,outputn);

an=sim(net,inputn);

error=sum(abs(an-outputn));
```

e.6 MATLAB® Program fun.m

```
function error =
fun(x,inputnum,hiddennum,outputnum,net,inputn,outputn)
%This function is used to calculate the fitness value
%x           input     Individual
%inputnum    input     Input layer nodes
%outputnum   input     Hidden layer nodes
%net         input     Network
%inputn      input     Training input data
%outputn     input     Training output data

%error       output    Individual fitness value

w1=x(1:inputnum*hiddennum);
B1=x(inputnum*hiddennum+1:inputnum*hiddennum+hiddennum);
w2=x(inputnum*hiddennum+hiddennum+1:inputnum*hiddennum+hiddennum+hid
dennum*outputnum);
B2=x(inputnum*hiddennum+hiddennum+hiddennum*outputnum+1:inputnum*hid
dennum+hiddennum+hiddennum*outputnum+outputnum);

net.trainParam.epochs=20;
net.trainParam.lr=0.1;
net.trainParam.goal=1e-3;
net.trainParam.show=100;
net.trainParam.showWindow=0;

net.iw{1,1}=reshape(w1,hiddennum,inputnum);
net.lw{2,1}=reshape(w2,outputnum,hiddennum);
net.b{1}=reshape(B1,hiddennum,1);
net.b{2}=B2;

net=train(net,inputn,outputn);

an=sim(net,inputn);

error=sum(abs(an-outputn));
```

e.7 MATLAB® Program Code.m

```
function ret=Code(lenchrom,bound)
%This function will scribe a flexible into chromosomes, for any
population
%of random initialization
% lenchrom   input : Chromosome length
% bound      input : Selection of variables
% ret        output: Chromosome encoding value
flag=0;
while flag==0
    pick=rand(1,length(lenchrom));
    ret=bound(:,1)'+(bound(:,2)-bound(:,1))'.*pick; %Linear
interpolation, coding leads to real vector in to the ret
    flag=test(lenchrom,bound,ret);     %Test the feasibility of
chromosomes
end
```

f. Settings of Back-Propagation in GAxxBPxx.m

BPXX.m	Number of Hidden Nodes in Hidden layer 1	Number of Hidden Nodes in Hidden layer 2	Transfer Function of Hidden layer 1	Transfer Function of Hidden layer 2	Transfer Function of Output layer	Network Training Function	Performance Function	Input and Output Processing Function	Learning Rate	Epochs of Training
BP01	10	10	logsig	logsig	tansig	trainlm	mse	mapminmax	0.10	100
BP02	10	10	logsig	logsig	logsig	trainlm	mse	mapminmax	0.10	100
BP03	10	10	logsig	logsig	purelin	trainlm	mse	mapminmax	0.10	100
BP04	10	10	tansig	tansig	tansig	trainlm	mse	mapminmax	0.10	100
BP05	10	10	tansig	tansig	logsig	trainlm	mse	mapminmax	0.10	100
BP06	10	10	purelin	purelin	tansig	trainlm	mse	mapminmax	0.10	100
BP07	10	10	purelin	purelin	logsig	trainlm	mse	mapminmax	0.10	100
BP08	10	10	purelin	purelin	purelin	trainlm	mse	mapminmax	0.10	100
BP09	10	10	tansig	tansig	purelin	trainlm	mse	mapminmax	0.10	100
BP10	10	10	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP11	10	10	logsig	logsig	tansig	trainlm	msereg	mapminmax	0.10	100
BP12	10	10	logsig	logsig	tansig	trainlm	msereg	mapstd	0.10	100
BP13	10	10	logsig	logsig	tansig	traingdx	mse	mapminmax	0.01	100
BP14	10	10	logsig	logsig	tansig	traingdx	mse	mapstd	0.01	100
BP15	10	10	logsig	logsig	tansig	traingdx	msereg	mapminmax	0.01	100
BP16	10	10	logsig	logsig	tansig	traingdx	msereg	mapstd	0.01	100
BP17	10	10	tansig	tansig	purelin	trainlm	mse	mapstd	0.10	100
BP18	10	10	tansig	tansig	purelin	trainlm	msereg	mapminmax	0.10	100
BP19	10	10	tansig	tansig	purelin	trainlm	msereg	mapstd	0.10	100
BP20	10	10	tansig	tansig	purelin	traingdx	mse	mapminmax	0.01	100
BP21	10	10	tansig	tansig	purelin	traingdx	mse	mapstd	0.01	100
BP22	10	10	tansig	tansig	purelin	traingdx	msereg	mapminmax	0.01	100
BP23	10	10	tansig	tansig	purelin	traingdx	msereg	mapstd	0.01	100
BP24	2	2	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP25	3	2	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP26	5	2	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP27	10	2	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP28	20	2	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP29	2	3	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP30	3	3	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP31	5	3	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP32	10	3	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP33	20	3	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP34	2	5	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP35	3	5	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP36	5	5	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP37	10	5	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP38	20	5	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP39	2	10	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP40	3	10	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP41	5	10	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP42	20	10	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP43	2	20	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP44	3	20	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100

BPXX.m	Number of Hidden Nodes in Hidden layer 1	Number of Hidden Nodes in Hidden layer 2	Transfer Function of Hidden layer 1	Transfer Function of Hidden layer 2	Transfer Function of Output layer	Network Training Function	Performance Function	Input and Output Processing Function	Learning Rate	Epochs of Training
BP45	5	20	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP46	10	20	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP47	20	20	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	100
BP49	1		logsig		tansig	trainlm	mse	mapstd	0.10	100
BP50	2		logsig		tansig	trainlm	mse	mapstd	0.10	100
BP51	3		logsig		tansig	trainlm	mse	mapstd	0.10	100
BP52	5		logsig		tansig	trainlm	mse	mapstd	0.10	100
BP53	8		logsig		tansig	trainlm	mse	mapstd	0.10	100
BP54	13		logsig		tansig	trainlm	mse	mapstd	0.10	100
BP55	21		logsig		tansig	trainlm	mse	mapstd	0.10	100
BP56	34		logsig		tansig	trainlm	mse	mapstd	0.10	100
BP57	55		logsig		tansig	trainlm	mse	mapstd	0.10	100
BP58	89		logsig		tansig	trainlm	mse	mapstd	0.10	100
BP59	144		logsig		tansig	trainlm	mse	mapstd	0.10	100
BP60	10	10	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	10
BP61	10	10	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	20
BP62	10	10	logsig	logsig	tansig	trainlm	mse	mapstd	0.10	50

g. Simulation Results

Record File Name	Mean Error on Test Sets	SD of the errors on test sets	Mean error on training sets	SD of the errors on training sets
GA00BP01A	3.83	8.69	7.76	14.43
GA00BP02A	547.19	10.41	6.77	14.43
GA00BP03A	3.77	8.44	7.76	14.43
GA00BP04A	3.77	8.27	7.09	14.43
GA00BP05A	547.19	10.41	6.77	14.43
GA00BP06A	3.84	8.21	7.77	14.43
GA00BP07A	547.19	10.41	5.77	14.43
GA00BP08A	4.60	8.22	28.64	13.62
GA00BP09A	3.63	8.19	4.09	9.98
GA00BP10A	3.53	8.61	4.20	12.32
GA00BP11A	4.24	11.00	4.26	10.45
GA00BP12A	3.61	8.53	4.17	12.30
GA00BP13A	4.81	10.41	5.77	14.43
GA00BP14A	4.40	8.44	4.77	12.58
GA00BP15A	4.81	10.41	5.77	14.43
GA00BP16A	4.26	8.33	4.54	12.42
GA00BP17A	4.15	7.95	4.17	10.06
GA00BP18A	3.82	8.80	4.28	10.41
GA00BP19A	4.16	8.21	4.27	10.49
GA00BP20A	35.29	55.23	25.74	38.72
GA00BP21A	4.16	8.22	4.57	11.88
GA00BP22A	100.85	94.51	45.17	45.06
GA00BP23A	3.90	8.21	4.50	11.88
GA00BP24A	3.67	8.54	4.40	12.37
GA00BP25A	3.88	8.42	4.54	12.42
GA00BP26A	3.57	8.55	4.26	12.34
GA00BP27A	3.66	8.45	4.32	12.33

Record File Name	Mean Error on Test Sets	SD of the errors on test sets	Mean error on training sets	SD of the errors on training sets
GA00BP28A	3.83	8.59	4.23	12.30
GA00BP29A	3.66	8.57	4.38	12.36
GA00BP30A	3.61	8.58	4.31	12.36
GA00BP31A	3.66	8.54	4.30	12.34
GA00BP32A	3.60	8.50	4.29	12.34
GA00BP33A	3.58	8.42	4.13	12.28
GA00BP34A	3.61	8.54	4.38	12.36
GA00BP35A	3.66	8.57	4.39	12.36
GA00BP36A	3.64	8.55	4.26	12.31
GA00BP37A	3.54	8.57	4.20	12.32
GA00BP38A	3.71	8.52	4.12	12.28
GA00BP39A	3.79	8.42	4.47	12.40
GA00BP40A	3.62	8.51	4.29	12.34
GA00BP41A	3.58	8.56	4.24	12.33
GA00BP42A	3.79	8.61	4.15	12.30
GA00BP43A	3.60	8.52	4.34	12.35
GA00BP44A	3.55	8.52	4.29	12.33
GA00BP45A	3.60	8.57	4.23	12.32
GA00BP46A	3.59	8.47	4.18	12.30
GA00BP47A	3.56	8.53	4.07	12.26
GA00BP49A	5.01	9.17	5.46	13.35
GA00BP50A	5.08	8.35	5.49	12.15
GA00BP51A	5.09	8.27	5.51	12.17
GA00BP52A	5.10	8.28	5.48	12.13
GA00BP53A	5.08	8.29	5.42	12.10
GA00BP54A	5.06	8.35	5.45	12.10
GA00BP55A	4.97	8.40	5.40	12.10
GA00BP56A	5.10	8.32	5.37	12.08

Record File Name	Mean Error on Test Sets	SD of the errors on test sets	Mean error on training sets	SD of the errors on training sets
GA00BP57A	5.15	8.25	5.31	12.04
GA00BP58A	5.26	8.49	5.29	12.01
GA00BP59A	5.16	8.32	5.29	12.02
GA00BP60A	3.67	8.48	4.15	12.30
GA00BP61A	3.61	8.52	4.15	12.29
GA00BP62A	3.60	8.55	4.18	12.29
GA01BP01A	3.78	8.26	7.76	14.43
GA01BP01B	3.78	8.26	7.76	14.43
GA01BP01C	4.03	8.22	6.82	14.43
GA01BP02A	547.19	10.41	6.77	14.43
GA01BP02B	547.19	10.41	6.77	14.43
GA01BP02C	547.19	10.41	6.77	14.43
GA01BP03A	4.22	19.20	7.73	14.43
GA01BP03B	4.22	19.18	7.73	14.43
GA01BP03C	3.80	8.36	4.89	13.63
GA01BP04A	3.88	8.70	7.75	14.43
GA01BP04B	3.88	8.70	7.75	14.43
GA01BP04C	4.13	8.21	5.77	14.43
GA01BP05A	547.19	10.41	6.77	14.43
GA01BP05B	547.19	10.41	6.77	14.43
GA01BP05C	547.19	10.41	6.77	14.43
GA01BP06A	3.84	8.21	7.77	14.43
GA01BP06B	3.84	8.21	7.77	14.43
GA01BP06C	3.84	8.21	7.77	14.43
GA01BP07A	547.19	10.41	6.77	14.43
GA01BP07B	547.19	10.41	6.77	14.43
GA01BP07C	547.19	10.41	5.77	14.43
GA01BP08A	4.60	8.22	28.64	13.62

Record File Name	Mean Error on Test Sets	SD of the errors on test sets	Mean error on training sets	SD of the errors on training sets
GA01BP08B	4.60	8.22	28.64	13.62
GA01BP08C	4.60	8.22	28.64	13.62
GA01BP09A	3.67	8.48	4.25	10.14
GA01BP09B	3.67	8.48	4.25	10.14
GA01BP09C	3.67	8.48	4.25	10.14
GA01BP10A	3.53	8.61	4.20	12.31
GA01BP10B	3.53	8.61	4.20	12.31
GA01BP10C	3.57	8.53	4.16	12.30
GA01BP11A	3.70	8.51	4.27	10.29
GA01BP11B	3.70	8.51	4.27	10.29
GA01BP11C	3.70	8.51	4.27	10.29
GA01BP12A	3.57	8.57	4.18	12.32
GA01BP12B	3.57	8.57	4.18	12.32
GA01BP12C	3.57	8.57	4.18	12.32
GA01BP13A	4.81	10.41	5.77	14.43
GA01BP13B	4.81	10.41	5.77	14.43
GA01BP13C	4.81	10.41	5.77	14.43
GA01BP14A	4.16	8.73	4.88	12.57
GA01BP14B	4.16	8.73	4.88	12.57
GA01BP14C	4.16	8.73	4.88	12.57
GA01BP15A	4.24	8.90	4.74	12.27
GA01BP15B	4.24	8.90	4.74	12.27
GA01BP15C	4.24	8.90	4.74	12.27
GA01BP16A	4.85	8.70	5.09	12.71
GA01BP16B	4.85	8.70	5.09	12.71
GA01BP16C	4.85	8.70	5.09	12.71
GA01BP17A	3.75	8.37	4.27	10.90
GA01BP17B	3.75	8.37	4.27	10.90

Record File Name	Mean Error on Test Sets	SD of the errors on test sets	Mean error on training sets	SD of the errors on training sets
GA01BP17C	3.75	8.37	4.27	10.90
GA01BP18A	3.70	8.61	4.29	10.47
GA01BP18B	3.70	8.61	4.29	10.47
GA01BP18C	3.70	8.61	4.29	10.47
GA01BP19A	3.84	8.54	4.26	10.41
GA01BP19B	3.84	8.54	4.26	10.41
GA01BP19C	3.84	8.54	4.26	10.41
GA01BP20A	7.98	9.79	7.16	13.36
GA01BP20B	7.98	9.79	7.16	13.36
GA01BP20C	7.98	9.79	7.16	13.36
GA01BP21A	5.38	8.68	5.05	12.67
GA01BP21B	5.38	8.68	5.05	12.67
GA01BP21C	5.38	8.68	5.05	12.67
GA01BP22A	32.27	39.86	24.76	46.80
GA01BP22B	32.27	39.86	24.76	46.80
GA01BP22C	32.27	39.86	24.76	46.80
GA01BP23A	4.13	8.88	5.05	12.62
GA01BP23B	4.13	8.88	5.05	12.62
GA01BP23C	4.13	8.88	5.05	12.62
GA01BP24A	3.77	8.47	4.47	12.39
GA01BP24B	3.67	8.54	4.40	12.37
GA01BP24C	3.71	8.51	4.38	12.38
GA01BP25A	3.65	8.57	4.33	12.36
GA01BP25B	3.63	8.56	4.33	12.35
GA01BP25C	3.65	8.57	4.33	12.36
GA01BP26A	3.61	8.51	4.30	12.34
GA01BP26B	3.64	8.61	4.29	12.34
GA01BP26C	3.61	8.51	4.30	12.34

Record File Name	Mean Error on Test Sets	SD of the errors on test sets	Mean error on training sets	SD of the errors on training sets
GA01BP27A	3.55	8.65	4.22	12.32
GA01BP27B	3.59	8.66	4.20	12.30
GA01BP27C	3.55	8.65	4.22	12.32
GA01BP28A	3.68	8.65	4.18	12.29
GA01BP28B	3.67	8.53	4.14	12.28
GA01BP28C	3.68	8.65	4.18	12.29
GA01BP29A	3.74	8.45	4.38	12.39
GA01BP29B	3.56	8.53	4.36	12.39
GA01BP29C	3.74	8.45	4.38	12.39
GA01BP30A	3.61	8.58	4.31	12.36
GA01BP30B	3.66	8.60	4.32	12.37
GA01BP30C	3.61	8.58	4.31	12.36
GA01BP31A	3.61	8.55	4.26	12.34
GA01BP31B	3.65	8.56	4.28	12.35
GA01BP31C	3.61	8.55	4.26	12.34
GA01BP32A	3.60	8.62	4.21	12.33
GA01BP32B	3.56	8.57	4.23	12.32
GA01BP32C	3.60	8.62	4.21	12.33
GA01BP33A	3.55	8.51	4.11	12.28
GA01BP33B	3.54	8.72	4.16	12.29
GA01BP33C	3.55	8.51	4.11	12.28
GA01BP34A	3.70	8.51	4.38	12.37
GA01BP34B	3.68	8.49	4.35	12.41
GA01BP34C	3.70	8.51	4.38	12.37
GA01BP35A	3.68	8.48	4.36	12.38
GA01BP35B	3.73	8.54	4.34	12.35
GA01BP35C	3.68	8.48	4.36	12.38
GA01BP36A	3.55	8.51	4.26	12.34

Record File Name	Mean Error on Test Sets	SD of the errors on test sets	Mean error on training sets	SD of the errors on training sets
GA01BP36B	3.56	8.61	4.25	12.33
GA01BP36C	3.62	8.50	4.28	12.34
GA01BP37A	3.61	8.61	4.23	12.33
GA01BP37B	3.61	8.61	4.23	12.33
GA01BP37C	3.59	8.53	4.15	12.30
GA01BP38A	3.59	8.55	4.13	12.27
GA01BP38B	3.64	8.53	4.12	12.28
GA01BP38C	3.66	8.49	4.13	12.28
GA01BP39A	3.56	8.51	4.36	12.36
GA01BP39B	3.56	8.51	4.36	12.36
GA01BP39C	3.67	8.56	4.39	12.36
GA01BP40A	3.62	8.51	4.32	12.34
GA01BP40B	3.62	8.51	4.32	12.34
GA01BP40C	3.56	8.53	4.31	12.36
GA01BP41A	3.60	8.61	4.26	12.35
GA01BP41B	3.60	8.61	4.26	12.35
GA01BP41C	3.55	8.56	4.24	12.34
GA01BP42A	3.57	8.48	4.14	12.29
GA01BP42B	3.70	8.53	4.13	12.28
GA01BP42C	3.56	8.60	4.10	12.28
GA01BP43A	3.52	8.51	4.30	12.37
GA01BP43B	3.52	8.51	4.30	12.37
GA01BP43C	3.66	8.57	4.38	12.36
GA01BP44A	3.62	8.53	4.34	12.35
GA01BP44B	3.62	8.53	4.34	12.35
GA01BP44C	3.64	8.51	4.33	12.35
GA01BP45A	3.54	8.51	4.22	12.34
GA01BP45B	3.54	8.51	4.22	12.34

Record File Name	Mean Error on Test Sets	SD of the errors on test sets	Mean error on training sets	SD of the errors on training sets
GA01BP45C	3.60	8.57	4.38	12.35
GA01BP46A	3.51	8.55	4.13	12.29
GA01BP46B	3.51	8.55	4.13	12.29
GA01BP46C	3.56	8.50	4.10	12.28
GA01BP47A	3.63	8.66	4.07	12.26
GA01BP47B	3.63	8.66	4.07	12.26
GA01BP47C	3.61	8.57	4.19	12.37
GA01BP49A	5.11	8.22	5.55	12.18
GA01BP49B	5.01	9.17	5.46	13.35
GA01BP49C	5.11	8.22	5.55	12.18
GA01BP50A	5.07	8.28	5.53	12.21
GA01BP50B	5.11	8.22	5.55	12.18
GA01BP50C	5.07	8.28	5.53	12.20
GA01BP51A	5.01	8.44	5.47	12.14
GA01BP51B	5.11	8.34	5.48	12.15
GA01BP51C	5.01	8.44	5.47	12.14
GA01BP52A	5.08	8.29	5.48	12.13
GA01BP52B	5.09	8.37	5.48	12.13
GA01BP52C	5.08	8.29	5.48	12.13
GA01BP53A	5.13	8.27	5.46	12.12
GA01BP53B	5.03	8.28	5.46	12.14
GA01BP53C	5.13	8.27	5.46	12.12
GA01BP54A	5.10	8.34	5.45	12.13
GA01BP54B	5.19	8.07	5.42	12.10
GA01BP54C	5.10	8.29	5.40	12.11
GA01BP55A	5.08	8.35	5.42	12.11
GA01BP55B	5.06	8.22	5.37	12.08
GA01BP55C	5.08	8.35	5.42	12.11

Record File Name	Mean Error on Test Sets	SD of the errors on test sets	Mean error on training sets	SD of the errors on training sets
GA01BP56A	5.13	8.34	5.34	12.06
GA01BP56B	5.06	8.23	5.35	12.07
GA01BP56C	5.13	8.34	5.34	12.06
GA01BP57A	5.09	8.50	5.33	12.04
GA01BP57B	5.07	8.49	5.33	12.05
GA01BP57C	5.18	8.32	5.36	12.08
GA01BP58A	5.18	8.30	5.30	12.02
GA01BP58B	5.50	8.75	5.27	12.00
GA01BP58C	5.04	8.39	5.29	12.01
GA01BP59A	5.27	8.77	5.25	11.98
GA01BP59B	5.20	8.71	5.22	11.96
GA01BP59C	5.20	8.71	5.22	11.96
GA01BP60A	3.74	8.55	4.32	12.34
GA01BP60B	3.66	8.56	4.28	12.37
GA01BP60C	3.71	8.48	4.37	12.33
GA01BP61A	3.52	8.54	4.20	12.33
GA01BP61B	3.52	8.54	4.20	12.33
GA01BP61C	3.53	8.58	4.18	12.34
GA01BP62A	3.49	8.62	4.20	12.32
GA01BP62B	3.58	8.55	4.24	12.34
GA01BP62C	3.76	8.51	4.21	12.31
GA02BP10A	3.55	8.49	4.17	12.31
GA03BP10A	3.50	8.57	4.17	12.31
GA04BP10A	3.52	8.51	4.18	12.32
GA05BP10A	3.64	8.71	4.20	12.32
GA06BP10A	3.83	8.52	4.19	12.31
GA07BP10A	3.57	8.45	4.16	12.30
GA08BP10A	3.60	8.47	4.18	12.31

Record File Name	Mean Error on Test Sets	SD of the errors on test sets	Mean error on training sets	SD of the errors on training sets
GA09BP10A	17.14	7.15	16.27	11.36
GA10BP10A	3.64	8.57	4.17	12.31
GA11BP10A	3.60	8.54	4.16	12.30
GA12BP10A	3.53	8.58	4.18	12.32
GA13BP10A	3.49	8.53	4.20	12.32
GA14BP10A	3.80	8.49	4.16	12.30
GA15BP10A	3.57	8.63	4.20	12.32
GA16BP10A	3.60	8.77	4.20	12.32
GA17BP10A	3.59	8.44	4.16	12.30
GA18BP10A	3.65	8.45	4.18	12.29
GA19BP10A	3.63	8.60	4.19	12.32
GA20BP10A	3.59	8.55	4.17	12.31
GA21BP10A	3.53	8.56	4.14	12.29
GA22BP10A	3.58	8.57	4.22	12.32
GA23BP10A	3.60	8.48	4.15	12.30
GA24BP10A	3.64	8.60	4.15	12.30
GA25BP10A	3.63	8.63	4.18	12.31
GA26BP10A	3.58	8.57	4.17	12.30
GA27BP10A	3.60	8.71	4.18	12.31
GA28BP10A	3.59	8.54	4.22	12.32
GA29BP10A	3.63	8.55	4.15	12.29
GA30BP10A	3.56	8.55	4.26	12.34
GA31BP10A	3.61	8.52	4.15	12.31
GA32BP10A	3.58	8.73	4.17	12.31
GA33BP10A	3.57	8.55	4.18	12.31
GA34BP10A	3.52	8.63	4.18	12.31
GA35BP10A	3.70	8.44	4.15	12.30
GA36BP10A	3.56	8.47	4.12	12.29

Record File Name	Mean Error on Test Sets	SD of the errors on test sets	Mean error on training sets	SD of the errors on training sets
GA37BP10A	3.66	8.52	4.19	12.32
GA56BP10A	3.58	8.47	4.16	12.30
GA57BP10A	3.50	8.48	4.18	12.31
GA58BP10A	3.51	8.66	4.17	12.30
GA59BP10A	3.51	8.59	4.19	12.32
GA60BP10A	3.52	8.46	4.19	12.32
GA61BP10A	3.47	8.59	4.15	12.32
GA62BP10A	3.66	8.71	4.17	12.32
GA63BP10A	3.68	8.50	4.19	12.30
GA64BP10A	3.64	8.49	4.19	12.31
GA65BP10A	3.75	8.58	4.21	12.32
GA66BP10A	3.67	8.47	4.19	12.32
GA67BP10A	3.57	8.56	4.20	12.31
GA68BP10A	3.71	8.47	4.18	12.31
GA69BP10A	3.56	8.57	4.19	12.31
GA70BP10A	3.52	8.74	4.17	12.30
GA71BP10A	3.49	8.56	4.18	12.31
GA72BP10A	3.57	8.68	4.20	12.32
GA73BP10A	3.60	8.62	4.18	12.31
GA74BP10A	3.58	8.57	4.18	12.31
GA75BP10A	3.74	8.64	4.18	12.32
GA76BP10A	3.78	8.33	4.18	12.31

Reference

Abdalla O. A. [et al.] A comparison of feed-forward back-propagation and radial basis artificial neural networks: A Monte Carlo study [Conference] // 2010 International Symposium on Information Technology. - 2010. - Vol. 3. - p. 994/998. - DOI: 10.1109/ITSIM.2010.5561599.

Acar Y., Kadipasaoglu S., Schipperijn P. A decision support framework for global supply chain modelling: an assessment of the impact of demand, supply and lead-time uncertainties on performance [Article] // International Journal of Production Research. - 2010. - Vol. 48(11). - pp. 3245–3268.

Adkins N. Trains delayed by line side fire [Online]. - 08 01, 2013. - 01 18, 2015. - http://www.getreading.co.uk/news/local-news/trains-delayed-line-side-fire-5429716.

Ahmed O., Nordin M., Sulaiman S. Study of Genetic Algorithm to Fully-automate the Design and Training of Artificial Neural Network [Article] // International Journal of Computer Science and Network Security. - 2009. - 1 : Vol. 9. - pp. 217-226.

Amos O. Cable theft delays on railways fall sharply [Online]. - BBC News, 09 11, 2014. - 01 18, 2015. - http://www.bbc.com/news/uk-29109733.

Anderson J. A. An introduction to neural networks [Book]. - Cambridge, Mass. (i.a.) : MIT press, 1995. - Vol. A Bradford book.

Aschauer G. J. [et al.] The Reduction of Planning Uncertainty and Ineffective Time in Supply Chains from a Transport Point of View [Book Section] // Pioneering Solutions in Supply Chain Management / book auth. Kersten Wolfgang, Blecker Thorsten and Lüthje Christian. - Göttingen : Erich Schmidt Verlag, 2010.

Barta J. [et al.] Statistical modelling of delays in a rail freight transportation network [Conference] // Proceedings of the Winter Simulation Conference. - Berlin, Germany : [s.n.], 2012. - Vol. Article No. 286.

Beckman C. M., Burton M. D., O'Reilly C.III Early teams: the impact of team demography on VC financing and going public [Article] // Journal of Business Venturing. - 2007. - Vol. 22.

Bendul J. Integration of Combined Transport into Supply Chain Concepts: Simulation-based Potential Analysis and Practical Guidance [Book]. - Wiesbaden : Springer Gabler, 2013. - Vols. Supply-Chain-Management : XXI.

Beresford A. K. C. Modelling Freight Transport Costs: A Case Study of the UK-Greece Corridor [Article] // International Journal of Logistics Research and Applications. - 1999. - 3 : Vol. 2. - pp. 229-246.

Bishop C. Pattern Recognition and Machine Learning [Book]. - New York : Springer, 2006. - Vol. Information Science and Statistics : XX.

Boldt O. Unternehmensübergreifendes Qualitätsmanagement für korridorbezogene Kombinierte Güterverkehre Schiene/Straße [Book]. - Lohmar-Köln : Josef Eul Verlag, 2009.

Bozorgirad S., Desa M. I., Wibowo A. Genetic Algorithm Enhancement to Solve Multi Source Multi Product Flexible Multistage Logistics Network [Article] // International Journal of Computer Science. - 2012. - 3 : Vol. 9.

BSL Management Consultants of the Lloyd's Register Group Surface Transport Networks Improving Reliability and Levels of Service [Online] // Survey on price and demand elasticity. - 05 2008. - 01 19, 2015. - http://www.internationaltransportforum.org/jtrc/infrastructure/networks/08BSL.pdf.

Burn C. British Transport Police: ‘Miracle’ that train in 80mph South Yorkshire crash did not overturn [Online]. - 11 09, 2014. - 01 18, 2015. - http://www.thestar.co.uk/news/local/british-transport-police-miracle-that-train-in-80mph-south-yorkshire-crash-did-not-overturn-1-6942559.

Caris A., Macharis C., Jansse G. K. Decision support in intermodal transport: A new research agenda [Article] // Computers in industry. - 2013. - Vol. 64. - pp. 105-112.

Carvalho J. B. [et al.] A Web-Based Decision Support System for Supply Chain Operations Management Towards an Integrated Framework [Article] // Decision Support Systems III - Impact of Decision Support Systems for Global Environments. - 2014. - pp. 104-117. - 10.1007/978-3-319-11364-7_10.

Cavinato J. L. Supply chain logistics risks; From the back room to the board room [Article] // International Journal of Physical Distribution & Logistics Management. - 2004. - Vol. 34 (5). - pp. 383-387.

Chalabi M. UK rail suicides: a decade of data [Online]. - 09 11, 2013. - 01 23, 2015. - http://www.theguardian.com/news/datablog/2013/sep/11/uk-rail-suicides-decade-data.

Chen C.-C. (Frank), Schonfeld P. A dispatching decision support system for countering delay propagation in intermodal logistics networks [Article] // Transportation Planning and Technology. - 2016. - 3 : Vol. 39. - pp. 254-268. - http://dx.doi.org/10.1080/03081060.2016.1142222.

China Real Time How China's Train Tragedy Unfolded [Online]. - 12 29, 2011. - 01 23, 2015. - http://blogs.wsj.com/chinarealtime/2011/12/29/wenzhou%E2%80%99s-black-box-how-china%E2%80%99s-train-tragedy-unfolded/?mod=WSJBlog.

Chiou Y.-C., Lan L. W., Chang K.-L. Sustainable consumption, production and infrastructure construction for operating and planning intercity passenger transport systems [Article] // Journal of Cleaner Production. - 2013. - Vol. 40. - pp. 13-21.

Choy K. L. [et al.] Managing uncertainty in logistics service supply chain [Article] // International Journal of Risk Assessment and Management. - 2007. - 1 : Vol. 7. - pp. 19-43.

Christopher M., Lee H. Mitigating supply chain risk through improved confidence [Article] // International Journal of Physical Distribution & Logistics Management. - 2004. - 5 : Vol. 34. - pp. 388 - 396.

Christopher M., Peck H. BUILDING THE RESILIENT SUPPLY CHAIN [Article] // International Journal of Logistics. - 2004. - 2 : Vol. 15. - pp. 1-13.

Christopher M. Logistics & supply chain management [Book]. - Harlow [i.a.] : Financial Times Prentice Hall, 2011. - 4. .

Closs D. J., Keller S. B., Mollenkopf D. A. Chemical Rail Transport: The Benefits of Reliability [Article] // Transportation Journal. - 2003. - Vol. 42(3). - pp. 17-30.

Cohen Galit, S. I., Mijkampa P. Information–communications technologies (ICT) and transport: does knowledge underpin policy? [Article] // Telecommunications Policy. - 2002. - 26. - Vols. 1-2. - pp. 31–52.

Corry P., Kozan E. An assignment model for dynamic load planning of intermodal trains [Article] // Computers & Operations Research. - 2006. - 1 : Vol. 33. - pp. 1-17.

Crainic T. G., Kim K. H. Intermodal Transportation [Article] // Handbooks in Operations Research and Management Science. - 2007. - Vol. 14. - pp. 467-537.

Datta P. P., Christopher M. G. Information sharing and coordination mechanisms for managing uncertainty in supply chains: a simulation study [Article] // International Journal of Production Research. - 2011. - Vol. 49(3). - pp. 765–803.

Davis T. Effective Supply Chain Management [Article] // Sloan Management Review. - 1993. - Vol. Summer. - pp. 35-46.

DB Intermodal Services GmbH DB Intermodal Services – Your Specialist for Complementary Intermodal Transport Services // Brochure. - 2011.

DB Pünktlichkeitsentwicklung 2014 [Online]. - 2014. - 11 30, 2014. - http://www.bahn.de/p/view/buchung/auskunft/puenktlichkeit_personenverkehr.shtml.

de Jong G. [et al.] The value of reliability [Report] : Conference paper. - European Transport Conference : [s.n.], 2004.

Deb K. Multi-Objective Optimization Using Evolutionary Algorithms [Book]. - Chichester [i.a.] : Wiley, 2009. - 1. .

Dullaert W. [et al.] MamMoeT: An intelligent agent-based communication support platform [Article]. - 2009. - Vol. 36. - pp. 10280-10287.

Dündar S., Sahin I. Train re-scheduling with genetic algorithms and artificial neural networks for single-track railways [Article] // Transportation Research Part C. - 2013. - Vol. 27. - pp. 1-15. - http://doi.org/10.1016/j.trc.2012.11.001.

Enăchescu C., Rădoiu D., Adjei O. Learning strategies using prior information [Article] // International Journal of Intelligent Computing and Information Science. - 2005. - 1 : Vol. 5. - pp. 381-393.

Engartner T. Die Privatisierung der Deutschen Bahn. Über die Implementierung marktorientierter Verkehrspolitik // Dissertation. - Wiesbaden : VS Verlag, 2008.

Esper T., Williams L. The Value of Collaborative Transportation Management (CTM): Its Relationship to Collaborative Planning, Forecasting and Replenishment (CPFR) and The Role of Information Technology (IT) [Article] // Transportation Journal. - 2003. - 4 : Vol. 42. - pp. 55-65.

European Commission Eurostat Energy, transport and environment indicators - 2013 edition [Report]. - Luxemburg : European Commission Eurostat, 2013.

European Commission Transport 2050: The major challenges, the key measures // Memorandum. - Brussels : [s.n.], 3 28, 2011. - MEMO/11/197.

European Commission Transport White Paper: Roadmap to a Single European Transport Area – Towards a Competitive and Resource Efficient Transport System [Report]. - 2011.

European Environment Agency EEA greenhouse gas - data viewer [Online]. - 12 29, 2013. - http://www.eea.europa.eu/data-and-maps/data/data-viewers/greenhouse-gases-viewer.

Eurostat Freight transport statistics - modal split [Online]. - 04 2016. - 04 02, 2017. - http://ec.europa.eu/eurostat/statistics-explained/images/f/f9/Freight_transport_in_the_EU-28_%281%29_modal_split_of_inland_transport_modes%29_%28%25_of_total_tonne-km%29new.png.

eurostat Goods transport by rail [Online]. - 12 11, 2014. - 01 20, 2015. - http://ec.europa.eu/eurostat/tgm/table.do?tab=table&init=1&language=en&pcode=ttr00006&plugin=1.

eurostat Illustrated Glossary for Transport Statistics // Working paper. - 2009. - 4..

eurostat Total length of railway lines [Online]. - 12 11, 2014. - 01 19, 2015. - http://ec.europa.eu/eurostat/tgm/mapToolClosed.do?tab=map&init=1&plugin=1&language=en&pcode=ttr00003&toolbox=types#.

Fanti M. P. [et al.] A simulation based Decision Support System for logistics management [Article] // Journal of Computational Science. - 2015. - Vol. 10. - pp. 86-96. - http://doi.org/10.1016/j.jocs.2014.10.003.

Fowkes A. S. [et al.] How highly does the freight transport industry value journey time reliability – and for what reasons? [Article] // International Journal of Logistics: Research and Applications. - 2004. - Vol. 7(1). - pp. 33-43.

Frankfurter Allgemeine Zeitung 142 Minuten Verspätung sind kaum ein Problem [Article] // Frankfurter Allgemeine Zeitung. - 06 03, 2014. - p. 19.

Gaur A. S. [et al.] Environmental and Firm Level Influences on Inter-Organizational Trust and SME Performance [Article] // Journal of Management Studies. - 2011. - 8 : Vol. 48. - pp. 1752-1781.

George M. Over-running engineering works delay trains between Norwich and London Liverpool Street; train fault causes other cancellations [Online]. - 10 24, 2014. - 01 20, 2015. - http://www.edp24.co.uk/news/over_running_engineering_works_delay_trains_between_norwich_and_london_liverpool_street_train_fault_causes_other_cancellations_1_3818910.

Gerdes I., Klawonn F., Kruse R. Evolutionäre Algorithmen [Book]. - Wiesbaden : Vieweg, 2004. - 1..

Giannakis M., Louis M. A multi-agent based system with big data processing for enhanced supply chain [Article] // Journal of Enterprise Information Management. - 2016. - 5 : Vol. 29. - pp. 706-727. - doi: 10.1108/JEIM-06-2015-0050.

Goverde R. M. P. A delay propagation algorithm for large-scale railway traffic networks [Article] // Transportation Research Part C. - 2010. - Vol. 18. - pp. 269–287. - http://doi.org/10.1016/j.trc.2010.01.002.

Griefahn B., Marks A., Robens S. Noise emitted from road, rail and air traffic and their affects on sleep [Article] // Journal oF Sound and Vibration. - 2006. - Vol. 295. - pp. 129-140.

Gulati R., Wohlgezogen F., Zhelyazkov P. The Two Facets of Collaboration: Cooperation and Coordination in Strategic Alliances [Article] // Academy of Management Annals. - 2012. - 6. - pp. 531–583.

Günther O. Kodierung der Zusatzverspätungen // Richtlinie Bahnbetrieb. - 2010. - 420.9001 00. - http://fahrweg.dbnetze.com/file/2950288/data/snb_2014_anlage_6.2.pdf.

Hagan M. T., Demuth H. B. Neural Network Design [Book]. - Boston : PWS Publishing Co., 2014. - 2..

Häme L., Hakula H. Dynamic journeying under uncertainty [Article] // European Journal of Operational Research. - 2013. - Vol. 225. - pp. 455-471.

Hasan M. K. A Framework for Intelligent Decision Support System for Traffic Congestion Management System [Article] // Scientific Research. - 2010. - 4 : Vol. 2. - pp. 270-289.

Hassoun M. H. Fundamentals of Artificial Neural Networks [Book]. - Massachusetts : The MIT Press, 1995.

Haykin S. Neural Networks and Learning Machines [Book]. - New Jersey : Pearson Education, Inc., 2009. - International Edition.

Hebb D. O. The Organization of Behavior [Book]. - New York : Wiley & Sons, 1949.

Hecht-Nielsen R. Neurocomputing [Book]. - Reading, Mass. (i.a.) : Addison-Wesley, 1991. - Reprint, with corr..

Heckmann I., Comes T., Nickel S. A critical review on supply chain risk – Definition, measure and modeling [Article] // Omega. - 2015. - Vol. 52. - pp. 110-132. - http://doi.org/10.1016/j.omega.2014.10.004.

Hernández J. E. [et al.] A decentralised and collaborative supply [Article] // chain planning model supported by a multiagent-based negotiation approach. - 2013. - Vol. 23. - pp. 235–269. - DOI 10.1007/s10726-013-9358-2.

Hilletofth P., Lättilä L. Agent based decision support in the supply chain context [Article]. - [s.l.] : Industrial Management & Data Systems, 2012. - 8 : Vol. 112. - pp. 1217-1235. - http://dx.doi.org/10.1108/02635571211264636.

Hilletofth P., Hilmola O.-P., Wang Y. Simulation based decision support systems in the supply chain context [Article] // Industrial Management & Data Systems. - 2016. - 2 : Vol. 116. - doi: 10.1108/IMDS-11-2015-0477.

Holzhey M. Schienennetz 2025/2030 - Ausbaukonzeption für einen leistungsfähigen Schienengüterverkehr in Deutschland [Report] : Study. - Dessau-Roßlau : Umweltbundesamt, 2010.

Inderfurth K., Sadrieh A., Voigt G. The Impact of Information Sharing on Supply Chain Performance under Asymmetric Information [Article] // Production Operations Management > Production and Operations Management. - 2012. - 2 : Vol. 22. - pp. 410-425. - DOI: 10.1111/j.1937-5956.2012.01372.x.

Ivanov D., Sokolov B. Adaptive Supply Chain Management [Book]. - London : Springer Verlag, 2010.

Janic M. An assessment of the performance of the European long intermodal freight trains (LIFTS) [Article] // Transportation Research Part A. - 2008. - Vol. 42. - pp. 1326–1339.

Janic M. Modelling the full costs of an intermodal and road freight transport network [Article] // Transportation Research Part D. - 2007. - Vol. 12. - pp. 33–44.

Janowicz M., Noorderhaven N. G. Levels of inter-organizational trust: conceptualization and measurements [Book Section] // Handbook of Trust Research / book auth. Bachman R. and Zaheer A.. - Cheltenham : Edward Elgar, 2006.

Jeong S.-J., Lee C.-G., Bookbinder J. H. The European freight railway system as a hub-and-spoke network [Article] // Transportation Research Part A: Policy and Practice. - 2007. - Vol. 41 (6). - pp. 523-536.

Jonsson P. Logistics and Supply Chain Management [Book]. - New York : McGraw-Hill, 2008.

Kang S. G., Choi S. H. Multi-agent based beam search for intelligent production planning and scheduling [Article] // International Journal of Production Research. - 2010. - Vol. 48 (11). - pp. 3319–3353.

Kaparias I., Bell M. G. H., Belzner H. A New Measure of Travel Time Reliability for In-Vehicle Navigation Systems [Article] // Journal of Intelligent Transportation Systems: Technology, Planning, and Operations. - 2008. - 4 : Vol. 12. - pp. 202-211.

Kelleher G., El-Rhalibi A., Arshad F. Scheduling for intermodal transport [Article] // Logistics Information Management. - 2003. - 5 : Vol. 16. - pp. 363-372.

Kengpol A., Tuammee S. The development of a decision support framework for a quantitative risk assessment in multimodal green logistics: an empirical study [Article] // International Journal of Production Research. - 2016. - 4 : Vol. 54. - pp. 1020-1038. - http://dx.doi.org/10.1080/00207543.2015.1041570.

Ketchen Jr. D. J. [et al.] Best value supply chains: A key competitive weapon for the 21st century [Article] // Business Horizons. - 2008. - 3 : Vol. 51. - pp. 235–243.

Kolmogorov A. N. On the Representation of Continuous Functions of Several Variables by Superposition of Continuous Functions of one Variable and Addition [Article]. - 1957.

Kroll A. Computational Intelligence [Book]. - München : Oldenbourg Verlag, 2012.

Küpper P., Saalmann P., Hellingrath B. An Approach for Assessing the Applicability of Collaborative Planning Concepts [Conference] // System Sciences (HICSS), 2015 48th Hawaii International Conference onHawaii International Conference on System Science. - 2015. - pp. 1049-1058.

LeCun Y., Bengio Y., Hinton G. Deep Learning [Article] // Nature. - 2015. - Vol. 521. - pp. 436–444. - doi:10.1038/nature14539.

Lewellen M., Tumay K. Network simulation of a major railroad [Conference] // Simulation Conference Proceedings, 1998. Winter. - Washington D.C., USA : [s.n.], 1998. - pp. 1135-1138.

Lin C. [et al.] A decision support system for optimizing dynamic courier routing operations [Article] // Expert Systems with Applications. - 2014. - 15 : Vol. 41. - pp. 6917–6933.

Lin Y.-H., Tseng M.-L. Assessing the competitive priorities within sustainable supply chain management under uncertainty [Article] // Journal of Cleaner Production. - 2016. - Part 3 : Vol. 112. - pp. 2133-2144.

Lippmann R. An introduction to computing with neural nets [Article] // IEEE ASSP Magazine. - 1987. - 2 : Vol. 4. - pp. 4-22. - DOI: 10.1109/MASSP.1987.1165576.

Liu Z. [et al.] Evolving neural network using real coded genetic algorithm (GA) for multispectral image classification [Article] // Future Generation Computer

Systems. - 2004. - 7 : Vol. 20. - pp. 1119-1129. - http://doi.org/10.1016/j.future.2003.11.024.

London Evening Standard London Evening Standard [Online]. - 07 08, 2013. - 1 22, 2015. - http://www.standard.co.uk/news/transport/london-weather-trains-go-slow-as-heat-buckles-rails-8695389.html.

Lu Q., Dessouky M., Leachman R. C. Modeling of train movements through complex networks [Article] // ACM Transactions on Modeling and Computer Simulation. - 2004. - Vol. 14. - pp. 48-75.

Ludvigsen J., Klaebe R. Extreme Weather Impacts in Freight Railways in Europe [Article] // Natural Hazards. - 2014. - Issue 1 : Vol. Volume 70. - pp. pp 767-787.

Macharis C. [et al.] A decision support framework for intermodal transport policy [Article] // European Transport Research Review. - 2011. - Vol. 3. - pp. 167–178.

Macharis C., Bontekoning Y. M. Opportunities for OR in intermodal freight transport research: A review [Article] // European Journal of Operational Research. - 2004. - 2 : Vol. 153. - pp. 400-416.

Magoulas G. D., Vrahatis M. N., Androulakis G. S. Improving the Convergence of the Backpropagation Algorithm Using Learning Rate Adaptation Methods [Article] // Neural Computation. - 1999. - 7 : Vol. 11. - pp. 1769-1796.

Márquez A. C. Dynamic Modelling for Supply Chain Management [Book]. - London : Springer, 2010.

Mathisen T. A., Hanssen T.-E. S. The academic literature on intermodal freight transport [Conference] // Transportation Research Procedia. - Sevilla, Spain : [s.n.], 2014. - Vol. 3. - pp. 611-620.

MathWorks Multilayer Neural Network Architecture [Online] // Function Approximation and Nonlinear Regression. - MathWorks. - August 27, 2014. - http://www.mathworks.de/de/help/nnet/ug/multilayer-neural-network-architecture.html.

McCarren R. Why is Carload Service So Unreliable? [Article] // Railway Age. - 2000. - 11 : Vol. 201. - p. 10.

McKinnon A., Ge Y. Use of a synchronised vehicle audit to determine opportunities for improving transport efficiency in a supply chain [Article] // International Journal of Logistics: Research and Applications. - 2004. - 3 : Vol. 7. - pp. 219-238.

Meers D. [et al.] Modal choice preferences in short-distance hinterland container transport [Article] // Research in Transportation Business & Management. - 2017. - Vol. 23. - pp. 46-53.

Miles R. E., Miles G., Snow C. C. Collaborative entrepreneurship: How communities of networked firms use continuous innovation to create economic wealth [Book]. - Stanford, California : Stanford University Press, 2005.

Milinković S. [et al.] A fuzzy Petri net model to estimate train delays [Article] // Simulation Modelling Practice and Theory. - 2013. - Vol. 33. - pp. 144-157. - http://doi.org/10.1016/j.simpat.2012.12.005.

Mitchell T. M. Machine Learning [Book]. - New York : McGraw-Hill Science/Engineering/Math, 1997. - International edition.

Moreira M., Fiesler E. Neural Networks with Adaptive Learning Rate and Momentum Terms [Report] / INSTITUT DALLE MOLLE D'INTELLIGENCE ARTIFICIELLE PERCEPTIVE. - Suisse : [s.n.], 1995.

Murali P. [et al.] A delay estimation technique for single and double-track railroads [Article] // Transportation Research Part E. - 2010. - Vol. 46. - pp. 483–495.

Murali P. [et al.] A Delay Estimation Technique for Single and Double-track Railroads [Online] // http://www-bcf.usc.edu/~maged/publications/tre_trains.pdf. - Dept. of Industrial & Systems Engineering, University of Southern California, 2009. - August 15, 2015. - http://www-bcf.usc.edu/~maged/publications/tre_trains.pdf.

Nash C., Smith A. Modelling Performance: Rail [Book Section] // Handbook of Transport Modelling / book auth. David A. Hensher Kenneth J. Button. - Amsterdam : Elsevier, 2008. - 2.

Network Rail Performance [Online]. - 03 2017. - 03 26, 2017. - http://www.networkrail.co.uk/about/performance/.

Neumann L., Scharfschwerdt J. Zukünftige Trends des Schienengüterverkehrs in Deutschland und Europa [Report]. - 2010.

Ngai E.W.T. [et al.] Decision support and intelligent systems in the textile and apparel supply chain: An academic review of research articles [Article] // Expert Systems with Applications. - 2014. - Vol. 41. - pp. 81-91.

Noche B., Hu J. Pflichtenheft für ein Dispositionsinstrument [Report] / Lehrstuhl Transportsystem und logistik. - 2014. - Version 4.3.

Noorul Haq A. [et al.] A hybrid neural network–genetic algorithm approach for permutation flow shop scheduling [Article] // International Journal of Production Research. - 2010. - 14 : Vol. 48. - pp. 4217-4231.

Nuhn H., Hesse M. Verkehrsgeographie: Grundriss, Allgemeine, Geographie [Book]. - [s.l.] : UTB, 2006. - 1..

Palit A. K., Popovic D. Computational Intelligence in Time Series Forecasting [Book]. - London : Springer-Verlag, 2006.

Pinkus A. Approximation theory of the MLP model in neural networks [Article]. - 1999. - Vol. 8. - pp. 143-195. - https://doi.org/10.1017/S096249290002919.

PLANCO Consulting GmbH Marktanalyse für die Kölner Häfen - Nachfrage und Kapazität bis 2030 [Report]. - 2012.

PLANCO Consulting GmbH Verkehrswirtschaftlicher und ökologischer Vergleich der Verkehrsträger Straße, Bahn und Wasserstraße [Report]. - Essen : [s.n.], 2007.

Pradeep T. [et al.] Comparison of variable learning rate and Levenberg-Marquardt back-propagation training algorithms for detecting attacks in Intrusion Detection Systems [Article] // International Journal on Computer Science and Engineering. - 2011. - 11 : Vol. 3.

Qian N. On the momentum term in gradient descent learning algorithms [Article] // Neural Networks. - 1999. - Vol. 12. - pp. 145–151.

Qrunfleh S., Tarafdar M. Supply chain information systems strategy: Impacts on supply chain performance and firm performance [Article] // International

Journal of Production Economics. - 2014. - Part B : Vol. 147. - pp. 340-250. - http://doi.org/10.1016/j.ijpe.2012.09.018.

Quintiq, DB Schenker Rail Quintiq setzt neue Maßstäbe für die Ressourcenplanung im Schienenverkehr [Online]. - 2013. - 02 06, 2015. - http://cdn.quintiq.com/content/Case-Study-DB-Schenker-Rail-DE.pdf.

Racunica I., Wynter L. Optimal location of intermodal freight hubs [Article] // Transportation Research Part B: Methodological. - 2005. - Vol. 39 (5).

Rai B. Umesh Handbook of Research on Emerging Innovations in Rail Transportation Engineering [Book]. - Hershey PA : [s.n.], 2016.

Rangel D. A., de Oliveira T. K., Leite M. S. A. Supply chain risk classification: discussion and proposal [Article] // International Journal of Production Research. - 2015. - 22 : Vol. 53. - pp. 6868-6887. - DOI: 10.1080/00207543.2014.910620.

Rehman M. Z., Nawi N. M. Improving the Accuracy of Gradient Descent Back Propagation Algorithm (GDAM) on Classification Problems [Article] // International Journal on New Computer Architectures and Their Applications. - 2012. - 4 : Vol. 1. - pp. 838-847.

Reis V. [et al.] Rail and multi-modal transport [Article] // Research in Transportation Economics. - 2013. - Vol. 41. - pp. 17-30.

Rizzoli A. E., Fornara N., Gambardella L. M. A simulation tool for combined rail/road transport in intermodal terminals [Article] // Mathematics and Computers in Simulation. - 2002. - Vol. 59. - pp. 57-71.

Rodrigues V. S. [et al.] Establishing a transport operation focused uncertainty model for the supply chain [Article] // International Journal of Physical Distribution & Logistics Management. - 2008. - Vol. 38(5). - pp. 388-411.

Roy C. S., Mandal R., Chakraborty M. A Comparative Analysis of Several Back Propagation Algorithms in Wireless Channel for ANN-Based Mobile Radio Signal Detector [Article] // International Journal of Science and Modern Engineering. - 2013. - 9 : Vol. 1.

Rumelhart D. E., Hinton G. E., Williams R. J. Learning internal representations by error propagation [Book Section] // Cognitive Modeling / book auth. Polk Thad A. and Seifert Colleen M.. - Cambridge : MIT Presse, 2002.

Rumelhart D. E., Hinton G. E., Williams R. J. Learning representations by back-propagating errors [Article] // Nature. - 1986. - Vol. 323. - pp. 533 - 536.

Russell S. J., Norvig P. Artificial intelligence: a modern approach [Book]. - Harlow [i.a.] : Pearson, 2003. - internat. ed., 2. ed. .

Sabri E. H., Beamon B. M. A multi-objective approach to simultaneous strategic and operational planning in supply chain design [Article] // Omega. - 2000. - 5 : Vol. 28. - pp. 581–599.

Satin D., Delgado F. J., Valiño A. The measurement of technical efficiency: a neural network approach [Article] // Applied Economics. - 2004. - 6 : Vol. 36. - pp. 627-635. - http://dx.doi.org/10.1080/0003684042000217661.

Schmidhuber J. Deep learning in neural networks: An overview [Article] // Neural Networks. - 2015. - Vol. 61. - pp. 85-117. - http://doi.org/10.1016/j.neunet.2014.09.003.

Schöbel A. Optimization in public transportation [Book]. - New York : Springer, 2006.

Schöneburg E., Heinzmann F., Feddersen S. Genetische Algorithmen und Evolutionsstrategien: eine Einführung in Theorie und Praxis der simulierten Evolution [Book]. - Bonn (i.a.) : Addison-Wesley, 1994. - 1..

Seebacher G., Winkler H. A capability approach to evaluate supply chain flexibility [Article] // International Journal of Production Economics. - 2015. - Vol. 167. - pp. 177-186.

Senties O. B. [et al.] A Neural Network and a Genetic Algorithm for Multiobjective Scheduling of Semiconductor Manufacturing Plant [Article] // Industrial & Engineering Chemistry Research. - 2009. - Vol. 48(21). - pp. 9546-9555.

Sexton R. S., Dorsey R. E., Johnson J. D. Toward global optimization of neural networks: A comparison of the genetic algorithm and back propagation [Article] // Decision Support System. - 1998. - Vol. 22. - pp. 171–185.

SIGNIFICANCE, GOUDAPPEL COFFENG, NEA Erfassung des Indikators Zuverlässigkeit des Verkehrsablaufs im Bewertungsverfahren der Bundesverkehrswegeplanung: Schlussbericht [Report] : final report. - 2012. - available online at: http://www.bmvi.de/SharedDocs/DE/Anlage/VerkehrUndMobilitaet/bvwp-2015-machbarkeitsstudie-zuverlaessigkeit.pdf?__blob=publicationFile, last checked on Jan. 22nd, 2015.

Simangunsong E., Hendry L. C., Stevenson M. Supply-chain uncertainty: a review and theoretical foundation for future research [Article] // International Journal of Production Research. - 2012. - 16 : Vol. 50. - pp. 4493-4523. - http://dx.doi.org/10.1080/00207543.2011.613864.

Simchi-Levi D., Kaminsky P., Simchi-Levi E. Designing and managing the supply chain: concepts, strategies, and case studies [Book]. - Boston (i.a.) : McGraw-Hill, 2009. - 3..

Singhal P., Agarwal G., Mittal M. L. Supply chain risk management: review, classification and future research directions [Article] // International Journal of Business Science and Applied Management. - 2011. - 3 : Vol. 6. - pp. 15-42.

Smirnov A., Shilov N., Kashevnik A. Analysing Supply Chain complexity via Agent-Based Negotiation [Book Section] // Complexity Management in Supply Chains: Concepts, Tools and Methods / ed. Blecker Thorsten and Kersten Wolfgang. - Berlin : Erich Schmidt Verlag, 2006. - 1. Ed..

Smith G. E. [et al.] A critical balance: collaboration and security in the IT-enabled supply chain [Article] // International Journal of Production Research. - 2007. - Vol. 45 (11). - pp. 2595-2613.

Sprecher D. R. A universal mapping for kolmogorov's superposition theorem [Article] // Neural Networks. - 1993. - 8 : Vol. 6. - pp. 1089–1094. - http://doi.org/10.1016/S0893-6080(09)80020-8.

Srinivasan M., Mukherjee D., Gaur A. S. Buyer–supplier partnership quality and supply chain performance: Moderating role of risks, and environmental uncertainty [Article] // European of Management Journal. - 2011. - Vol. 29. - pp. 260-271.

Stadtler H. Supply chain management and advanced planning : concepts, models, software, and case studies [Book]. - Berlin : Springer, 2011. - 4..

Statistisches Bundesamt [Online] // Schienengüterverkehr 2009:Transportrückgang um 15,9%. - 3 5, 2010. - 12 30, 2013. - https://www.destatis.de/DE/PresseService/Presse/Pressemitteilungen/2010/03/PD10_0.

SteadieSeif M. [et al.] Multimodal freight transportation planning: A literature review [Article] // European Journal of Operational Research. - 2014. - 1 : Vol. 233. - pp. 1-15.

Stiftung Warentest Pünktlichkeit der Bahn: Geheimnis gelüftet [Online]. - 04 27, 2011. - 11 30, 2014. - https://www.test.de/Puenktlichkeit-der-Bahn-Geheimnis-gelueftet-4229388-0/.

The Lokal de Rail strike cripples Germany's train lines [Online]. - 10 18, 2014. - 01 18, 2015. - http://www.thelocal.de/20141018/rail-strike-cripples-german-train-users.

The National Railway Company „CFR" - S.A. CFR Network Statement (I. A. R. Office, Trans.) (5.0 ed.) [Report]. - Romania : [s.n.], 2013.

The Sedney Morning Herald Sydney train drivers left in communications void by delays to safety upgrade [Online]. - 08 19, 2014. - 02 08, 2015. - http://www.smh.com.au/nsw/sydney-train-drivers-left-in-communications-void-by-delays-to-safety-upgrade-20140818-105g0v.html.

Törnquist J. Computer-based decision support for railway traffic scheduling and dispatching: A review of models and algorithms [Report] / Department of Software Engineering and Computer Science, Blekinge Institute of Technology, Soft Center. - [s.l.] : OpenAccess Series in Informatics, 2006. - pp. 1-23.

Torretta V. [et al.] Decision support systems for assessing risks involved in transporting hazardous materials: A review [Article] // Safety Science. - 2017. - Vol. 92. - pp. 1-9. - http://doi.org/10.1016/j.ssci.2016.09.008.

Tsamboulas D., Vrenken H., Lekka A.-M. Assessment of a transport policy potential for intermodal mode shift on a European scale [Article] // Transportation Research Part A. - 2007. - Vol. 41 (8). - pp. 715–733.

Turban E., Sharda R., Delen D. Decision support and business intelligence systems [Book]. - New Jersey : Pearson, 2011. - 9..

UIC - International union of railways Combined Transport [Online]. - 04 05, 2017. - http://www.uic.org/combined-transport.

UIC - International Union of Railways PRESS RELEASE N° 18/2011 [Online] // Freight transport growing across all regions of the world Passenger. - 07 27, 2011. - 03 25, 2014. - http://www.uic.org/com/IMG/pdf/cp18_uic_stats_2010_en-2.pdf.

Vahrenkamp R. Logistik: Management und Strategien [Book]. - [s.l.] : Oldenbourg Wissenschaftsverlag, 2007. - 6.

Van Dank D. P., Van der Vaart J. T. A critical review of surveys in supply chain integration research [Conference] // Innovation in Global Supply Chain Networks, proceedings of the 10th International / ed. Pawar K.S. et al.. - Lisbon : [s.n.], 2005. - pp. 32-39.

van der Vorst J. G. A. J., Beulens A. J. M. Identifying sources of uncertainty to generate supply chain [Article] // International Journal of Physical Distribution & Logistics Management. - 2002. - Vol. 32(6). - pp. 409-430.

van Donk D. P., van der Vaart T. A case of shared resources, uncertainty and supply chain integration in the process industry [Article] // International Journal of Production Economics. - 2005. - 1 : Vol. 98. - pp. 97–108. - http://doi.org/10.1016/j.ijpe.2004.03.002.

van Lint, J.W.C., van Zuylen Henk J., Tu H. Travel Time Reliability on Freeways [Article] // Transportation Research Part A: Policy and Practice. - 2008. - 1 : Vol. 42. - pp. 258-277.

van Loon R., Rietveld P., Brons M. Travel-time reliability impacts on railway passenger demand: a revealed preference analysis [Article] // Journal of Transport Geography. - 2011. - 4 : Vol. 19. - pp. 917–925.

Verband Deutscher Verkehrsunternehmen e.V. VDV-Statistik [Report]. - Köln : [s.n.], 2013.

Verbano C., Venturini K. Managing Risks in SMEs: A Literature Review and Research Agenda [Article] // Journal of Technology Management &

Innovation. - 2013. - 3 : Vol. 8. - pp. 186-197. - http://dx.doi.org/10.4067/S0718-27242013000400017 .

Vilko J. P. P., Hallikas J. M. Risk assessment in multimodal supply chains [Article] // International Journal of Production Economics. - 2012. - 2 : Vol. 140. - pp. 586-595. - http://doi.org/10.1016/j.ijpe.2011.09.010.

Vinodh S. [et al.] Development of decision support system for sustainability evaluation: a case study [Article] // Clean Technologies and Environmental Policy. - 2014. - 1 : Vol. 16. - pp. 163–174.

Wang J. Information technologies, methods, and techniques of supply chain management [Book]. - Hershey : PA: Business Science Reference, 2012.

Webb A. R., Copsey K. D. Statistical Pattern Recognition [Book]. - Chichester : John Wiley & Sons, Ltd, 2011. - 3.. - DOI: 10.1002/0470854774.

Western Morning News One rail line reopens east of Exeter as travel chaos continues [Online]. - 2 9, 2014. - 7 30, 2014. - http://www.westernmorningnews.co.uk/Rail-line-closed-east-west-Exeter-fresh-storm/story-20589957-detail/story.html.

Whitley D, Starkweather T., Bogart C. Genetic algorithms and neural networks: optimizing connections and connectivity [Article] // Parallel Computing. - 1990. - 3 : Vol. 14. - pp. 347–361.

Widrow B., Hoff M. E. Adaptive Switching Circuits [Conference] // IRE WESCON Convention Record. - 1960. - Vol. 4. - pp. 96-104.

Wilson N. [et al.] Neural Network Simulation and the Prediction of Corporate Outcomes: Some Empirical Findings [Article] // International Journal of the Economics of Business. - 1995. - 1 : Vol. 2. - pp. 31-50. - http://dx.doi.org/10.1080/758521095.

Wittmann E. Risikomanagement im internationalen Konzern [Book Section] // Praxis des Risikomanagements / book auth. Dörner D., Horváth P. and Kagermann H.. - Stuttgart : Springer, 2000.

Woodman P. Rail passengers face more delays due to overhead wire problems [Online]. - The Independent, 04 05, 2013. - 01 20, 2015. -

http://www.independent.co.uk/news/uk/home-news/rail-passengers-face-more-delays-due-to-overhead-wire-problems-8561380.html.

Woxenius J., Pesson P. A., Davidsson P. Utilising more of the loading space in intermodal line trains – Measures and decision support [Article] // Computers in Industry. - 2013. - Vol. 64 (2). - pp. 146–154.

Wu Y. [et al.] Cloud Computing in Support of Supply Chain Information System Infrastructure: Understanding When to go to the Cloud [Article] // Journal of Supply Chain Management. - 2013. - 3 : Vol. 49. - pp. 25-41. - DOI: 10.1111/j.1745-493x.2012.03287.x.

Xia Y. [et al.] Railway infrastructure disturbances and train operator performance:the role of weather [Article] // Transportation Research Part D. - 2012. - Vol. 18. - pp. 97-102.

Yu H., Wilamowski B. M. Levenberg–Marquardt Training [Book Section] // Intelligent Systems / book auth. Irwin David J. and Wilamowski Bogdan M.. - Boca Raton, Florida : CRC Press, 2011.

Zhang Q.-J., Gupta K. C. Neural networks for RF and microwave design [Book]. - Boston [i.a.] : Artech House, 2000. - Vol. 1..

Zhang X., van Donk D. P., van der Vaart T. Does ICT influence supply chain management and performance?: A review of survey-based research [Article] // International Journal of Operations & Production Management. - 2011. - 11 : Vol. 31. - pp. 1215-1247. - doi: 10.1108/01443571111178501.

Zouaghi I., Saikouk T., Spalanzani A. Interdenpendencies and Supply Chain Bipolar Strategies: Between Co-Opetition and Comperation [Book Section] // Pioneering Solutions in Supply Chain Management / book auth. Kersten Wolfgang, Blecker Thorsten and Lüthje Christian. - Göttingen : Erich Schmidt Verlag, 2010.

Zuppo C. M. DEFINING ICT IN A BOUNDARYLESS WORLD: THE DEVELOPMENT OF A WORKING HIERARCHY [Article] // International Journal of Managing Information Technology. - 2012. - 3 : Vol. 4. - pp. 13-22. - DOI : 10.5121/ijmit.2012.4302.

Zweiri Y. H., Seneviratne L. D., Althoefer K. Stability analysis of a three-term backpropagation algorithm [Article] // Neural Networks. - 2005. - Vol. 18. - pp. 1341-1347.

李(Li) 航(Hang) 统计学习方法 (statistical learning methods) [Book]. - 北京 (Beijing) : 清华大学出版社 （Tsinghua University Press）, 2012.

韩 (Han) 力群 (Liqun) 人工神经网络教程 (Course of Artificial Neural Network) [Book]. - 北京 (Beijing) : 北京邮电大学出版社 (Press of Beijing University of Post and Telecommunications), 2006.