

Evaluation of efficient and resilient production strategies of future car production networks considering power train diversity

Maximilian Hilmer*, Ralph Riedel**, Thomas von Unwerth*

*Chemnitz University of Technology, Chemnitz, Germany (e-mail: maximilian.mh.hilmer@gmail.com, thomas.von-unwerth@mb.tu-chemnitz.de).

**University of Applied Sciences, Zwickau, Germany, (e-mail: ralph.riedel@fh-zwickau.de)

Abstract: The automotive industry is currently facing significant uncertainties and challenges. At the same time, efforts to achieve emission-free mobility are leading to power train diversity. In this complex environment, it is essential for car producers to define an efficient and resilient production strategy of future car production networks. This article provides a universal approach and simulation model to evaluate production strategies considering power train diversity. A case study, mirroring possible scenarios for automotive manufacturers, shows that a certain proportion of mix production can have an advantage in terms of resilience compared to a highly efficient pure-variant network, especially by marked uncertainties.

Copyright © 2025 The Authors. This is an open access article under the CC BY-NC-ND license (<https://creativecommons.org/licenses/by-nc-nd/4.0/>)

Keywords: vehicle production, production networks, mix production, production strategy, production flexibility, power train diversity, resilience.

1. INTRODUCTION

The global automotive industry is currently navigating a period of changes, challenges and uncertainties. After the pandemic-induced disruptions, sales are gradually returning to pre-pandemic levels, with 2024 expected to reach around 88.3 million new vehicle sales globally, see IHS Markit (2023). Nevertheless, there are major challenges such as geopolitical uncertainties and general economic pressure. At the same time, due to efforts by lawmakers and customers' expectations to achieve more climate-neutral mobility, a shift is taking place, from a single power train variant to a diversity of power trains. Also, the market characteristics are quite different, China is a key player in global automotive sales, especially in the electric vehicle (EV) segment. Europe is facing a dynamic transition, particularly in EV adoption. In the U.S. market, increases of EV sales are also expected, as the number of available models continues to rise, see IHS Markit (2023). The different market situations and characteristics of power trains leads to a transition phase of power train diversity. All in all, this shows a challenging and uncertain situation for the automotive industry, especially for the traditional and European OEMs (Original Equipment Manufacturers), see IHS Markit (2024).

Prevention of unforeseen disruptions demands resilience in the supply chain design, see Ivanov et al. (2019). But also, unpredictable situations, market dynamics, and technological developments make resilience essential to handle changes without cost escalation. Most of resilience approaches focus on the classical supplier structure (Tier1-TierN). Furthermore, it is important to take resilience into account in the own production network, especially in vehicle production where in addition to the general politic and economic challenges a technology transition is taken place.

A current major challenge for the automotive industry is to determine the best strategy for distributing vehicles with different powertrains across the vehicle production network in

order to produce the powertrain mix in the most efficient but also resilient way. In this context it is important to find the right balance between flexible mix production of different power train types and efficient single-variant production. The current approaches of automotive manufacturers differ significantly. In 2020 the situation was even described as a “war of beliefs”, see Berlin & Bretting (2020).

To support decision-making, there is currently a lack of suitable modeling approaches which consider the diversity of power trains and analyze the resilience of the approach, or the production network, respectively. This article contributes to close this gap by providing a systematic approach for identifying the best production strategy for a mix of cars with different power train types within a production network. In the remainder of the article the current state of research and technology is outlined first, followed by a description of the model approach, which is then applied in a case study.

2. STATE OF RESEARCH & TECHNOLOGY

2.1 Powertrain technologies and vehicle production

Currently, mainly two different types of powertrain concepts are being produced in series: Internal Combustion Engine Vehicles (ICEs) and Electric Vehicles (EV) which can either use a batterie (BEV) or hydrogen in combination with a fuel cell (FCEV) as energy storage.

ICEs operate by burning fossil fuels in a combustion chamber to produce thermal energy which is used to drive the vehicle. By using E-Fuels in the future it is possible to have a neutral CO₂ balance, see Baldinelli et al. (2024). However, at the moment E-Fuels are very limited available and expensive. BEVs use lithium-ion batteries to store electrical energy, which is converted into mechanical power by electric motors. These batteries are recharged via external electricity sources, making BEVs zero-emission vehicles during operation, see Karki et al. (2020). However, challenges remain, such as

limited driving range and dependence on the availability of charging infrastructure. FCEVs use hydrogen fuel cells to generate electricity through an electrochemical process. The only by-products of this process are water and heat. Despite hurdles like rare availability and underdeveloped infrastructure, hydrogen's high energy density and quick refueling times offer advantages, particularly for heavy-duty vehicles and long-range applications, see Baldinelli et al. (2024). Each power train system presents unique advantages and challenges. BEVs are currently leading the push towards electrification, while FCEVs offer a promising solution for sectors where battery limitations hinder performance. Meanwhile, ICEs continue to dominate the global vehicle market but face increasing pressure due to their environmental impact and the growing emphasis on sustainability. This situation combined with general political uncertainty and hard to predict customer behavior leads to a mix of power train systems in the future, where the exact distribution of each technology is difficult to foresee. Due to the different main components of a vehicle depending on the power train type it has a significant influence on the vehicle production, see Hilmer et al. (2022). Therefore, it is important for global vehicle manufacturers to find the right strategy for their production network to produce this diversity in an efficient way.

2.2 Supply chain resilience in vehicle production

The efficiency of production networks has been a widely discussed topic in research for decades, becoming even more complex due to powertrain diversity. But unforeseen disruptions such as the semiconductor shortage have made resilience a central topic. Lückert et al. (2024) illustrate in their literature review, that only recently the research has begun to examine efficiency and resilience in combination. Balancing these two aspects is very important especially in uncertain markets, such as the automotive industry. In this context resilience can mean, avoiding production cost increases due to unexpected changes e.g. volume shifts because of lower EV demands. Ivanov (2022) criticized that resilience is often treated as a passive measure, only utilized in emergency situations such as COVID-19. He recommends actively integrating resilience through the AURA Framework (Active Usage of Resilience Assets). However, due to the specific characteristics of vehicle production networks this approach cannot be directly applied. Nevertheless, following this approach, resilience should already be actively incorporated into the definition of the production strategy.

According to Ivanov et al. (2019) there are three main elements of resilience in the supply chain: Robustness, redundancy and flexibility. But, as previously mentioned, it is not trivial to transfer these elements to a vehicle production network. The vehicle production is a chain of specifically designed process steps and reacts very sensitively to changes, especially by volume decreases, see Roscher (2008). This means proactive robustness is only possible to a limited extent. High investments also make it difficult to set up redundant vehicle production systems. Volume or power train flexibility within the production network can help to increase resilience, but flexibility usually corresponds with efficiency losses. This

demonstrates that vehicle production is highly specific and requires individual approaches to balance resilience and efficiency. Also Aldrighetti et al. (2024), who propose a methodological framework for designing efficient and resilient supply chains, considers specific case studies as essential focus for further research.

2.3 Vehicle production strategies and model approaches

The production of vehicles with diverse configurations is a well-established practice within the automotive industry and has been analyzed in various literature (e.g. Roscher (2008)). However, the type of power train should not be seen equal to vehicle or equipment variants; rather, it represents an additional dimension of vehicle variance as a fundamental component of the vehicle. The general optimized distribution of derivatives across production plants has already been discussed in the literature. Jordan and Graves (1995) have mathematically proven that the chaining of vehicle derivatives, across at least two plants, provides an advantage in satisfying customer demand. In Vivek et al. (2018) it is also mathematically proven that chaining across the entire network is not compelling a general advantage. The recommendation is to use chaining only in a small proportion of the network. Direct production cost analyses have not been carried out so far. General mathematical modeling approaches for flexibility and agility in production strategies for automotive components also exist. In Brintrup and Puchkova (2018) a systematic literature review was done and based on an analysis of genetic algorithms a model was designed to find an optimum of redundancy and flexibility in production networks, however, this is not directly usable for vehicle production. A specific vehicle production case was discussed by Ferber (2005) and a model for plant distribution, that primarily takes market requirements into account, was created. The complexity of power train diversity and influence on production costs was not considered. In sum, there is no existing approach that examines manufacturing costs in vehicle production networks while considering the increasing complexity due to powertrain diversity and linking efficiency and resilience to derive the optimal production strategy.

3. PRODUCTION STRATEGY SIMULATION MODELL

Our approach to determining the best production strategy is divided into four steps. In the first step, the influence of the powertrain type on vehicle production is assessed by using the results of expert interviews described in Hilmer et al. (2022). The next step establishes a database of production costs, investments and volume design points for vehicle plants thorough analysis of available studies and press reports from OEMs, based on Hilmer et al. (2023). This is followed by a scenario simulation in which manufacturing costs for various strategies are simulated, including a sensitivity analysis to determine resilience. In the fourth and final step, the results of the strategies and the sensitivity analysis are evaluated with a probability of occurrence. The results are used to draw conclusions about the optimal production strategy. In this article, we use a case study based on European OEMs to illustrate the approach. The applied approach and simulation model can be used universally, but it always must be adapted to case specific conditions e.g. investments.

3.1 Influence of the power train type on vehicle production

Expert interviews indicate that the type of power train in general has an evident impact on vehicle production in various intensities across different areas of the production. The stamping, body, and paint shops are generally assessed as being low influenced by the type of power train. In contrast, pre-assembly processes, particularly the assembly of drive components, are more heavily influenced. The final assembly is a complex series of operations that follow a specific sequence – experts attribute a significant influence on this area. The electric drive changes the work content in many steps of the final vehicle assembly, for example, the installation of flexible high voltage wiring and connectors compared to exhaust-related components for combustion engines. Also testing methods and requirements are changed by producing an electric car with an increased focus on high-voltage and acoustic testing due to the higher perceptibility of sounds in electric vehicles, sometimes resulting in increased rework. For details, see Hilmer et al. (2022).

Based on this determined influence of the power train type on the vehicle production it is important to estimate the impact of a mix production. The interviews revealed that the main disadvantage of mixed production of different power drive types lies in synchronizing takt time. Asynchronous work tasks make it "impossible" to optimize station timing, requiring additional flexible staff or stations. Another significant challenge is internal logistics, particularly the increased variety and differing characteristics of components, which complicates handling, storage, and line filling. In production planning, mixed lines must often adhere to more constraints, leading to higher complexity. Quality assurance also becomes more demanding, as more diverse equipment and components must be tested. Overall, mixed production of different power drive types has a negative impact on factors like production efficiency, which experts suggest can lead up to a 20% efficiency loss compared to single-type production, according to Hilmer et al. (2022). These efficiency losses due to mix production will be later used for the model as a surcharge factor.

3.2 Database vehicle production costs and investments

Acquiring data on automotive production is challenging as OEMs rarely publish detailed information. To create a basis for the scenario simulation, various studies and press reports were thoroughly analyzed. The data obtained were combined to create an overview of investment costs for vehicle production facilities, yearly volumes per plant and production costs. To ensure comparability of the data, the focus is on European OEMs in the mid- to premium segment.

In total, over 50 sources were reviewed and analyzed. For example, the investments of BMW in a new plant in Hungary, the addition of new assembly lines at the BMW plant in Munich as well as at VW in Wolfsburg, the construction of a flexible mix production facility of Mercedes in Sindelfingen, the establishment of a body shop for Porsche in Zuffenhausen and Audi in Ingolstadt, and the construction of a paint shop for Skoda in Boleslav. These and other investments were consolidated into a general investment overview: press shop

approx. €200 million, body shop approx. €350 million, paint shop approx. €200 million, and assembly approx. €700 million. All considered plants report an annual production volume between 110,000 and 150,000 vehicles per assembly line; see Hilmer et al. (2023).

The direct production costs are significantly influenced by the required manual workforce, therefore the level of automation in each area is important. In body construction and in the paint shop the automation degree of over 90% are reported across OEMs, whereas final assembly is heavily dependent on human assembly skills with only 10% to a maximum of 28% automation, see Hilmer et al. (2023). The assembly time is given as 12h to 23h per car. Based on these findings, it is assumed that in best case the assembly costs will be around €1,700 per car. These costs increase depending on the external conditions, for example mixed assembly of different drive types or volumes under or over the design point; see Hilmer et al. (2023). Design point describes the production volume which was considered as the optimal operating point when designing the assembly line.

3.3 Simulation of production strategies

The focus of the simulation is on the final assembly. In this area the power train type has the biggest impact, the highest investments are needed, and the largest share of direct production costs occur due to many manual activities.

The question to be examined by the simulation model is, how a defined portfolio of vehicles with different power train types can be optimally distributed across an existing or planned production network. An example of an initial situation is shown in figure 1, which will be later analyzed in the case study. According to Anu (1997), a good model is a judicious tradeoff between realism and simplicity. It also should not be so complex that it is impossible to understand and interpret the results. Therefore, a deterministic manufacturing cost simulation model is used, which calculates the costs of various distribution scenarios based on the repetition of fixed mathematical operations with varying input parameters.

The target metric of the model is defined as fleet manufacturing costs. This metric represents the total cost of all vehicles produced within the network in relation to one vehicle that corresponds to an average vehicle. This target metric ensures that optimization does not focus on individual plants or vehicle types but rather aims to determine an overall optimum for the network. This approach is similar to the CO2 fleet value definition, where the focus is also not on single vehicles but on the CO2 emissions of the entire fleet. The results of the model are the fleet manufacturing costs of various distribution scenarios and the composition of the fleet

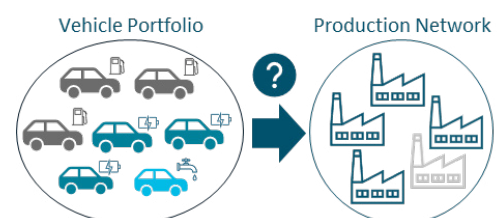


Figure 1. Illustration of initial situation.

costs, which can be used to analyze the scenario and related strategies. Additionally, it is also possible to simulate changes in the parameters (e.g. volume) and their influence on the fleet manufacturing costs. Based on this, a calculation of strategies sensitivities, which describes the effects of changes, is possible. These analyses can be used to make conclusions about the resilience of the strategies.

Simulation model and application through a case study

The mathematical logic of the deterministic cost simulation consists of three interlinked calculation levels/loops. In the top level, all possible allocation scenarios are determined through combinatorial methods. In the second level, each plant is simulated for each scenario. Finally, in the lowest level, the manufacturing costs of each vehicle from a plant are calculated annually for a defined time period. The calculation of the manufacturing costs consists of two components: the allocated investment costs and the assembly costs per vehicle. The starting point for investment costs is the initial expenditure per plant, which is allocated to each vehicle by accounting for capital costs and depreciation. In the case of a volume increase over the design point, further investments are added. Additional capability investments resulting from new vehicle launches during the investigation period or ability extension for mix production are also applied. It is possible that already implemented capability is not used in some scenarios. Analogous to the investments, a starting point is also defined for the assembly costs. This is the best practice assembly cost value, which reflects the costs under optimal boundary conditions for a plant (pure production at the design point). From this, the scenario specific conditions of the plant are considered as a surcharge calculation. Additional assembly costs, resulting from under- or over-utilization relative to the design point, are accounted by a volume factor. Depending on the mix of drive trains produced at a plant, additional costs due to efficiency losses are added (mix losses). After completing all loops and compiling the results, all costs are available to draw conclusions about an optimal production strategy.

For application, the definition and initialization of the basic parameters is necessary. These parameters were defined as follows, in accordance with Hilmer et al. (2024): capital costs per year 2.5%, depreciation period 20 years, best practice assembly costs per vehicle 1,700€. Depending on the conformity or deviation of essential components of cars with different power trains the mix losses are defined as shown in Table 1.

Tabel 1. Mix Losses.

	BEV	FCEV
ICE	20%	22%
BEV	0%	3%

If the volume is below the design point, it is assumed that, by 50% underutilization, the assembly costs will increase around 30%, as the efficient use of personnel and equipment is lower compared to the original design. If volume increases, unscheduled investments will be necessary, e.g. for additional screwing technology or stations to reduce cycle times. It is assumed that the investments per vehicle increase by 12.5% for a 50% increase in volume according to Roscher (2008). For

a volume change of +/- 10%, no additional costs are assumed, as this can be compensated for by basic flexibility such as shift adjustments. Based on these assumptions an almost linear progression of additional costs due to volume deviation is assumed. In alignment with strategic planning processes, the simulation period is set to 15 years.

In addition to the basic parameters, specific parameters are required. These contain the vehicle portfolio including volumes and specifications for the existing or planned production network: number of plants, design points (number of units produced per year), qualified drive type, initial and capability investments. To carry out the simulation, a simplified case study was created based on European OEMs.

The vehicle portfolio consisting of three ICE and three BEV is used as a basis. Sub-variants (e.g. body shape) of vehicle types as well as hybrid variants were not explicitly considered to reduce complexity. The three ICE vehicles are already in production and their volumes are declining over the planning horizon. One of the BEV vehicles is also already in production. The launch of the other two BEVs is in the second year of the period under review. An FCEV is also considered, which will be ramped up in the fourth year. The assumed volume of all vehicles results in a share of 30% electric vehicles at the beginning of the period and increases to around 70% by the end of the period. The increasing proportion of electric vehicles is based on a meta-study of Kampker et al. (2021). Five plants are available for the production of the vehicles, which have the following framework conditions: Plant 1 & 2, exists, currently pure ICE, design point 150k & 110k vehicles per year, initial investment €700 million & €600 million; plant 3, exists, currently pure BEV, design point 125k vehicles per year, initial investment €700 million; plant 4, exists, currently mixed production, design point 130k vehicles per year, initial investment €700 million; plant 5, new, design point 100k vehicles per year, initial investment €500 million. In case of additional capability investments are needed, €100 million are assumed for the launch of a new vehicle or ability extension for additional power trains.

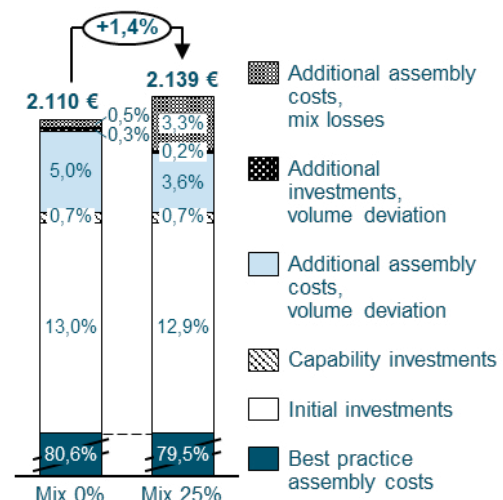


Figure 2. Fleet Manufacturing Costs per Strategy.

The distribution of seven vehicles across five plants results in 78,125 possible allocation scenarios. Applying the constraints that existing plants should be utilized and not more than three vehicles should be distributed to a single plant reduces the number of scenarios to 24,360. For these scenarios, the model was applied, and the fleet manufacturing costs were calculated. The results are discussed in the following analyses.

Analysis of fleet manufacturing costs

The analysis of the results shows that there are essentially two different strategies within the 25 best scenarios (lowest fleet manufacturing costs). In the pure-variant strategy, vehicles are allocated in such a way that no plant produces a mix of powertrain types (Mix 0%). In contrast, the second strategy involves producing approximately 25% of the total vehicle volume in a powertrain mix (Mix 25%). For further investigations, the best scenarios of these two strategies are analysed and compared. Figure 2 shows the fleet manufacturing costs of these two strategies. Due to the restriction of the pure-variant strategy (Mix 0%), that only the same power train types are produced in one plant, the volumes cannot be distributed as well across all plants and higher surcharges are incurred for volume deviations from the design point. However, these costs are compensated by the minimum mix loss and overall, the single-variant strategy leads to 1,4% lower fleet manufacturing costs compared to the mix strategy (Mix 25%).

Sensitivity & resilience analysis

The basis of a planning process is an assumption of future volumes. In the automotive industry this prediction is highly complex and subject to uncertainty due to unforeseeable market developments. For this reason, in addition to the basic volume assumption, a sensitivity analysis is carried out. The sensitivity has a link to the resilience of strategies. If the sensitivity of a strategy is low, the potential increase of manufacturing costs due to unforeseen volume changes is reduced, and this increases the resilience of the production network. For this purpose, a general decrease and increase in volume as well as a shift of the power train mix are simulated. The results of the sensitivity analysis are shown in Figure 3. In general, the sensitivity curves are U-shaped. The flatter the curve, the more resilient the strategy is to unforeseen changes.

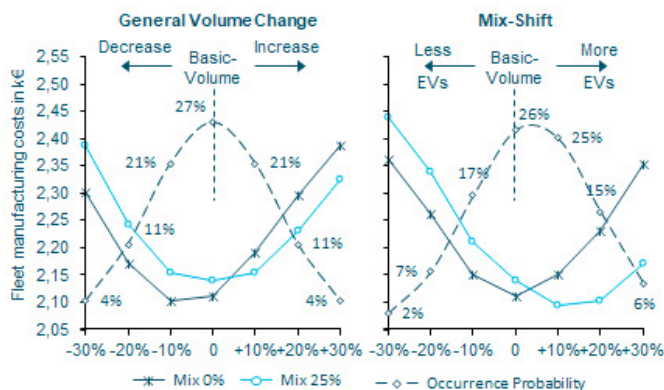


Figure 3. Sensitivity & Resilience Analyses and Occurrence Probability.

For the investigation of the general volume change, the volumes were varied in 10% steps from -30% to +30%. In the case of a general volume reduction, the advantage of the single-variant strategy remains nearly constant. With an increase in volume, the cost curve of the single-variant strategy rises more sharply, leading to higher costs from +5%. This can be attributed to a more balanced volume distribution in the mix strategy. When considering a mix shift, the ratio between EVs and ICEs is also varied stepwise from -30% to +30%. The minimum of the mix strategy curve occurs at 10% more EVs (less ICEs), and from this point it is below the pure-variant strategy. This can be explained in this specific case by the fact that the mix shift does not lead to such a strong imbalanced capacity utilization in the network. In summary, it can be stated that if the assumed volume (basic volume) is precisely achieved, the pure-variant strategy performs best. However, this may change or even reverse in the event of unforeseen changes. Therefore, it is crucial to analyze scenarios regarding potential unexpected changes when determining the optimal production strategy.

3.4 Expected value for fleet manufacturing costs

To provide assistance in determining the optimal production strategy, considering sensitivity and resilience due to market uncertainties and potential volume or mix changes, an “expected fleet production cost value” is introduced. Hereby, the fleet manufacturing costs of the volume and mix shifts are weighted by a probability of occurrence. The basis for this probability is a standard normal distribution. However, their parameters (mean and standard deviation) can be adjusted by a team of experts or empirical studies to consider expected or unexpected deviations. In this case study, it is assumed that the volume decrease and increase are considered as equally probable. For the mix shift, it is assumed that a deviation in the direction of more electric vehicles is more likely, but an increase in combustion engines cannot be completely excluded. Therefore, the means of the distribution is shifted towards more electric vehicles. The occurrence of probability curves can be seen in Figure 3 for both cases (Volume change and mix shift). To calculate the expected value, the sum of the fleet production costs per sensitivity is multiplied by the probability and an average is calculated between the general volume and mix shift. The comparison of the fleet costs in the base Volume and expected value are shown in Figure 4. The expected value of fleet manufacturing costs shows that the advantage has reversed, and the mix strategy is 0,2% cheaper than the single-variant strategy. This example shows that better transparency through sensitivity analysis of changes can lead to a decision-making basis for a more resilient strategy.



Figure 4. Comparison fleet manufacturing costs

4. CONCLUSION

The case study has shown that the strategy of single-variant production leads to the lowest costs when the forecast volume is achieved due to high efficiency. However, it has also been shown that a mix share in the network can increase its resilience and can have positive effects through avoiding cost increases when changes occur, as fluctuations can be better balanced. It is therefore recommended to include a certain proportion of mix production in the vehicle production network, especially in a market situation that is difficult to predict. This is also reflected in the current problems of the OEMs. The modelling approach and the simulation procedure described in this article can be generally applied to determine the optimal strategy of production networks for a mix of vehicles with different power train types on a high planning level. It can also be used to validate current strategies and for analyzing the impact of volume or mix changes. However, this procedure does not replace detailed planning and plausibility checks by experts. Also, the parameters need to be adjusted on the respective application. In reality, there are more effects which were simplified for the case study (e.g. influence of hybrid or car body variants) to handle the complexity. For subsequent research, the model can be supplemented with additional effects e.g. the impact of punitive tariffs. But it is important to ensure an appropriate level of detail and interpretability in order to ensure applicability in practice. This article contributes to the evaluation of vehicle production strategies through a general simulation approach including the influence of power train delivery which can be used for further research discussions. Additionally, the method of sensitivity analyses and the direct link to resilience can be used for other use cases and industries.

REFERENCES

- Aldrighetti, R., Calzavara, M., Martignago, M., Zennaro, I., Battini, D., Ivanov, D. (2024). A methodological framework for the design of efficient resilience in supply networks. *International Journal of Production Research*, 62(1-2), 271-290
- Anu, M. (1997): Introduction to modeling and simulation. In: *Proceedings of the 29th conference on Winter simulation - WSC '97*. New York, ACM Press, S. 7–13.
- Baldinelli, A., Francesconi, M., Antonelli, M. (2024). Hydrogen, E-Fuels, Biofuels: What Is the Most Viable Alternative to Diesel for Heavy-Duty Internal Combustion Engine Vehicles? In *Energies* 17 (18)
- Berlin, C., Bretting, R. (2020). Vorsicht Baustelle. integrieren, umrüsten, neu bauen - die Fertigung von Elektroautos hat massive Auswirkungen auf die Produktionsstrategien der Hersteller, 2020, In *AUTOMOBIL-Produktion* Nr. 3
- Brintrup, A., Puchkova, A. (2018). Multi-objective optimisation of reliable product-plant network configuration, In: *Applied Network Science* 3 (1)
- Ferber, S. (2005). *Strategische Kapazitäts- und Investitionsplanung in der globalen Supply Chain eines Automobilherstellers*. Shaker Verlag
- Hilmer, M., Riedel, R., von Unwerth, T. (2022). Gestaltung von effizienten Produktionsnetzwerken in der Automobilindustrie, Einfluss alternativer Antriebe. In *ZWF*, 117 (2022) 12
- Hilmer, M., Riedel, R., von Unwerth, T. (2023). Bewertung von Produktionsstrategien bezüglich Mix- oder sortenreiner Produktion von Fahrzeugen mit alternativen und konventionellen Antrieben, in *ZWF*, 118 (2023) 12
- Hilmer, M., Riedel, R., von Unwerth, T. (2024). Simulation und Bewertung von Fahrzeug-Produktionsstrategien vor dem Hintergrund unsicherer Marktentwicklungen, In *ZWF*, 119 (2024) 12
- IHS Markit (2023). S&P Global Mobility forecasts 88.3M auto sales in 2024. online: <https://www.spglobal.com/mobility/en/research-analysis/sp-global-mobility-forecasts-883m-auto-sales-in-2024.html>
- IHS Markit (2024). Understanding Global Automotive Demand in 2024. online: <https://www.spglobal.com/mobility/en/research-analysis/state-of-global-automotive-demand-2024.html>
- Ivanov D. (2022). Lean Resilience: AURA (Active Usage of Resilience Assets) Framework for Post-COVID-19 Supply Chain Management. *International Journal of Logistics Management*, 33(4), 1196-1217
- Ivanov, D., Tsipoulanis, A., Schönberger, J. (2019): Supply Chain Risk Management and Resilience. In: *Global supply chain and operations management. A decision-oriented introduction to the creation of value*. Second edition. Springer Verlag S. 455–479.
- Jordan, W., Graves, S. (1995). Principles on the Benefits of Manufacturing Process Flexibility, *Management Science* Vol.41/4, S. 577
- Kampker, A., Offermanns, C., Heimes, H., Bi, P. (2021). Metaanalyse zur Marktentwicklung elektrifizierter Fahrzeuge, In *ATZ – Automobiltechnische Zeitung*, Vol.123 (7/8), S. 60–64
- Karki, A., Phuyal, S., Tuladhar, D., Basnet, S., Shrestha, B. (2020). Status of Pure Electric Vehicle Power Train Technology and Future Prospects. In *Applied System Innovation* 3 (3), S. 35
- Lücker, F., Timonina-Farkas, A. & Seifert, R. W. (2024). Balancing Resilience and Efficiency: A Literature Review on Overcoming Supply Chain Disruptions. *Production and Operations Management* 1-17
- Roscher, J. (2008). *Bewertung von Flexibilitätsstrategien für die Endmontage in der Automobilindustrie*, Universität Stuttgart
- Vivek, C., Sameer, H., Serguei, N. (2018). Do Flexibility and Chaining Really Help? An Empirical Analysis of Automotive Plant Networks, *INSEAD Working Paper* No. 2018/58/TOM