Procedure Model to Estimate Bundled Energy Demand for Energy-oriented Simulation Studies

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Abstract. Industrial parks are the backbone of every developed industry. They exist in various forms, differing in the composition of resident companies, their size and their underlying energy infrastructure. In the ERDF-funded research project "GRIDS - Green Energy for Industrial Networks" the potentials and improvement possibilities of innovative energy supply concepts in commercial and industrial parks were investigated. An elementary challenge is the prediction of the (bundled) energy demand, which is necessary for the ecologically and economically sustainable long-term design of energy supply concepts. The data available to planners and researchers for such projects is usually incomplete and undetailed or simply non-existent. Therefore, this paper presents an approach that uses statistical methods to provide better estimates of the bundled energy demand of business parks. This method supports the efficient planning of sustainable energy concepts.

Introduction

For an initial assessment of sustainable and cost-effective energy concepts in industrial parks, direct data collection and measurement is usually too costly and time-consuming. Analyzing comparable energy consumers alone is also unable to provide comprehensive information about the situation at the planning site. Because it cannot be assumed that even companies of identical industry, size and structure have the same load profile. Another barrier is that energy data is often not made available because it is frequently considered sensitive data in manufacturing companies.

In addition, particularly smaller companies lack transparency with regard to their energy data. These are usually very undetailed e.g., based solely on monthly invoices from the energy supplier. The result is that in many projects there is only an insufficient data basis for the reliable planning of energy networks.

However, knowledge about the temporal course of the energy and power demand is a basic prerequisite for a sustainable design of the energy supply system with the aim of increasing the share of renewable energies and the integration of energy storage options. In this context, the integration of hydrogen-based energy systems is attracting increasing interest in science and practice, which will be discussed in more detail in the application section. Only with the right and accurate information is it possible to plan operating resources efficiently, which is important given the often enormous amounts of investment involved, the long-term nature of the largely irreversible investments and lock-in effect of greenhouse gas emissions associated with the energy infrastructure in use [1, 2].

Based on this, a methodology was developed that provides a process model for estimating the energy demand of bundled supply concepts. By using the of the proposed method to estimate the energy demand of (heterogeneous) energy consumer groups, as they are represented by companies in business parks, the simulation and the design of the energy systems can be improved, thus the network planning based on empirical values can be supported by a target-oriented method [3].

The aim is not to establish new standard load profiles, but to apply the established ones in such a way that they can be used at the company and business park level. For that purpose, the paper presents a brief overview of the state of the art of energy data collection, followed by a short introduction of the the proposed procedure model.

Based on this, results of the methodology are presented and illustrated by an application example for the integration of hydrogen into an industrial park. This paper is an extended and adapted version of the original paper by Jacobsen and Stange presented in 2020 [4].

1 State of the Art

The identification of internal optimisation potentials and the requirements of external stakeholders (e.g., energy suppliers, customers etc.) make energy data collection necessary and helpful for many companies. Examples of external drivers are:

- In Germany companies with an annual requirement of ≥ 100,000 $\frac{kWh}{a}$ must record their actual load profile (according to §12 StromNZV).
- Introduction of an energy management system according to DIN EN ISO 50001 in order to receive refunds on electricity tax (according to §10 StromStG).
- Energy data as a basis for calculating company-wide carbon emissions in order to achieve carbon neutrality for example in accordance with BSI PAS 2060 [5]. This results from growing demands from customers regarding sustainability.

In general, a distinction can be made between three types of energy data collection [6].

1.1 Calculation

The calculation of energy values requires a comprehensive basis of technical and organizational data, which is not always readily available. For example, an annual energy requirement can be estimated with the help of the performance data of a machine and its operating times. The advantage of this method is that no measuring equipment or intervention in the running operation is necessary. A disadvantage is the complexity of the calculations, e.g. to calculate the total energy demand of a building. It can be assumed that smaller companies in particular do not have the necessary knowledge to carry out these calculations [7].

1.2 Temporary measurement

With the help of temporary measurements, the data basis for the calculations of energy data can be improved. The costs are higher than for a simple calculation, but the data basis and the calculation results can be validated. In addition, the costs are lower than those of permanently installed measuring devices [7].

1.3 Permanently installed measuring device

This type of energy data collection is particularly suitable for in-depth analyses and offers automation options for the collection of energy-related data. On the other hand, however, the acquisition costs are high and the data volumes require a great deal of evaluation [7].

Any type of energy simulation, be it simulations for the design of supply grids, an energy-oriented material flow simulation to investigate the effects of energy flexibility measures or the simulation of technical building services in a factory, require a suitable database to create energy models [8]. The underlying approaches to energy data collection for the simulation are based primarily on temporary energy measurements [8]. Such approaches can still be justified on the scale of a production system or factory, but for the energy analysis of an entire commercial or industrial park, the effort is too high in most cases.

In order to generate energy data for commercial and industrial parks without much measurement effort, standard load profiles could theoretically be used. Standard load profiles are representations of a load curve over a defined period of time. The German Association of Energy and Water Industries (BDEW) has created such profiles for the commercial and household sectors [9]. Reliable standard load profiles do not exist for industrial companies, as the load profiles exhibit very different patterns [10]. In order to nevertheless generate standard load profiles from a few measurements, Emde et al. developed a method for energy-intensive industry [10]. One of the advantages is a faster simulation of energy efficiency measures.

In the aforementioned project GRIDS it was also confirmed that the known standard load profiles should not be used to simulate the electrical energy demand of modern industrial enterprises without some adjustments. Contrary to the approach presented by Emde et al. [10] a bundled load profile is aggregated in the present paper through the synthesis of different standard load profiles of the BDEW [9].

2 Methodology

The procedure model is based on the use of standard load profiles. When using standard load profiles, general statements on the consumption behaviour of electrical energy can only be created for certain user groups [9]. Accordingly, it is necessary that the energy consumers grouped together are regarded as homogeneous.

Only in this way can an estimation of the energy demand of an entire area be realised in the necessary quality. However, project results have shown that such assumptions cannot be made [11]. For this reason, the procedure model for the improved estimation of bundled energy demand was developed. This model can form the basis for the demand planning of the electrical power supply network. The aim is to select the appropriate standard load profiles in such a way that the security of supply of the networks is maintained and supported. Oversizing, as is the case with the classic application of standard load profiles, is thus to be avoided. The basic procedure for network planning with the help of standard load profiles is shown in Figure 1.

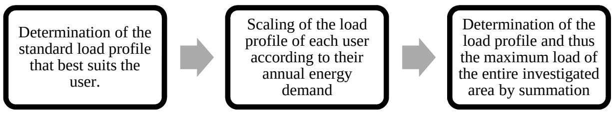

Figure 1: Procedure for determining the load profile and the maximum loads when standard load profiles are used.

With the help of stochastic methods, such as correlations and further significance analyses, connections of the individual actual and summarised load profiles to known standard load profiles are investigated [12].

The correlation coefficient (r) describes the correlation between two variables [13]. This coefficient has a range of values between -1 and 1 ($W_r = [-1; 1]$). The more it approaches 1, the more pronounced the correlation between the two variables, whereby a positive correlation coefficient ($r > 0$) indicates an equally positive correlation; if one variable increases, the other also increases. In general, a correlation coefficient greater than 0.5 ($|r| > 0{,}5$), is considered a high correlation [14]. Various methods can be used to calculate the correlation. Many variables examined and simulated in practice are normally distributed, so Pearson's method is usually used. However, in many cases it becomes apparent that a test of the type of distribution should be carried out before the method is selected [15]. The presence of a normal distribution can be checked by determining skewness and kurtosis. For normally distributed variables, both values should be close to 0. The following table shows a significant deviation of the standard load profiles from this criterion.

	G0	G1	G2	G3
Skew	6,14	11,28	-0,09	1,14
Kurtosis	-6,63	-3,06	-7,12	-8,38

Table 1: Skewness and kurtosis of the standard load profiles G0 to G3.

The standard load profiles (SLP) G0 to G3 describe the load profiles usually used as a basis, differentiated by trade type, whereby G0 describes general trades (formed from the mean value of the SLP G0 to G6), G1 describes trades with working hours from 8 a.m. to 6 p.m. on weekdays, G2 describes trades with a predominant energy demand in the evening hours and G3 describes passing trades [12].

Due to the distribution type of the data, the calculation of the correlation coefficients according to Spearman is used here. The test for standard normal distribution according to skewness and kurtosis has shown that the examined load profiles and standard load profiles are not normally distributed quantities. Therefore, no parametric methods can be applied to the examined variables and the use of Spearman correlation is preferable to Pearson correlation [16].

In the case of a mere mathematical analysis of the correlations, however, errors can occur in the application even with the correct choice of method; these are often described in the literature by so-called spurious correlations. These are mathematically correctly calculated correlations which, however, only allow insufficient conclusions to be drawn about the real dependency when viewed causally [17]. When investigating the correlation between standard load profiles and the actual load profile, a spurious correlation must be ruled out.

The load profiles were created on the basis of a representative sample. The sample results from surveys conducted as part of a research project. Real load profiles of medium-sized companies located in an industrial park in Saxony were collected and evaluated. Consequently, as it was expected there was a correlation between the examined real load profiles and the standard load profiles. After all, energy requirements of commercial customers were investigated and the standard load profiles are intended to reflect the requirements of this very customer group. Nevertheless, an additional graphical application of the maximum likelihood method takes place. The necessity of the additional graphical evaluation becomes clear in Figure 2.

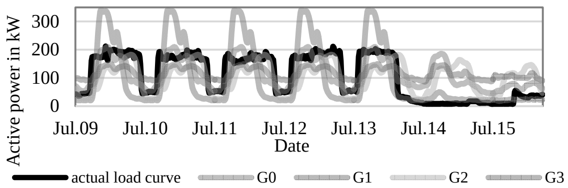

Figure 2: Comparison of the standard load profiles with an examined actual load profile within one week.

It becomes apparent that, in addition to purely mathematical methods, graphical methods should also be used to determine the best fit in order to evaluate the deviation of the actual power demand. This is because the use of correlations only examines the formal correlation of the different load profiles; it does not ensure the actual deviation of the (normalised) energy demand. This additional step enables an improvement of the estimation of energy demands and must be automated in the future by suitable procedures. The improvement is mainly achieved by separating the load profiles by time of day as well as by day of the week. Finally, an adapted synthetic load profile is composed in such a way that a best fit can be ensured according to visual progression (whereby correlation, energy quantity and peak load are equally represented) for day and night as well as for weekdays and weekends combined. After adjusted synthetic load profiles (load profiles for night - working day; day - working day; weekend) are formed for the prediction of the bundled energy demand and combined into a load profile, they are scaled on the basis of the expected total energy demand. The scaling in this case is done with the aim of equality of the expected annual energy demand and the integral of the modelled adjusted synthetic load profile.

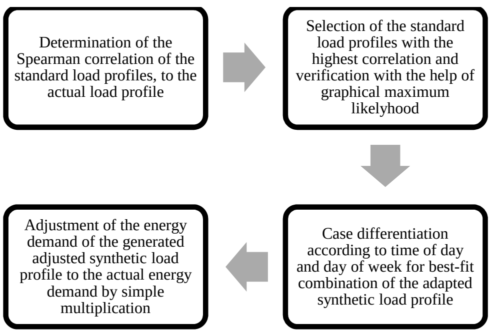

Figure 3: Procedure for determining the load profile and the maximum loads when using adapted synthetic load profiles.

The advantage of the method comes into play when a sufficiently large database is available due to continuous application. It is thus possible that only the industry, as well as the shift model and the expected annual energy demand and the expected maximum load are required as input parameters for later simulations. The initial implementation of the method presented here has shown that it is able to reproduce load profiles more accurately than with the help of the established standard load profiles. A possible extension of the method is the comparison of the results with reality and an adjustment of the used parameters.

3 Results

The procedure model leads to an improvement of the technical design of supply networks and thus supports the ecological and economic optimisation in planning and simulation. The formation of adapted combined synthetic load profiles enables an efficient estimation of the energy and power demand of user groups of electrical energy. The lack of a normal distribution of the energy demand leads to the use of Spearman correlations and thus to deviating results compared to the generally accepted use of Pearson correlations [18, 19]. However, it could be shown that a normal distribution cannot be spoken of for (standard) load profiles. In order to be able to apply the generally used Pearson method correctly, the (normalised) skewness and kurtosis would have to be within limits close to zero [20].

Nevertheless, the results showed a clear deviation of the parameters from a normal distribution. To illustrate the importance of schoosing the correct method for determining correlation, the results according to Pearson and Spearman for the sample studied are shown in the following table.

	Spearman	Pearson
G0	0.43	0.44
G1	0.51	0.29
G2	0.31	0.33
G3	0.37	0.66

Table 2: Comparison of the correlation coefficients according to Spearman and Pearson.

Choosing an unsuitable method is particularly critical, as this can lead to an incorrect selection of the standard load profiles to be used, as Table 2 shows. Nevertheless, this imprecision would not lead to unusable results through the use of graphical methods (maximum likelihood) and the division of the standard load profiles according to time periods. Yet, it has been shown that the quality of the result of the method for creating the adjusted synthetic load profiles depends significantly on the correct correlation analysis. In the example shown, it can be clearly seen that if the standard load profile G3 (highest correlation according to Pearson's method - compare Table 2) was chosen, a standard load profile would be chosen whose assumptions do not correspond to the actual mode of operation of the companies investigated (G3 applies to throughput businesses, but the local companies usually work in one-shift operation, at most in two-shift operation). Thus, the combination of the standard load profiles G0 to G3 forms a much better estimation of the actual conditions.

At this point it should be pointed out again that the application of the wrong correlation analysis with the right conclusions (choice of SLP G3) already leads to a considerable improvement compared to the conventional approach. According to the approach shown in Figure 1, standard load profile G1 would be used for the industrial park to predict the load profile with its peak load. However, Figure 2 shows that the actual peak load is only about 60 % of the peak load of G1. In current network planning, however, planning is done according to the standard load profiles (so that G1 is usually used as a basis for planning). Thus, a contribution to the optimisation of network planning can be made simply by applying a correlation analysis and deriving correct conclusions. The full potential of the method presented is only exploited by applying the correlation analysis according to Spearman to create adapted synthetic load profiles. Only the combination of the standard load profiles with the highest correlation (only these are shown in Table 1) provides the basis for an improved estimation of the bundled energy demand.

By combining these standard load profiles, not only the load but also the load profile can be predicted very accurately. Finally, overcapacities of the energy grid can be avoided by the presented method. In the example studied, the installed grid capacity can be reduced by 30 % during planning. Nevertheless, an installed transmission capacity of 125 % of the actual maximum load remains, so that no capacity bottlenecks are to be expected.

The method presented also succeeds very well in reproducing the actual load profile. There is an improvement in the average deviation of the predicted from the actual energy consumption of 50 %. This parameter is particularly important for the planning and simulation of possible flexibility measures and their control.

4 Application

Data acquisition is an indispensable phase in any simulation project, as described, for example, in the procedure model by Rabe et al. [21]. It strongly influences the quality of the simulation study. On the other hand, in most simulation projects there are temporal restrictions that prevent or at least limit the collection of primary data. Obtaining meaningful energy data is particularly problematic.

With the help of the procedure presented here, more accurate input data for simulation models can be generated more quickly. This may reduce the the time and quality of simulation projects in the area of energy efficiency and energy flexibility measures in commercial and industrial parks significantly and improves the quality and validity of planning measures. The presented method can be applied in the planning of the energy demand of industrial and commercial networks. It is no longer necessary to use the simple standard load profiles, which, from the current point of view, are not applicable for the detailed planning of the supply concept of industrial (and commercial) companies, neither with regards to the peak load nor the load profile. The consequences would usually be overcapacities in network planning and poorly adapted schedules for the supply of electrical energy. The presented method thus makes a decisive contribution to the simulation of energy flows in industrial parks.

Through the increasing adoption of renewable energy sources the energy supply system is being transformed from a central to a more decentralized approach. The grid supply is extended by decentralized energy sources such as photovoltaic and wind energy as well as new energy carriers such as hydrogen. Additionally, cogeneration plants may also supply electricity as well as heat and are a beneficial addon for renewable energies due to their independence from actual weather.

The share of companies that invest in on-premise energy supply systems is rising constantly mainly to cope with high energy prices and to decrease overall carbon emissions.

Furthermore, storage technologies are established to compensate the fluctuating character of renewable energies and smoothen energy load levels. This may be battery, heat, or even hydrogen storages. Especially green hydrogen is a promising energy carrier to raise self-supply level and store energy for future industrial applications. In combination with fuel cells and cogeneration plants, another decentral supply technology can be established to decarbonize industrial processes.

Thus, the energy supply structures are getting more complex in green- and brownfield planning but also operations. Still, some of these technologies are cost-intense and many companies do not provide the prerequesites to utilize these technologies in the most cost-efficient way. To address this shortcoming, one solution may be the shared usage of decentralized supply and storage technologies within industrial parks of several companies. According to individual load levels and overall energy demands a shared supply and storage infrastructure can be established which focuses on a high usage of energy from various sources. In this regard, Wei et al. provide an overview of previous publications that consider water electrolysis and the use of hydrogen as one component of the decarbonization of industrial parks [22]. In their publication, they also argue that in the future such hydrogen-based energy supply systems in industrial parks will represent the most economical form of decarbonization [22].

By using the load profiles one can estimate the energy surplus coming from the renewable energy sources. This electrical energy can be used in an electrolyzer to generate green hydrogen. Hydrogen can be used in a fuel cell to cogenerate heat and electrical energy in times of little renewable energy yield. The dimension of those cogeneration units and the combined storage technologies needs to be planned carefully, since the prices for those units are high. An oversized system will never reach its peak performance and leads to unnecessary high investment costs, whereas an undersized unit will not be able to power the grid. For factories, which are in most cases the most common users of industrial parks, there are several more possible applications of hydrogen. The most promising applications are high grade heat generation, the refuelling of fuel cell powered utility vehicles or as feedstock for certain chemical processes [23]. Fig. 4 illustrates a scenario which includes both, centralized and decentralizend energy supply and storages for electrical energy as well as hydrogen.

The scenario was modelled for the project H2Wind. Aim of the project is the development of a novel, compact water electrolyzer that operates efficiently and quasi-autonomously in harsh conditions at sea in order to provide green hydrogen for industrial applications, either by pipeline or other means of transport. A simulation can support the investigation of the economical and ecological sustainability of using off-shore green hydrogen in a medium sized industrial park. Users of this industrial park located near the shorelines of the North Sea include a factory for machine tools, a textile factory, a logistics facility and some offices.

The theoretical potentials of these operational scenarios require integrated planning approaches. Especially energetic data of all relevant energy consumers, in this case the companies itself, need to be transparent. Here, the introduced approach can be used to determine the load levels of all the companies and generate an overall load profile to scale the storages and the supply with hydrogen, the cogeneration plant and the physical energy supply infrastructure accordingly. Furthermore, common load profiles can be matched with typical data of solar gains to scale photovoltaic systems and estimate dimensions of battery storages as well.

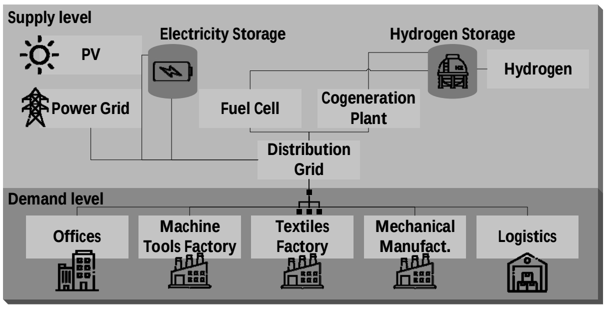

Figure 4: Application of energy supply and storage technologies.

5 Discussion

The procedure model is able to reliably generate energy demands based on the expected total annual energy demand and the assumed peak load. There is an enormous improvement compared to the conventional use of standard load profiles. A disadvantage of the method is the graphical control decision for the choice of the corresponding standard load profile within the individual time periods.

The quality of the control decision again depends on experience and subjective feeling. This procedure is optimised in the course of the further development of the methodology towards an automatic selection, which ensures an objective selection. It has been shown that this additional graphical control or selection of the composition of the adjusted synthetic load profiles limits the effects of a possibly incorrect choice of method for determining the correlations. The finding, which indicates that (standard) load profiles are not normally distributed quantities, shows that data series should always be examined with regard to their distribution type and, if necessary (if no distribution type can be determined), non-parametric methods must be used. It should also be noted that the need to predict energy demand as accurately as possible with the help of synthetic load profiles exists only for electrical energy. When resorting to gas (here in the form of green hydrogen), the pipeline and storage network provides a buffer. However, load profiles must be used again to scale resources for sector coupling (gas to power). This is the only way to efficiently deploy hydrogen fuel cells for system service provision as described by Jacobsen in 2022 [24].

In summary, the presented method contributes to a better simulation of energy demands of industrial companies and industrial and commercial associations. The method itself thus simulates the load profile of companies.

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References

[1] Sauer M. Das Recht der Vergabe von Strom- und Gas-Konzessionsverträgen im EnWG: Legitimität und Anwendung eines Wettbewerbsinstruments im Kontext des Unions- und deutschen Verfassungsrechts. 1st ed. Baden-Baden: Nomos, 2012.

[2] Guo Y, Tian J, Chen L. Managing energy infrastructure to decarbonize industrial parks in China. Nature communications, vol. 11, no. 1, p. 981, 2020,. doi: 10.1038/s41467-020-14805-z.

[3] Werth T. Netzberechnung mit Erzeugungsprofilen: Grundlagen, Berechnung, Anwendung. Wiesbaden: Springer Vieweg, 2016. [Online]. Available: https://ebookcentral.proquest.com/lib/gbv/detail.action?docID=4504392

[4] Jacobsen B, Stange M. Vorgehensmodell zur Simulation von gebündeltem Energiebedarf. In *Proceedings ASIM SST 2020: 25. ASIM Symposium Simulationstechnik : 14.10.-15.10.2020 : Online-Tagung*, 2020, pp. 295–301.

[5] Specification for the demonstration of carbon neutrality. PAS 2060:2014, The British Standards Institution, Apr. 2014.

[6] Geilhausen M, Bränzel J, Engelmann D, Schulze O. Energiemanagement: Für Fachkräfte, Beauftragte und Manager. Wiesbaden: Springer Vieweg, 2015. [Online]. Available: http://gbv.eblib.com/patron/FullRecord.aspx?p=3567708

[7] Wenzel S, Peter T. Simulation in Produktion und Logistik 201, Kassel. Kassel University Press GmbH, 2017. [Online]. Available: https://ebookcentral.proquest.com/lib/gbv/detail.action?docID=5091317

[8] G. Posselt G. Towards Energy Transparent Factories. 1st ed. s.l.: Springer-Verlag, 2016. [Online]. Available: http://ebooks.ciando.com/book/index.cfm/bok_id/1960675

[9] Vereinigung Deutscher Elektrizitätswerke - VDEW, “Umsetzung der Analytischen Lastprofilverfahren - Step-by-step,” Frankfurt am Main, 2000.

[10] [Emde A, Zimmermann F, Feil M, A. Sauer A. Erstellung und Validierung von Lastprofilen für die energieintensive Industrie, *ZWF*, vol. 113, no. 9, pp. 545–549, 2018, doi: 10.3139/104.111977.

[11] Stange M, Jacobsen B, Schubert S, Richter M, Wolf T, Meynerts L. Leitfaden Green Energy Parks, 2021.

[12] Bundesverband der Energie- und Wasserwirtschaft e.V. - BDEW, Standardlastprofile Strom.

[13] Held U. Tücken von Korrelationen: die Korrelationskoeffizienten von Pearson und Spearman. Swiss Medical Forum, vol. 10, no. 38, 652-653-653, 2010. [Online]. Available: https://www.zora.uzh.ch/id/eprint/46199/

[14] Cohen J. Statistical Power Analysis for the Behavioral Sciences. 2nd ed. Hoboken: Taylor and Francis, 2013. [Online]. Available: http://gbv.eblib.com/patron/FullRecord.aspx?p=1192162

[15] Sedlmeier P. Jenseits des Signifikanztest-Rituals: Ergänzungen und Alternativen. [Online]. https://www.dgps.de/fachgruppen/methoden/mpr-online/issue1/art3/article.html (accessed: Sep. 14 2020).

[16] Schober P, Boer C, Schwarte LA. Correlation Coefficients: Appropriate Use and Interpretation. Anesthesia and analgesia, vol. 126, no. 5, pp. 1763–1768, 2018. doi: 10.1213/ANE.0000000000002864.

[17] Schäfer A, T. Schöttker-Königer T. Statistik und quantitative Methoden für Gesundheitsfachberufe. 1st ed. Berlin: Springer, 2015. [Online]. Available: http://search.ebscohost.com/login.aspx?direct=true&scope=site&db=nlebk&AN=1078892

[18] Myers L, Sirois MJ. Spearman Correlation Coefficients, Differences between. in Encyclopedia of statistical sciences, Kotz S, Read CB, Balakrishnan N, Vidakovic B, Johnson NL, Eds., 2nd ed., [Hoboken, N.J.]: Wiley, 2010.

[19] de Winter JCF, Gosling SD, Potter J. Comparing the Pearson and Spearman correlation coefficients across distributions and sample sizes: A tutorial using simulations and empirical data. Psychological methods, vol. 21, no. 3, pp. 273–290, 2016. doi: 10.1037/met0000079

[20] Field A. Discovering statistics using SPSS: (and sex and drugs and rock 'n' roll). 3rd ed. Los Angeles, Calif.: Sage, 2011. [Online]. Available: http://www.uk.sagepub.com/field3e/main.htm

[21] Rabe M, Spiekermann S, Wenzel S. Verifikation und Validierung für die Simulation in Produktion und Logistik: Vorgehensmodelle und Techniken. Berlin, Heidelberg: Springer, 2008. [Online]. Available: http://nbn-resolving.de/urn:nbn:de:1111-2008093035

[22] Wei X *et al.*Roadmap to carbon emissions neutral industrial parks: Energy, economic and environmental analysis. Energy, vol. 238, p. 121732, 2022. doi: 10.1016/j.energy.2021.121732

[23] Imdahl C, Blume C, Blume S, Zellmer S, Gensicke M, Herrmann C. Potentials of Hydrogen Technologies for Sustainable Factory Systems. Procedia CIRP, vol. 98, pp. 583–588, 2021. doi: 10.1016/j.procir.2021.01.158

[24] Jacobsen B. Green flexibility Market – Platform development for system services using fuel cells. Procedia CIRP, vol. 105, pp. 158–163, 2022 doi: 10.1016/j.procir.2022.02.027