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A comparative analysis of the application of Fourth Industrial Revolution technologies in the energy sector: A case study of South Africa, Germany and China

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Abstract
Fourth Industrial Revolution (4IR) technologies have elevated the capabilities and possibilities of improvement and efficiency in the energy sector. This paper interrogates how energy companies in South Africa, Germany and China apply 4IR technologies. A total of 26 energy companies in those countries were surveyed. An analysis was carried out using the Cronbach Alpha, Kruskal-Wallis and Mann-Whitney tests. Survey results indicate that 85% of companies acknowledge good levels of participation in the 4IR, and were clear about which 4IR technologies are important, although few companies develop these themselves. Technologies enabling access to big, real-time data (BRTD) and BRTD analysis software, are valued the most in measured importance, efficiency, reliability and ability to be integrated across the energy system. The transfer of data using the Internet of things ranked highly as a 4IR technology, whereas artificial intelligence, robotics and machine-human integration (also referred to as machine-human interaction) are considered less important, efficient, and reliable. China rates 4IR technologies as more important than South Africa and Germany do. For South Africa to be competitive in the global energy sector it needs to engage with and embrace 4IR technologies to a greater extent.

Keywords: *4IR technologies; energy sector; Internet of things; big, real-time data; artificial intelligence; robotics; machine-human integration*

Highlights:
- *4IR technologies are applied within the energy sector.*
- *China rates 4IR technologies higher in importance than South Africa and Germany.*
- *The Internet of things is a highly ranked 4IR technology.*
- *South Africa needs to embrace 4IR technologies within the energy sector.*

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1. Introduction

The global technological landscape is flourishing and the Fourth Industrial Revolution (4IR) is providing a pathway to this change (Ng et al, 2020; Pfeiffe, 2017). A 'hyper-connected' world enabled by 5G and complex digital interfaces are connecting electricity grids with multiple digital devices and systems (Shapsough et al, 2020; ESI Africa, 2018; Chen et al, 2016) and improving their resilience. Figure 1 illustrates the advanced 4IR technologies leading innovation in the production and distribution of renewable energy. New build for energy production plants is more efficient and cost-effective, and 4IR technologies have created conditions under which these plants may be managed and maintained remotely, in real time, using devices such as unmanned aerial vehicles (UAVs), remotely operated underwater vehicles (ROUVs), autonomous underwater vehicles (AUVs), and drones to collect live data on environmental conditions. The ability to access and analyse big, real-time data (BRTD), which according to Sigwadi (2020) may be presented as data science, is applied in energy plant operations.

There has been a move towards expanding smart energy (Knieps, 2017). Smart devices, sensors and microgrids, connected to multiple mobile and other technical devices, enable consumers and producers to interact in real time to better manage their demand and supply of electricity, improving resource efficiency and sustainability (Ng et al, 2020; United States Department of Energy, 2015). A 'bi-directional flow of power' has emerged with consumers accessing electricity from the grid and supplying electricity to the grid (Lund et al, 2017).

Artificial intelligence (AI) presents a huge opportunity for developing smart solutions for energy production and distribution. Dong et al (2021: 2) define AI as 'the science of simulating a series of human intelligent behaviors, such as autonomous learning, decision making, and judgments'. AI is incorporated into the design, production and distribution of wind, solar, geothermal, hydro, ocean, bio, hydrogen, and hybrid energy (Jha et al, 2017). Voyant et al (2017) speak of machine learning (or AI) techniques that may be used to better forecast solar radiation, which allows solar plants to optimise productivity. Yunfeng and Mingming (2019) and Liao et al (2019) explain how AI (or virtual reality) is being used to reproduce various operational environments in the power system for power grid simulation teaching and training, safety and rescue training, and virtual maintenance testing of power system equipment, as well as addressing training-related challenges such as lack of personnel and the need for expensive testing equipment. Machines are being developed to carry out what Makala and Bakovic (2020, 2) refer to as 'deep learning' to 'help discern patterns and anomalies across very large datasets – both on the power demand and power supply sides – that otherwise would be nearly impossible to achieve.'

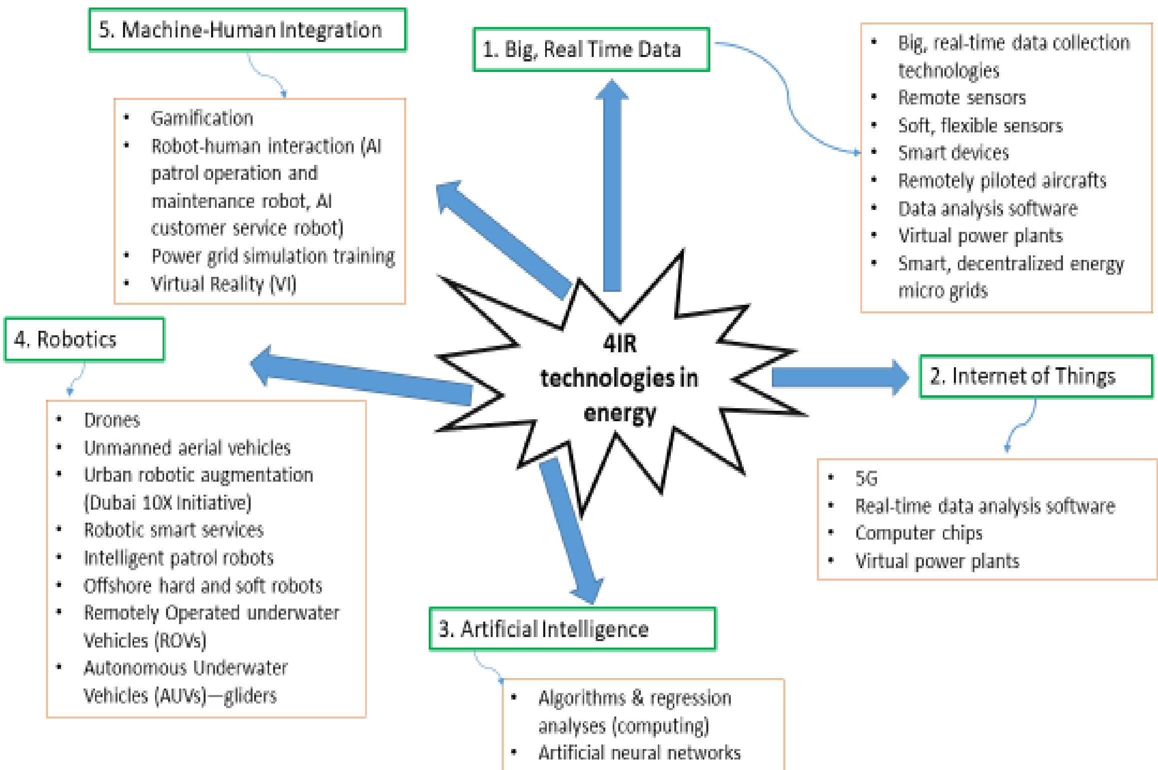

Figure 1: 4IR technologies in the energy sector

Robotics, according to Lyu and Liu (2021: 2) 'is at the intersection of computer science and engineering, involving design, construction, oper-ation, and use of robots, increasingly adopted in the energy sector to reduce set-up time and cost and improve quality and productivity'. Intelligent patrol robots are used to patrol outdoor power substations remotely, detecting defects in equipment and machinery in real time (Yunfeng and Mingming, 2019).

Machine-human integration (MHI), referred to by Yunfeng and Mingming (2019) as machine-human interaction, has developed from simple switches that used analogue systems to using computer systems to collect and analyse data at power terminals to dispatch this power within the grid, and to the use of voice to promote knowledge learning and transmission of data. Today, fifth generation MHI technology facilitates the friendly interaction between users and various systems with information tasks being exchanged between humans and various systems, such as computers and mechanical systems (Yunfeng and Mingming, 2019). Here, multi-sensor fusion technology is used as the interface for more intelligent interaction between staff and robots, initiated by robots themselves. The fifth generation of MHI, although still in the early stages of implementation, includes robot-human interaction, such as the AI power supply service robot, to integrate the 'basic abilities of speech recognition, dialogue management, real-time communication, image recognition, process automation and professional knowledge aggregation to 'understand customer demands, understand grid indicators, control power system business processes, issue command orders, transfer service information and remind abnormal behaviour' (Liu et al 2018 and Yin et al 2015, as cited by Yunfeng and Mingming, 2019: 3). MHI in energy may also be applied to gamification. Here, energy users interact with the energy system, through games such as Energy battle, that encourage households to take cogniscence of their behaviour towards energy consumption and in turn change such behaviour to reduce their energy usage and associated costs as well as their carbon footprint (AlSkaif et al, 2018).

Germany, China, Australia, the Netherlands and Japan have implemented systemic changes, choosing to decentralise energy, using computer chips installed in individual households allowing these households to control their energy grid and distribution via the internet (Burger et al, 2020; Viétor et al, 2015; Kafle et al, 2016). Nigeria is researching how to integrate AI into the regression analyses of solar energy estimation studies and to apply artificial neural networks to develop time-series data (Ozoegwu, 2018). India has identified the use of remotely piloted aircraft-based infrared imaging for monitoring and analysing photovoltaic energy systems in less accessible locations (Rahaman et al, 2020). The German Energiewende policy is driving the expansion of renewable and decentralised energy systems (Kuittinen and Velte, 2018; German Federal Ministry of Economic Affairs and Energy, 2019). The co-ownership of German energy production facilities, enabled by a decentralised energy sector and rising demand-side management of energy resources by consumers, has promoted the development and use of renewable energy (Roth et al, 2018). China continues to drive Renewable Energy Technologies particularly in industrial regions, such as Jiangsu Province, facing bigger climate change challenges (Lin and Zhu, 2019). Through nationwide policy initiatives such as the Made in China 2025 strategy, the Chinese government is driving Renewable Energy Technologies through investments in 'smart manufacturing' (Wübbeke et al, 2016, 15). China is using virtual power plants that combine gas turbines, renewable energy units and flexible loads using advanced technologies and software (Liu et al, 2018).

Globally, there has been a shift towards using new technologies across most sectors. The energy sector is no different. Fourth Industrial Revolution technology in South Africa likewise offers opportunities for improving the production and distribution of renewables, whilst at the same time enabling the achievement of the United Nations Sustainable Development Goal 7 – referring to expanding access to 'modern' and 'sustainable' forms of energy (United Nations, 2020). The focus of research in energy over the past decade has predominantly been on expanding the capacity of the South African electricity public utility, Eskom, and not private sector partnerships. The result has been increased power failures and load-shedding (Joffe, 2012). The United States Energy Information Administration (cited by Urban, 2018) has calculated the economic loss of income in South Africa due to the energy crisis to be between USD 253 and USD 282 million. A centralised and highly monopolised energy industry, driven by Eskom, has concentrated risks and challenges incurred relating to energy production and distribution, especially for renewables. South Africa, as an industrial powerhouse in Africa, depends on energy efficiency for economic development and on making energy more sustainable in terms of being efficient, more reliable and integrated across the system with minimal detriment to the natural environment. What is not known is the extent to which the energy sector in the country has leveraged these 4IR technologies and whether technologies applied are improving levels of efficiency, reliability and sustainability in the South African context.

In South Africa, industry leaders have studied the wider impacts of the 4IR on employment and society at large (O'Reilly et al, 2018; Aspen Institute, 2019). Central to this research was achieving a clearer understanding of whether countries are ready for the 4IR and what its socio-economic impact will be on society as we know it (Deloitte Insights, 2018; World Economic Forum, 2017). In addition to the effects of 4IR on the production and distribution of goods, research includes how curricula, as well as teaching and learning, need to change to incorporate the skills and knowledge needs of industry within the 4IR (Penprase, 2018; Stewart and Stanford, 2017; Chinese University of Hong Kong, 2020). To reiterate, this review does not focus on the education sector but on manufacturing in the energy industry. In addition to academic research, there have also been a number of studies conducted by institutions, such as the World Bank (2019), on how to harness the digital revolution to eradicate poverty in Africa. The argument presented is that digital technologies 'offer a chance to unlock new pathways for rapid economic growth, innovation, job creation, and access to services in Africa' (World Bank, 2019, 81).

A Scopus search for the years 2019-2021 yielded interesting results. A search on '4IR+ South+ Africa' brought up a total of 58 publications, but none referred to 4IR and the energy sector. A search on '4IR+technologies+South+Africa' presented 33 publications. These referred to the impact of 4IR on certain sectors including education (Pretorius and Kotze, 2021) and the future of the workplace (Scopus, 2021); O'Reilly et al, 2018; Aspen Institute, 2019). A refined search on '4IR+energy+South+ Africa yielded zero results. By searching for 'renewable+energy+technology', a total of 220 publications, from the past three years, were displayed. At a quick glance, these publications are centred on developments in particular types of renewable energy such as tidal (Sewnarain et al., 2020), solar (Obiora et al., 2020) and wind (Neshat et al., 2021); the creation of hybrid energy systems; access to energy (Monyei and Akpeji, 2020); decentralisation of the energy system in the country and using individual technologies such as solarvoltaics in specific sectors such as agriculture (Obiora et al., 2020). This Scopus search, then, suggests that there is little research on using a range of 4IR technologies across the energy sector in South Africa.

As the global energy sector steers its way through 4IR, it is critical to examine how renewable energy companies apply 4IR technologies. Research behind this paper examined this relationship by exploring the applicability of 4IR technologies in the energy sector in Germany, China and South Africa. It investigated what renewable energy companies understand by 4IR, and the contribution that the application of such technologies make towards their companies becoming more efficient, reliable, and integrated.

2. Methodology

A quantitative research design was applied, surveying 26 German, Chinese and South African energy companies, online. The analysis was carried out through the Statistical Package for the Social Sciences, using the Cronbach Alpha test, frequencies and descriptives, and the Kruskal-Wallis test. The data collected was all validated. It was Cronbach Alpha tested for internal consistency – in other words, whether the variables (different 4IR technologies) are all measuring the same underlying construct identified in each question, these being, the importance of these technologies to the global economic sector (GES), the importance of using 4IR technologies within individual companies, and the levels of efficiency, reliablility and integration of 4IR technologies within companies. An ordinal, Likert scale was used to test respondents' perceptions of the different sections – with 1 being the most important and 7 the least important. A descriptive statistical analysis was the first step in the data analysis process. The nature of the variables used in the survey was explored through an assessment of the response frequencies, percentages and means. This provided details on how respondents perceived different 4IR technologies and what the average, overall view was concerning these technologies. A clear set of descriptors of 4IR technology was used. The 4IR descriptors were: the interactions between human and machines (MHI) to improve productivity in industry; creating technology to connect globally; developing and using AI in industry; developing other, new technologies to improve efficiencies; all of these; and none of these. Respondents ticked the appropriate descriptor box based on the one which was best aligned with their understanding of 4IR. The Kruskal-Wallis test was used to test for country-specific similarities and differences in the measured importance of using 4IR technologies within the GES and companies themselves. The test was based on the country in which each company was located.

2.1 Sampling techniques

Using purposive sampling, of the 26 companies surveyed and compared, nine were Chinese (five of them based in South Africa and the other four in China), eight German (all based in Germany), and the remaining nine South African, situated across the country. The German and Chinese companies were selected based on their leading role in using 4IR technologies and their prioritisation of expanding digital renewable energy solutions in their countries. South Africa was chosen because of the gap in the literature on whether and how 4IR technologies are being applied across the energy sector and the impact of these technologies on enhancing efficiency in the energy system.

Germany has been a 'highly industrialised, pioneer of Industry 4.0' (Beier et al., 2017, 227). Industry 4.0 has affirmed its commitment, at all levels of society, business, unions and government, toward promoting digitisation as a socio-economic growth discourse that is driven nationally. Its strong participatory and cooperative links with business, civil society and unions, a defining feature of the German industrial model, make it very different from most other leading and emerging economies such as the United States and China (Schroeder, 2016). Germany was selected as a research subject for several reasons. There are ideological, policy-based, similarities between the participatory nature of Industry 4.0 and the social compact envisaged for South Africa in its National Development Plan (Presidency of South Africa, 2012); historical ties exist (South African-German Energy Partnership Secretariat, 2018); and interest has grown in the way the German energy sector is constituted – highly decentralised, driven by local municipalities, displaying a mix of private and public sustainable energy provision (Viétor et al., 2015; Beerman and Tews, 2017; Burger et al., 2020; South African Local Government Association, 2018; all priorities highlighted in the 2019 Integrated Resource Plan (South African Department of Mineral Resources and Energy, 2019). Local firms and leaders are driving renewable energy developments through 'regional spillovers' (Horbach et al., 2018: 404).

The selection of China in this study was also carefully considered. The Made in China 2025 strategy (Wübbeke et al, 2016) exemplifies China's remarkable strides in becoming a leader of the 4IR in sectors including new and renewable energy, with expanded efforts to develop 'intelligent manufacturing' (Institute for Security & Development Policy, 2018, 1). Already China is a leading, global manufacturer, exporter and installer of renewable, clean energy technologies, with plans to produce 80% of these technologies in China by 2025 (Wübbeke et al, 2016). There are valuable lessons to be learnt from China. Bilateral relations between South Africa and China are expanding through developments such as coal-fired energy plants in the Waterberg (Limpopo Economic Development Agency, 2019). Such relations may provide future spill-overs for renewable energy relations.

2.2 Data collection methods

The next part of the data collection process was the online sourcing of company names, again using the Google search engine to find company websites. Environmental conditions brought about by the COVID-19 global pandemic meant that the most efficient way to compile a list of companies and their details was via the internet, telephone calls to these companies, and word of mouth referrals. There were challenges experienced in communicating with the companies in Germany and China including communication challenges because of language differences. Access-related challenges emerged with these countries being identified as COVID-19 hotspots, resulting in an extensive economic shutdown. These circumstances all contributed to delays in the collection of survey data. As part of addressing these challenges, the offices of both the German and Chinese High Commissions in Johannesburg were contacted for assistance in providing the names of German and Chinese companies and for facilitating participation in the survey. Once translated into Chinese and German, the survey was sent to 56 energy companies, of which 26 responded.

3. Results and discussion

The findings are based on an overall positive submission rate of 47%, with 26 out of 55 companies responding positively to the survey. Again, the main reason for the sample size was the onset of the Covid-19 pandemic and the resultant poor response rate. Despite the smaller sample size, the data was considered reliable and statistically significant findings did emerge.

The reliability of the data was tested using the Cronbach alpha coefficient for each construct (Table 1), of which all are above the recommended value of 0.7 (Pallant, 2007), indicating the reliability of the data constructs.

Table 1: Cronbach's alpha values of the data constructs (importance, efficiency, reliability, and integration).

Constructs	*Cronbach's alpha coefficient*
The importance of 4IR technologies to the GES	0.73
The importance of using 4IR technologies for companies	0.80
The efficiency of 4IR technologies within companies	0.70
The reliability of 4IR technologies within companies	0.78
The integration of 4IR technologies within companies	0.80

3.1 Descriptive statistical analysis

Almost 65% of all respondents described the 4IR to be a combination of the above survey descriptors (all of these). No respondent ticked 'none,' implying the legitimacy of descriptors. Participants were then asked to indicate the level of importance of 4IR technologies, collectively, for the GES. The data was coded using a tick-box rating. Respondent percentages were used to break down the levels of importance of 4IR technologies in the GES (Figure 2). The degrees of importance varied, yet all respondents agreed that 4IR technologies were important. 73% ticked very important, 23% ticked important and only 4% selected somewhat important. There were no respondents who believed that 4IR technologies were not important, indicating the high value placed on the importance of technology in the GES.

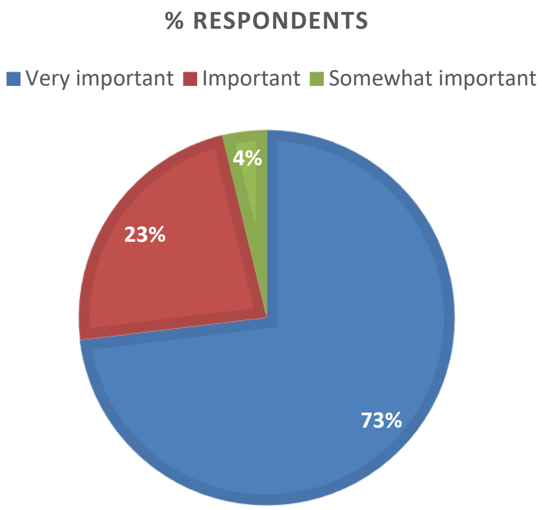

Figure 2: The importance of Fourth Industrial Revolution technologies to the global energy sector.

Technology categories were broken down into seven variables (Table 3). Three of the seven variables were tied to data access and usage. The remaining four comprised AI, ROB, MHI and the IoT. Participants were requested to rank each technology variable on a Likert scale of 1-7, with 1 being the most and 7 the least important to the GES. The results showed that, instead of ranking technologies, respondents chose to rate each one. As such, the analysis of the ranking questions drew on calculated means and standard deviations. In Table 2, mean ranks all fell below 4, implying that, using the 1–7 ranking scale, all described technologies were considered important to the GES. RTD was ranked as most important to the GES. The survey results pointed to fundamental influencers of this result as being the development of drones and UAVs, rapid advancements of faster and more reliable mobile networks, and the creation of huge data storage facilities in the cloud. The importance of ROB and MHI was considered far less important, with means of 3.96 and 3.65, respectively. Further research needs to establish why this may be the case.

There were two, key high-level conclusions linked to the global energy sector. The first was consistency in how respondents interpreted 4IR, with all describing it as one or a combination of interactions between machines and humans to improve productivity in industry; creating technology to connect globally; developing and using AI in the industry; developing other, new technologies to improve efficiencies. The global importance of 4IR technologies was clearly articulated. Secondly, leading in importance were the technologies providing access to real-time data (RTD), possibly influenced by the expansive use of drones, AUVs and ROVs in the sector. ROB and MHI fared the least in their importance to the GES. Interviews with experts in the sector will be important for determining why this may be the case.

The survey then referred to individual companies and their involvement with 4IR technologies. Respondents rated their company's involvement in the 4IR, in totality (Figure 3). Interestingly, most companies (85%) were confident about such participation, suggesting that the majority felt connected to the 4IR. 8% were unsure, whilst 8% believed that they were not participating at all in 4IR. If 85% of companies felt that they were a part of the 4IR, what were the reasons provided for the remaining companies that considered themselves to not be part of the 4IR? Data collected showed that the reasons were not that these companies had not heard of 4IR technologies but, rather, that the technologies were too expensive.

Table 2: Ranking the importance of each Fourth Industrial Revolution technology in the global energy sector

Importance to the GES of:	*Big data*	*Real-time data*	*Big real-time data analysis*	*Artificial intelligence*	*Robotics*	*Machine-human integration*	*Internet of things*
Mean rank	2.50	2.00	2.12	2.81	3.96	3.65	2.42
Std deviation	1.273	1.575	1.306	1.575	2.236	1.896	1.501

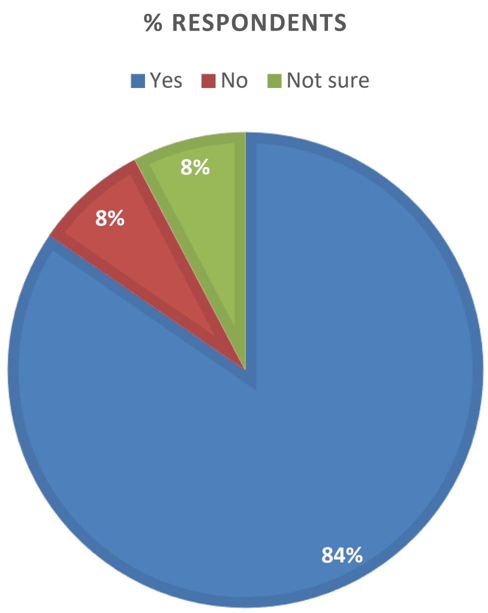

Figure 3: Company participation in the Fourth Industrial Revolution.

Once the respondents had rated their company's involvement in 4IR, they went on to describe their company's usage of these technologies. Descriptors ranged from no use of 4IR technologies, partial use, good use, very good use, and pioneer or leader of 4IR technologies development. Half (50%) of the respondents described their company usage as 'very good' or 'good,' whilst a third were more modest, with a rating of 'fair or partial.' Only one company believed they were a 'pioneer' or 'leader' in the development of 4IR technologies, despite their country of origin. The pioneer identified was a South African energy company.

Respondents were asked to name specific 4IR technologies they used. Some referred to distinct names. Others were non-specific, broadly categorising the technologies into whether they could best be described as tools enabling the collection of BRTD, the analysis of BRTD, the IoT, AI, ROB and MHI. All responses, specific and non-specific, were then clustered according to these category descriptives. Specific technologies referred to included: remote-controlled drones, uncrewed aerial vehicle (UAV) inspection technology, smart thermal and infrared sensors, microcontrollers (MCUs), digital signal controllers (DSCs) and advanced computer chip technology. Drones for thermal capturing use special, thermal and infrared sensors to capture invisible temperature and other climate data. UAVs also use drones equipped with infrared and thermal sensors to inspect energy infrastructure and capture various geographical information. The latter comprises relief data of land and climatic conditions such as temperature, wind speed, rainfall, etc. The data are then used to create 3D models and maps that provide important information for new, energy production site planning and current site management. It is accepted that technologies such as UAVs and robots are not new, but,the way in which they are being used is different and they offer a greater range of capabilities than general purpose technologies. UAVs and robots have been repurposed to collect large amounts of RTD that are transferred rapidly using 5G networks, to mobile devices and sophisticated computers that use complex algorithms to analyse the data in ways that are more accurate and therefore reliable.

The IoT is about connecting and integrating multiple smart devices and users across the globe through the internet. Examples of IoT identified by the survey respondents were 5^{th} generation mobile networking technology (5G) to transfer bigger quantities of data to a range of smart, digital devices (mobile phones, smart meters, smart grids, virtual power plants and smart, remote environmental sensors). It must be noted that access to 5G is still limited, particularly in rural areas of South Africa, and this presents an imbalance in terms of who benefits from 4IR technologies such as the IoT (facilitated by 5G). That said, Jordaan et al. (2019: 12) indicate that, although 5G 'applications pose a series of challenges including practical implementation, cost of implementation, and stakeholder and citizen commitment among others, the benefits that smart cities offer for the South African context, like smart resource management, energy efficiency, long term cost saving, improved services, etc. will definitely out-weigh the challenges.'

Devices such as smart meters transmit data between consumers and suppliers in real time. Consumers themselves can measure their consumption of energy in real time. Energy suppliers can also use smart meters to monitor energy consumption patterns, adjust supply accordingly and subsequently draw an energy billing system that is more accurate and efficient. Smart sensors that are connected through the IoT are used to collect operational data relating to a particular energy plant to monitor operations and where necessary carry out maintenance remotely.

BRTD analysis incorporates implementing intelligent information control and management systems, including grid management systems, remote monitoring and control systems, building information management systems, supervisory control and data acquisition systems, intelligent monitoring and controlling photovoltaic systems, and other advanced software tools to analyse large quantities of data as it comes in live time. Such tools are used for managing and supervising process operations remotely and in real time. Detailed images of energy site infrastructure are assessed when addressing maintenance-related matters for the plant.

AI is associated with respondent references to using smart machines (that enable clean energy solutions), algorithms and algorithmic trading systems (where computers conduct complicated, online, electricity trading activities, at much faster speeds, based on live energy market data and without human intervention) and, of course, virtual power plants. Virtual power plants are used to relieve the electricity load on the grid by enabling the distribution of excess power generated during off-peak load times to individuals during periods of high demand. Excess electricity may then be traded, algorithmically, on the energy exchange system. Five of the 22 referenced technologies referred to the use of AI, one to algorithmic trading and two to running plants virtually.

ROB is referred to twice without listing any technology names. South African firms surveyed are not using ROB in their operations. The two firms that are using ROB are from China and Germany. MHI-augmented reality using MHI that combines machine and human intelligence, was only mentioned by one respondent. Again, no technology names were provided. Like ROB, technologies enabling MHI are used even less.

A glance at the number of times certain technologies and technology groupings were named suggest a clear disparity between using technologies presented in categories one to four, focusing on accessing, storing, transferring and analysing BRTD and the technologies that drew on AI, ROB and MHI. Most of companies use 4IR technologies to collect and access plant data remotely, using drones and the IoT, and then analyse them using various data management systems. MHI appeared as an uncharted territory in energy, with one German company reporting to be using it. Further investigation is needed. ROB are also minimally applied in China and Germany. None of the South African firms are using ROB in the production and distribution of energy. The 4IR technologies recognised by South African firms all related to the collection, access and analysis of big, real-time data. Algorithmic trading stands out as underutilised, and the development of virtual power plants poor, with only two German companies adopting this.

According to respondents, most of these used technologies originated in the United States, Europe (predominantly Germany) and China. Yet, the German and Chinese companies interviewed indicated that they were not involved in the production and development of these technologies. So, a question that remains is why this may be the case, and which types of companies are producing these technologies in Germany and China (for example, is this a function of company size?).

Table 3 shows how respondents rated the level of company usage for each category of non-specific technology, from 1 being the most and 7 the least used. Calculated frequencies show that half of all respondents felt that using technology facilitating access to BD was of high importance. And those enabling access to real-time, live data was valued even more – in fact, the most. Rating levels 1 and 2 taken together, for the same technologies, equated to 78% of total respondents. The IoT, as the enabler of data access, also showed high levels of importance with 62% of participants scoring this 1 or 2. The inverse is true for AI, MHI and ROB. ROB was viewed by firms as being the least important to use.

Calculated means in Table 4 display the ranking for each variable. Access to BRTD, with a lower mean of 2.50, is ranked the highest in terms of the importance of using these technologies in the surveyed companies. The use of ROB, with the highest mean of 4.73, is ranked the lowest for its importance in the companies, followed by using of MHI (mean = 4.50) and AI (mean = 3.69). This mirrors the global scenario described previously in the paper.

Table 3: Respondent ratings of the level of usage for each criterion (non-specific technology) in their company.

Variables	*Most important*	*2*	*3*	*4*	*5*	*6*	*Least important*
BD (%)	19.2	30.8	7.7	15.4	11.5	7.7	7.7
RTD (%)	38.5	38.5	0.0	3.8	7.7	0.0	11.5
BRTD analysis (%)	19.2	26.9	23.1	19.2	7.7	0.0	3.8
AI (%)	3.8	34.6	19.2	3.8	19.2	7.7	11.5
ROB (%)	15.4	3.8	15.4	7.7	3.8	23.1	30.8
MHI (%)	0.0	23.1	15.4	7.7	7.7	34.6	11.5
IOT (%)	23.1	38.5	15.4	0.0	3.8	7.7	11.5

Table 4: Importance of companies using Fourth Industrial Revolution technologies.

Using:	*Big data*	*Real-time data*	*Big real-time data analysis*	*Artificial intelligence*	*Robotics*	*Machine-human integration*	*Internet of things*
Mean	3.23	2.50	2.85	3.69	4.73	4.50	2.92
Std. deviation	1.92	2.00	1.49	1.87	2.25	1.86	2.04

Table 5: Ranking the efficiency levels of company 4IR technologies.

Efficiency of:	*Big real-time data*	*Big real-time data analysis*	*Artificial intelligence*	*Machine-human integration*	*Internet of things*
Mean	1.73	1.54	2.16	2.20	1.80
Std. deviation	0.667	0.582	0.624	0.645	0.577

Table 6: Respondent ratings of the level of reliability for each criterion (non-specific technology) in their company.

Reliability of:	*Big real-time data*	*Big real-time data analysis*	*Artificial intelligence*	*Machine-human integration*	*Internet of things*
Mean	1.65	1.42	2.16	2.16	1.88
Std. deviation	0.63	0.50	0.80	0.75	0.67

Table 7: Respondent ratings of the level of integration for each criterion (non-specific technology) in their company.

Integrating:	*Big real-time data*	*Big real-time data analysis*	*Artificial intelligence*	*Machine-human integration*	*Internet of things*
Mean	1.96	1.84	2.33	2.33	2.08
Std. deviation	0.45	0.47	0.64	0.56	0.58

After ranking the importance of using different 4IR technologies in their companies. respondents had to consider how efficient they believed the technologies to be (Table 5). Technologies that enabled the analysis of real-time data collected by companies were seen to be the most efficient (mean = 1.54) as this is about how firms can use live data. This can only happen if firms have the tools to collect BRTD (with data access awarded a mean of 1.73) and the IoT that connects both processes together (mean = 1.80).

The technology variables were ranked according to their reliability (Table 6). The rankings were similar to those representing efficiency. Technologies used for analysing real time data were again considered the best in terms of being reliable (mean = 1.42). With a mean of 1.65. technologies used to

The importance of using 4IR technologies within energy companies and their contribution to efficiency, reliability and integration were all similarly ranked and clear patterns emerged. Technologies enabling access to BRTD and the processing and analysis of such data were valued the most with respect to all contributing to perceived importance, levels of efficiency, reliability, and ability to be

access such data ranked second. AI and technologies integrating machine and human learning held the lowest rank, with a mean of 2.16 for both variables, with the vast majority of respondents rating their reliability as poor. All respondents commended the reliability of data analysis technologies.

The level of integration of each variable within the sampled companies is ranked in Table 7. The integration of data analysis technologies outranks other technologies, with a mean of 1.84. Levels of integration of technologies used for accessing data and connecting multiple devices through the internet (IoT) are ranked second and third. The least integrated of all technologies identified were those using AI and the combining of machine-human intelligence (mean = 2.33).

integrated across the energy system. Of course, any analysis of such data will first and foremost require the IoT to store data and enable its transmission to multiple mobile and other devices in real-time. As such, the importance of this IoT was ranked third. ROB was recognised as least important for use by companies. AI and MHI were seen to be profoundly less reliable, efficient and integrated within the sur-

surveyed firms. For the GES, the importance of these technologies was the most poorly ranked.

3.2 Country analysis

China rated the importance of 4IR technologies to the GES as being higher than South Africa and Germany, with a mean of 2.6 (Table 8). South Africa and Germany had similar mean values for this construct. China also rated the importance of using 4IR technologies in their companies higher than both Germany and South Africa,. The means for Germany and South Africa were, again, much higher (3.9 and 4.4), indicating that they ranked these technologies as less important within their companies. Variances in the mean for the other 4IR technologies variables were minimal, indicating minimal country-level differences.

The Kruskal-Wallis and Mann-Whitney tests were used to assess country-specific differences in the survey data collected. As shown in Table 9, the data analysis calculated a statistically significant difference in the respondents' perceptions for two constructs. The first was in response to their perceived importance of 4IR technologies to the global energy sector. The p-value of 0.002 for this construct was lower than the recognised p-value of 0.05 required for statistical significance.

Secondly, there was a statistically significant difference in the responses of China, Germany and South Africa towards the perceived importance of using 4IR technologies within companies, with p-value = 0.005. Variables measuring efficiency, reliability and integration between countries were not statistically significant as each of the p-values were larger than 0.05 and so are excluded from the analysis (Table 9).

The Mann-Whitney test was used for post-hoc testing. This test was used to identify in which pair

Table 8: Kruskal-Wallis Test.

		N	*Mean*	*Std. deviation*
Importance to GES	China	9	1.8	0.5
	Germany	9	3.1	0.9
	South Africa	8	3.4	0.8
	Total	26	2.8	1.0
Use	China	9	2.6	1.4
	Germany	9	3.9	0.9
	South Africa	8	4.4	1.0
	Total	26	3.6	1.3
Efficiency	China	9	1.8	0.3
	Germany	9	1.9	0.4
	South Africa	8	1.9	0.5
	Total	26	1.9	0.4
Reliability	China	9	1.8	0.6
	Germany	9	1.9	0.3
	South Africa	8	1.9	0.5
	Total	26	1.8	0.5
Integration	China	8	2.1	0.3
	Germany	9	2.2	0.3
	South Africa	8	2.1	0.6
	Total	25	2.1	0.4

Table 9: Statistical significance of country differences.

Mean descriptives	*Importance to GES*	*Use*	*Efficiency*	*Reliability*	*Integration*
Kruskal-Wallis H	12.13	10.71	0.08	0.03	0.39
Asymp. sig. (p-value)	0.002	0.005	0.960	0.986	0.823

Table 10: Mann-Whitney Test Statistics (China and Germany).

	Importance to GES	*Use*
Mann-Whitney U	11.50	11.50
Asymp. sig. (2-tailed) (p-value)	0.01	0.01

Table 11: Mann-Whitney Test Statistics (China and South Africa).

	Importance to GES	*Use*
Mann-Whitney U	3.00	7.50
Asymp. sig. (2-tailed) (p-value)	0.00	0.01

Table 12: Mann-Whitney Test Statistics (South Africa and Germany).

	Importance to GES	*Use*
Mann-Whitney U	29.50	21.50
Asymp. sig. (2-tailed) (p-value)	0.50	0.16

of countries the above differences lay. The p-values indicated in Tables 11 and 12 are lower than 0.05 for both the China/Germany pair (0.01) and the China-South Africa pair (0.00) for both descriptor constructs. There are significant differences between China on the one end and Germany and South Africa on the other (with a p-value of 0.50 in Table 12). In both cases, China has amplified the importance of 4IR technologies in energy globally and at the company level. The results of the Mann-Whitney test also point to significant differences between China, on the one end, and Germany and South Africa (Table 12) on the other. In both cases, China has amplified the importance of 4IR technologies in energy globally and within their companies. What remains uncertain, again, is why this is the case.

Variances in the variables measuring the efficiency, reliability and integration of 4IR technologies were minimal and of no statistical significance, and therefore excluded.

In summary, and despite China placing a higher value on the importance of 4IR technologies within Chinese energy firms, there was still a complete recognition of the importance of 4IR technologies by all of the surveyed companies. In fact, 85% of these companies believed themselves to be a part of the 4IR, although in the context of users and not pioneers of these technologies. When ranked according to how important it is to access and use 4IR technologies in energy, particularly for adding to the reliability, sustianability, and interconnectedness of the sector, access to BRTD dominated.

4. Limitations of the study

A key limitation impacting the study was the challenges experienced during the data collection stage. All data were collected during 2020, when the effects of the Covid-19 pandemic in China, Germany and South Africa peaked. Economic lockdowns further reduced the number of responses received, resulting in a smaller than expected sample size. Despite this, the surveys were conducted online and the data findings and analysis concluded are considered statistically reliable. The second occurrence worth considering was that respondents rated variables in some survey questions, rather than ranking them. This did not present a significant limitation and was compensated for by using other forms of ranking techniques: in this case, mean and standard deviation calculations.

5. Conclusions

Despite the smaller than ideal size of the sample surveyed, clear conclusions emerged from this resarch. There was a shared understanding of the meaning of the 4IR and its relationship with the energy sector. Whether viewed separately or together, these meanings included the interactions between human and machines to improve productivity in industry; creating technology to connect globally; developing and using AI in industry; and developing other, new technologies to improve efficiencies. Most energy companies (85%) believed themselves to be playing a recognisable role in the 4IR, although only one (a South African company) described itself as a leader in 4IR technologies development. Additional research should investigate which countries and which companies are involved in pioneering developments in 4IR energy technologies. Next, the analysis delivered conclusions about the measured importance of using these technologies, as well as the extent to which they are reliable, efficient, and integrated within the energy companies. Surveyed firms identified technologies providing access to and analysis of BRTD as being most important for usage in the wider, global energy sector as well as at local, company level. Energy production and distribution technologies of least importance were MHI technologies, followed by ROB. For levels of efficiency, reliability, and ability to be integrated across the energy system, technologies enabling access to BRTD and the processing and analysis of such data were, again, valued the most. The IoT was ranked the third most important 4IR technology as it enables the storage and transmission of data to multiple devices in real-time. AI and MHI were seen to be much less reliable, efficient and integrated within the surveyed firms.

These conclusions suggest the need for further research on why there are these clear distinctions between the importance and usefulness (in terms of efficiency, reliability and intergratedness) of 4IR technologies linked to BRTD access and data analysis, and that associated with AI, ROB and MHI. Furthermore, it remains to be investigated why Chinese companies place more value on the importance of 4IR technologies in energy, than those of Germany and South Africa.

We recommend that for South Africa to be competitive in the global energy sector it needs to engage with and embrace 4IR technologies to a greater extent. Before this point can be reached, however, there needs to be an understanding as to whether 4IR technologies are being applied in the South African energy sector and, if this is the case, how they are being applied. Research reflected in this paper has shown that South African companies value 4IR technologies as tools to facilitate and improve efficiency, reliability and integration within the energy production and distribution systems, and that a higher value is placed on access to and analysis of BRTD and the IoT. Other 4IR technologies are, however, according to the survey results, not being applied in the South African energy sector. This is despite the fact that literature has also shown that there is huge potential for AI, ROB and MHI to advance the energy sector and that there is much to learn from countries such as China and Germany, who are already using these technologies. Data collected showed that the reasons were not that these companies had not heard of 4IR technologies but, rather, that the technologies were either too expensive or linked to other conditions, or for reasons not given. These other reasons will be explored during the interview stage of this study. Moreover, although expansion in 5G technology and the IoT does imply huge upfront and implementation costs (particularly in rural areas where infrastructure is lacking), the opportunities that smart cities provide – improved efficiency, better resource management, improved service provision and long-term cost saving (Jordaan et al., 2019) – are hugely appealing and must be explored. The focus of research in energy in South Africa over the past decade has predominantly been on expanding the capacity of Eskom. Research needs to expand into how 4IR technologies may be leveraged at different parts of the production and distribution systems to boost efficiency, reliability and integration.

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Author roles

N. Bhagwan was responsible for conceptualising the study, as part of her broader PhD study, collecting, analysing and writing up the data, and was the main author of the publication. M. Evans provided key conceptual and editorial inputs into the redrafting of the publication until its completion.

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