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The Energy Industry in the Czech Republic: On the Way to the Internet of Things

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Abstract: This article describes and discusses research into the perspectives for deploying the IoT (Internet of Things) within the Czech energy industry. Our conclusions are based on empirical research performed among 50 energy-industry experts in 2016 and 2017. This was two-stage research in which we held interviews with these experts in order to select the set of the most acceptable IoT technologies for deployment in the energy industry, and then used the TOPSIS method to select the most suitable technologies among them for deployment in the Czech environment. For use in determining the most suitable technologies, we also defined—with the help of the mentioned experts—individual selection parameters and weightings for them, enabling us to apply the TOPSIS method to the selected set of technologies. Our result was the selection of the SIGFOX IoT technology.

Keywords: cyber risk; energy industry; industry 4.0; Internet of Things; standards; technologies

JEL Classification: D81; M21; Q47; L86

1. Introduction

Humans are consuming more energy every year, and utility companies are scrambling to meet the demand. When we think about the energy industry, we do not always think fast-paced innovation (Sládek and Maryska 2017). While we are making advancements in wind and solar, much of today's energy still relies on fossil fuels—a substance literally formed millions of years ago. The general model for energy has not changed very much in the last century either. Today, energy is generated in centralized locations, powered by a few major fuel sources, and distributed by the electrical grid for use in homes and businesses. This model has proven to be reliable and everyone has standardized it, making widespread innovation difficult (IoT 2017). The International Energy Agency expects global energy demand to increase by 37% by 2040, which would likely put a strain on energy supplies. Utility companies are finding solutions thanks to the Internet of Things (IoT). The IoT is making energy use more efficient, which should help relieve some of the pressure on energy resources (Meola 2016).

The Internet of Things (IoT) represents a new reality. The impact of this trend is described in more detail in (Saidu et al. 2015; Stevenson 2018). The insight derived from data collected from new Internet-connected devices can be used to develop new services, enhance productivity and efficiency, improve real-time decision making, solve critical problems, and create new and innovative experiences. However, as more devices connect, companies face increased fragmentation, interoperability, and security challenges. Smart meters have become the top IoT device among utility companies in the last several years. These devices attach to buildings and connect to a smart energy grid, which allows these companies to more effectively manage energy flow into buildings. For example, the number of hits related to the Internet of Things is 248 million (Industry 4.0 is 209 million; Industrial Internet of Things 157 million); when we compare it with the number of hits related to Google (11 billion) or Yahoo (2.2 billion) in 2017 we see that this new topic has a significant number of searches.

The Internet of Things can be described as an evolution of the Internet in a way that integrates not only mobile devices but also other objects like sensors attached to cars, home appliances, and different devices into one interconnected mesh (Perera et al. 2014). Smart things integrated in IoT context are able to perform three basic tasks (Miorandi et al. 2012):

- Communication: the ability to wirelessly communicate among themselves, and form ad hoc networks of interconnected objects;
- Identification with a digital name: relationships among things can be specified in the digital domain whenever physical interconnection cannot be established;
- Interaction with the local environment through sensing and actuation capabilities whenever present.

In general we can say that the Internet of things is a network of intelligent devices and objects that harness and share huge amounts of data. The IoT increases automation in homes, schools, stores, and many industries (Manogaran et al. 2018).

The Industrial Internet of Things (IIoT) is part of the same concept as the IoT. The application of the IoT to the manufacturing industry is called the IIoT (or Industrial Internet or Industry 4.0) (Stankovic 2014). The IIoT is revolutionizing manufacturing by enabling the acquisition and accessibility of far greater amounts of data, at far greater speeds, and far more efficiently than before (Kalál 2016).

One perspective is to think of the Industrial Internet as connecting machines and devices in industries and helps with predictive maintenance or help to reduce risky situation (Basl and Sasiadek 2017). The second perspective of the Internet of Things includes consumer-level devices such as heart monitoring fitness bands or smart home appliances (Manogaran et al. 2018). In the end we can say that Industrial Internet of Things and Industry 4.0 are similar activities that are using the Internet of Things as a basis. All of these terms are also closely connected with Cloud Computing, which means that an application (from IoT, IIoT, Industry 4.0) is running on a computer located remotely (Basl 2017).

The different variations on the IoT, i.e., the Industrial Internet of Things and Industry 4.0, can be specifically defined, but for the purposes of this article we will be viewing them as synonyms.

The vision of the future is of a smart world in which interconnected smart devices enable qualitatively new services. In this concept, the Industry of Things (IoT) plays a crucial role (Stankovic 2014). Most global companies (56%) are viewing the IoT as a strategic activity (Kalál 2016) where the motivation for implementation is an increase in productivity (24%), decreasing time to market (22.5%) and improving process automation (21.7%). The Vodafone IoT Barometer 2016 survey identified that 63% of businesses will have launched IoT projects in the next year and 76% of businesses say that IoT will be "critical" to their future success (Sládek and Maryska 2017; IoT 2016).

The importance of the IoT is confirmed by IDC, which expects that in 2020 the IoT in Central and Eastern Europe will be composed of 1.4 billion connected things (globally, 37 billion) and the market opportunity for IoT will be $24 billion (Sládek and Maryska 2017; Kalál 2016). However, the IoT approach could not be implemented and explored without linking to other technologies (Manogaran et al. 2018). Other emerging technologies are overlapping with IoT. Big Data technology could be used to handle the massive amounts of data that IoT sensors can produce (Treurniet et al. 2015). Machine learning and advanced analytics are needed to process and analyze IoT data in real time. Voice-based human–machine interface is the way users will interact with devices connected and integrated in the IoT world. Another aspect of using Big Data technology is ownership of the data (Mashhadi et al. 2014).

For many corporations, getting the best use out of the IoT is key to their further strategic development. Its importance is especially growing for fields that are key to how our society runs and functions. This includes the energy industry.

Although this paper is mainly devoted to the application of IoT in the energy industry, the IoT is general approach that can be applied almost in all industries and in our framework as well.

2. Problem Formulation

The use of the IoT within the energy industry is a very current topic, and it is being addressed by nearly every energy company worldwide. The problem that interests energy companies the most is the identification of those activities that should be supported through the IoT in the future. The next step will be to select appropriate technologies that are optimal from the standpoint of business deployment.

Within the rest of this article, we will primarily be answering this question: what technologies are potentially suitable for deployment within the Czech energy industry? Here we will be working from an analysis of the available sources on the individual technologies, which we will then compare using the TOPSIS method for multi-criteria optimization.

3. Methodology

The data used within this article come from guided interviews with experts from the energy industry in the Czech Republic in 2016/2017. A total of 50 experts took part in this research. Over 60 workshops with the participants were held; during them, a total of 124 opportunities in which the IoT can be sensibly utilized within the energy industry were identified.

Our process for asking questions and identifying opportunities was based on guided questioning, with the use of both open and closed questions (Řezanková 2010).

This then led to a list of 124 application opportunities that can potentially be implemented in the energy industry, and a further total of 13 different technologies and 23 selection criteria for them.

Our comparison of the individual IoT technologies was based on the principle of multi-criteria decision-making, which enables weighting and work with a large attribute set and above all is generally user-friendly, comprehensible, and acceptably mentally demanding in its processing and evaluation. Our method for obtaining our shortlist of technologies and their parameters and setting individual parameters' weights was the evaluation of guided interviews. These proved especially useful when we were determining our discrimination criteria, both for selecting the technologies to include in the group and for selecting their parameters.

Numerous methods are known in the area of multi-criteria decision-making (an overview and description can be found, e.g., in Evans (1984)); from among these we chose, as mentioned, the TOPSIS method for use in our analysis.

The TOPSIS Method

In the end we decided on the TOPSIS method (Jee and Kaang 2000) out of the various methods for multi-criteria optimization. TOPSIS is an abbreviation for "Technique for Order Preference by Similarity to Ideal Solution." The method chosen belongs to the group of tools that work with cardinal information—i.e., the weights of the individual selected criteria are known and identified—and to the tools that utilize the principle of minimizing the distance from an ideal solution. Its implementation dates back to 1981 (Hwang and Yoon 1981). In the scientific literature, we can find the use of this method for a variety of comparisons and evaluations that incorporate multiple criteria. Examples include its use for selecting appropriate materials (Jee and Kaang 2000) or comparing electrical energy generation methods (Sarkar 2014). It is also used for such things as comparing the EU countries from the standpoint of information society's evolution in 2005–2010 (Latuszynska 2014) and the penetration of ICT into the EU countries (Kuncová and Doucek 2013). As to the utilization of this method in economic applications, we can note, e.g., the evaluation of the effects of the financial crisis on selected economic indicators in 2002–2009 in selected countries of the EU and in Turkey (Mangir and Erdogan 2011).

The core idea of the whole TOPSIS method is the assumption that the best variant has the smallest distance from the ideal variant and the largest distance from the base variant, where the ideal variant has the best value for each criterion (this is generally a hypothetical variant) and the base variant, on the other hand, has the worst value for each criterion.

All of the formulas are derived under the assumption that all criteria are maximization criteria—i.e., a higher value is preferred over a lower one. Thus it is necessary to convert minimization criteria—where a lower indicator value is preferred over a higher one—into maximization criteria, e.g., by subtracting data from the highest possible value for the given criterion. This approach, although not always ideal for the TOPSIS method, is a possible one for the data we are using in this specific case in light of the data's character.

Then in the next step of implementing the TOPSIS method comes the data normalization itself, i.e., the conversion of all criteria to the same scale within the interval (0:1). In our case this may seem to be an unnecessary step, as the values are already within the given scale; however, this normalization is also what rids us of extreme values.

The normalized criteria matrix can thus be constructed based on the relationship

$$r_{ij} = \frac{y_{ij}}{\sqrt{\left(\sum_{i=1}^{p}(y_{ij})^2\right)}},\ i = 1,\ 2,\ \ldots,\ p,\ j = 1,\ 2,\ \ldots,\ k, \tag{1}$$

where

r_{ij}—indicates the normalized value for the i-th variant and the j-th criterion and
y_{ij}—the original criterion value for the i-th variant and the j-th criterion after conversion of the criteria into maximalization criteria.

In the next step, the weighted criteria matrix $\boldsymbol{W} = (w_{ij})$ needs to be constructed based on the relationship

$$w_{ij} = v_j \cdot r_{ij}, \tag{2}$$

where v_j indicates the weight for the criterion j. We then use the matrix $\boldsymbol{W}$ to determine the theoretical ideal (H) and base (D) variant, where $H_j = max_i\, w_{ij},\ j = 1,\ 2, \ldots,\ k$ (k gives the number of criteria) and $D_j = min_i\, w_{ij},\ j = 1,\ 2,\ \ldots,\ k$.

For each variant there follows a calculation of the distance from the ideal variant $\sqrt{\sum_{j=1}^{n}\left(w_{ij} - H_j\right)^2}$ and from the base variant $d_i^- = \sqrt{\sum_{j=1}^{n}\left(w_{ij} - D_j\right)^2}$. Then in the last step we calculate the so-called relative indicator of the distance from the base variant $c_i = \frac{d_i^-}{d_i^+ + d_i^-}$.

The variants are then organized by descending value of c_i.

4. Results

The first group of results that we obtained when processing the data from the guided interviews is data that first restrict, using discrimination criteria, the technologies (Section 4.1.1—"Key Communication Technologies") and thus also the parameters used for multi-criteria optimization.

4.1. Starting Points for the Optimization of Technology Deployment

4.1.1. Key Communication Technologies

There currently exist a large number of communication technologies that can be used within the IoT. Based on research into the field literature and the state of the market in the Czech Republic, we identified 13 technologies that can be utilized within the IoT and described these using a set of defined criteria. The key technologies that we consider worthy of mention within this article include:

- GSM dial-up, digital dial-up connections, first-generation GSM digital mobile networks,
- WiFi, the 802.11 family of standards, local wireless networks,
- ZigBee, a low-power personal area network with a limited range,
- Ingenu, a proprietary technology for wireless communication,
- SIGFOX, a low-power narrow-band technology for wireless communication,
- LoRa, a low-power narrow-band technology for wireless communication,
- Telensa, a low-power narrow-band technology for wireless communication, and
- Weightless, a low-power narrow-band technology for wireless communication.

4.1.2. Key Parameters for Communication Technologies

Just as many communication technologies exist that can be used within the IoT, there are also many parameters enabling the characterization and description of these technologies (D'Angelo et al. 2018). Within our research and solution, we worked from 23 parameters. In our view, the following are among the primary key attributes/questions we can use to characterize communication technologies for our assessment:

- Coverage of Czech territory (rating scale—qualitative; nationwide coverage, local coverage, no coverage, with possible further specification)—this specifies how the given technology is limited within the individual areas of the Czech Republic. This parameter is key in the energy industry, for example when deploying IoT technologies to monitor high-tension distribution systems: these lead throughout the whole republic, and often entirely outside populated areas (forests, mountainous regions, etc.)
- The frequency band (the range of evaluations—qualitative; licensed, ISM—free; potentially other specifications) helps to ensure a clear connection. In general it can be hard to find a free frequency band at present in the Czech Republic. The choice of a suitable frequency band has a key influence on connection quality.
- Is long-term availability expected for the network (rating scale—qualitative; No, Yes, Unevaluated)? This parameter is connected with the provider's financial strength and long-term development plans.
- Is there an SLA guaranteeing message delivery (rating scale—qualitative, binary; No, Yes)?—an SLA is key for ensuring the reliability and completeness of messages delivered from IoT devices to the end user of their data (Sha et al. 2018).
- The power consumption of the modem, its battery life (rating scale—qualitative; days, months, months/year, years, over 10 years) is among the most important parameters. This influences not only further parameters such as the range and downlink/uplink speeds, but also, and especially, devices' financial angle. The higher the consumption and thus the more frequently the battery must be replaced, the higher the replacement costs and thus the device's operating cost. Another angle to look at here is an IoT device's being "single-shot," if its battery is an integral part of the device and cannot be replaced during operational servicing. In that case, any kind of battery discharge ends in the physical replacement of the whole device (Behera and Mohapatra 2018).
- Range (kilometers) country/rural (rating scale—quantitative; kilometers or meters)—this is closely linked to the number of devices that have to be installed. The higher the device's range, the larger the area it covers, and thus the fewer devices need to be used (Escriva et al. 2018).
- The uplink capacity (rating scale—quantitative; line throughput in kbps, potentially including a specification of the transmission mode)—this affects how much information can be uploaded onto the device per unit of time.

- The downlink capacity (rating scale—quantitative; line throughput in kbps, potentially with a specification of the transmission mode)—this is the opposite of uplink. This factor is substantially more important, as data are primarily downloaded from IoT devices, not uploaded to them.
- Latency during normal operations: 7 s (sensor into internal DB) rating scale—0; single-digit seconds—1; within 100 ms—4 (due to the significant difference between seconds and milliseconds). Differing latencies are required for different devices and different ways of using IoT devices. Devices e.g., for monitoring the operations of an electricity-generating turbine will demand minimal latency relative to devices that monitor a building entry (Sharma et al. 2018).
- Device jammability (rating scale—qualitative; easy, easy using a jammer, significant jamming resistance, extreme jamming resistance) is closely tied to the frequency band that can naturally jam the device. It is important that it be hard to jam the device; a sensor in a car monitoring its motion is a good example here. If you jam it, then the deployment of such a sensor loses all added value.
- Network jammability (rating scale—qualitative; easy, easy using a jammer, enhanced multi-provider resistance, significant jamming resistance, extremely jamming resistant) is like the last parameter, but applied to the whole IoT network for the given technology.
- Data integrity protection (rating scale—qualitative; No, Yes, Yes—at the IP-protocol level, Yes—at the physical-layer level)—this influences the trustworthiness and completeness of the data provided. Each provider strives to ensure full integrity, such that it is impossible to disrupt "their" data's integrity in any way during its transfer (Sharma et al. 2018)
- Encryption (rating scale—qualitative; No, Yes incl. name of algorithm). Encryption is a very specific parameter; its importance is connected to a given IoT technology's specific application. Only light encryption will be needed e.g., when monitoring access doors, but encryption will be of critical importance e.g., when monitoring calls on BTS mobile calling stations (Sha et al. 2018).
- Number of end-user devices per base station (rating scale—qualitative; less than 10, 32, dozens, hundreds, from hundreds to thousands, up to 2500, single thousands, 5000 max, 6000 with average communication of one sensor once per hour, tens of thousands, hundreds of thousands) influences the device's accessibility for end users. The higher the possible number of end-user devices, the more beneficial the given technology is for its users, since this reduces the risk of the base station being overloaded by a large number of IoT sensors (Sharma et al. 2018).

Besides describing every technology via the parameters defined here, we also expanded on this with a description using a modified SWOT analysis. The heart of this modification was a division into internal and external factors, with the internal factors having strengths and weaknesses, and the external factors having opportunities and threats—Table 1.

Table 1. SWOT analysis of technologies.

Factors	Strengths	Weaknesses
Internal	Choice of multiple mobile operators Network coverage Network stability Transmission capacity	Modem price Billing based on actual data transferred
External	Opportunities Deployment speed High transmission capacity Stable technology	Threats Transmission security Bandwidth guarantee

4.2. Key Communication Technologies and Key Communication Technology Parameters

Due to the large number of communication technologies that can be used, it is appropriate to narrow them down for the purposes of this article. Variants will be eliminated through the choice of one or more discrimination criteria. Variants not meeting these criteria will be eliminated from the assessment. Two criteria will be chosen here with a view to the Internet of Things and its requirements. These are the communications technology's range and the power requirements/battery life of the communicating device. The discrimination requirement for the range criterion will be specified as a range over 5 km in open territory and 1 km in developed urban areas. One fundamental aspect of the IoT is that it must be possible to spread devices over a large area in light of a significant part of the use cases with which the IoT is connected. The discrimination requirement for energy demands will be set as a modem battery life on the order of years. A significant portion of the use cases for the IoT are associated with the placement of communication sensors in spaces where no other power source than a battery can be guaranteed.

Applying the abovementioned discrimination criteria leaves us with only these technologies for evaluation: Ingenu, SIGFOX, LoRa, Telensa, and Weightless.

Similarly to our restriction of the technology selection above, we used discrimination criteria to narrow down the parameters used for choosing technologies. We established two criteria for this narrowing-down:

- The criterion is of fundamental importance for creating IoT applications.
- The differences between the assessed variants (if one criterion is not significantly different from another criterion, then there is no need to include it in our evaluation)—this is de facto the removal of duplicate criteria from the selection.

After applying these two restrictions, the following parameters were selected, through which the individual communication technologies will be evaluated. They are:

- SLA guaranteeing message delivery: a guarantee of message delivery is important in many situations.
- Modem's power requirements, battery life: a longer battery life means a longer service cycle for communication equipment.
- Range (km) country/rural; a higher range means better coverage.
- Downlink capacity; a higher transmission capacity enables the sending of e.g., images or video.
- Latency during normal operations.
- Device jammability; easy jamming excludes a given technology from use cases where communication must be guaranteed.
- End user/device count per base station; a high number of devices per station is a prerequisite for a network's having a high local capacity, where a large sensor count can be considered for a single locality.

5. Selection of the Optimum Technology

Applying the Selected Criteria and Preparing Them for the TOPSIS Method

One prerequisite for comparing the individual communication technologies in terms of their attributes via the selected multi-criteria values is to set a base variant and an ideal variant and simultaneously to convert the attributes into numeric expressions.

The key parameters and their qualitative assessments for the six preselected technologies are given in Table 2 below.

Table 2. Information on the assessed technologies and on their parameters.

Parameter	NB-IoT (LTE)	Ingenu	SIGFOX	LoRa	Telensa	Weightless
SLA guaranteeing message delivery	N	N	Y	N	N	N
Modem's power requirements (expressed as battery life)	years	years	years (>10 years)	years (>10 years)	years	years
Range (km) country/rural	15/6	20/2	50/3	20/2	10/2	10/2
Downlink capacity	160 kbps	19 kbps	4 × 8 Byte (ČTU restriction 10% of time at base station)	0.3–50 kbps, communication is possible from one concentrator max. 10% in an hour	62.5 kbps	0.2–100 kbps
Latency during normal operations	within 100 ms	single-digit s	7 s (sensor into internal DB)	7 s (sensor into internal DB)	single-digit s	single-digit s
Device jammability	Easy using a jammer	Easy	Extremely jamming resistant	Easy	Extremely jamming resistant	Easy
Number of end-user devices per base station	tens of thousands	single thousands	hundreds of thousands	6000 with average communication of one sensor once per hour	5000 max.	hundreds of thousands

The individual qualitative values for the parameters were converted to the quantitative values required by the TOPSIS method as follows:

- SLA guaranteeing message delivery: Yes—1; No—0.
- Modem's energy demands (expressed as battery life): Years—0; Years (>10 years)—1.
- Range (km) country/rural: 10/2—0; 20/2—1; 15/6—2 (due to good performance in developed areas); 50/3—3.
- Downlink capacity: 4 × 8 Byte—0; 19 kbps—1; 0.3 kbps–50 kbps—1; 62.5 kbps—2; 0.2–100 kbps—2; 160 kbps—3.
- Latency during normal operation: 7 s (sensor into internal DB)—0; single-digit s—1; up to 100 ms—4 (due to the significant difference between seconds and milliseconds).
- Device jammability: Easy—0; Easy using a jammer—1; Significant jamming resistance—2; extremely jamming resistant—3.
- Number of end-user devices per base station: single thousands—0; 5000 max.—1; 6000 with average communication of 1 sensor once per hour—1; tens of thousands—2; hundreds of thousands—3.

Another essential step for the effective use of the TOPSIS method was to set weights for the individual parameters. Based on our assessment of our survey among respondents, we reached the following weightings listed in Table 3.

Table 3. Weights for the selected criteria.

Weight ID	Weight Name	Point Score	Weight
K1	Delivery SLA	8	0.08
K2	Battery life	40	0.40
K3	Range	25	0.25
K4	Downlink capacity	10	0.10
K5	Latency	7	0.07
K6	Device jammability	5	0.05
K7	Devices per base	5	0.05
	Total	100	1.00

The first step in the application of TOPSIS is the identification of normalized values, which will be used in TOPSIS. This is mentioned in the Table 4.

Table 4. Qualitative values and base and ideal variant.

Technology	K1	K2	K3	K4	K5	K6	K7
NB-IoT (LTE)	0	0	2	3	4	1	2
Ingenu	0	0	1	1	1	0	0
SIGFOX	1	1	3	0	0	3	3
LoRa	0	1	1	1	0	0	1
Telensa	0	0	0	2	1	2	1
Weightless	0	0	0	2	1	0	3
Base variant	0	0	0	0	0	0	0
Ideal variant	1	1	3	3	4	3	3

The next step is the preparation of data for normalization, which is shown in Table 5.

Table 5. Input qualitative values for calculation normalized matrix.

Technology	K1	K2	K3	K4	K5	K6	K7
NB-IoT (LTE)	0.00	0.00	0.67	1.00	1.00	0.33	0.67
Ingenu	1.00	1.00	1.00	0.00	0.00	1.00	1.00
SIGFOX	0.00	1.00	0.33	0.33	0.00	0.00	0.33
LoRa	0.00	0.00	0.00	0.67	0.25	0.67	0.33
Telensa	0.00	0.00	0.00	0.67	0.25	0.00	1.00
Weightless	0.00	0.00	0.67	1.00	1.00	0.33	0.67

Normalized values, with weights mentioned in Table 3 and identified base and ideal variant are shown in Table 6.

Table 6. Normalized values, weight and base and ideal variant.

Technology	K1	K2	K3	K4	K5	K6	K7
NB-IoT (LTE)	0.00000	0.00000	0.53452	0.70711	0.94281	0.26726	0.40825
Ingenu	1.00000	0.70711	0.80178	0.00000	0.00000	0.80178	0.61237
SIGFOX	0.00000	0.70711	0.26726	0.23570	0.00000	0.00000	0.20412
LoRa	0.00000	0.00000	0.00000	0.47140	0.23570	0.53452	0.20412
Telensa	0.00000	0.00000	0.00000	0.47140	0.23570	0.00000	0.61237
Weightless	0.00000	0.00000	0.53452	0.70711	0.94281	0.26726	0.40825
Veight	0.08	0.10	0.40	0.25	0.07	0.05	0.05
Base variant	0.08000	0.07071	0.32071	0.17678	0.06600	0.05000	0.05000
Ideal variant	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.01021

Next two steps are about identification of difference from ideal and based variant. These steps are shown in Tables 7 and 8.

Table 7. Difference from base variant (DBV).

Technology	K1	K2	K3	K4	K5	K6	K7	DBV
NB-IoT (LTE)	0.00000	0.00000	0.04571	0.03125	0.00436	0.00018	0.00010	0.28566
Ingenu	0.00640	0.00500	0.10286	0.00000	0.00000	0.00161	0.00042	0.34100
SIGFOX	0.00000	0.00500	0.01143	0.00347	0.00000	0.00000	0.00000	0.14107
LoRa	0.00000	0.00000	0.00000	0.01389	0.00027	0.00071	0.00000	0.12196
Telensa	0.00000	0.00000	0.00000	0.01389	0.00027	0.00000	0.00042	0.12074
Weightless	0.00000	0.00000	0.04571	0.03125	0.00436	0.00018	0.00010	0.28566

Table 8. Difference from ideal variant (DIV).

Technology	K1	K2	K3	K4	K5	K6	K7	DIV
NB-IoT (LTE)	0.00640	0.00500	0.01143	0.00000	0.00000	0.00134	0.00088	0.15826
Ingenu	0.00000	0.00000	0.00000	0.03125	0.00436	0.00010	0.00038	0.18995
SIGFOX	0.00640	0.00000	0.04571	0.01389	0.00436	0.00250	0.00158	0.27284
LoRa	0.00640	0.00500	0.10286	0.00347	0.00245	0.00054	0.00158	0.34972
Telensa	0.00640	0.00500	0.10286	0.00347	0.00245	0.00250	0.00038	0.35079
Weightless	0.00640	0.00500	0.01143	0.00000	0.00000	0.00134	0.00088	0.15826

After incorporating weights into the TOPSIS method, we reached the conclusions listed in Table 9.

Table 9. Selection of the best technology using the TOPSIS method—variant ranking.

TOPSIS	Distance from Ideal Variant (H)	Distance from Base Variant (H)	Relative Distance from Base Variant (cij)	Variant Ranking
NB-IoT (LTE)	0.30279	0.16582	0.35385	3.
SIGFOX	0.09672	0.35861	0.78758	1.
LoRa	0.18127	0.29158	0.61665	2.
Telensa	0.36080	0.05665	0.13569	4.
Weightless	0.36220	0.05395	0.12965	5.

Through our application of the TOPSIS method, we established SIGFOX as the best technology; it had a relative distance from the base variant of 0.788 points. The second best technology here, LoRa, had a relative overall distance from the base variant of 0.617 points.

6. Discussion

A solution's device ownership factor is key from the standpoint of financial considerations on the implementation of that solution via a specific technology. Proposed business models are discussed in Niyato et al. (2016). When devices are user-owned, an initial investment is needed (often a substantial one), and yet it brings with it lower operating costs; these generally lie only in payments for the use of the communication services (data transmissions) and in the servicing payments for the given devices. The main risk resulting from this approach is the need for device servicing due to wear and tear, damage, etc. The advantage of this approach is that if the devices have a long service life, the user can save significantly relative to the situation where the devices are rented.

The main advantage of device rental is that responsibility for functionality and device uptime is transferred to a third party, who receives payment for this. The main disadvantage is the abovementioned higher operating costs, as well as an increase in total costs, since the provider must be paid not only for their costs, but also for their expected margin. To sum up these characteristics, rental's main advantage is an increase in up-front costs, while its main disadvantage is an increase in operating costs (Niyato et al. 2016; Boli et al. 2009).

A second angle is ownership of the data that the IoT devices produce. For the approach where the devices are owned by the user, the data owner is clear. Things become more problematic when the devices are rented and the data are collected by the device provider and then provided to the device renter. It is especially difficult here to ensure that the data are not also offered to other potential customers of the provider without the renter's knowledge. These situations must be addressed in the contract on the provision of the devices. If the data issue is not well-addressed, then the renter is potentially exposed to two kinds of problems. The first is the problem where the solution provider offers the collected data to someone else, who will in fact be reaping the benefits of the renter's analytical labors. The second risk lies in the fact that, if the renter has a contract for the provision of specific data or outputs from it, they must pay for any further outputs. From this standpoint, data from Czech mobile networks are a very interesting example of the use of the IoT in practice. This information is entirely publicly sold by operators to clients, and while it is anonymized, it is sold without the consent of mobile-network users. Here Regulation (EU) 2016/679 of the European Parliament and of the Council (i.e., the GDPR) is going to have a fundamental impact.

One key factor influencing the ranking of the variants in our selection of technologies for IoT deployment is the criteria weightings given in Table 3. If we adjust these weights slightly, for example by prioritizing the K3 and K4 criteria, i.e., range and downlink capacity, at the expense of battery life (the K2 criterion), the ranking becomes entirely different. We obtained similar results to those presented by Nivato et al. In this situation NB-IoT (LTE) is the most appropriate technology. This particular change in selection criteria weightings can be explained by a variety of factors:

- the user does not need to replace batteries or worry about energy consumption is a non-issue (Lallart et al. 2018),
- the user expects/requires a large quantity of information in the form of transmitted messages, or even requires a continual flow of data from the sensors ("stream data"),
- the user requires high coverage (range) e.g., due to having few active elements or being unable to deploy a large number of them in a certain environment.

The last interesting angle on IoT solutions discussed here—and it is one of the fundamental angles—is the financial aspect of the deployment and subsequent use of IoT technologies.

Every type of IoT device is connected to certain investments or operating costs. For a financial comparison, it is not the above criteria that are decisive, but rather very simple calculations:

- the number of devices,
- the device price (up-front),
- the device operating cost (if they are purchased), including telecommunication fees, etc.,
- the maintenance costs per device operated, and
- the IoT devices' provision fee (if they are rented).

The above factors enter into the cost side of calculations; it is appropriate to handle these not only in the short term, but also as total costs of ownership (TCO), and this with a horizon of at minimum five years, potentially more (e.g., 10 or 15 years). For IoT solutions, financial considerations with a 10-year horizon are typical (see Jesse 2018).

The costs determined must then be compared with the savings or other benefits, which—for example, for electricity meter readings—can lie in a decrease in the number of meter-reading employees needed and the possibility of quick detection of non-standard situations or incidents or of a change to the configuration of energy-grid parameters (Behera and Mohapatra 2018; Lallart et al. 2018). Other benefits that can significantly influence financial considerations lie, e.g., in the precision and speed of readings, an increase in their frequency, easier detection of energy-consumption fraud, proactive provision of more effective electrical energy consumption plans, and an increase in customer awareness.

These savings and benefits—which can in many cases also be calculated as dollars and cents—are a further important factor that must be taken into account when deciding on a suitable IoT technology, ownership method, and operations and billing method.

7. Conclusions

The selection of a suitable technology for IoT implementation based on specific measurable attributes such as range, latency, etc. presented in this article is but one out of the possible ways to view the IoT's penetration into daily life. Based on our assessment of the selected parameters, we arrived at the choice of the SIGFOX technology for application within the Czech energy industry. However, another, no less important angle, and one that is rather critical within a free-market society, is the angle based on the question of a given device's ownership. It is open to question whether such a device is in the ownership of the IoT solution provider, or whether it is owned by the specific user, who is "only" using the provider's information transmission service itself. Another important angle at present is the entry into force of GDPR—and simultaneously the absence of implementing regulations for it within the Czech Republic—and the ownership of the data that are generated and then stored and processed by the given IoT device (Mashhadi et al. 2014; Knight 2017; Basl 2017).

The future of the IoT implementation is bright and we can expect really high growth in this area.

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