AKADÉMIAI KIADÓ

Pollack Periodica •
An International Journal
for Engineering and
Information Sciences

16 (2021) 2, 86–91

DOI:
[10.1556/606.2020.00263](https://doi.org/10.1556/606.2020.00263)
© 2020 The Author(s)

ORIGINAL RESEARCH
PAPER

Reducing power requirement of LPWA networks via machine learning

Husam Rajab*, Mussa Ebrahim and Tibor Cinkler

Department of Telecommunications and Media Informatics, Faculty of Electrical Engineering and Informatics, Budapest University of Technology and Economics, Műegyetem rkp. 3, H-1111 Budapest, Hungary

Received: August 5, 2020 • Revised manuscript received: December 9, 2020 • Accepted: December 16, 2020
Published online: April 30, 2021

ABSTRACT

Recently, one of the most common needs of people are to be connected to the Internet anytime, anywhere, anyhow. The Internet of Things is a materialized paradigm in which everyday objects are implemented with Internet connectivity, enabling them to collect and interchange information. As energy is expected to be more expensive, the energy supply is often not available for IoT devices, the low power wide area networks attempt to be the solution to this problem. LoRaWAN provides radio coverage over long distances by enhancing the reach of the base stations via adapting transmission rates, transmission power, modulation, duty cycles, etc. This paper aims to decrease the power consumption using machine learning and deep neural network by applying support vector regression and deep neural network algorithms, which can support to extend the battery lifetime.

KEYWORDS

internet of things, low power wide area network, machine learning, deep neural network, support vector regression

1. INTRODUCTION

The exponential growth of using the Internet of Things (IoT) is becoming an increasingly challenging problem. IoT includes a group of devices connected to the Internet, which are usually defined by their low complexity, long-range transmission, and their low power consumption, most likely battery-powered sensors connected to the Internet [1]. IoT is a burgeoning field that could be employed in various areas, intelligent fridges to wearable devices [2, 3]. Due to amount of IoT devices increasing ubiquity and connected to Low Power Wide Area Networks (LPWANs) is forcing the network operators to enhance the scalability of their networks [4].

Moreover, a small battery that requires enduring for several years typically powers these mobile devices. Wide Area Networks (WANs) play an essential role in connecting the primary facilitation through LPWAN is enabling power-efficient wireless communication over long distances [5]. Figure 1 illustrates the comparison between LPWAN technologies.

In each approach, a trade-off between location accuracy and energy consumption must be taken into consideration. However, when investigating various studies of the same method, many other parameters need to be considered. In this concern, the efficient use of data compression and local data analysis to decrease the required transmission bandwidth is a realizable strategy, which could be emerged with the use of long-range small-bandwidth protocols [6]. One of LPWAN technologies that have reached great interest and importance is Long Range (LoRa) (a long range, low power, low bit rate wireless transmission and networking protocol). LoRa is one of the promising solutions that is significant for many IoT application scenarios, in particular smart grids, smart cities, smart metering, smart agriculture, geological monitoring, etc. [7].

*Corresponding author.
E-mail: husamrajab@tmit.bme.hu

Furthermore, it is a non-cellular modulation technology for LoRaWAN. LoRaWAN is the standard protocol for WAN part of the communications. LoRa is the physical layer of the radio network for IoT solutions and has more reliable link budgets than other comparable radio technologies [8]. LoRaWAN is mainly designed and optimized for uplinks where the end devices broadcast data to the gateway using periodic and aperiodic communication or due to a specified radio duty-cycle [9]. However, this design does not support extensive data communication, like video, photos [10] but works rather on the milibit per second speeds when averaged over a day or a week. Overall, LoRaWAN networks are remarkably customizable wireless networks fitted to individually adapting the transmission parameter of their constituting devices. Accordingly, from the networking prospect, an optimal configuration can be found for each node that embraces transmission parameters of every node [11]. That would allow us to optimize the use of the available communication bandwidth effectively, so some predefined figures of merit, one is the throughput, battery lifetime, which could be maximized. Machine Learning (ML) techniques like Q-learning and multi-armed bandit can play a significant role in scheduling and random access to manage the resources in the smart cities and smart home environment. It is because these ML methods learn and can adapt dynamically to the variations (changes) in the network ecosystem [12].

Moreover, several machine-learning algorithms are evaluated in terms of power consumption and battery lifetime in [13]. This research investigates and assesses Support Vector Regression (SVR) and Deep Neural Network (DNN) algorithms applied to the LoRaWAN protocol to decrease the power consumption and extend the battery lifetime.

2. RELATED WORK

Several works have studied the impacts of different LoRa transmission configurations onto IoT networks, for instance, determining the overall network capacity of single-gateway networks [9,12]. Machine learning is being applied on the edge nodes to reduce power consumption and transmission bandwidth. Soto et al. [14] provide a theoretical framework for employing machine learning to the IoT. In [15, 16] the isolated energy requirements of the edge devices are investigated without examining the communication protocols involved. The communication protocol is a power-consuming component. Accordingly, various communication technologies for IoT devices such as LoRa, NarrowBand (NB-IoT), and Bluetooth Low Energy (BLE), which are Low Power Wide Area (LPWA), are illustrated in Figure 1. The advantage of LPWA is that it can communicate over long distances with low power consumption. Therefore, the authors in [17] investigated the LoRa application and indicated that the decreased bitrate is one of the most confining factors in facilitating ubiquitous real-time IoT applications. [18, 19] investigated transmission parameters of each node to

Fig. 1. Low power wide area technologies

improve network throughput. To the best of knowledge, there is no work that evaluates the power requirements for a system that combines the low power protocol LoRa with machine learning algorithms for further decreasing power requirements, that is the main result of this paper. A solution to extend the battery lifetime of IoT devices primarily for LoRa/LoRaWAN is proposed, however, without loss of generality these results are applicable to various other LPWAN technologies.

3. PROBLEM STATEMENTS

The massive use of IoT devices, and its further rapid growth requires more focus on power consumption of these devices and these networks. The main goal of the LPWAN network is to use as low power as possible, even for long-distance transmissions. This requires to optimize the power consumption of the IoT devices and of the IoT network. This research aims to optimize the power consumption of LoRaWAN using ML (Machine Learning) algorithms. The LoRaWAN device power consumption depends on various parameters for instance user requirements, territorial limit, and resource allocation, etc. Optimizing parameters like transmit on time, tsystm, BW, tcycle, etc. is managing the demands and values of LoRaWAN limitation depending on their consumption. This research proposes two machine-learning algorithms to optimize the power consumption of the LoRaWAN device, which is the SVR and DNN model. Based on the parameters to configure the parameters of the LoRaWAN device and predict different metrics based on the needs of the user. Mathematically, x -coordinate represents the independent variables or user requirement for LoRaWAN, and y -coordinate represents the dependent variables. Thus, the correlation between dependent variables and independent variables maximizes the probability of observing the event according to the random error. Moreover, observing a simple linear relationship between the two sets of values to calculate the battery life in years of IoT devices.

3.1. Data set

In regards to optimizing the power consumption and to implement ML algorithms, data collection procedure and group of trainable data sets for LoRaWAN devices is as follow: the data set preparation takes the first step – the

implementation of machine learning algorithms is the second step. Machine learning in IoT devices takes place in this step after finding real-life data. Thirdly, simulation and implementation of LoRaWAN device is to measure the power consumption as a function of different factors. One of the challenging issues is to find real-life data and preparing the data set for the model. In this research, the proposed data set is implemented using power consumption factors formula, which is derived from The Things Network United Kingdom (TTN UK), which gives us close to the real-life data [20]. Moreover, as it is shown in Table 1, the input parameters are generated randomly using the rules and regulations of things network of Europe environmental parameters. Furthermore, in the first step, 20-power consumption factor parameters that have impact on LoRaWAN. However, to make the proposed dataset more efficient, exploring, reducing and refining additional parameters was relevant. Afterword, the input dataset winded up with 15 main power consumption parameters and generate their value according to the TTN policy [20]. The total number of data set entries used is 35,192, which is appropriate for this purpose.

The output parameter is generated using the input parameter, by applying the formula that is provided in Table 2. Therefore, the histogram shows the calculated outcome of each parameter and its range.

Data reduction and cleaning should be done before loading the data into the model because unreliable or misleading data can lead us to inevitable or incorrect results. In other words, data cleaning and reduction means deleting or removing unnecessary parameters. The heat map correlation system is used to recognize the correlation between each parameter and remove some parameters from the dataset, which have no impact on the optimization process. The correlation of all the dependent and independent parameters is evaluated using numerical values. The value one is the highest correlation, which means the relationship

Table 1. Sample Input parameters and range used

Input	Minimum-input	Maximum-input
Battery capacity (mAh)	600	1,500
Spreading factor (SF)	7	12
Custom payload	1	100
Overhead payload	1	50
Transmission (Tx) Max (dB)	50	90
14 current		
Sleep current (mA)	0.01	0.5
Sensor current (MA)	10	60
Lead lag time (ms)	1	20
Low data rate optimize	"0" (If SF ≥ 7 and SF ≤ 10)	"1" (If SF > 10)
Codding rate	1	4
Band width	125	500
Explicit header	0	1
Sensor on time (ms)	600	1,000
Tx cycle period (ms)	60	500

Table 2. Sample formula for output parameters

Output parameters	Optimization formula
Tsym (ms)	$2^{SF}/(BW \times 1,000) \times 1,000$
Transmit on time (ms)	Tpacket
Tpacket (ms)	Tpreamble + Tpayload
TTN 30 sec/Day fair use	$((24 \times 3,600)/\text{Tx cycle period(s)}) \times \text{Transmit on Time (ms)}/1,000/30$
Radio (MPU (per Cycle period))	Transmit on Time (ms) $\times$ Tx max dB14 current
Lag/lead MCU (per cycle period)	The sensor on time $\times$ Lead lag time/1,000,000
Sensor (per Cycle period)	Sensor current $\times$ Sensor on time/1,000,000
Sleep current (in Cycle period)	Sleep current $\times$ Tx Cycle period(s)
Summery (per Tx Cycle)	(Radio (MPU (per cycle period))) + (Lag/lead MCU (per cycle period)) + (Sensor (per cycle period)) + (Sleep current (in cycle period))
Average battery life in the year	Tx cycle period(s) $\times$ Battery capacity/(24 $\times$ Summery (Per Tx cycle))/365

between the parameters is similar. Furthermore, zero value or less than one shows how much the parameters are correlated to each other. Nevertheless, after reduction and cleaning, it winded up with 15 independent input parameters and 10 dependent output parameters.

3.2. Data loader

As it was mentioned in the previous section, the dataset is prepared efficiently with proportional parameters through the reduction and cleaning methods.

Before starting the implementation using the proposed ML algorithms preparing the training dataset was relevant, afterwards, using the data loader to load the dataset.

In this section, the data loading process separated into two steps, data splitting and data scaling:

1. Data splitting

Since the generated data set is 35,192, in the data splitting section, the division of the data into to train set and test set, 80–20% respectively for the ML model was sufficient.

Let x = train set; y = test set; z = length of the dataset,

$$x = z \times 0.8, \quad (1)$$

$$x = z \times 0.2. \quad (2)$$

2. Data scaling

In the data scaling section, the used mini-max system is in the interval of [0..1] which means it takes the smallest value and the most significant value of each column in the dataset and represents than in the range of 0 and 1 respectively.

3.3. Proposed ML algorithms

3.3.1. Support vector regression. SVR algorithm was used to verify and optimize the power consumption of LoRaWAN because it is composed of the linear regression function. However, SVR is used for predictions instead of classification, which have multiple input (x -features) features and numerous output features (y -features).

$$y = b_0 + b_1 x_1. \quad (3)$$

where $y = y_1, y_2, y_3 \dots y_n$; $x = x_1, x_2, x_3 \dots x_n$; $b_0 = \text{bias}$ and $b_1 = \text{weight of the parameter}$.

The dataset is composed of multiple input parameter (x) and a various output parameter (y), x -independent variables and y -dependent variables respectively. In the model it takes 15 independent variables and tries to map them, gives us the predicted value then compare the expected value with the real value by calculating the absolute difference.

3.3.2. Deep neural network. A DNN is an ANN with multiple layers between the input and output layers [21]. The DNN finds the correct mathematical manipulation to turn input into the output, whether it is a linear relationship or a non-linear relationship.

In this research DNN is used in addition to SVR for comparison purposes and to find more results that are efficient by optimizing the power consumption of LoRaWAN. The DNN consists of multiple linear regression functions. It has three layers, including an input layer, a hidden layer and an output layer, therefore 15 input, 100 hidden layers, and 10 output.

4. RESULTS AND SIMULATION

In the previous section, the performance of two different learning algorithms parameters in a network in which all devices use the same standard was analyzed. In this section, the ability of these two algorithms are confirmed to reduce power consumption and highlight the strength of the proposed algorithms to cope with different attributes. For that purpose, comparing the SVR model with DDN are shown in Figs 2 and 3, respectively. Through evaluating the performance of these learning algorithms, considering that the predicted columns the absolute difference of the expected value with the real value. Firstly, by analyzing the number of transmissions in each channel by setting the batch size to five, since the total number of datasets is 35,192 and choose 5-batch size is relevant for the training, every batch will have 4,689 rows of data after training. Figures 2 and 3 show the absolute difference of each batch, which means that after training it is taking five rows of the test-dataset in every epoch and demonstrate the absolute difference. The maximum absolute difference is 0.025 for SVR and 0.040 for DNN respectively, which makes DNN closer to 0 or close to real value than SVR. However, when experimenting on a random epoch number, it gives different values in every trial

Fig. 2. Absolute difference SVR model

Fig. 3. Absolute difference of DNN

even with bigger epoch; it might generate a more considerable absolute difference.

Accordingly, when analyzing the evolution of power consumption using DNN and SVR ML algorithms and compare it to the real data. In addition, choosing the number randomly for the batch and epochs, we used five batches, and 200 epochs with random parameters.

Figures 4 and 5 show the battery consumption in years of the real data and the predicted data using both ML algorithms. Eventually, the results in both the ML algorithm is most likely similar to the actual data's battery consumption. However, when checking the details of predicted values versus the real values, the result was changeable, which means the battery life of the predicted is more significant than the real-life in most cases. For instance, in Fig. 4, on row 2, 4, 6, 7, and 8, the expected result is higher than the real. Furthermore, at some point, the real-life values are more notable than the predicted.

Fig. 4. Power consumption comparison SVR

Fig. 5. Power consumption comparison DNN

5. CONCLUSION

In this work, after an extensive analysis of the power consumption requirements, we evaluated two different Machine Learning algorithms on a dataset to optimize the power consumption of the LoRaWAN device, which is the SVR and DNN model.

Based on the parameters to configure the parameters of the LoRaWAN device and predict different metrics based on the needs of the user. Thus, the correlation between dependent variables and independent variables maximizes the probability of observing the event according to the random error. Moreover, because of the lack of power and implications on battery life for the device, preserving a simple linear relationship between the two sets of values to calculate the battery life is essential.

The future work consists of further improving the dataset representation by preprocessing the dataset using a Genetic Algorithm (GA). Finally, to integrate LoRaWAN networks with multiple gateways.

ACKNOWLEDGEMENTS

"This work was supported by the Ericsson – BME 5G joint research and cooperation project, partly funded by the National Research, Development and Innovation Office, Hungary with project number 2018-1.3.1-VKE-2018-00005." Also, this research is supported by Tempus Public Foundation, Stipendium Hungaricum Scholarship Programme and High Speed Networks Lab, Department of

Telecommunications and Media Informatics, Budapest University of Technology and Economics.

REFERENCES

- [1] R. S. Sinha, Y. Wei, and S. H. Hwang, "A survey on LPWA technology: LoRa and NB-IoT," *ICT Express*, vol. 3, no. 1, pp. 14–21, 2017.
- [2] K. Mekki, E. Bajic, F. Chaxel, and F. Meyer, "A comparative study of LPWAN technologies for large-scale IoT deployment," *ICT Express*, vol. 5, no. 1, pp. 1–5, 2019.
- [3] M. Haghi, K. Thurow, and R. Stoll, "Wearable devices in medical internet of things: Scientific research and commercially available devices," *Healthc. Inform. Res.*, vol. 23, no. 1, pp. 4–15, 2017.
- [4] O. Georgiou and U. Raza, "Low power wide area network analysis: Can LoRa scale?" *IEEE Wirel. Commun. Lett.*, vol. 6, no. 2, pp. 162–165, 2017.
- [5] H. Linka, M. Rademacher, O. G. Aliu, K. Jonas, B. Rhein-sieg, and S. Augustin, "Path loss models for low-power wide-area networks: Experimental results using LoRa," in *Conference on 23. ITG Fachtagung Mobilkommunikation, Technologien und Anwendungen*, Osnabrück, Germany, May 16–17, 2018, 2018, pp. 10–14.
- [6] B. Djail, W. K. Hidouci, and M. Loudini, "A comparative evaluation of techniques for N-way joins in wireless sensors networks," *Pollack Period.*, vol. 15, no. 2, pp. 13–24, 2020.
- [7] D. F. Carvalho, P. Ferrari, E. Sisinni, A. Depari, S. Rinaldi, M. Pasetti, and D. Silva, "A test methodology for evaluating architectural delays of LoRaWAN implementations," *Pervasive Mobile Comput.*, vol. 56, pp. 1–17, 2019.
- [8] D. Bankov, E. Khorov, and A. Lyakhov, "Mathematical model of LoRaWAN channel access with capture effect," in *IEEE 28th Annual International Symposium on Personal, Indoor and Mobile Radio Communications*, Montreal, QC, Canada, Oct. 8–13, 2017, 2017, pp. 1–5.
- [9] H. Rajab, T. Cinkler, and T. Bouguera, "IoT scheduling for higher throughput and lower transmission power," *Wireless Networks*, <https://doi.org/10.1007/s11276-020-02307-1>, 2020.
- [10] SX1272 development kit, User guide, Wireless and sensing products. [Online]. Available: www.semtech.com. Accessed: May 26, 2020.
- [11] F. Adelantado, X. Vilajosana, P. Tuset-Peiro, B. Martinez, J. Melia-Segui, and T. Watteyne, "Understanding the limits of LoRaWAN," *IEEE Commun. Mag.*, vol. 55, no. 9, pp. 34–40, 2017.
- [12] S. Ali, A. Ferdowsi, W. Saad, N. Rajatheva, and J. Haapola, "Sleeping multi-armed bandit learning for fast uplink grant allocation in machine type communications," *arXiv*, vol. 68, no. 8, pp. 5072–5086, 2018.
- [13] S. Bozkurt, G. Elibol, S. Gunal, and U. Yayan, "A comparative study on machine learning algorithms for indoor positioning," in *2015 International Symposium on Innovations in Intelligent Systems and Applications, Proceedings*, Madrid, Spain, Sep. 2–4, 2015, 2015, pp. 1–8.
- [14] J. Á. C. Soto, M. Jentsch, D. Preuveneers, and E. Ilie-Zudor, "CEML: Mixing and moving complex event processing and machine learning to the edge of the network for IoT applications," in *Proceedings of the 6th International Conference on the Internet of Things*, Stuttgart, Germany, Nov. 7–9, 2016, 2016, pp. 103–110.

- [15] I. Péntek, Á. Garai, and A. Adamkó, “Open iot-based telemedicine hub and infrastructure,” *Pollack Period.*, vol. 13, no. 1, pp. 33–44, 2018.
- [16] N. El Rachkidy, A. Guitton, and M. Kaneko, “Collision resolution protocol for delay and energy efficient LoRa networks,” *IEEE Trans. Green. Commun. Netw.*, vol. 3, no. 2, pp. 535–551, 2019.
- [17] R. Bonnefoi, L. Besson, C. Moy, E. Kaufmann, and J. Palicot, “Multi-armed bandit learning in IoT networks: Learning helps even in non-stationary settings,” in *12th EAI International Conference on Cognitive Radio Oriented Wireless Networks*, Lisbon, Portugal, Sep. 20, 2017, 2017, pp. 173–185.
- [18] A. Sabovic, C. Delgado, D. Subotic, B. Jooris, E. De Poorter, and J. Famaey, “Energy-aware sensing on battery-less lorawan devices with energy harvesting,” *Electron.*, vol. 9, no. 6, Paper no. 904, pp. 1–18, 2020.
- [19] M. Bor and U. Roedig, “LoRa transmission parameter selection,” in *Proceedings – 2017 13th International Conference on Distributed Computing in Sensor Systems*, Ottawa, ON, Canada, June 5–7, 2017, 2017, pp. 27–34.
- [20] LoRaWAN|The Things Network. [Online]. Available: <https://www.thethingsnetwork.org/docs/lorawan/>. Accessed: Dec. 8, 2020.
- [21] F. Granata, S. Papirio, G. Esposito, R. Gargano, and G. De Marinis, “Machine learning algorithms for the forecasting of wastewater quality indicators,” *Water*, vol. 9, no. 2, Paper no. 105, pp. 1–12, 2017.