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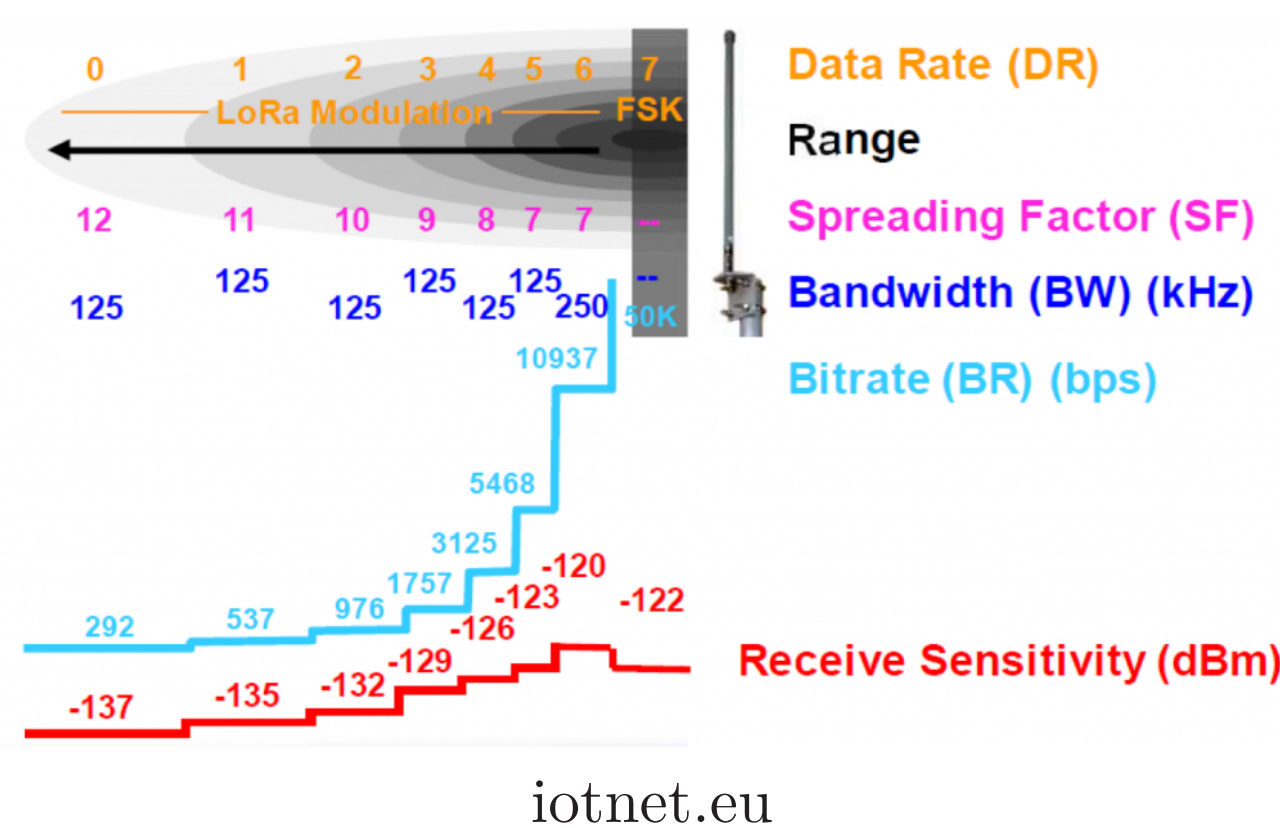
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ÉCOLE D'INGÉNIEURS

The need of a new kind of wireless communication that could send data far away with limited resource constraints emerged recently to support IoT applications like smart building and smart environment monitoring. **LoRaWan** is one of this emerging wireless networks [1], it allows end-devices to reach the gateway in a range up to 5Km, Unlike other technologies LoRaWan is the best versatile solution to deploy IoT application in both urban and rural area where there is no communication infrastructure.

The physical layer of LoRa technology (Semtech SX1276) has 4 parameters which make 6720 possible settings [2]:

- **SF:** Spreading factor [SF7 - SF12]
- **CR:** Coding rate [4/5 - 4/8]
- **BW:** Bandwidth [7.8Khz - 500Khz]
- **Tx:** Transmission power [-4dBm +20dBm]



A genetic algorithm is a heuristic search that is used to deal with selection and ranking problems [3]. This algorithm reflects the process of natural selection where the fittest configurations are selected for reproduction in order to produce offspring of the next generation.

- ➡ **Gene:** QoS metric.
- ➡ **Chromosome:** QoS of one configuration.
- ➡ **Population:** QoS of all configurations.

The diagram is divided into two main sections. The left section, labeled 'Population' in purple, shows four individuals (A1, A2, A3, A4) with their genotypes represented as 8-bit binary strings. A green box highlights the first seven bits of each genotype, representing the 'Chromosome'. A red box highlights the eighth bit of A1's genotype, representing the 'Gene'. The right section shows the same four individuals with their genotypes. A vertical red line is placed between the fourth and fifth bits of each genotype. Green arrows point to the bits on either side of this line: the first three bits are on the left, and the last three bits are on the right, illustrating the process of identifying a gene within a chromosome.

Individual	Genotype (8 bits)
A1	0 0 0 0 0 0 0 0
A2	1 1 1 1 1 1 1 1
A3	1 0 1 0 1 1 1 1
A4	1 1 0 1 1 1 0 1

Population

Chromosome

Gene

towardsdatascience.com

- [1] W. Ayoub, A. E. Samhat, F. Nouvel, M. Mroue, and J.-C. Prevotet, “ Internet of Mobile Things: Overview of LoRaWAN, DASH7, and NB-IoT in LPWANs Standards and Supported Mobility ”, *IEEE Communications Surveys & Tutorials*, vol. 21, no. 2, pp. 1561–1581, 22–2019, 00000.
- [2] M. Noura, M. Atiquzzaman, and M. Gaedke, “ Interoperability in Internet of Things: Taxonomies and Open Challenges ”, *Mobile Networks and Applications*, Jul. 21, 2018, 00004.
- [3] E. I. Vlahogianni, M. G. Karlaftis, and J. C. Golias, “ Optimized and Meta-Optimized Neural Networks for Short-Term Traffic Flow Prediction: A Genetic Approach ”, *Transportation Research Part C: Emerging Technologies*, vol. 13, no. 3, pp. 211–234, Jun. 2005, 00506.

The diagram illustrates a cloud-based IoT architecture. On the left, two desktop computers are connected to two server racks via HTTP. The server racks are connected to a central wireless router via MQTT and HTTP. The router is connected to a cloud containing various IoT devices (light bulb, camera, traffic light, thermometer, and microchips) via MQTT and COAP.

Definition: stopping criteria, population size P , and mutation probability p_m

Generate randomly the initial configurations

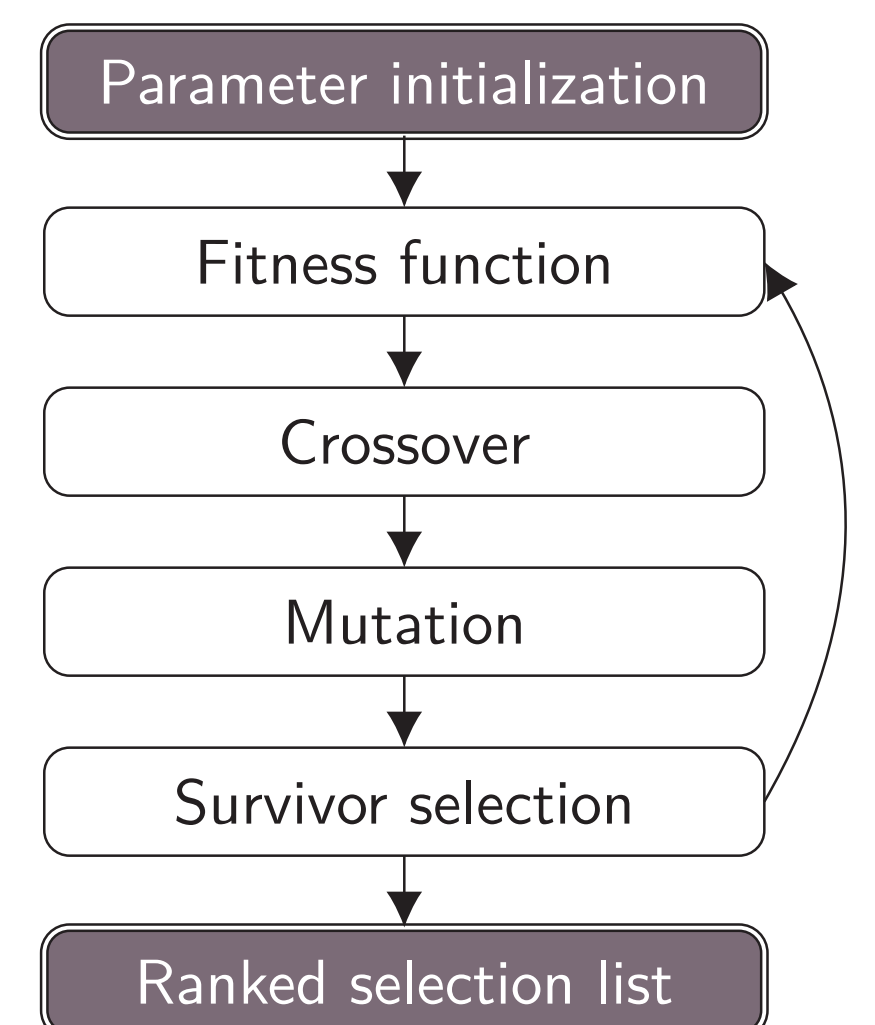
repeat:

```

... for each configuration do
...     Train a model & compute configuration's fitness
... end
... for each reproduction 1 ... P/2 do
...     Select: 2 configurations based on fitness
...     Crossover: Produce 2 child configurations
...     Mutate: child configurations with  $p_m$ 
... end

```

until stopping criterion are met



```

graph LR
    subgraph Input
        D[Device conditions]
        Q[QoS requirements]
        A[App preferences]
        O[Operator policies]
    end

    subgraph Training
        subgraph 1st_component [1st component]
            C1[FL Criteria C1]
            C2[FL Criteria C2]
            C3[FL Criteria C3]
            CN[FL Criteria CN]
        end
        C1 -- d1 --> MCDM
        C2 -- d2 --> MCDM
        C3 -- d3 --> MCDM
        CN -- dn --> MCDM
        subgraph 3rd_component [3rd component]
            GA[GA weights]
        end
        GA -- "(w1, ..., wn)" --> MCDM
        subgraph 2nd_component [2nd component]
            MCDM[MCDM]
        end
    end

    D --> 1st_component
    Q --> 1st_component
    A --> 1st_component
    O --> 1st_component

    MCDM --> Output

    subgraph Output
        Out[Map configuration to the application]
    end

```

The proposed scheme for LoRa transmission parameters selection based on GA, FL and Multi-Criteria Decision Making MCDM .

- **Ongoing:** In order to generate all the required metrics of each LoRa configuration, we use ns3 simulator with 2 nodes and one gateway. The distance between nodes and the gateway is 1km.

➡ **Advantages:** Genetic algorithms can manage data sets with many features. They don't need additional knowledge about the problem under study. In fact, such iterative algorithms require only the result of the last fitness value of the previous generation,

➡ **Conclusion:** LoRa transmission parameter selection problem by nature is a selection problem, thus, in our work we use genetic algorithm with a selection process to get the optimal subset of parameters that match better required QoS. Knowing the impact of each LoRa parameter on the output configuration still a big issue in research area. Our first results show that the transmission delay is more impacted by the SF and BW but less impacted by the CR.