Digital Water **Understanding of Water Demand**

The state of *Nuevo León*, where the metropolitan area of *Monterrey* is located, provides its citizens with water from different sources. These can be segmented into two main categories: surface (50%) and underground (50%). Surface water sources include 3 water dams (*La Boca*, *Cerro Prieto*, and *Cuchillo*). Underground sources are segmented into different categories such as wells, natural springs and qanats. In total, there are 406 underground sources (Source / Spanish). These water sources are exclusively for the state of *Nuevo León*. Most of the sources are allocated to the metropolitan area of Monterrey (around 90%), while the rest is shared with less populated locations outside the metropolitan area of *Monterrey*.

Each of these sources has its own pump system, and it is mandatory to specify the volumetric flow rate of water (how many liters per second) that **each pump system** needs to extract. In our prediction model, we assume demand is equal to volumetric flow rate. With this being said, there has to be a demand value in mind before extracting. After water is extracted from a source, it is then pumped towards a regulation tank or a water treatment plant and finally channeled into the distribution network (Source / Spanish).

Our water demand model forecasts the volumetric flow rate of water needed to extract from each individual water source[1] to fulfill demand. This includes both surface and underground sources. Unlike electricity, in the water industry, there's no such concept as "excess water", as it can be stored to a certain limit. However, a fine AI model that can understand water demand is crucial in order to determine the daily and monthly amount of water that you need to extract with the pump system from each individual water source to fulfill demand. Both the daily and monthly demand forecast are important as they provide different scope and objectives. Daily demand forecast it's relevant for day-to-day operations, or short term objectives. While, monthly demand forecast it's relevant for medium and long term strategic planning, meaning counter active actions, such as limit extraction to avoid over-exploiting of sources. In summary, it is not sustainable, nor strategic to simply extract a fixed amount of water from each source every day (even if it can be stored to a certain limit) as water demand is not fixed, but variable.

Lastly, it's also important to note that water sources are limited. There is a reason behind the amount of water extracted from each source. Sustainably, it is not possible to fulfill 100% of the demand with a single or a couple of water sources. Doing this would cause an imbalance in the long term. Therefore, fulfilling demand is a task that is distributed among sources. All sources contribute to a part of the demand, and this prevents over-exploitation on a water source.

 **Understanding our AI Models**

As we have previously discussed, our main model forecasts the amount of water that it is needed to extract from each individual water source to fulfill demand. As Note [1] states, as of right now, due to time constraints, we built such a model to output a total value, meaning the sum of all individual sources. See Table A for exemplified explanation.

Table A: Exemplified Demand Forecast

| **Source** | **Volumetric flow rate of water extracted [L/s]** |
|---|---|
| Surface sources (3) | x = the sum of 3 sources |
| Underground sources (406) | y = the sum of 406 sources |
| Total value | z = x + y |

In order to build this model, we used 32 unique features, from different categories such as weather, solar and time (Appendix A). Now, since we are trying to forecast water demand on days in the future, we rely on other forecasts to make our own forecasts. Most of the action in our platform takes place in the background, through scheduled task flows. In these flows, we first use forecast models available through external APIs to gather weather and solar forecasts. These values are fed into our water demand model, to output our final predictions for several days into the future. So, in simple terms, the outputs of several models are fed as inputs for our model, in a collaborative effort to forecast future water demand.

Our second AI model forecasts water dams (surface sources) capacity. This outputs a forecasted volume of water that the water dam will have every day, which depends on factors like consumption, evaporation and rainfall. Given that now we know the volumetric flow rate of water that it is needed to extract from sources to fulfill demand from our first model, both models collaborate to automatically calculate the days available before reaching under capacity (threshold set at 40%). This is an important metric to deliver, as it would allow the water agency to evaluate how sustainably water is being consumed. With it, we empower water agencies to take more preventive actions rather than reactive.

Our third model, detects and locates pipe leakages in the network. Since this model requires extensive fluid mechanics and engineering modelling, as of right now, it is still in progress, however, in the future, we will connect this model to the first model (and hence the second one also) to collaborate and make the forecast more accurate. The amount of water that the first model forecasts does not take into account the water that is being lost due to leakages. Therefore, the real total volumetric flow rate will be what was forecasted plus what is being lost due to pipe leakages. See Table B for a exemplified case where collaboration from all three models is included.

**Table B:** Exemplified Collaboration (Note that the values shown are just for simplified example purposes and **not real values.** For real values visit our dashboard)

<table>
<tr><td colspan="2">Exemplified source: Water Dam “El Cuchillo”</td></tr>
<tr><td>(1) Demand Forecast model outputs:</td><td>100 L/s</td></tr>
<tr><td colspan="2">That means that today, it is needed to extract 100 L/s of water from this specific source to fulfill demand. Assuming that no water is lost</td></tr>
<tr><td>(2) Pipe leakages model detects that close to this source, around:</td><td>20 L/s of water is being lost (while not repaired)</td></tr>
<tr><td colspan="2">Collaboration of (1) and (2) AI models results in 120 L/s of water needed to extract to fulfill demand. That is the true value, taking into account losses.</td></tr>
<tr><td>(3) Water Dam Capacity model forecasts:</td><td>100M L of capacity</td></tr>
<tr><td colspan="2">Previous collaboration now collaborates with the (3) model to calculate the days available before reaching under-capacity (40% or below)<br><br>Under-capacity = $0.4 * 100M\ L = 40M\ L$<br><br>Days available before reaching under-capacity = $\frac{40M\ L}{120\ L/s} = 333,333\ s = 3.8\ days$</td></tr>
</table>

Through these insights, a water agency might decide that they need to take urgent action to gather water from somewhere else before dam *El Cuchillo's* supply is exhausted.

To summarize, we had established that one of the underlying problems with water supply in Monterrey was the reactive approach to its management, which was unsustainable. Digital Water is our approach to better management, based on predictive knowledge. To achieve it, we rely on our model collaboration. On one hand, a water agency can observe how much water will be needed, based on predicted demand (water demand model) and loss (leakage detection model). On the other hand, the agency can gauge at what capacity the main sources will be (water dam capacity model), to determine beforehand what new policies or actions to take, if needed. You need both: to know how much you will have versus how much you will need to put things in perspective and understand how your situation will progress in the future. Through such visionary knowledge, water agencies can better decide the next steps and thus ensure a more sustainable water supply, without waiting for the city to be in danger of Day Zero.

**Notes:**

1: Note that as of right now, we have built our model as a total value, meaning that we have summed up all volumetric flow rates from all sources into one value. The reason is strictly due to time constraints. However, the total value follows the same logic and modelling as an individual source. Given more time, we will forecast the volumetric flow rate of water for each individual source. See Table A to further understand “total value”.

**Appendixes**

Appendix A

Features used for Demand Forecast

| Category | Feature | Type | Units | Explanation |
|---|---|---|---|---|
| (1) Solar Irradiance | DHI | Min, Ave, Max | [w/m$^2$] | Diffuse Horizontal Irradiance |
| | DNI | Min, Ave, Max | [w/m$^2$] | Direct Normal Irradiance |
| | GHI | Min, Ave, Max | [w/m$^2$] | Global Horizontal Irradiance |
| (2) Weather | DP | Min, Ave, Max | [°C] | Dew Point |
| | WS | Min, Ave, Max | [m/s] | Wind Speed |
| | Rain | Min, Ave, Max | [cm] | Rain |
| | RH | Min, Ave, Max | [%] | Relative Humidity |

| | | | | |
|---|---|---|---|---|
| | T | Min, Ave, Max | [°C] | Temperature |
| | P | Min, Ave, Max | [mbar] | Pressure |
| (3) Time | YEAR | - | Numeric year | Year (2013-2018) |
| | MONTH | - | Numeric month | Month |
| | DAY | - | Numeric day | Day (1-31) |
| | Weekday | - | 0: Not weekday<br>1: It is weekday | Weekday (Monday - Thursday) |
| | Weekend | - | 0: Not weekend<br>1: It is weekend | Weekend (Friday-Sunday) |
| | Festive | - | 0: Not festive<br>1: It is festive | If festive |
| (4) Water Volumetric Flow rate | Q | - | [L/s] | Yesterday's water volumetric flow rate |