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10th International Conference on Smart Cities and Green ICT Systems

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An Artificial Neural Network-based Real Time DSS to Manage the Discharges of a Wastewater Treatment Plant and Reduce the Flooding Risk

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Introduction

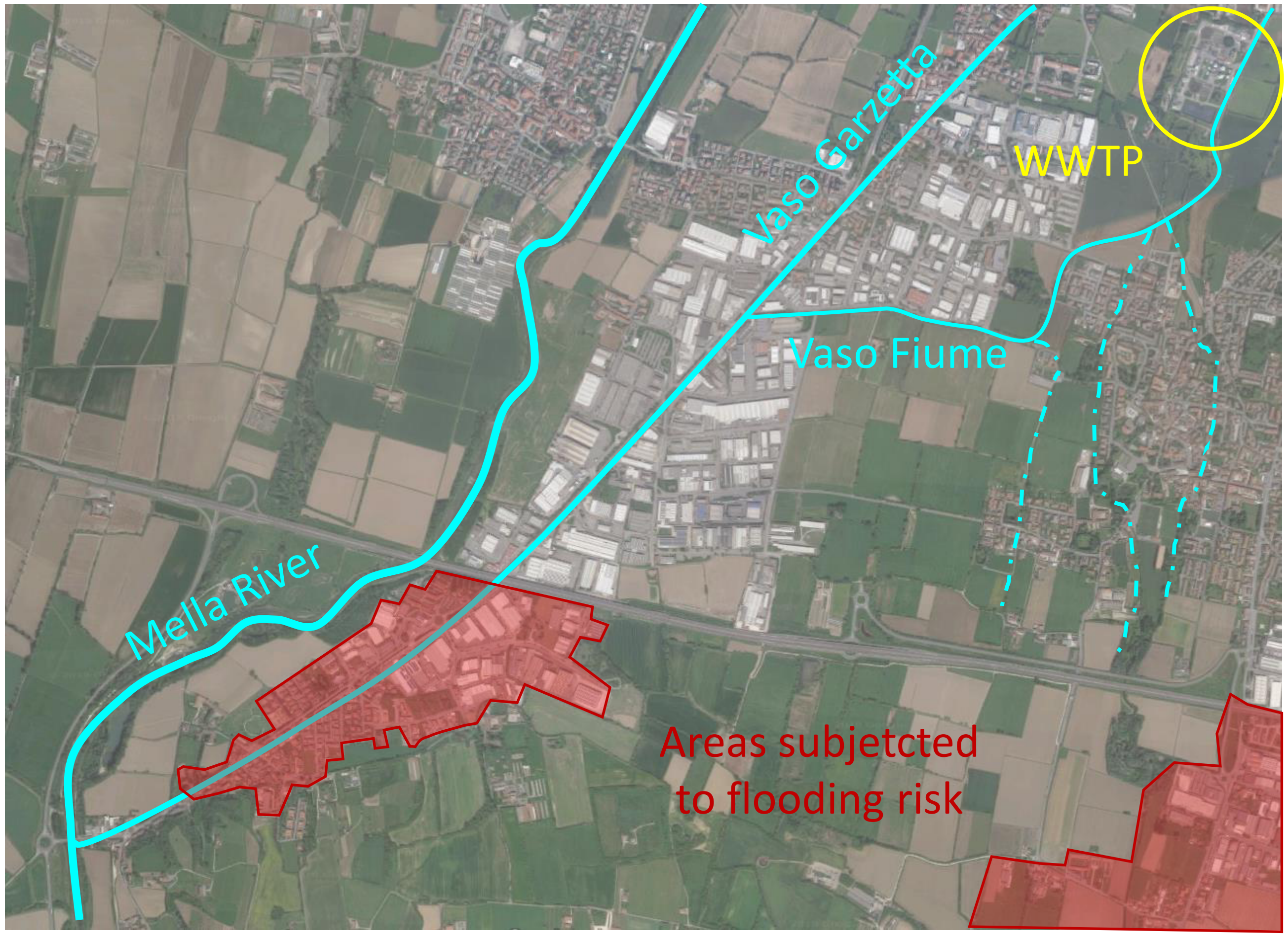
A2A Ciclo Idrico manages the **sewage network** in the city of Brescia, Italy, and its surrounding area.

It also manages the **wastewater treatment plant** located in the Verziano district, south of the city.

a2a
ciclo idrico

Issues

The whole system is subjected to several issues in case of high-intensity rainfall events.



Upstream

Combined sewer flows must be spilled before entering the WWTP, respecting environmental law limitations.

Downstream

- Critical management of Vaso Fiume due to raise in Vaso Garzetta level;
- Limit lateral spillways from Vaso Fiume within law limitations;
- Several floods over the years.

Previously

Acquired data were stored in diverse databases and visualized in separate interfaces.

Rainfall data
(measurements from 6 pluviometers)

Gate openings and VF levels

Sewer flows

Lack of comprehensive view!

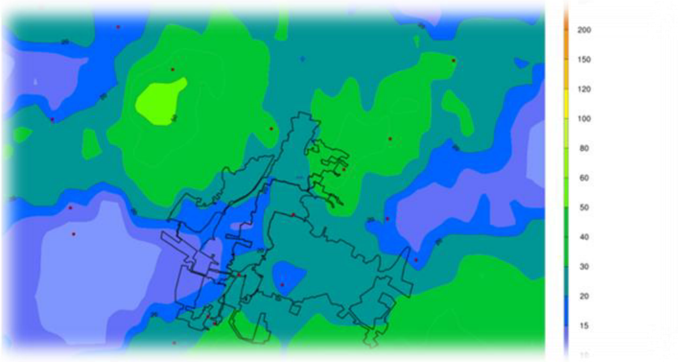
No information about forthcoming rainfall, levels and flows

Mitigation strategies based on operator experience

VG levels

Now: data collection

All acquired and computed data are collected in a dedicated DB.

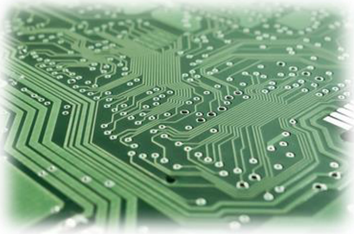


Rainfall data
(pluviometers and radar measurements + nowcasting)

Gate openings and VF levels

PostgreSQL

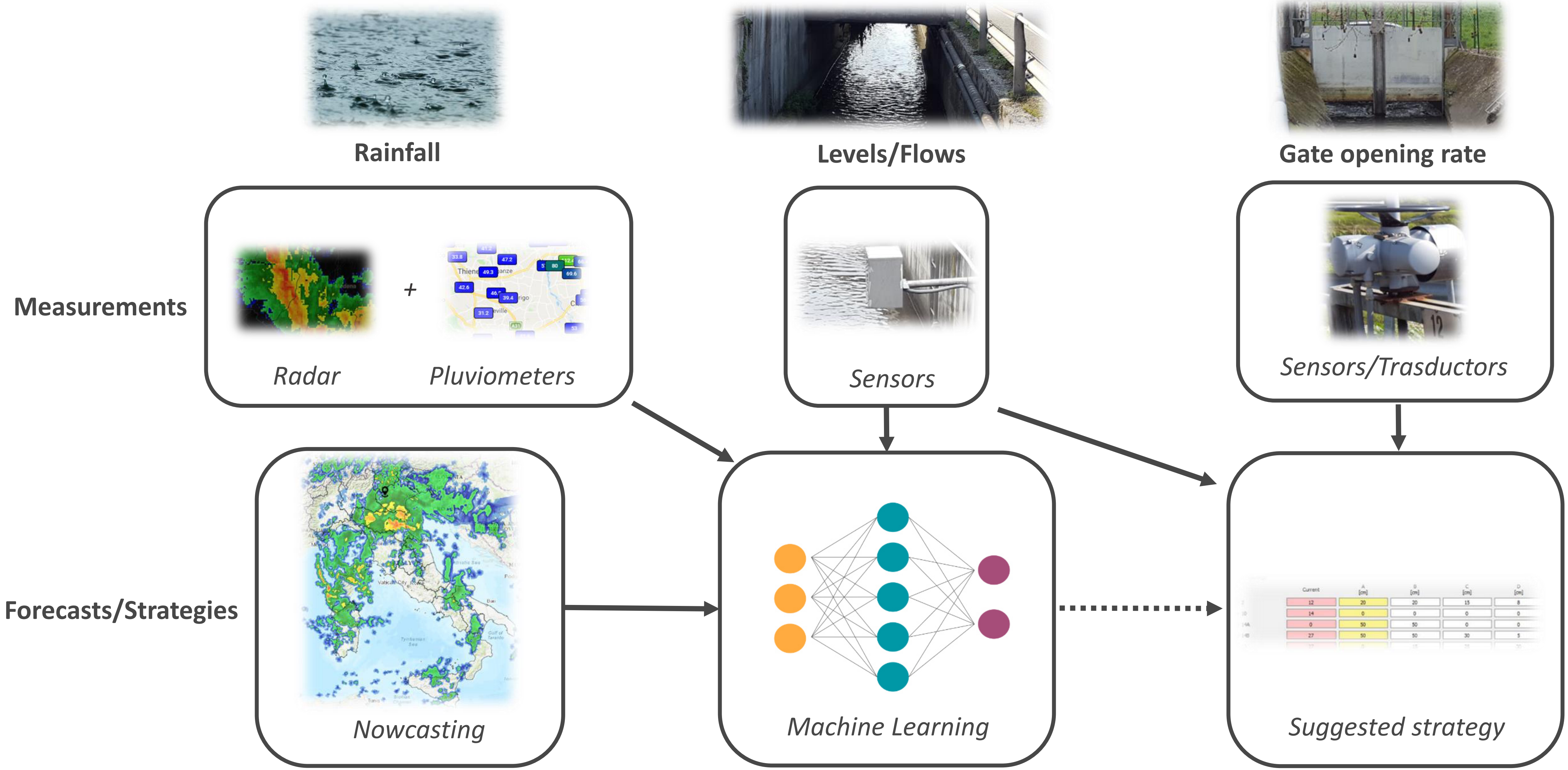
Sewer flows



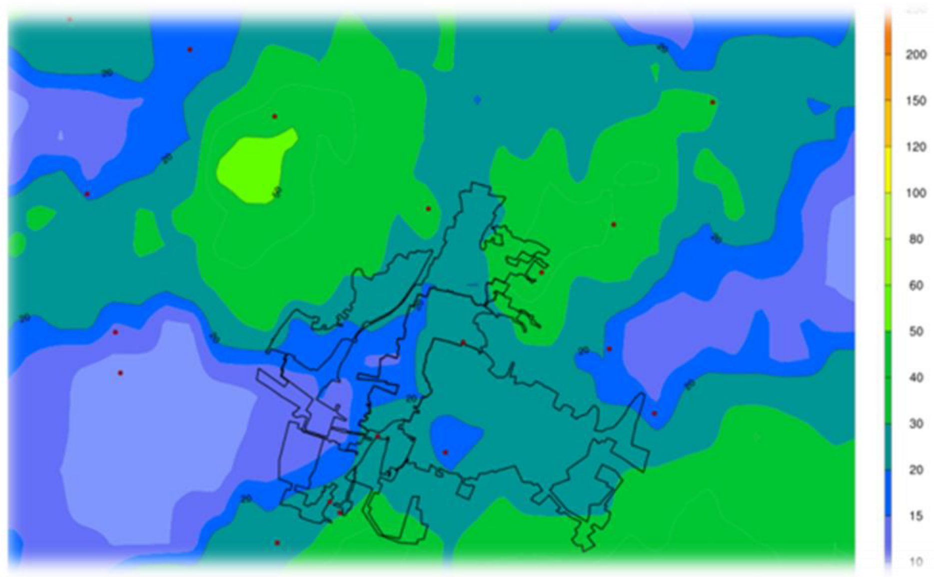
Computed data (including future levels and flows)

VG levels

The DSS structure



Rainfall data



Measurements

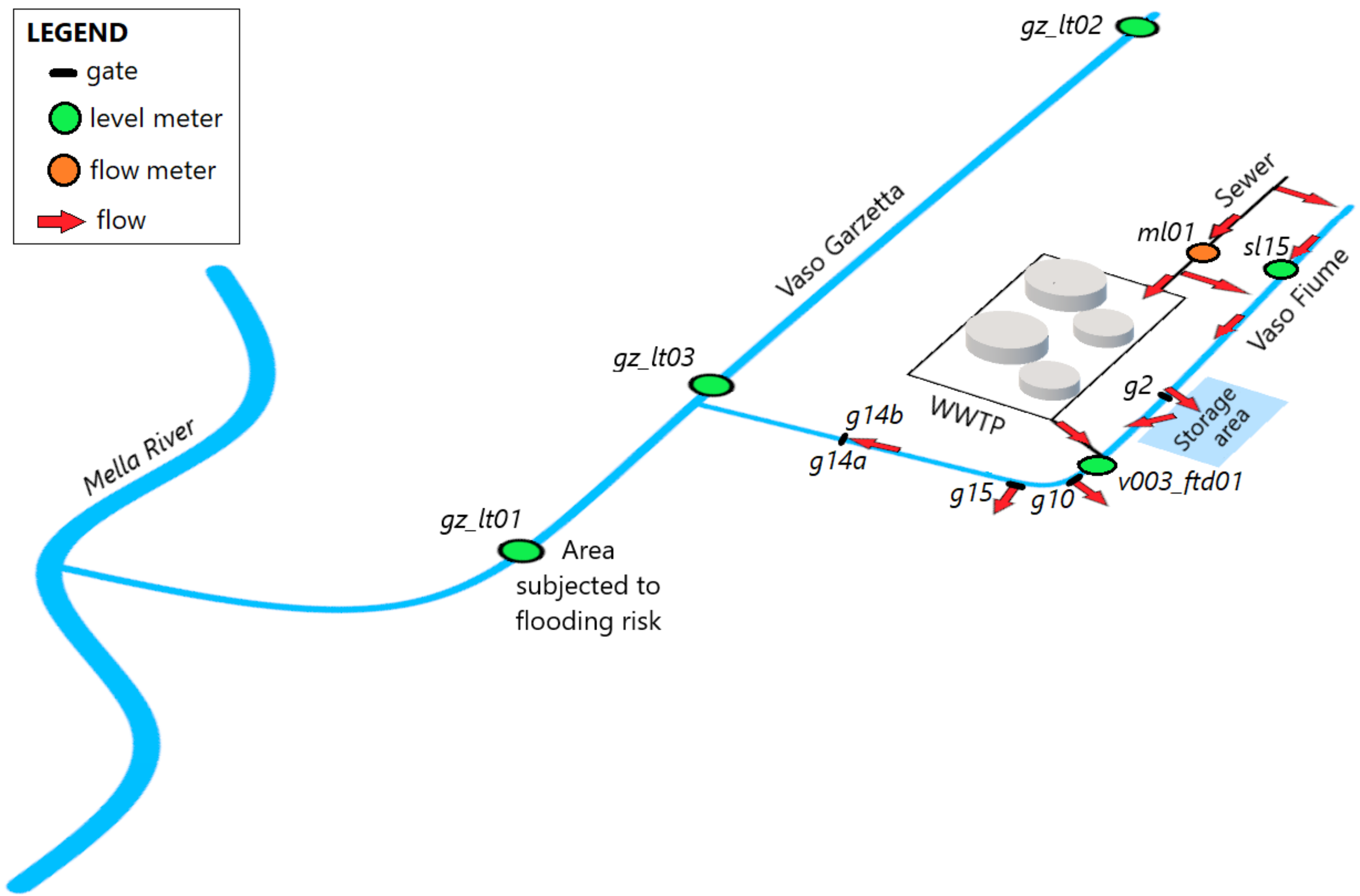
- Merging of pluviometers and radar data
  - distributed measurements are calibrated through punctual records
  - 1×1 km spatial resolution
  - 10-min time resolution
  - reliability: value accuracy and spatial variability

Forecasts

- Very-short-term Quantitative Precipitation Estimates (“Nowcasting”)
  - algorithms working on radar measurements
  - up to +180 minutes (up to +80 minutes are used)
  - 5 to 20-min update frequency

All rainfall measurements and forecasts are averaged over the whole catchment to obtain single values to be used for next computations.

Level and flow measurements



- New meters were added to those which were already installed
- VG level is monitored at 3 strategic locations
- All flows are measured or computed by means of algebraic sum of known values
- Sewer flow at *ml01* is an important piece of information to manage internal WWTP operations

Artificial Neural Networks for level and flow forecasts

Predicted variables

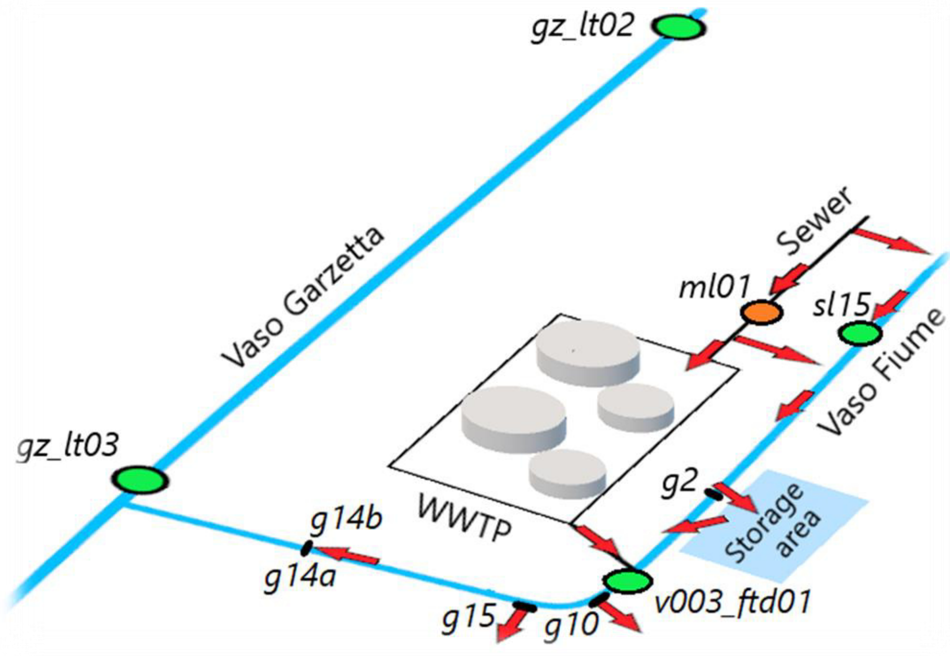
- VG level at *gz_lt02* meter: to promptly act on VF gates
- Sewer flow at *ml01* meter: to manage internal WWTP operations

Two time horizons

- "Short-term": up to + 60 min
  - based on measured rainfalls only
- "Long-term": up to + 140 min
  - based on measured rainfalls and nowcasting up to +80 min

ANNs details

- 20-nodes single hydden layer MLP
- Data subsetting: approx. 80% for training, 20% for validation
- 2000 runs for each ANN training, Levemberg-Marquadt BP algorithm
- Multi-objective optimization to select the best performing ANNs



Artificial Neural Networks for level and flow forecasts

3 thresholds were defined for *gz_lt02* level (70, 100, 140 cm) and for *ml01* flow (2.5, 3.5, 4.5 m^3/s).

Accuracy and timing of threshold crossing prediction play a key role in optimization criteria.

		Threshold 1	Threshold 2	Threshold 3
ANN_{LS} Level Short-term	n. observed.	22 (17 / 5)	9 (6 / 3)	4 (2 / 2)
	n. predicted.	22 (17 / 5)	6 (4 / 2)	3 (2 / 1)
	predicted %	100.0 (100.0 / 100.0)	66.7 (66.67 / 66.67)	75.0 (100.0 / 50.0)
	a.w.t. (min)	36.8 (35.2 / 42.0)	25.0 (27.5 / 20.0)	33.3 (35.0 / 30.0)
	a.p.d. (min)	3.2 (3.6 / 2.0)	1.7 (0.0 / 5.0)	-3.3 (0.0 / -10.0)
	false alerts	10 (7 / 3)	1 (1 / 0)	0 (0 / 0)
ANN_{LL} Level Long-term	n. observed.	22 (17 / 5)	9 (6 / 3)	4 (2 / 2)
	n. predicted.	22 (17 / 5)	5 (3 / 2)	3 (2 / 1)
	predicted %	100.0 (100.0 / 100.0)	55.6 (50.0 / 66.67)	75.0 (100.0 / 50.0)
	a.w.t. (min)	97.7 (91.8 / 118.0)	116.0 (110.0 / 125.0)	113.3 (115.0 / 110.0)
	a.p.d. (min)	-7.3 (-5.9 / -12.0)	-10.0 (-3.3 / -20.0)	3.3 (0.0 / 10.0)
	false alerts	9 (6 / 3)	4 (2 / 2)	0 (0 / 0)
ANN_{LS} Flow Short-term	n. observed.	56 (45 / 11)	11 (7 / 4)	2 (1 / 1)
	n. predicted.	34 (31 / 3)	7 (4 / 3)	2 (1 / 1)
	predicted %	60.7 (68.9 / 27.3)	64.7 (57.1 / 75.0)	100.0 (100.0 / 100.0)
	a.w.t. (min)	35.9 (36.4 / 30.0)	22.9 (22.5 / 23.3)	45.0 (30.0 / 60.0)
	a.p.d. (min)	0.0 (0.3 / -3.3)	5.7 (15.0 / -6.7)	5.0 (20.0 / -10.0)
	false alerts	16 (10 / 6)	2 (1 / 1)	0 (0 / 0)
ANN_{FL} Flow Long-term	n. observed.	56 (45 / 11)	11 (7 / 4)	2 (1 / 1)
	n. predicted.	36 (32 / 4)	9 (5 / 4)	2 (1 / 1)
	predicted %	64.3 (71.1 / 36.4)	81.8 (71.4 / 100.0)	100.0 (100.0 / 100.0)
	a.w.t. (min)	71.4 (69.7 / 85.0)	73.3 (98.0 / 42.5)	100.0 (70.0 / 130.0)
	a.p.d. (min)	8.9 (8.4 / 12.5)	5.6 (2.0 / 5.0)	15.0 (30.0 / 0.0)
	false alerts	15 (5 / 10)	2 (2 / 0)	0 (0 / 0)

a.w.t.: average warning time; a.p.d.: average prediction delay.

- Predicted crossing: signalled to occurr at least once in the available time horizon
- Average warning time: first alert of impending crossing with respect to actual crossing
- Average prediction delay: predicted anticipation – actual anticipation at the time of first alert

✓ The majority of the most severe threshold crossings are predicted

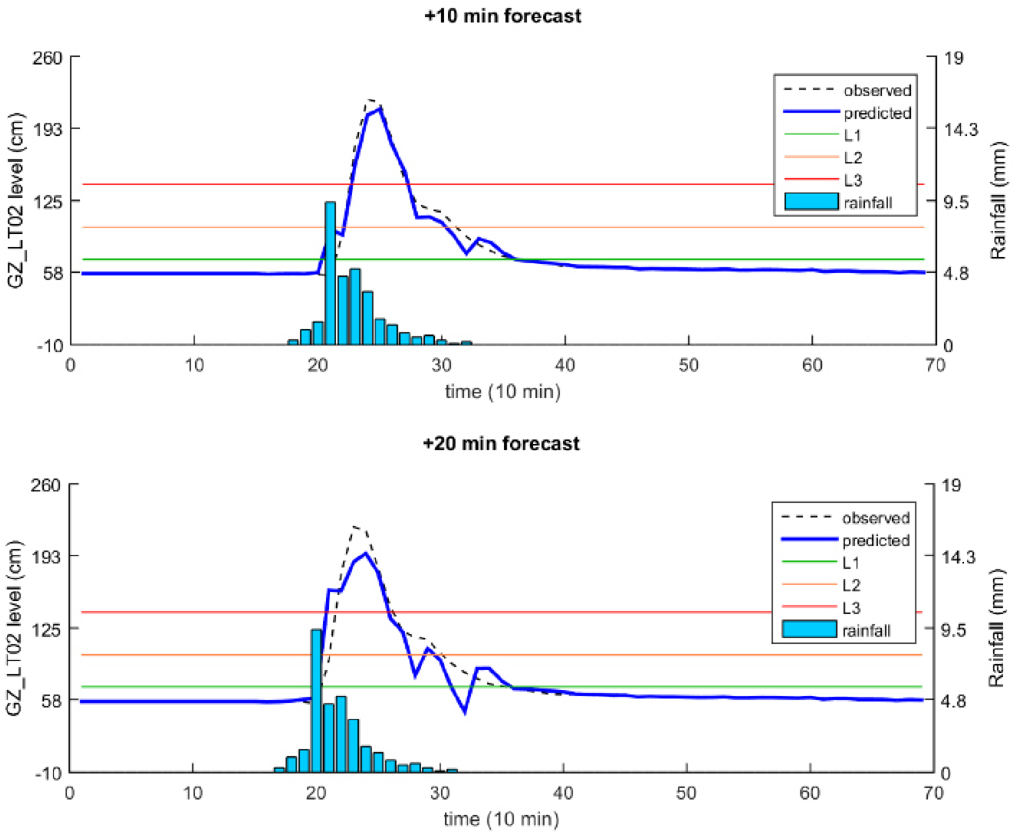
✓ All the lower threshold crossings at *gz_lt02* are predicted

✓ a.w.t. ≃ 25÷40 min for short-term, up to 120 min for long-term

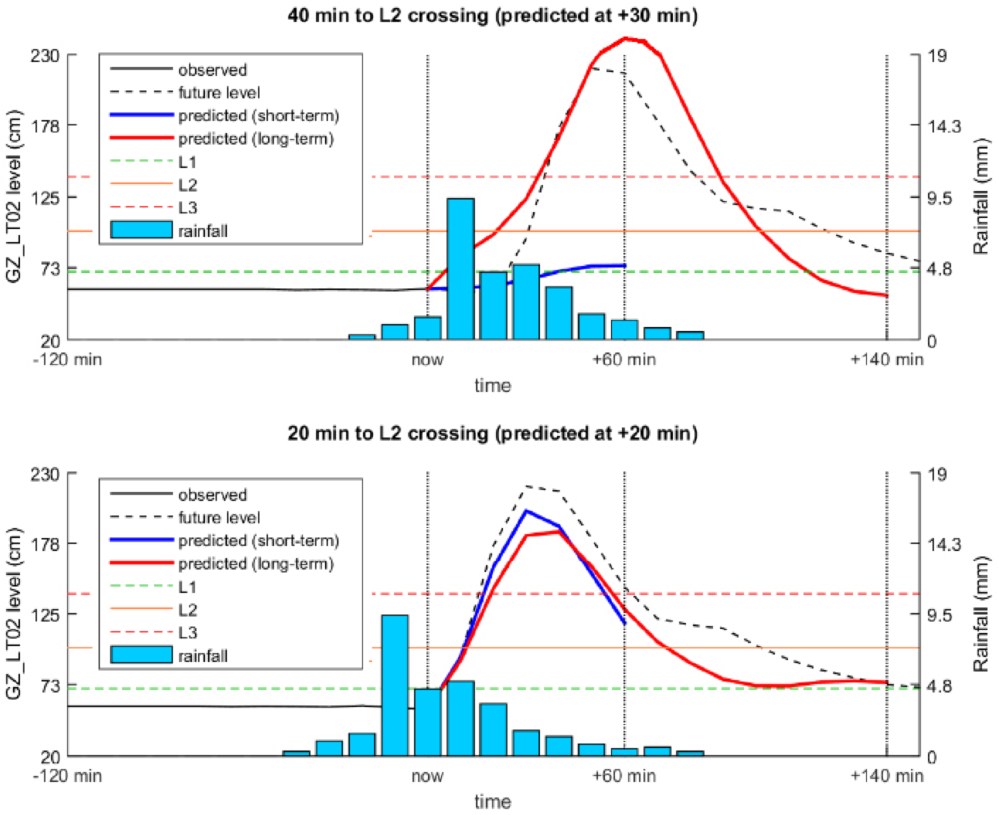
✓ a.p.d. generally lower than 10 min

✓ Flow predictions slightly outperformed by level predictions

Artificial Neural Networks for level and flow forecasts



Envelop of +10-min and +20-min level forecast for a given event



"Snap-shot" of prediction window 40 minutes and 20 minutes before crossing of 100 cm level threshold

User Interface

- Qgis plugin running on remote desktop
- Measured and forecasted rainfall
- *gz_lt02* level and *ml01* flow in the past 6 hours and forecasts up to +60 and +140 minutes
- Current and suggested gate openings: 4 strategies depending on observed crossings of the defined thresholds at *gz_lt02*
- Embedded HEC-RAS model of VF

Simplified User Interface

- Visualization-only interface
- Available on desktop and mobile devices
- 3 dashboards:
  - real-time (in figure)
  - past data
  - accuracy of past predictions

Further developments

- **Enhancement of ANNs performance**
  - *more data*
  - *different structures (e.g. LSTM)*
  - *analysis on unseen data (testing set)*
- **Investigation of rainfall forecast accuracy** (perfect forecast hypothesis was used in developing the DSS)
- **Improvement of the current mitigation strategies,** based on long-time experience and triggerd by measured *gz_lt02* level
  - *ex-post testing of different gate opening combinations and threshold through the HEC-RAS model*
  - *integration of real-time multi-objective functionalities*
- **Installation of automatic actuators in order to implement a Real-Time Control System**

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Thank you for your attention!