Several small or single large? Quantifying the catchment-wide performance of on-site wastewater treatment plants with inaccurate sensors

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S1. Model concept

The article aims to estimate accuracy requirements on soft sensors to minimize effects on environmental and human health by unobserved faults and failures due to insufficient monitoring of OST. Therefore, we developed a stochastic model to explore the true and by sensors observed mean treatment performance of a large number of OSTs within a catchment with Monte Carlo simulations. The model quantitatively connects the various elements needed to operate and supervise many OSTs in a catchment.

True performance

The true performance is described in two modules: the failure module (I) and the performance module (II). Together they mimic the underlying true performance of the individual OST, from which the overall true performance of all OSTs in a catchment is quantified.

The *failure module* (I) defines when the operational state of an OST unit changes. Its output is the state of the unit. This state describes normal operation as well as technical and biological malfunctions. A failure state is the most relevant and can be categorized, for example, as reversible or irreversible. Reversible failures are faults from which the OST recovers without intervention such as a minor toxic shock, while irreversible failures can only be fixed through intervention such as broken aeration equipment. The input to the failure module comes from the intervention module, and the output goes to the performance module (see Figure 1).

Based on the OST state output from the failure module, the *performance module* (II) estimates the true performance of every OST in the catchment. Performance can be defined in different terms, but the true and the observed performance (derived from the monitoring module) should be compatible.

Observed performance and sensor-based maintenance strategies

The observed performance characterizes the operational part of an OST system and consists of three modules:

The *monitoring module* (III) includes measurement accuracy and data transmission. The monitoring module processes measurements by soft sensors and human observations, e.g., inspectors or local operators. The accuracy of the measurements determines how accurate the true treatment performance is represented. The module output is the observed performance of the OST, and the output is the input for the alarm management and the observed overall catchment performance quantification.

The *alarm management module* (IV) aggregates and interprets the output from the monitoring module on the level of individual OST. The output of the alarm management module is a flag on units that need intervention.[35] The rules for flagging depend on the soft sensor's accuracy. If the soft sensor is inaccurate, then the observed state can be aggregated over time to provide enough certainty to trigger the required accuracy threshold defined in this module (see Section 2.2 for the implementation). The alarms can be labeled, for example, with different flags for different levels of intervention urgency.

The *intervention module* (V) defines the different types of interventions, the effort to carry out the intervention, and its effect on the unit's state defined in the failure module. Possible interventions are regular servicing (decreasing the failure probability) or maintenance called for by the alarm management module. In the simplest case, the intervention module issues a maintenance intervention whenever the alarm module flags an OST. Further examples of rules, which we did not implement for this study are: technicians are sent out depending on the state of the surrounding OSTs by a shortest path algorithm, or the mean observed treatment performance in the catchment could be used as a rule for the intervention module (if the system is in a critical state, interventions are carried out faster).

Model walkthrough

I. Failure module: The model starts with a unit age t = 0 in the failure module. The hazard rate of the Weibull distribution is calculated based on the unit age, and then a number from a uniform random distribution is drawn which is compared to the hazard rate. E.g. for λ = 365 days (so a mean survival time of a OST unit of one year), the hazard rate would be:

$$hazard\ rate(t, k, \lambda) = \frac{k}{\lambda}\left(\frac{t}{\lambda}\right)^{k-1} = \frac{2}{365}\left(\frac{1}{365}\right)^{2-1} = 1.5 * 10^{-5}$$

Therefore, the chance that the random number is below the hazard rate is very low. However, after one year the hazard rate is already 0.005. Which means 0.5% of the units are expected to fail on that day.

II. Performance module: Here, the true (effective) performance of an OST is modeled. If the unit failed then the performance is 0, if the unit is fully functional, then the performance is 1.

III. Monitoring module: Does the soft sensor monitor the true performance of the plant correctly? To determine if the soft sensor monitor correctly, a random number is drawn from a uniform distribution and compared to the specificity respectively sensitivity. If the random number is below the sensitivity respectively specificity, the prediction is true (correct); if it is above the prediction is false. Based on if the performance is 0 (down) or 1 (up) the specificity, respectively the sensitivity is used to compare the random number with. Based on the true performance and the sensor prediction, the observed performance is determined. For example, if the true performance is up and the soft-sensor is true, the observed performance is also up. If the true performance is up and the soft sensor is false, the observed performance is down.

IV. Alarm management module: Four different alarm management strategies were implemented. They are described in detail in the main article. To decide if an alarm is issued the binary input from the monitoring module was taken over time and the consecutive down states were used to cause an alarm.

V. Intervention module: Whenever an alarm is issued for an OST, an intervention takes place. In the implemented case this means that the true performance is set to 1 (up), independent if it was 1 or 0 before.

S2. Influence of the modeled number of units on the variance

Goal of the comparison of the results was to investigate how the variance changes for various catchment sizes over a period of ten years. It seems that the variance is already very small due to the long time period. Therefore, the number of units has a rather small influence on the variance.

S3. Results for a fleet of 10 units

The results are for soft-sensor accuracies of [50%, 60%, 70%, 80%, 90%, 100%] respectively

variance real treatment performance: [0.0025820987051979752, 0.004248948020266468, 0.0015901339838618887, 8.512591480577957e-05, 0.0002488271720773127, 0.0003604736348282982],

variance of maintenance: [1.0301, 2.2221, 1.8849, 0.24049999999999994, 1.6144000000000003, 5.0596000000000005],

variance observed treatment performance: [0.0, 1.8936261345123424e-10, 1.6593272156146452e-09, 4.4996688533731963e-10, 1.254363515274734e-08, 0.0010949774027157184]

average real system performance: [0.9443013698630137, 0.9385479452054794, 0.954849315068493, 0.9876986301369863, 0.9830136986301371, 0.9829315068493152],

average maintenance per unit per year: [11.830000000000002, 7.07, 3.4899999999999998, 1.3499999999999999, 1.4600000000000002, 2.02],

display: [0.5004109589041096, 0.5838630136986301, 0.6798630136986301, 0.7858082191780822, 0.8845753424657534, 0.9686575342465753]

Average treatment performance without monitoring for [0, 1, 3] scheduled inspections respectively: [0.3352602739726027, 0.702082191780822, 0.8607123287671232],

S4. Results for a fleet of 100 units

The results are for soft-sensor accuracies of [50%, 60%, 70%, 80%, 90%, 100%] respectively.

variance real treatment performance: [0.004753162507036968, 0.003929296115593921, 0.0008758656408331768, 0.00039054363670482225, 0.0003842555376243198, 0.00018928231187840118],

variance of maintenance: [0.9844510000000001, 1.9276639999999998, 1.4078440000000003, 1.4623359999999996, 3.0928999999999998, 2.7180839999999993],

variance observed treatment performance: [0.0, 1.300526239547236e-06, 5.215523179791499e-09, 2.272459201338749e-09, 2.989716753338844e-08, 0.0005769935582040898]

average real system performance: [0.9270821917808217, 0.9451095890410955, 0.9694794520547946, 0.9812821917808221, 0.9820986301369864, 0.9868712328767124],

average maintenance per unit per year: [12.193, 6.943999999999999, 3.266000000000001, 1.6080000000000003, 1.61, 1.5539999999999998],

average observed treatment performance: [0.4999095890410959, 0.5877643835616438, 0.6856794520547944, 0.7870684931506848, 0.8823123287671233, 0.9727232876712328]

Average treatment performance without monitoring for [0, 1, 3] scheduled inspections respectively: [0.3552328767123288, 0.682227397260274, 0.8039479452054796],

S5. Results for a fleet of 1,000 units

The results are for soft-sensor accuracies of [50%, 60%, 70%, 80%, 90%, 100%] respectively.

variance real treatment performance: [0.006212189627997748, 0.0029949382698442484, 0.0011836524673297052, 0.0005765992541940327, 0.00031181912223681737, 0.00020362656791142805],

variance of maintenance: [1.01547831, 1.37643159, 1.86931151, 2.1619075899999998, 2.42633084, 2.8090607600000004],

variance observed treatment performance: [3.009265538105056e-36, 2.0291128685224486e-07, 1.7875112182200727e-08, 4.036700376117136e-09, 2.153540005577033e-08, 0.0006270762166798214]

average real system performance: [0.9151942465753425, 0.947772602739726, 0.9676717808219177, 0.9781386301369863, 0.983948493150685, 0.9871252054794522],

average maintenance per unit per year: [12.148700000000002, 6.7279, 3.3043, 1.8078999999999998, 1.4554, 1.5118],

average observed treatment performance: [0.5000232876712328, 0.5884758904109589, 0.6858739726027397, 0.7845131506849315, 0.8840424657534247, 0.9733112328767122]

Average treatment performance without monitoring for [0, 1, 3] scheduled inspections respectively: [0.3105608219178082, 0.6556142465753425, 0.8405131506849315],

S6. Results for a fleet of 10,000 units

The results are for soft-sensor accuracies of [50%, 60%, 70%, 80%, 90%, 100%] respectively.

variance real treatment performance: [0.006808424498386188, 0.0027978142869814226, 0.0012425578111548135, 0.0006324162874655658, 0.0003262736529510227, 0.0001864488894539313],

variance of maintenance: [1.0181498599, 1.3613447324, 1.9137342075999997, 2.3430549479000002, 2.5211581710999997, 2.5904881056],

variance observed treatment performance: [3.009265538105056e-36, 1.6435894773439042e-07, 2.0166825167338428e-08, 7.404536991616862e-09, 2.330157495406327e-08, 0.0005676790661175882]

average real system performance: [0.9143343835616439, 0.9490133424657535, 0.9668844657534246, 0.9768501917808219, 0.9835392876712329, 0.9875971232876712],

average maintenance per unit per year: [12.155489999999999, 6.660259999999999, 3.3411800000000005, 1.88211, 1.49233, 1.46288],

average observed treatment performance: [0.4999458356164384, 0.5891453150684931, 0.6852874794520548, 0.7837873150684932, 0.8836648219178082, 0.9739280547945205]

Average treatment performance without monitoring for [0, 1, 3] scheduled inspections respectively: [0.31298246575342464, 0.6618068493150684, 0.8273238904109589],