Simulation and System Dynamics / Practical Assignment

Authors

Sergey Zakrytnoy - 0533981
Imrich Stoffa - 0539875
Ayushma Rayamajhi - 0532898

Introduction

Our task was to optimize the yearly maintenance schedule of two hydroelectric power plants located subsequently in a same river to try and maximize the total yearly revenue. For both power plants the number of days required for maintenance are 2 weeks, which can be either done as a whole set or divided into 1-week stoppages. The variables provided in the model are:

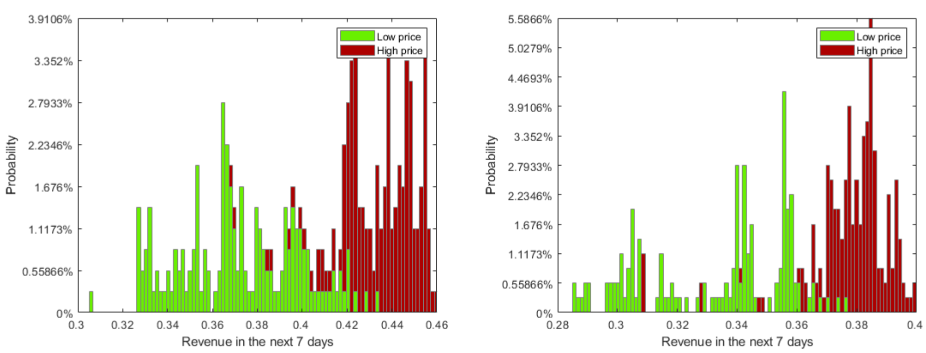
- Amount of daily rainfall (drawn from a generalized Pareto distribution, “rain”)
- Price of electricity (geometric Brownian Motion, “price”)

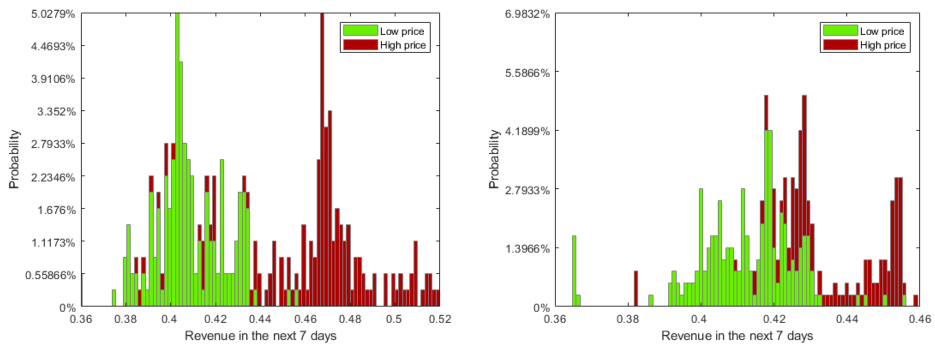
The total yearly mean revenue with default maintenance schedules is at 17.33 million with the 10% quantile at 14.96 and the 90% quantile at 19.91.

Solution Description

For this task, as maintenance of the plants starts, it means that the plant would stop working (produce no revenue) for at least 7 days or up to 14 days. To better understand the factors that could influence the total revenue, some preliminary research is done via simulation decomposition.

We ran the model with default parameter and no changes and tried to decompose the revenue in the next 7 days by rainfall, storage capacity, outflow of water and price. The results indicated that only the price of the electricity made an effect in the total yearly revenue i.e., lower the electricity price, lower the revenue. Several plots of simulation decomposition by price from randomly drawn rounds can be found in picture 1.





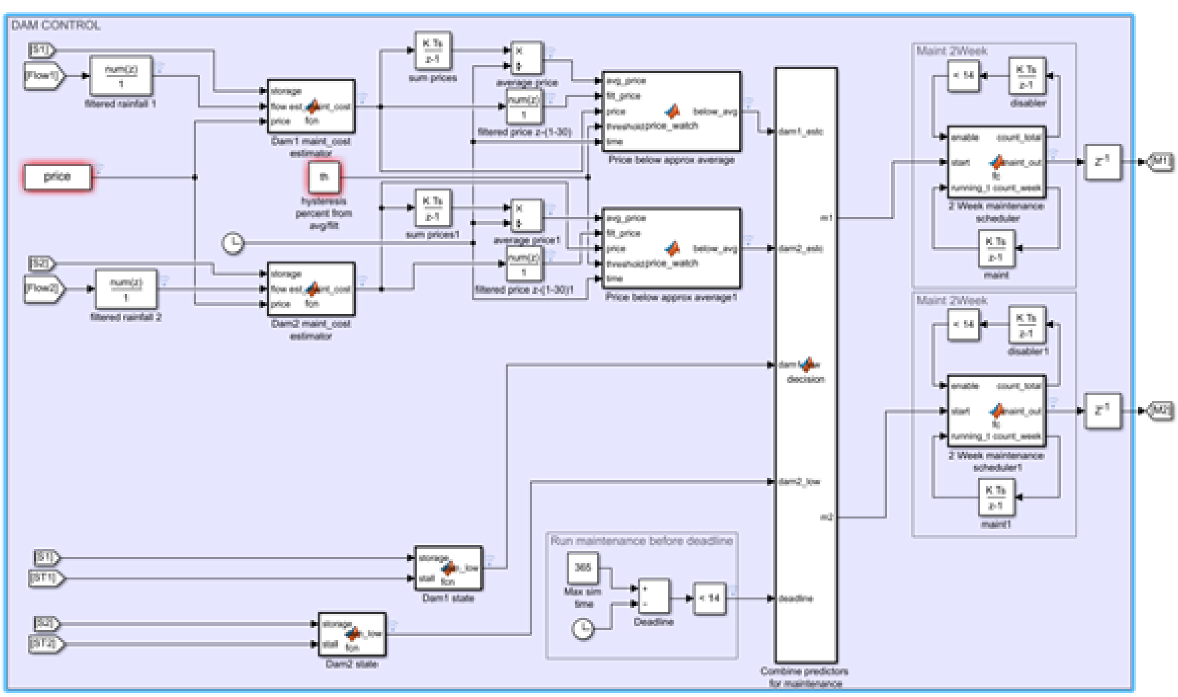
Picture 1. Simulation decomposition of revenue in the next 7 days by current price

We thus decided to only take into consideration the price when working on the model. To tackle this, we have looked at 2 different approaches.

Approach 1: Optimal stopping theory application. Generic solution to the secretary problem is applied. In this method, the previous research by one of the co-authors is used. We make no change in the actual Simulink model but instead, we try to work with prices. The maintenance schedule is created externally and fed into the model.

Approach 2: Changes to the Simulink model using combination of strategy called "deviation from mean" and moving average convergence and divergence (MACD indicator). For this approach we basically try to find points when the price value is going higher or lower than the mean value in that area and send signals to the model when the average price is lower, to start the maintenance scheduling. To make the signals more accurate moving averages are used and signals are sent if current value is a certain percentage below the moving average.

Function Block for Deviation from mean & MACD



In both approaches, if an ideal solution is not reached and no maintenance is triggered, the default setting is such that maintenance would take place in the last 2 weeks of the year.

Detailed Algorithm Description

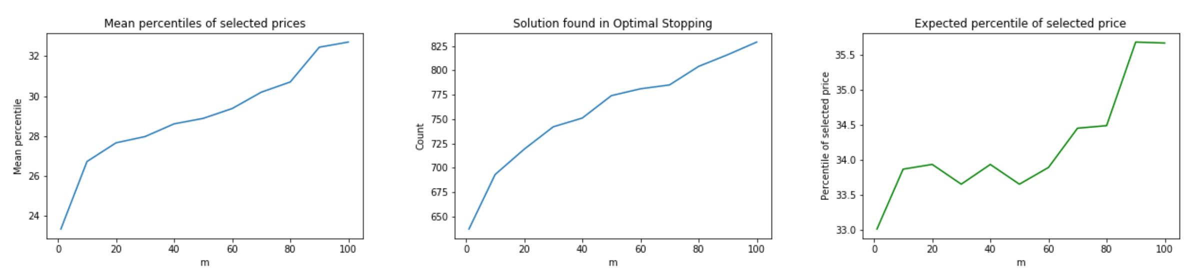
Approach 1: Optimal Stopping

In this approach, we are using an algorithm based on the theory of optimal stopping. The theory of optimal stopping is concerned with the problem of choosing a time to take a given action based on sequentially observed random variables in order to maximize an expected payoff or to minimize an expected cost[1].

The algorithm used in this research helps us solve the problem: given the total number of values n, identify if the currently observed value belongs to bottom m elements of the sorted list. According to the initial problem statement, $n = 365$ (number of days in a year), while m remains a parameter that is subject to further research. We experiment with the value of variable 'm' to see the various results that can be found. In this algorithm to define and understand whether the result is good or not, we use expected percentiles of the selected values in the overall set. In the course of experimenting, we limited m to range from 1 to 100. This value was chosen for 2 reasons:

- Exponential increase in computational time required;
- we already start to see a trend within these numbers that makes us able to understand how good the value of m is.

For each m we calculate the expected value of how good the selected price value would be (percentile) with formula $mean\_percentile * success\,rate + 0.5 * (1 - success\_rate)$, where $mean\_percentile$ is the average percentile of selected values across 1000 rounds of simulation for each given m, $success\_rate$ is the proportion of rounds in which at least some value was selected as optimal. In other cases (1 – $success\_rate$), we assume random choice and 0.5 mean percentile. We then look at all the given m values and pick the one which has the best expected solution.



Picture 2. Decision on parameter m for Optimal stopping approach

Based on the graphical analysis, we stick to m = 1 and m = 36 (as bottom 10% of the price that we are targeting). The two first values identified as optimal in the course of analysis for each round of simulation (standing at least 7 time steps apart) are taken as start dates for the maintenance.

[1] https://www.math.ucla.edu/~tom/Stopping/sr1.pdf

Approach 2: Deviation from mean & cost estimate

In this approach we are trying to see if we can estimate the time when the maintenance costs the least amount of money in the window of 7 days. We compute and observe the maintenance cost estimate evolution and try to decide from previous samples in the model. The variables used in this approach are:

- Price
- Dam input flow
- Dam storage
- Threshold

Idea

Main idea of solution is to create module that estimates when it is optimal to run maintenance, then combine the signals in one module which makes the decision.

For each dam, once there is a certain percentage drop in the estimated maintenance cost, a signal is sent to the model to start the maintenance process. If it exceeds certain threshold, there will be signal to enable maintenance.

The signals we considered for decision on maintenance triggering are:

- Next day there is outage in power production, or state of dam is low 0-2
- The estimated maintenance cost is below average, considering some threshold (parameter of simulation). 0-2

In the end we decided to combine all the cues into maintenance cost estimator, which provides better basis for threshold decision than multiple independent signals.

Algorithm

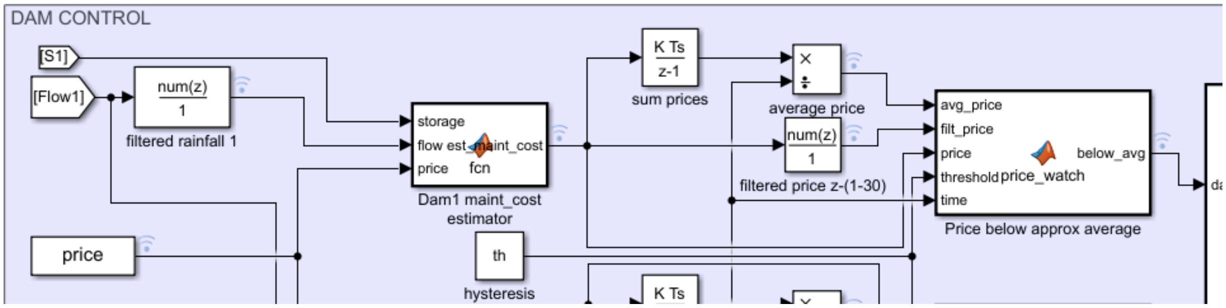
Price time series is modelled in MATLAB using the GBM equation, values are built using initial value, drift and volatility which is component generated using zero mean random distribution.

$$dS_t^i = \mu_i S_t^i \, dt + \sigma_i S_t^i \, dW_t^i$$

From this we inferred that If drift component is zero, best sample estimate for next time step is present sample, therefore it can be used as good enough predictor for next 7 timesteps. Module computes the estimates for each day (simulation time step), thus generating modified time series of estimated cost for the maintenance.

Inputs used for estimation of cost are:

- State of dam SX
- Consumption of generator stage 5 or 10
- Flow into dam FlowX, using rainfall, ground water and input from previous dam if any. This is filtered with moving average of size 30 samples.
- Actual price of electricity



Estimated cost is then processed to mean and moving average, and at each time step evaluated against them. Price below approx. average searches for fluctuations and if threshold is exceeded, pulse with levels 1-2 are generated.

Mentioned signals can look like on following figure 1. It is proposing itself to make 2 level decision with thresholding. However, until averages are somewhat stable decision should not be made.

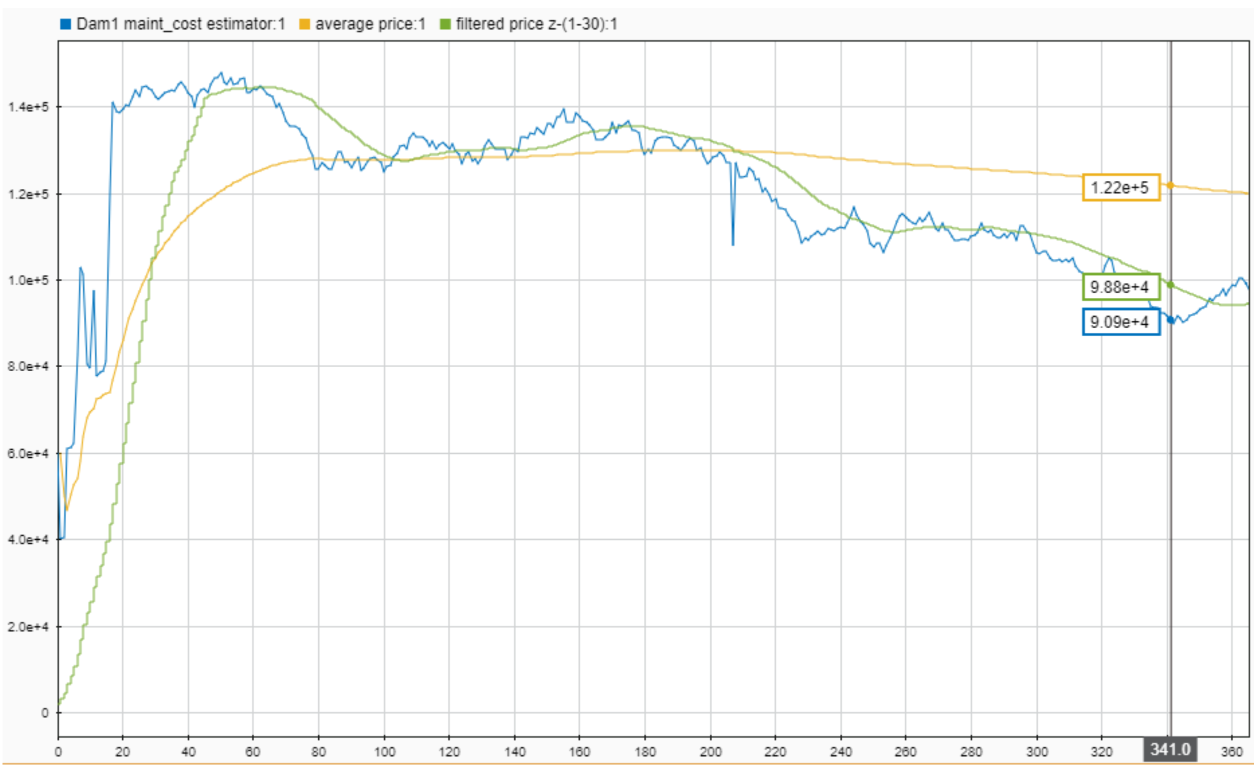


Figure 1 Cost estimation signals

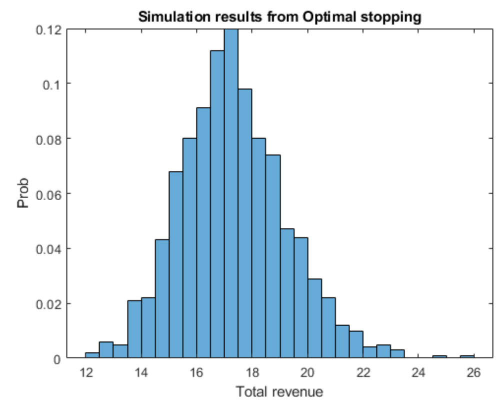
Simulation Results

The two approaches applied to the simulation analysis resulted in very different results in terms of the total revenue. It was useful to note that without any maintenance scheduled, the highest mean total revenue we could achieve was 17.99MEur.

Optimal stopping

Despite promising results received from preliminary analysis on the generated prices GBMs, the application of optimal stopping theory to scheduling maintenance did not produce positive improvement in mean value but contributed to a more robust approach (pushed both 10% and 90% quantiles to the mean).

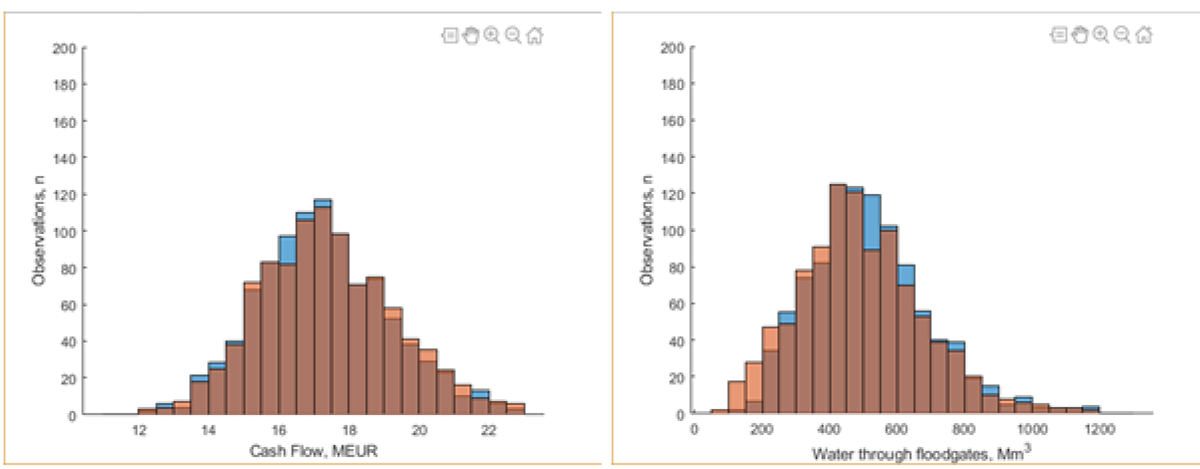
	Default	Optimal Stopping
Mean Value	17.33	17.32
10%	14.96	15.01
90%	19.91	19.84



Picture 3. Results from Optimal stopping approach

Deviation from mean & cost estimate

The histograms below provide a graphical comparison of our SD approach to the problem and simulation with default settings. We observe considerable improvement of almost 100k EUR of average total revenue in absolute terms.



Picture 5. Comparison to default

	MEUR Controlled	Default	Mm^3 Controlled	Default
Mean Value	17.4204	17.3250	491.8326	516.4554
10%	15.0257		254.0147	
90%	20.0581		740.6595	

The results presented above were achieved using just maintenance cost estimation and control decision using below_avg==2 condition. Clearly, tracking water outflows that do not contribute to production (water management) is better since it implies more efficient use of the resources, which results in higher mean and quantiles.

One of the possible problems related to the described approach is the rounds when the simulated price series is too stable to provide enough triggers from mean deviation. However, our decision making model also considers estimated amount of water available in 7 timesteps into future which can create dips below average too. Sensitivity analysis is therefore required to have a more profound understanding of the results.

The figure below demonstrates that the maintenance planning is far from being random or static. Reason for bias in planning towards beginning might be error in actual mean estimation and effects of different kinds of scenarios (constant rising, falling or stable oscillating of cost estimate). Columns represent amount of maintenance days out of all simulations at each time step. The peak in the last two weeks of simulation stand for the scenarios when no maintenance was triggered from the observed events.

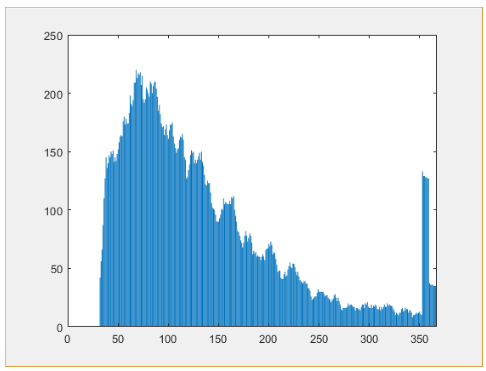
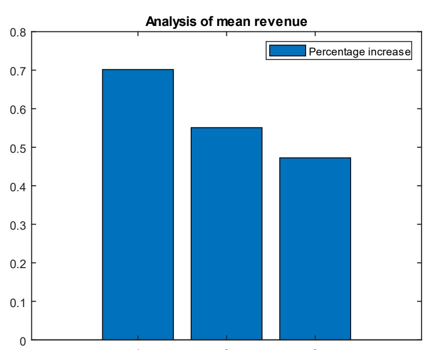
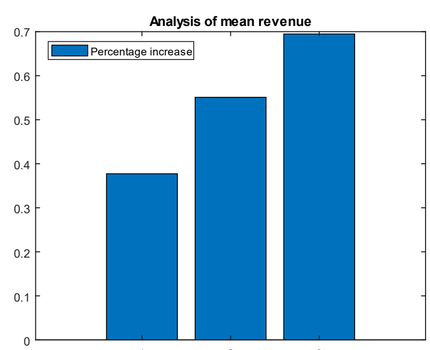


Figure 2 Vector sum of maintenance plan

Sensitivity analysis

To identify possible opportunities and weaknesses of the model, we conducted sensitivity analysis of percentage improvement relative to default plan (y-axis) against two parameters: volatility and drift of the generated price.





Picture 6. Sensitivity analysis against volatility (left) and growth (right).

The scenarios from 1 to 3 in case of analysis against volatility correspond to 10, 20 and 30% respectively, and the scenarios in case of drift are for -10, 0 and 10% growth. Thus, we see that our model is robust for all of the mentioned scenarios. However, we can see that the improvement is stronger in cases of stronger growth of price and lower volatility.

Conclusion

Through multiple approaches, optimal stopping and deviation from mean, we explored anomalies in model behavior which decreases mean revenue and tried to turn them into signals for decision.

The general description of the problem that a decision maker is facing in case of using this model is that the future is too uncertain, i. e. we have limited knowledge regarding the probabilities of observed events happening in the future. Optimal stopping to some extent provides a probabilistic solution to this problem.

Deviation from mean strategy yielded good results just by itself. Maintenances reliably run mostly in local minima of price, dam state and low rain combinations, this improves revenue and water utilization. If not for the exponentially growing computational requirements, the best thing would be to combine these two approaches: cost estimation and optimal stopping.