Machine Learning and Its Application at Nooksack Falls Hydroelectric Station

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The objective of this project is to control water delivery and distribution at Nooksack Falls Hydroelectric Station (NFHS) in order to maximize efficiency of the system, thereby increasing energy generation. Two machine learning algorithms will be applied. (1) Q-learning - a reinforcement learning approach to obtain a set of roughly optimal configurations. (2) Recurrent Neural Network (RNN) - rough configurations gathered by the Q-learning agent will be used to train the RNN. The RNN will refine these configurations as well as enabling lifelong learning. The significance of this project is to demonstrate the practical utility of the machine learning techniques described above when applied to real-world processes such as NFHS.

Utility process control has advanced towards increasing productivity and reliability, while decreasing operating costs by replacing humans with automated systems. When NFHS began operation in 1906, it required 24-hour manned operation, a job shared by several men with families living on site. In the 1970s a system of electromechanical relays, DC positioning motors, and low pressure hydraulics were added, decreasing the need for operator attendance. In 2003 a more sophisticated set of controls were added including: high pressure hydraulics, a programmable logic controller (PLC), and a host of relay and analog sensors providing information on plant state.

The evolved control configuration outlined above is typical of modern utility process control. Sensor inputs, along with a control scheme devised by plant operators and engineers are programmed into the PLC, which operates the plant according to adjustable set-points. This works well for static processes, those without a great variance of operating conditions. However, NFHS is a dynamic process. Fluctuating river flow conditions, waterborne debris, equipment wear, and mechanical problems are variables impacting NFHS's energy production. For the process to remain optimal, set-points should be adjusted accordingly.

$$KW = \frac{H \times Q \times E}{11.8}$$

Figure 1. Kilowatt Production

When discussing optimization it is helpful to revisit the main goal: maximize energy (kilowatt) production given current resources. According to the formula in Figure 1, an increase in variables Head (H), Flow (Q), or Efficiency (E) will increase kilowatt production. Optimization for NFHS can be divided into two pieces relative to these variables: H and Q - delivery of water, E - distribution of water.

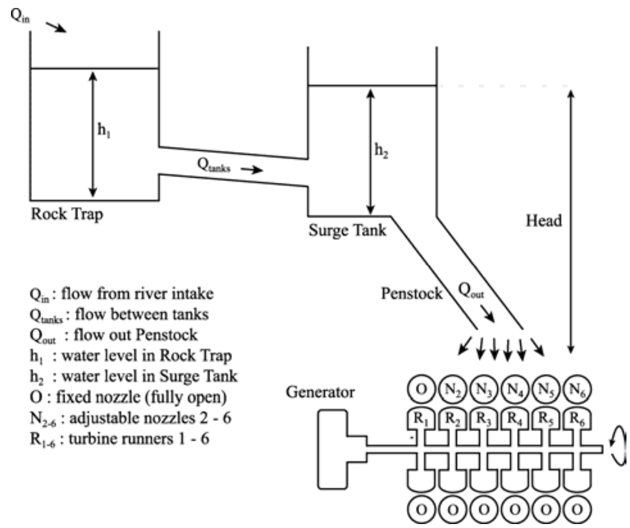

Figure 2. NFHS Process Diagram

Water delivery is optimized by maximizing both H and Q from Figure 1. Figure 2 shows how H and Q relate to NFHS. Head is the vertical height from the water level in the Surge Tank to the level where the water leaves the runner nozzle. Q_{out} is the flow rate of water passing through the penstock that is available to be distributed amongst runners $R_{1\text{-}6}$. Head is adjusted by controlling the water level in the Surge Tank. This is accomplished by adjusting Q_{out} via nozzles $N_{2\text{-}6}$. Q_{tanks} is the maximum rate at which water flows between the tanks. This is controlled primarily by the difference in tank levels, also known as the pressure gradient. As water is diverted from the river it travels a distance of 2,600 feet between the dam and the turbine, losing an elevation of 206 feet. This diversion includes a combination of box section flume, wood pipe, steel pipe, and unlined rock tunnel. The wood and steel pipe section existing between the two tanks (see Q_{tanks} in Figure 2) is the most restrictive section of water conveyance and limits the flow available to the Surge Tank regardless of river flow or Q_{in}. Let's look at some cases that show how these variables interact in order to clarify the problem.

Case 1: Due to recent heavy rainfall, river flow is higher than normal. The extra river flow increases Q_{in} which increases water level at the Rock Trap, increasing the pressure gradient between the Rock Trap and the Surge Tank. The increased pressure differential allows Q_{tanks} to equal or exceed maximum turbine flow. This allows us to set the Surge Tank level (head water level set-point) to its maximum (maximizing H) and open up all adjustable nozzles $N_{2\text{-}6}$ (maximizing Q_{out}).

Case 2: Due to cold temperatures and lack of precipitation Q_{in} is lower than normal. From years of experience, the station operator knows that the current Q_{in} will sustain a Surge Tank level of 50% and a Q_{out} of 40%. Although this is sustainable it is not necessarily optimal. The optimal solution lies in one of two directions: lose Head and gain Q_{out}, or lose Q_{out} and gain Head. Located somewhere in the middle of this ratio lies an optimal configuration.

Water distribution is optimized by maximizing efficiency of the turbine. As shown in Figure 2, the system contains a single turbine with six runners R_1-R_6, each with an upper and lower nozzle. All lower nozzles and R_1's upper nozzle are fixed. That is, 100% open at all times. Upper nozzles N_2-N_6 are adjustable, capable of 0-100% flow adjustment. The goal of water distribution is to control flow through the nozzles $N_{2\text{-}6}$ in order to match Q_{in} and maintain the current head water level set-point. Each runner is of varying condition (wear) and efficiency (different design) so when Q_{out} is limited (all the nozzles are not wide open), E will increase if water flow is distributed to the most efficient runners, and more energy will be produced.

The process described previously is one with thousands of optimal configurations as a function of river input. Were this process to exist in a controlled environment with no equipment unknowns it would be relatively simple to perform physical calculations to obtain optimal configurations. The fact that NFHS exists in an uncontrolled environment (e.g. debris from river can enter system, river flows can vary widely) using legacy equipment with unknowns (e.g. individual runner efficiency) makes machine learning an ideal solution for determining optimal operation set-point configurations.

The first step in learning is to create a set of roughly optimal configurations. Since we have no data a priori we take a reinforcement learning approach, making Q-learning an ideal candidate. With Q-learning, the outcome associated with taking a particular action in any state encountered is learned through dynamic trial-and-error exploration of alternative actions and observation of the relative outcomes. Two agents will be used: Agent one is responsible for water delivery, controlling the Surge Tank level (Head) and being rewarded for sustainable increases in $Q_{out} * \text{Head}$ (see Figure 2). Agent two is responsible for water distribution, controlling adjustable nozzles $N_{2\text{-}6}$ and being rewarded for increases in E. Although the agents will be learning in tandem, since each agent is completely independent of the other they will not share information.

One major shortcoming for Q-learning in this project is its inability to handle continuous outputs. To overcome this limitation the output from adjustable nozzles $N_{2\text{-}6}$ are divided into a series of discrete outputs. For example, N_2's 0-100% analog range is converted to discrete output range {0%,10%,20%,...,100%}. This may seem like an undesirable loss in resolution, and it is, but as resolution decreases the probability of the Q-learning algorithm's success increases. Once we have these roughly optimal discrete valued configurations they may be used to train their respective RNN implementation.

The motivation for switching to a neural network implementation is to achieve a greater resolution in optimal set-point configurations. Neural networks with one or more hidden units have been proven capable of approximating any bounded continuous function to within an arbitrarily small error (Cybenko 1989), (Hornik, Stinchcombe, and White 1989). It is easy to see that the continuous output setting of N_2=83.4% will allow for a more optimal configuration than the discrete output setting of N_2=80%.

When choosing amongst varying neural network architectures, it was important to keep limitations of the training data in mind. Since NFHS exists in an uncontrolled environment, it is improbable that the data provided by the Q-learning agents accounts for all possible environmental conditions. For example, debris could make its way through the system and partially clog N_3. This effectively reduces the efficiency of R_3. It is important for the network to be able to notice this change in R_3 and adjust optimally.

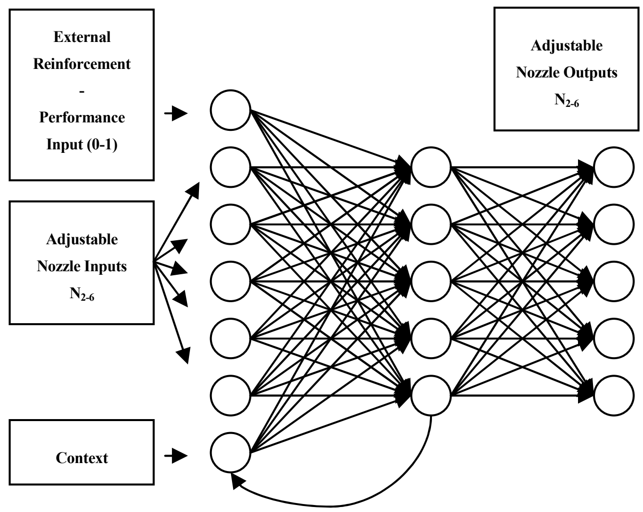

Figure 3. NFHS RNN Architecture

The RNN architecture shown in Figure 3 is an ideal candidate due to its feedback loop, allowing for information to be temporarily memorized by the network. This feedback loop paradigm, in combination with pre defined internal rules, and an external performance input, allows the RNN architecture to provide lifelong learning behavior. Let's look at the RNN for nozzle control more specifically. If a clog occurs in N_3 kilowatt output will decrease to a lower than expected value. This causes our external performance input to produce a low value which in turn violates an internal performance rule of the network. The network then switches into learning mode, in which it randomly modifies individual nozzle settings in an attempt to improve kilowatt output. This occurs for a predefined period of time or until the performance input no longer violates the internal performance rule.

References

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