DEVELOPMENT OF CROSS-FLOW HYDROKINETIC TURBINE CONTROLLER IN SIMULATION, EXPERIMENT, AND FIELD TESTING

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INTRODUCTION

A controller was developed for Ocean Renewable Power Company's RivGen® turbine (Figure 1), a cross-flow helical hydrokinetic turbine, using a combined approach of simulation, power train emulation, and small-scale flume testing. Conclusions from the different testing modes were found to be in general in agreement. This paper discusses simulation, flume testing, and field testing in Summer 2015. Emulation results are described in [1].

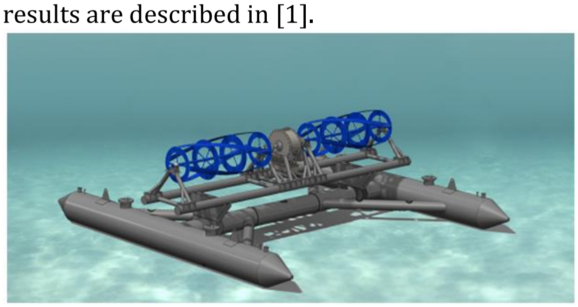

FIGURE 1. RENDERING OF RIVGEN TURBINE.

Controllers Considered

Two categories of controllers were evaluated: feedback and feedforward. Within each class, controllers were considered that required or did not require an estimate for free-stream velocity. Nonlinear feedforward control (Kω^2) is commonly used for maximum power point tracking in the wind industry [2]. Proportional-Integral feedback speed control (PIω) is a linear feedback controller on turbine angular velocity that has well-characterized responses to disturbances; and performance can be evaluated through linearization of the governing dynamics. Since turbine efficiency is a function of tip speed ratio (λ), feedback tip-speed control (PIλ) would be expected to outperform PIω in turbulent inflow. This controller has been shown to perform well for cross-flow hydrokinetic turbines [3], but requires an estimate of inflow velocity (U). Tip speed ratio and efficiency are defined, respectively, as

$$\lambda = R\omega / U \quad (1),$$

$$\eta = 2\tau\omega / (\rho A U^3) \quad (2)$$

where R is turbine radius, ω turbine angular velocity, τ is the torque produced, ρ water density, and A turbine projected area. If τ is specified as mechanical torque, η describes the turbine mechanical efficiency (i.e., C_P). If τ is specified as generator control torque, η describes the combined electrical efficiency of the turbine rotor and power take-off. For laboratory experiments, measurements of mechanical efficiency are possible, whereas in the field, electrical efficiency is quantified.

Controller Performance Metrics

Controller performance can be quantified as the ratio of energy produced by a candidate controller to an ideal controller that maintains optimal η. Energy loss, the percentage of energy lost due to non-ideal controller behavior, is defined to be

$$E_{loss} = 1 - \frac{\int_0^T \tau(t)\omega(t)dt}{\frac{1}{2}\rho A \eta_{max} \int_0^T U(t)^3 dt} \qquad (3)$$

where η_{max} is the maximum turbine efficiency and T is the duration over which controller performance is evaluated. A candidate controller approaches ideal as E_{loss} goes to zero.

In simulation, where all measures of turbine performance are known exactly, E_{loss} is an effective metric for distinguishing between candidate controllers. However, in laboratory and field tests, where certain quantities must be estimated from measurements, E_{loss} can only differentiate controllers with significantly different performance. To address this limitation, a comparison of the range of control torque demands (τ_c) and the set-point (ω, λ) holding ability of a controller were also evaluated to characterize performance.

SIMULATION

Methods

A simulation was implemented in MATLAB Simulink that numerically integrated the turbine dynamic equation to solve for ω based on a τ value prescribed by a controller and an unsteady U time series obtained from acoustic Doppler velocimeter (ADV) measurements in either the field or a flume. Because it is desirable that a control strategy be resilient to spurious noise, a logic block was included that allowed Gaussian noise to be added to the ω estimate used by the controller. Measurement noise can typically be represented as a Gaussian distribution around the true (mean) value [4]. The simulation also included a filter to attempt to recover performance in the presence of noise. Simulations were carried out for RivGen and flume turbines, the properties of which are summarized in Table 1.

TABLE 1. TURBINE PARAMETERS IN SIMULATION

	Flume	RivGen
Radius (m)	0.086	0.70
Length (m)	0.234	8.20
# of Rotors	1	2
Swept Area (m^2)	0.040	11.48
J (kg m^2)	0.005	277.5
Damping (N m s)	0.003	17

Non-dimensional performance estimates for RivGen were based on cubic polynomial fits of (λ,η) data from constant torque characterization of the turbine in 2014 [5]. The increase in performance in 2015 is discussed later. Flume turbine performance was approximated in a similar manner from laboratory measurements at a mean inflow velocity of 1.0 m/s (Figure 2).

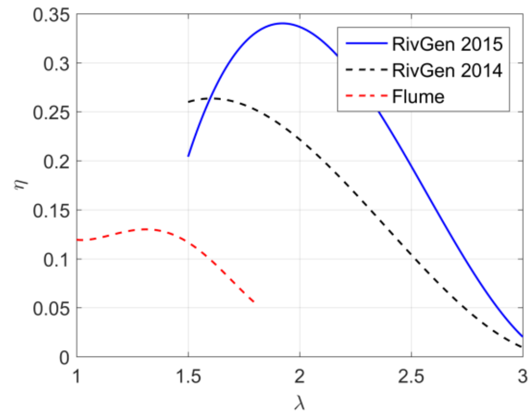

FIGURE 2. MEASURED PERFORMANCE CURVES FOR 2014 RIVGEN TURBINE, 2015 RIVGEN TURBINE AND FLUME TURBINE. RIVGEN EFFICIENCY IS ELECTRICAL, FLUME EFFICIENCY IS MECHANICAL.

The left edges of the performance curves correspond to the lowest λ achieved before stall. In simulation, if the instantaneous λ dropped below this value, turbine power generation was assumed to cease. This strict stall criteria provides a conservative estimate of controller performance and discourages operations in the marginally-stable near-stall region.

Results

In Table 2, E_{loss} (%) results are tabulated for unfiltered with no noise addition (or base, B), unfiltered with noise (N), and filtered with noise (FN) for each of the three turbines. The added noise is an extreme case, with a variance equal to the mean rotation rate.

TABLE 2. SIMULATED ENERGY LOSS

	PI-ω			*Kω²*			*PI-λ*		
	N	FN	B	N	FN	B	N	FN	B
R.G.	17	17	1	13	3	0	12	12	1
Flm	1	1	0	1	1	0	1	1	0

Performance of the RivGen turbine controllers were drastically reduced by spurious noise. $K\omega^2$ controllers were found to have superior base (B) energy loss values and the negative effects of noise could be mitigated by the simple addition of a filter to the ω signal. A 1st- order Butterworth filter with a cut-off frequency just below the turbulent kinetic energy (TKE) roll-off was found to perform best, as it attenuated high frequency noise while preserving energetic turbulent frequencies [5]. For PIω and PIλ controllers, reduced controller gains and higher cut-off frequencies were needed to prevent instability, increasing energy loss and reducing the benefit of filtering. The flume turbine is not affected commensurately by noise as the field scale devices due to its dynamics being dominated by servomotor damping, rather than control torque (Figure 3).

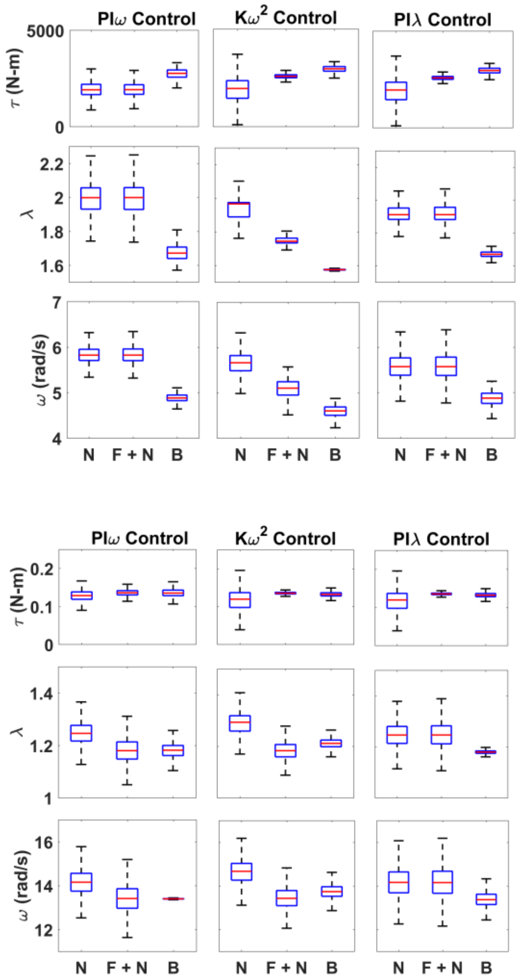

FIGURE 3. BOX PLOTS OF SIMULATION RESULTS FOR RIVGEN (TOP) AND FLUME TURBINE (BOTTOM).

An ideal controller would hold a set point (λ for $K\omega^2$ or $PI\lambda$, ω for $PI\omega$) perfectly with minimal torque fluctuations (i.e. show a small spread in the box plots). The plotted cases correspond to the lowest energy loss achieved for a given configuration. Thus, a mean shift in set point for N and F+N groups indicate noise did not allow for stable operation at maximum efficiency, with the magnitude of the shift indicative of the diminishing operating efficiency by an amount related to this mean shift (Figure 2). For all controllers, operating at higher λ improves stability.

Simulation results informed controller implementation for field-scale systems. In addition to suggesting a need to minimize spurious noise, simulation evaluated the effect of controller update rate. It was found by iteration that a minimal update rate of 10 Hz was necessary to maintain stable operation. This update rate corresponds to 50x the turbulent kinetic energy roll-off of the inflow time series [5]. Consequently, for flume experiments, an update rate 50x faster than flume TKE roll-off was maintained.

FLUME EXPERIMENTS

Methods

The experimental set up consisted of a pair of 6-axis load cells, a computer-controlled servomotor, turbine and drive shaft, and an ADV placed 5 diameters upstream to provide an estimate of inflow velocity at the turbine center point. Prior to installation of the assembly, ADV profiling confirmed the turbine center point velocity to be an accurate estimate of the nearly-uniform inflow velocity. Blockage from the turbine was 6.7%, and is not likely to affect turbine dynamics and performance.

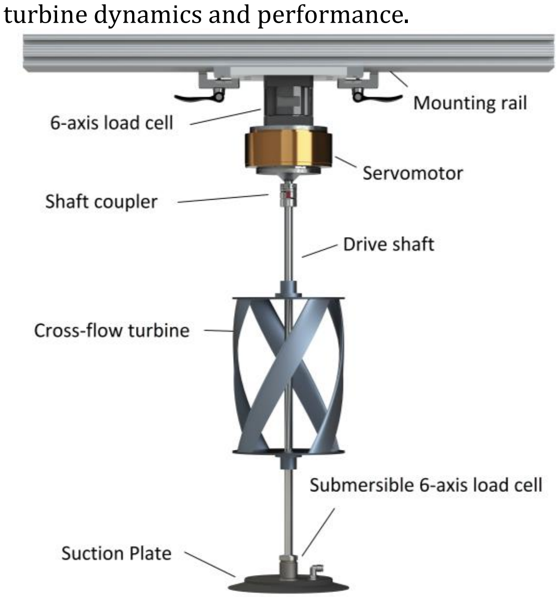

FIGURE 4. FLUME TEST ASSEMBLY.

The servomotor control was implemented in Simulink, which allowed simulated turbine control architectures to be ported directly into the experimental set up with minimal modification.

The flume turbine was first characterized in 30-s long constant command torque tests (Figure 2). Controls tests were carried out at 1 m/s mean flow velocity for 30-s. Base (with no added noise or filters), noise addition, and noise and filter addition were each tested under $K\omega^2$, $PI\omega$, and $PI\lambda$ control. Flume inflow velocity statistics during testing are summarized in [6]. Turbulence intensity was calculated as

$$TI = (\sigma_U / \overline{U}) \quad (5)$$

where $\overline{U}$ is mean flow speed (m/s) and σ_U is the standard deviation of the mean flow (m/s) for a 30- s time series.

TABLE 3. FREE STREAM STATISTICS

Statistic	Flume (N=538)	RivGen (N=117)
Mean Speed U (m/s)	0.98	1.95
Standard Error U (m/s)	0.02	0.02
TI (%)	3.6	8
Standard Error TI(%)	0.1	2

Scaling Considerations

Scaling results with respect to the effect of noise on controller performance between flume experiment and field-scale was necessary to ensure simulation results could be validated experimentally (at low cost) before implementation on the field-scale device (at high cost).

Through direct manipulation of the turbine dynamic equation, it can be shown that, when operating near ideal tip speed ratio, the same noise-induced relative error (e.g. 10%) in ω measurement will accelerate the RivGen turbine ~6.5x as much as the flume turbine. The impact of this on controller performance has been demonstrated in simulation (Table 2), in that the flume turbine was relatively unaffected by controller noise. This, and the flatter performance curve for the flume turbine, meant significantly elevated noise levels were necessary to produce a controller response in experiment that would approximate RivGen dynamics. Through iteration in simulation, noise levels with variance ranging from 50 to 250 rad^2/s^2 were found to create disparities in E_{loss} likely to be measureable in experiment.

Results

Experimental results for the flume turbine are presented in Figure 6 and are consistent with simulation results with two exceptions. First, linear controllers that were unstable in simulation for certain combinations of noise and filtering were stable in experiment. Second, E_{loss} was comparable between a well-behaved controller and one severely contaminated by noise. Both results are likely due to the turbine exhibiting gradual stall behavior and the relatively flat performance curve, such that small deviations in instantaneous λ did not significantly affect η, nor cause the turbine to cease rotation [6].

As in simulation, noise addition limited the minimum tip-speed ratio at which the turbine could operate without experiencing system stall (decelerating to zero rotation). As shown in Figure 5, the implementation of a filter can partially restore the stable operating range.

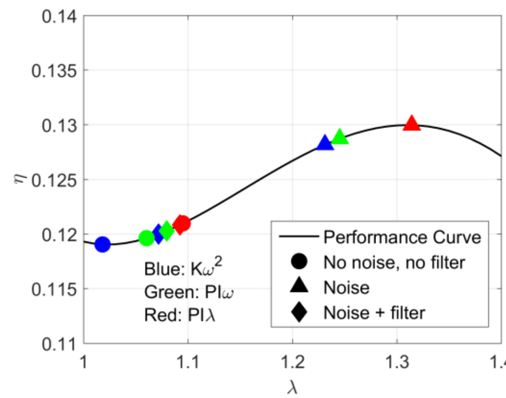

FIGURE 5. LOW SPEED LIMIT OF STABLE OPERATIONS FOR CONTROLLERS TESTED IN FLUME. NOTE, FOR PIΛ, THE MINIMUM STABLE OPERATING POINT WITH NOISE AND FILTERING IS NEARLY COINCIDENT WITH THE BASE CASE.

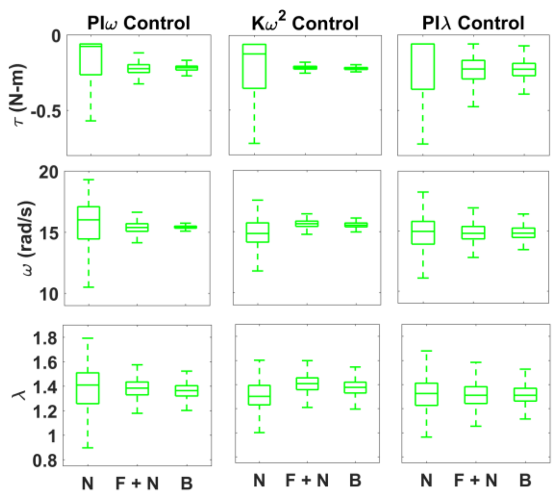

FIGURE 6. BOX PLOT OF FLUME EXPERIMENT RESULTS.

FIELD TESTS

Methods

For control testing, the RivGen turbine was deployed in the Kvichak River in Igiugig, AK in Summer 2015. The turbine was instrumented with two 2-beam acoustic wave and current (AWAC) devices at either end with upstream and cross-stream looking beams to spatially resolve inflow velocity. Using a weighted spatial averaging scheme similar to that used in [5] and assuming steady flow statistics, a representative U was determined. Kω^2 and PIω were implemented through programming on a Variable Frequency Drive (VFD) regulating turbine torque and compared against a built-in VFD speed control mode. Control tests were run for <300 s, a time scale for which flow was statistically stationary [5]. A turbine performance curve was developed from measured η at various control set points. Only base case operation was successfully tested (i.e., no spurious noise or filtering).

Results

As shown in Figure 2, the turbine performance in 2015 tests was substantially improved over the 2014 tests. The most likely causes for the observed increase in η are the addition of a fairing to the turbine structure between 2014 and 2015 tests and a different position on the river that may have affected vertical blockage. This change in performance is beneficial for control, as $K\omega^2$ control can operate at lower tip speed ratios without stall, as shown in Figure 7. Simulation results suggest that these observed results are likely possible only with a low-noise estimate of ω being used for control, such that additional filtering would be unnecessary. $K\omega^2$ control was stable over a broader range of λ set points than $PI\omega$, and was able to more tightly hold operating set points. The speed control built in to the VFD (an alternative $PI\omega$ controller) was unable to operate stably at ideal λ, suggesting that the details of controller implementation remain important.

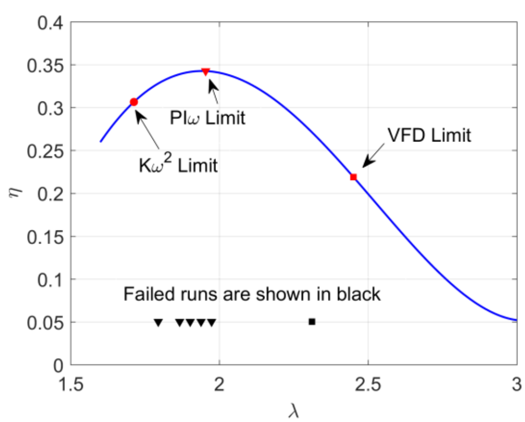

FIGURE 7. RIVGEN MINIMUM TIP-SPEED RATIO STABILITY LIMITS (2015 PERFORMANCE CURVE).

CONCLUSIONS

Turbine controller performance was evaluated for a cross-flow helical device in simulation, experiment, and field tests. Results were found to translate well between testing methodologies, provided that dynamic variables were appropriately scaled. The non-linear $K\omega^2$ controller outperformed other architectures by most metrics. In all cases, spurious noise was found to degrade controller performance, although the level of noise needed to incur a meaningful penalty varied with turbine damping and inertia. In simulation and experiment, filtering was found to be effective at mitigating the effects of spurious noise in the estimate for ω. Moving forward, expanding the experimental test assembly to allow for the addition of actual (or virtual) inertia or damping would allow for more thorough investigation of the relevant scaling effects.

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REFERENCES

[1] R. J. Cavagnaro, J. C. Neely, F. Faÿ, and J. L. Mendia, "Dynamic Evaluation of Electromechanical Emulators for Power Systems that include Hydrokinetic Sources," *IEEE Trans. Power Syst.*, pp. 1–8, 2015.

[2] L. Y. Pao and K. E. Johnson, "Control of Wind Turbines: Approaches, Challenges, and Recent Developments," *IEEE Control Syst. Mag.*, no. APRIL, pp. 44–62, 2011.

[3] V. J. Ginter and J. K. Pieper, "Robust Gain Scheduled Control of a Hydrokinetic Turbine," *IEEE Trans. Control Syst. Technol.*, vol. 19, no. 4, pp. 805–817, 2011.

[4] F. X. Diebold, *Elements of Forecasting*, Fourth Edi. Mason, OH: Thomson Southwestern, 1998.

[5] D. Forbush, B. Polagye, J. Thomson, B. Fabien, J. Donegan, and J. McEntee, "CHARACTERIZATION AND CONTROL OF CROSS-FLOW TURBINE IN SHEAR FLOW," in *Proceedings of the 3rd Marine Energy Technology Symposium*, 2015, pp. 3–8.

[6] R. J. Cavagnaro and B. Polagye, "DYNAMICS OF A STALLING CROSS-FLOW TURBINE," in *Proceedings of the 4th Marine Energy Technology Symposium*, 2016.