Dissertation Defense  
Master of Science in Information Science  

Optimal Entanglement Distillation Policies for Quantum Switches  
by Vivek Kumar  

Date:  November 28, 2023  
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Place:  Room 302, Information Sciences Building, 135 N Bellefield Ave,  
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Abstract:  
In an entanglement distribution network, the function of a quantum switch is to generate  
elementary entanglement with its clients followed by entanglement swapping to distribute end- 
to-end entanglement of sufficiently high fidelity between clients. The threshold on entanglement  
fidelity is any quality-of-service requirement specified by the clients as dictated by the  
application they run on the network. We consider a discrete-time model for a quantum switch  
that attempts generation of fresh elementary entanglement with clients in each time step in the  
form of maximally entangled qubit pairs, or Bell pairs, which succeed probabilistically; the  
successfully generated Bell pairs are stored in noisy quantum memories until they can be  
swapped. We focus on establishing the value of entanglement distillation of the stored Bell pairs  
prior to entanglement swapping in presence of their inevitable aging, i.e., decoherence: For a  
simple instance of a switch with two clients, exponential decay of entanglement fidelity, and a  
well-known probabilistic but heralded two-to-one distillation protocol, given a threshold end-to-  
end entanglement fidelity, we've employed both the Markov Decision Processes framework  
and a Reinforcement Learning approach to find optimal policies. This dual approach allows us  
to address the discrete state space assumptions that constrained the Markov Decision Process Model. By integrating Reinforcement Learning, we aim to enhance our model's flexibility. With  
these combined methodologies, our goal is to pinpoint the optimal action policy—whether it's  
waiting, distilling, or swapping—that can effectively maximize throughput. We compare the  
switch's performance under the optimal distillation-enabled policy with that excluding  
distillation. Simulations of the two policies demonstrate the improvements that are possible in  
principle via optimal use of distillation with respect to average throughput, average fidelity, and  
jitter of end-to-end entanglement, as functions of fidelity threshold. Our model thus helps  
capture the role of entanglement distillation in mitigating the effects of decoherence in a  
quantum switch in an entanglement distribution network, adding to the growing literature on  
quantum switches. We also compare the switch's performance found using simulations with  
theoretical bounds found out by employing queuing theory concepts on the same model.