Alan Turing’s observation that “we can only see a short distance ahead, but we can see plenty there that needs to be done” captures my motivation for a PhD in Computer Science: to design robust, interpretable machine-learning systems that make reliable decisions in high-stakes, real-time environments. My intellectual center of gravity is in CS/AI—learning theory, probabilistic modeling, reinforcement learning (RL), and large language models (LLMs). Power and other cyber-physical systems are where these ideas are stress-tested: partial observability, hard physics, and strict safety constraints make reliability non-negotiable.

My academic preparation began at the Pakistan Institute of Engineering and Applied Sciences (PIEAS), where rigorous coursework in Linear Control Systems, Power System Analysis, Protection, High Voltage Engineering, and instrumentation trained me to reason about coupled dynamics and operational constraints. Electives in robotics and microcontroller interfacing gave me an early appreciation for sensing, actuation, and feedback. This foundation—control, signals, and optimization—naturally evolved into CS questions I want to pursue at the doctoral level: how to learn from noisy, incomplete data; how to decide under uncertainty; and how to provide guarantees about system behavior.

I explored these questions through research-style projects that let me test ideas end-to-end. In my capstone, I optimized a 177-bus transmission network using Genetic Algorithms and later Particle Swarm Optimization, achieving a 12% reduction in line losses while improving economic dispatch; I presented the work at an international venue. That project taught me that algorithmic choices—objective shaping, constraints, and termination criteria—translate directly into system-level performance. Building on this, I developed a Python-based fault-detection pipeline for grid behavior using SVM, Random Forest, and Logistic Regression to classify anomalies, and ran a comparative study with Decision Trees and XGBoost to predict stability under variable load and renewable input. Alongside GEPCO workshop exposure to SCADA operations—and hands-on work with sensors and microcontrollers—these efforts reinforced a habit I value for CS systems research: follow the thread from data acquisition → modeling → inference → action, and evaluate against realistic failure modes.

Competitions and teaching sharpened both my algorithmic discipline and my communication. I placed third in the Un-hallucinate Challenge by building a retrieval-augmented, hallucination-resistant chatbot with Mistral-7B and Vectara, and I led deployment in the “Reasoning with o1” hackathon using OpenAI’s o1-preview—experiences that demanded fast iteration, careful evaluation design, and production-minded engineering. I also ranked among the top 10 nationally in Meta Hacker Cup 2024, which strengthened my ability to reason under pressure. Teaching keeps me grounded: selected from more than 30,000 applicants as a mentor for Stanford’s Code in Place, I taught Python, led interactive sessions, and provided one-to-one guidance; earlier, as a TA at PIEAS for Power Transmission, Distribution & Utilization, I helped students connect equations to system behavior. These roles reflect how I hope to operate in a PhD: build, test, explain, iterate—and help others do the same.

Industry experience gave me the systems instincts to make research deployable. At CureMD, I worked as a Robotic Process Automation Engineer, using UiPath and Automation Anywhere to streamline healthcare workflows and exploring AI-assisted validation and intelligent routing. I contributed to backend testing (SQL, API automation) and collaborated across Angular, Django, and .NET Core services. Earlier, at Mashal Construction Company, I worked with PLCs, motors, and control circuits in asphalt plants; at ROUSCH Power Plant, I observed large-scale generation and protection with gas and steam turbines. Across these roles, I learned to respect interfaces and invariants, anticipate failure modes, and ship solutions that integrate with legacy constraints—skills essential for CS/AI systems work.

My personal context shapes how I choose problems. I grew up in rural Pakistan as the son of a farmer and have managed a lifelong stammer. Scholarships opened the door to PIEAS; sustained practice, mentorship, and community made progress durable. I volunteer as a backend developer for Muaawin-e-Ilm, an education platform for underserved children, and mentor students in programming competitions. These experiences keep me focused on research that matters outside the lab: methods that are reliable, accessible, and attentive to their users.

I see a strong research fit with the University of Hawaiʻi at Mānoa. I recently met **Prof. Igor Molybog** (Computer Science) to discuss trustworthy ML for grid operations and, in particular, the emerging synergy between RL and LLMs in safety-critical settings. He encouraged me to study LLM-based assistants for operators and to engage with RL benchmarks for grid control. Guided by that conversation, I am reading work on explainable assistants for grid operation, **RL2Grid** for standardized RL evaluation, and recent methods that use **LLM priors** to accelerate and stabilize training. From these readings, a clear agenda emerges. I aim to develop **LLM co-pilots** that keep the earliest, riskiest phases of reinforcement learning within safe operating envelopes in Grid2Op-style settings; to **encode language-model priors**—for example, GFlan-style action biases or gentle KL-regularization—so agents **learn faster** and remain **stable under distribution shift**; and to **raise the practical reasoning** of grid assistants for topology changes, redispatch, and contingency analysis through precise prompting and lightweight fine-tuning. The objective is straightforward and testable: recommendations that are **effective, auditable, and understandable** to both operators and researchers.

These topics sit squarely within my broader interests in robust and interpretable ML for sequential decision-making and state estimation. They also connect to Prof. Molybog’s prior work on robust state estimation under nonconvexity and bad data. My goal is to develop algorithms and systems that (1) are resilient to corrupt or missing data, (2) provide explanations that support human oversight and compliance, and (3) meet the safety and latency constraints typical of real-time operations. I have begun experimenting with Grid2Op tasks and consolidating reading notes across explainable assistants, RL2Grid, and LLM-prior methods; this preparation will help me launch concrete experiments early in the program. Prof. Molybog also encouraged me to **apply for a TAship**, and my Code in Place mentorship and prior TA experience position me to contribute effectively from my first semester.

Long-term, I plan a research career—academic or industrial—building foundations and tooling for reliable, real-time ML in critical infrastructure. I want to mentor students, collaborate across disciplines, and translate advances in learning theory, RL, and LLM-guided decision-making into deployable platforms for grid automation, renewable integration, and predictive diagnostics. A PhD at UH Mānoa will provide the depth in learning theory, probabilistic modeling, and systems—and the collaborative environment—to pursue this agenda with rigor and impact. I look forward to bringing my end-to-end mindset, my experience at the intersection of AI and engineered systems, and my commitment to clear, collaborative research to your program.

Early in my role, I kept asking a question: how do we make systems choose safely when data is messy and time is short? That challenge moved me from power engineering toward Computer Science. I now focus on trustworthy ML—methods that explain themselves and act reliably in real time today. My current interests center on reinforcement learning and large language models. Power systems are my proving ground for these ideas. This curiosity has guided my academic journey and continues to shape my research ambitions in trustworthy decision-making.

My academic preparation began at the Pakistan Institute of Engineering and Applied Sciences (PIEAS), where a B.E. in Electrical Power and modules in Linear Control Systems, Power System Analysis, Protection, High Voltage Engineering and instrumentation trained me to reason about coupled dynamics and constraints. Electives in robotics and microcontroller interfacing built habits around sensing, actuation, and feedback. These foundations in control and optimization now underpin my shift toward CS: robust ML, reinforcement learning, and LLM-assisted decision-making for grid operations under uncertainty. Through discussions with Prof. Igor Molybog, I am exploring RL–LLM synergy for safe, interpretable control, drawing on RL2Grid and explainable operator assistants, and setting up the projects described next.