Accepted to 10th Intelligent Systems Conference 2024, 5-6 September 2024
Amsterdam, The Netherlands

Intelligent Automation with Quantum Optimization using Agent-Based Technology

Tammy R. Fuller[1] and Gerald E. Deane[2]

1 Chief Architect/VP, Echo Messaging Systems, Inc., 198 Chapel Street, Lincoln, Rhode Island 02865, USA
tammy@echomessaging.com
2 CEO/President, Echo Messaging Systems, Inc., 198 Chapel Street, Lincoln, Rhode Island 02865, USA
gerald@echomessaging.com

Abstract. Quantum computing is a near-term technology that through optimization will dramatically increase overall computing power. Intelligent Automation is a branch of Artificial Intelligence that streamlines complex tasks, often currently done by humans, that adapts to internal and external environmental factors. Leveraging quantum computing's ability to optimize for performance, scheduling, routing, and resource allocation orchestrated with agent-based technologies that divide large problems into smaller one produces systems that save time in a simple way. By extending the reach of agents into the physical work through agent-aware sensors and controls, solutions that bridge the physical world with the quantum world become a reality.

Keywords: Automation, Intelligent Automation, Artificial Intelligence, Intelligent Systems, Quantum Computing, Quantum, Agent-based technology, Intelligent Agents, IoT, Internet of Things.

1 Real-world Agent-Based Processing

Software agents are a proven technology, they have been around for decades and have shown through real-world applications to be a practical approach for solving difficult problems [1][2] by distributing their complexity into smaller more management problems and taking advantage of opportunities to adapt. Adaptation can be done in response to the type of data being processed, the amount and nature of the data, as well as the global environment within which agents are executing. Our approach to solving complex problems through an agent-based approach was to create a platform where agents are simply defined as having two primary components. These are a set of constraints that must all 'pass' and their associated action responses that execute when the agent is activated.

Each agent is part of an intelligent system and has health and integrity agents that monitor and ensure agents are working correctly. We created an intelligent automation system from a need to provide stable adaptive flexible solutions built off a common set of agent-based principles. By partitioning large problems into a set of sub-problems organized around triggering criteria and their associated actions, we created a platform that encourages repurposing and a building block approach that is quick to implement and configure as well as allow for evolving or rolling requirements.

ADIN [3], which stands for Anomaly Detection and Intelligent Notification is a platform where any number of agents are running asynchronously, where each is configured with their triggering criteria that will activate the agent, and once activated, will apply their associated actions. ADIN agents are configured to data sources, such as databases or APIs for both input criteria and action responses (Figure 1).

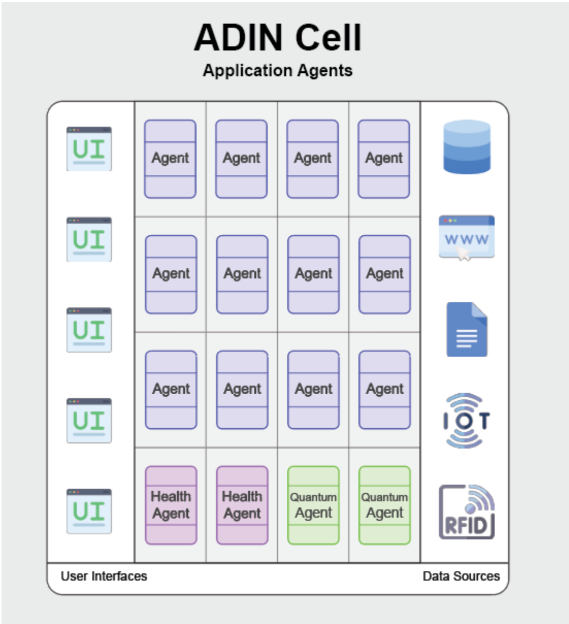

Fig. 1. An ADIN Cell is a grouping of ADIN Agents which can be designated for processing, monitoring health, interfacing with quantum processing, and more. Common user interfaces and data sources can be shared among agents.

For example, an action creates a new record via an API when a status changes in a database such as a warehouse robot crossing into a restricted area using geofencing. A secondary action could be to issue an IoT API call that actives a device such as a remote monitoring camera, to turn on and start recording. Additionally, a text notification could be sent to the administrator on the warehouse floor.

We have created software solutions using agent-based processing for many different domains including e-commerce, service, medical, government, military and more, over many years including automated workflows where agents monitor new job requests and dispatch notifications to service providers which can accept requests. Upon an accept request, another agent is monitoring for updated status and in turn, notifies the customers requesting service that the job has been assigned.

The tables below show the types of triggering criteria and action responses used by our agent-based platform.

Table 1. Types of Agent-Triggering Criteria

Criteria Type	Examples
Data	Database, Files, API, Webhooks, IoT interfaces
Time	Run at 9am Mon-Fri, run every 5 minutes, Run between 11pm and 3am at 10-minute intervals
Geographic Location	Geofenced region, Line based on 2 lat/long coordinates

Table 2. Types of Agent-Action Responses

Action Type	Examples
Data	Create new record, update status, create new file, call an API or IoT interface
Notification	Email, text, phone call, push notify and/or any digital based communication based on trigger result
Control	Start, stop, clone agents. Clone an agent and modify triggering criteria and/or action responses and/or processing parameters

Agents are different types (as shown in Figure 2) as a way to categorize them in larger and larger systems. Processing agents take on the work of smaller problems by monitoring new or updated data from configured data sources. This may occur within time-specific windows or at intervals such as every 5 minutes or once per hour. If a location such as GPS location is required, agents can query GPS enabled devices via their APIs and trigger when the GPS lands within a geofenced region. Agent criteria can get sophisticated where criterion types are combined. The warehouse robot that crossed into a restricted geofenced area between 11pm and 3am described above is an example of how criterion types can be combined. Agents that monitor other agents whose trigger is to make sure they are running on schedule are called Health agents. When a Heath agent triggers, it notifies an administrator that an agent isn’t running as expected. Integrity agents also monitor agents but look to internal signatures to make sure corruption hasn’t occurred due to a virus or malicious attack. The response is to stop the agent, notify an administrator of the occurrence, make an original copy of the agent from its original configuration, and terminate the failing agent. This is how Integrity agents act as a form of virus protection.

Agents run in a containerized environment, such as Docker Containers, and this means that only what an agent needs to run is in the container. This also limits the risk of viruses and hacking.

Communication agents focus on notification, adaptation agents focus on updating processing parameters of agents in response to the global environment. User interface agents target input requests from user interfaces. Quantum agents provide an interface to quantum computers by creating models that quantum computers need based on data the agents are connected to.

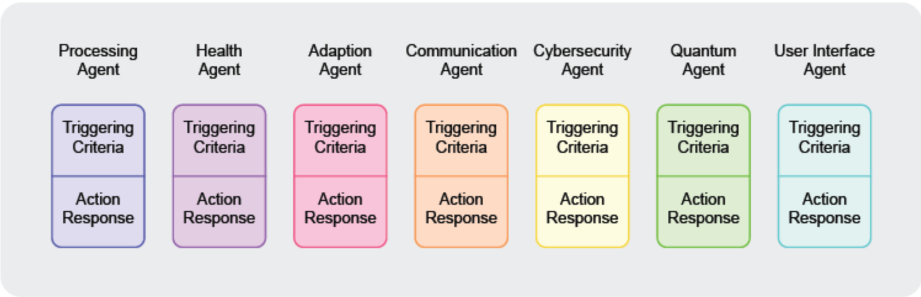

Fig. 2. Agents fall into categories based on how they are used in the ADIN cell. All agents are based on their triggering criteria and action responses.

2 Quantum Agents

Quantum computers are a computing resource that performs mathematical calculations over data in a manner that is different from classical computers, which are the ones everyone works with every day. Classical computers have microprocessors based on digital Boolean logic and are in almost all electric devices from a smart toaster to your mobile device, to your desktop computer, to massively parallel supercomputers.

Quantum computers are made of qubits, aka quantum bits, where classical computers use Boolean logic-based gates. A qubit can be between 0 and 1 and it's not required to be any particular value until it resolves into a solution. It can be both a zero and a one at the same time and its method of calculating data assumes this.

ADIN agents currently focus on a particular type of quantum computer that rather than perform all types of quantum process over its qubits, has opted for practicality to focus on one very useful application of quantum computing, called quantum annealing.

Annealing comes from metalwork where sheets of metal are heated and the annealling process transforms it into the desired shape as it is slowly cooled. Annealing in artificial intelligence is a technique for finding the global minimum over a large data set. Problems with large search spaces are those that AI often focusses on, and AI based annealing will produce good results.

For example, imagine you are searching for the lowest valley in a mountainous region. You can climb to the highest local peak and survey to find the lowest valley, but you can't be assured you found the lowest as it may exist just beyond the next ridge. This is also the case when searching for optimum data in a large multidimensional set of data (Figure 3).

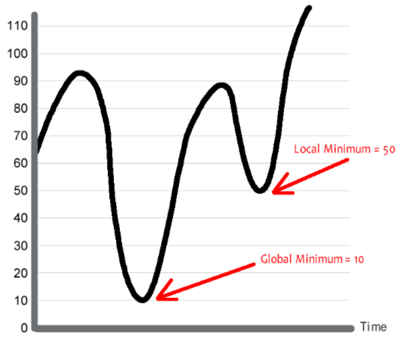

Fig. 3. Searching for Global vs Local minimum

DWave™ [4] is a quantum annealing processor that when given a problem that is modeled based on energy will return the lowest energy solution. The challenge is to transform real-world problems into energy models where the lowest energy solution represents that sought after solution.

For example, say you have a set of 10 warehouse robots that travel within a warehouse of food that is brought in daily, repackaged and distributed to their destination, which is a truck going straight to the food market. Trucks may travel hundreds of miles once they leave the warehouse and time is critical in dealing with food. A quantum annealing computer can be given the set of food ready for delivery along with their warehouse location, the set of trucks that need to have that type of food onboard, and the current tasks of the 10 robots.

The problem must first be described in terms of minimum energy. There are 10 warehouse robots to deliver the most amount of food in the shortest time. Furthermore, a robot must pick up as many items that belong in the same truck as possible. This is a problem that includes the minimum being sought after – minimum time spent moving food from their current location to the destination truck (which could be one of several options). Constraints maximize food going onto the same truck.

The constrained quadratic model (CQM) are problems of the form:

Minimize an objective:

$$\sum_i a_i x_i + \sum_{i \le j} b_{ij} x_i x_j + c,$$

Subject to constraints:

$$\sum_i a_i^{(m)} x_i + \sum_{i \le j} b_{ij}^{(m)} x_i x_j + c^{(m)} \circ 0, \quad m = 1, \dots, M,$$

where $\{x_i\}_{i=1,\dots,N}$ can be binary[1], integer, or continuous[2] variables, a_i, b_{ij}, c are real values, $\circ \in \{\ge, \le, =\}$ and M is the total number of constraints.

Fig. 4. Constrained Quadratic Model (CQM) for DWave™ quantum annealing processor.

The work is to transform this into a quadratic equation (Figure 4) where variables represent the minimum energy sought along with constraints to maximize items going to the same truck. The process of creating the quadratic equation is the most difficult part of working with a quantum annealing processor.

Using ADIN agents, we have created a mapping from a set of problems that involve optimization, scheduling, routing, and resource allocation. Scheduling for service-based enterprises is a particularly difficult problem especially as companies scale. Scheduling done manually is inefficient and sub-optimal in terms of time, gas usage, customer convenience or other resources. Figure 5 shows the results of quantum scheduling where routes match open drivers to customer deliveries.

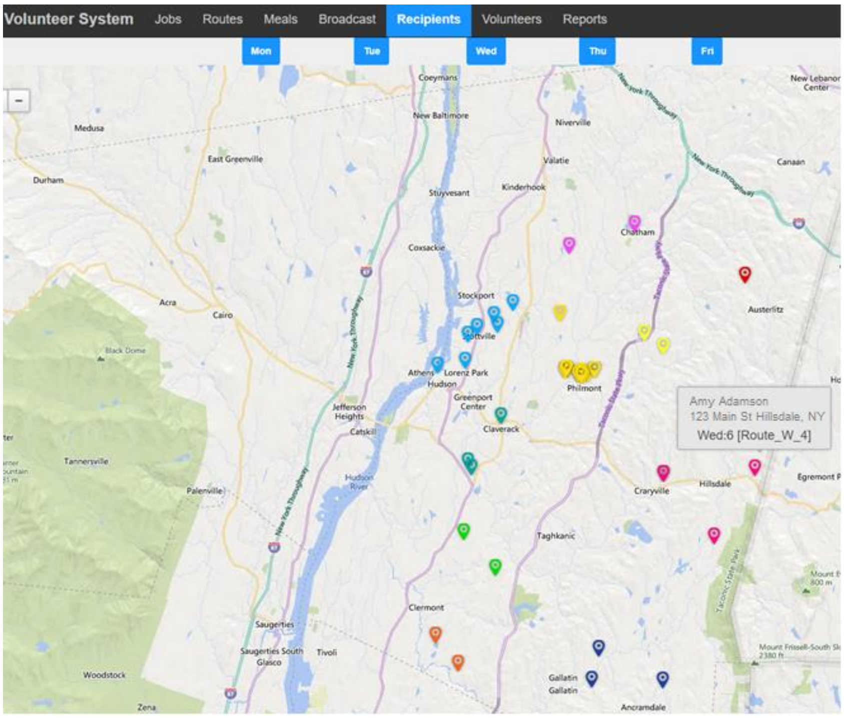

Fig. 5. Color routes after quantum annealing groups best deliveries.

3 Control Systems and Agent-Based Processing

Until recently, agents could only accept inputs and activate outputs in the virtual world such as databases or webhooks. By developing a module that acts as a bridge to interact with sensing devices or control electrically driven devices, agent interactions have crossed into the physical world beyond the limitations of the Internet of Things (IoT). IoT devices are already accessible to ADIN agents via their APIs, however this limits options in what can be connected to. To develop an IoT-enabled device is a costly undertaking requiring wide market support to justify high upfront development costs. Large companies can sometimes take on these expenses, but small and medium-sized businesses (SMBs) which are a key source of innovation are excluded.

The high cost of developing IT systems has resulted in tech giants controlling markets to a point where developing new products is difficult without heavily investing in high up-front development costs. This limits experimentation which is key to innovation. By offering a bridge between the physical world and intelligent software automation, SMBs have more tools to build with. By bridging to quantum computers for optimization in both the virtual world as well as the physical world, new opportunities for manufacturing are possible.

3.1 IoT and Virtual Interfaces

Agent-based control systems working in the physical work have been limited to IoT enabled devices. ADIN has been in constant use connecting camera enabled IoT devices that capture, normalize and store images from hundreds of globally placed sources for identifying insects in food storage warehouses [5], to assist in predicting outbreaks. This is an innovative use of technology to minimize use of pesticides, protect food stores from going bad, making it an important green technology. Future planned expansions are to establish food delivery ‘green-corridors’ where insects are monitored via agent-based intelligent automation from the original food source, through delivery routes that include trucking, train and shipping modes to food stores.

Many different types of processing agents are used, and each operate independently and asynchronously from each other. Agents detect new images which have been created by IoT-enabled cameras along with metadata such as temperature and humidity. The agent normalizes the data and stores it in a database where it can be browsed along with its metadata by users. Another agent detects the normalized data and applies a computer vision algorithm using Morphology techniques on the image pixels to identify regions where insects are likely to be found. The next step in this algorithm is to apply Machine Learning techniques of matching the most likely insect type to the image. Below are samples of different insect types that were used to train Deep Learning models [6] as shown in Figure 6. The trained models are applied to the sub-image where an insect is likely and if it returns a high score, the insect is identified and counted, as shown in Figure 7.

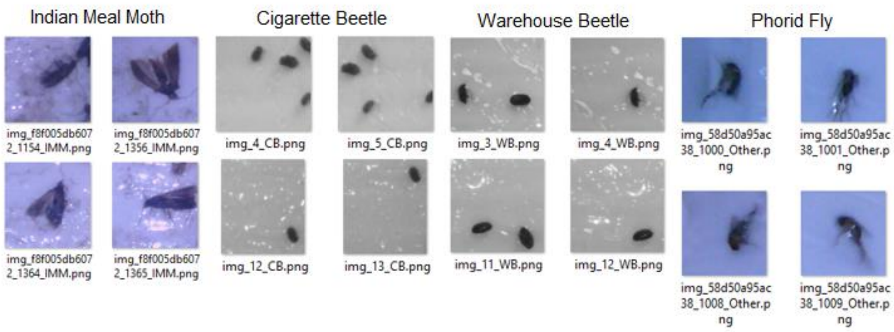

Fig. 6. Training models for automated bug detection and counting.

Fig. 7. 99% confidence Indian Meal moth

Another agent monitors insect counts and types for a region and if a spike is detected or a predefined threshold is crossed, it activates the agent, and will send out an email notification to the administrator of a potential infestation. This approach of using intelligent automation means that technicians are dispatched to where problems are most likely to occur, as it's common for each technician to cover a wide territory. Also, this targets the use of pesticides, making it better for the Earth, for people, and for wildlife too. With climate change, infestations can occur much faster, be more unpredictable and could involve insects that never caused infestations in the past that technicians never had to monitor for.

Quantum optimization can come into play by configuring a quantum agent to monitor potential infestations, technician current locations and scheduling to minimize time getting to a potential infestation site.

3.2 Virtual-world vs Real-world Interfaces

Lacking in the world of hardware-based control systems are programming options that are configurable and easy to integrate that also have the flexibility required by manufacturing operations. Controls for programmable logic controller (PLC) are outdated and in need of more powerful options provided by modern programming languages – even basic looping and decisions points are limited with options like 'ladder logic' approaches to programming PLCs [7]. Agents whose triggering criteria were triggered directly from the hardware sensors that if needed could be combined with other software-only type criteria, would extend Intelligent Automation into the hardware control systems. Furthermore, agents whose action response were tied directly to control motors, servos, solenoids, robot arms and more, could lower time to setup, as well as lower overall cost of investment for automated manufacturing. Figure 8 shows sensors and action responses for both the virtual and real-world.

Agents are not limited to only virtual or only real-world. For example, to build on an earlier example, in food stores with IoT-enabled cameras, aerosol pumps can be installed containing various types of pesticides that activated remotely by the agent to immediately address potential insect outbreaks, based on the type of insects that were detected.

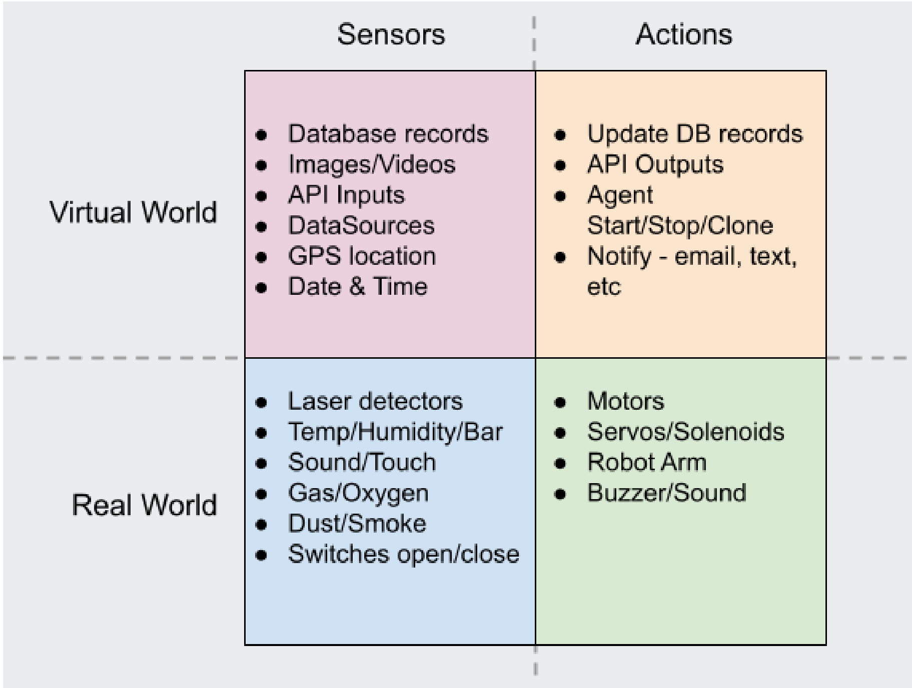

Fig. 8. Virtual vs Real-world sensors and actions.

3.3 Sensor-Control Module

Our agent-based processing has recently expanded into the physical world through the development of an ADIN Sensor-Control Module (SCM). This is an electronic device with a microprocessor running an embedded copy of an ADIN agent. Through Wi-Fi, Bluetooth or wired communication, the SCM is configured to react to its wired inputs and/or wired outputs to accept direct sensor data and/or control connected devices.

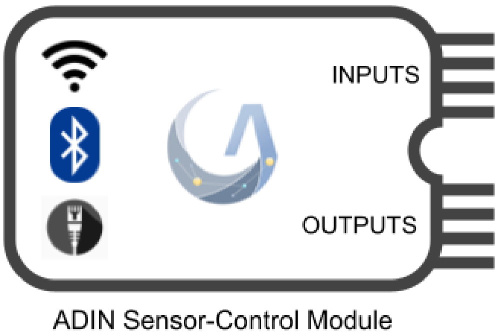

Fig. 9. ADIN Sensor-Control Module.

By adding an additional sensing and control dimension to the triggering criteria and action response options, we have extended agent-based processing into the physical realm without being limited by a device APIs or requiring IoT interfaces.

4 Sensor-Control Module and Quantum Optimization

Quantum optimization via quantum agents can optimize automation control systems that use real-world sensors and controls. For example, see Figure 10 where each station evaluates its own triggering criteria and if it passes, performs its associated action response.

This automated manufacturing process could involve dozens or more systems in a sealed clean room where a product is added to or modified at each station. Some stations involve introducing hazardous materials that must be kept to an overall minimum for safety reasons.

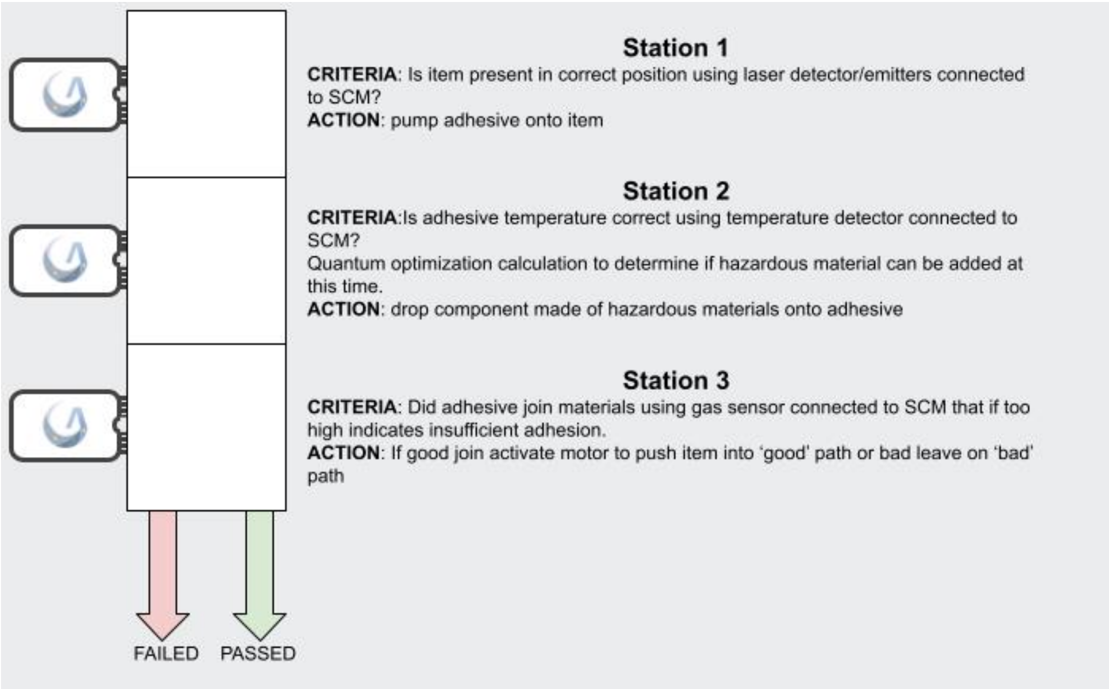

Fig. 10. Automated Assembly line.

Station 2 includes a quantum agent that builds the quadratic model based on all current levels of hazardous materials across all assembly lines and determines if this station passes to continue to the next step or must wait until hazardous material levels go down. Once the optimum levels are achieved in the global clean room environment, the item continues onto Station 3 where a QA test is run by analyzing sensor inputs. If it passes the agent controls a motor to send it forward. If it fails a solenoid is activated that pushes the failed item off the main line path.

Quantum optimization is a powerful tool that can be used in many different ways and is limited only by the ways sensors can be probed and controls can be activated as show in Figure 11.

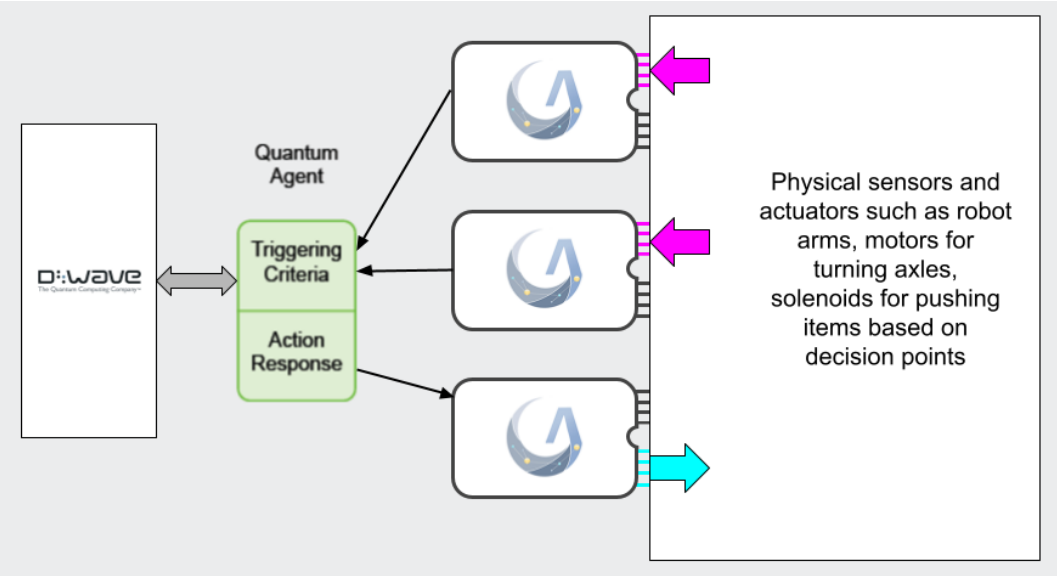

Fig. 21. Quantum Agent to optimize an automated manufacturing control system.

5 Conclusion

Quantum computing is an advanced topic with a long learning curve because quantum computers are based on logic gates that are different from classical computers. Boolean logic, AND gates and OR gates are, by definition, as simple as possible with only two inputs to produce one output. Quantum computers, such as DWave, that focus on quantum annealing to search for global minimums that represent a global optimum solution, are wired in ways to be highly connected and interconnected with many inputs and many outputs. Intelligent agent-based processes are far less complex than quantum computers, but nonetheless, an advanced topic of artificial intelligence. In describing our research, it is our intention to convey the meaning of our ideas, along with how and why they work, in a way that people will understand. We spend the bulk of our time implementing these concepts and putting them to practice in the everyday challenging world of solving problems using technology. Using real-world examples that draw straight from practical application is how we emphasize their merit, rather than focus on mathematical equations to represent the models involved.

5.1 Future Directions

Expanding opportunities to bridge to quantum computers remains a high priority as this technology, with its ability solve difficult problems quickly, will produce solutions to problems that are currently impossible on classical computers. Hybrid computing that uses both quantum and classical is the most practical use of quantum resources. Quantum computers, especially those like DWave that focus on optimization using annealing are a powerful tool in a larger solution when paired with classical computers. Agent-based technologies like ADIN, by their nature, split up bigger more complex problems into smaller ones to minimize overall complexity. This creates reliable, maintainable solutions for intelligent automation. Expanding further into the physical world of hardware control systems, via Sensor-Control Modules means an even broader reach for quantum optimization.

References

1. Hayes-Roth, Barbara: An architecture for adaptive intelligent systems. Artificial intelligence 72, no. 1-2: 329-365 (1995).
2. Jennings, Nicholas R., Wooldridge, Michael J.: Agent technology: foundations, applications, and markets. Springer-Verlag, Berlin, Heidelberg (1998).
3. Fuller, Tammy R., Deane, Gerald E.: Anomaly detection and intelligent notification. Future of Information and Communications Conference. (2018).
4. DWave-What is Quantum Annealing? https://docs.dwavesys.com/docs/latest/c_gs_2.html, last accessed 2024/02/15.
5. Feston, James, Kiever, Samantha, Kelley, Pat, Estabrook, Ethan: Advances in remote monitoring for stored product pests. In: Proceedings of the 13th Meeting, Integrated Protection of Stored Products, pp. 6-11 Barcelona, Spain (2022).
6. OpenCV: Deep Learning for Computer Vision: Essential Models and Practical Real-World Applications, https://opencv.org/blog/deep-learning-with-computer-vision/, last accessed 2024/02/15.
7. The Future of Ladder Logic, https://www.mroelectric.com/blog/the-future-of-ladder-logic/, last accessed 2024/02/15.