Efficient parameterised compilation for hybrid quantum programming

Anna M. Krol*, Koen Mesman, Aritra Sarkar, Zaid Al-Ars
Delft University of Technology
Delft, The Netherlands
Email: *a.m.krol[at]tudelft.nl

Abstract—Near term quantum devices have the potential to outperform classical computing through the use of hybrid classical-quantum algorithms such as Variational Quantum Eigensolvers. These iterative algorithms use a classical optimiser to update a parameterised quantum circuit. Each iteration, the circuit is executed on a physical quantum processor or quantum computing simulator, and the average measurement result is passed back to the classical optimiser. When many iterations are required, the whole quantum program is also recompiled many times. We have implemented explicit parameters that prevent recompilation of the whole program in the quantum programming framework OpenQL, called OpenQLPC. These parameters improve the compilation and therefore total runtime for hybrid quantum-classical algorithms. We compare the time required for compilation and simulation of the MAXCUT algorithm in OpenQLPC to the same algorithm in both PyQuil and Qiskit. We show that efficient handling of parameterised circuits results in up to 70% reduction in total compilation time for the MAXCUT benchmark, and leads to a reduced total execution time. When using OpenQLPC, compilation of hybrid algorithms is up to two times faster than when using PyQuil or Qiskit.

I. INTRODUCTION

Even though Google announced quantum supremacy in 2019 [1], universal, fault-tolerant quantum computers are still a thing of the future. In the meantime, Noisy Intermediate-Scale Quantum (NISQ) devices like the Google Sycamore Quantum Processing Unit (QPU) have the potential to outperform classical computers in specific cases [2].

The NISQ era means that anybody writing quantum algorithms has to contend with a limited number of qubits and a trade-off between circuit depth and error-rates. The demonstration from Google on a 53-qubit chip had a fidelity of only 0.2%, for example [1].

Quantum algorithm development in the NISQ era is largely done with simulations of quantum devices, which are more readily available and still faster than real quantum devices. And many algorithms require more (interconnected) qubits than the current state-of-the-art has to offer. In addition, simulators offer other advantages, such as access to the full state of all qubits, error-free execution, setting of specific error rates and repeatability of “random” results [3].

One such area of quantum algorithm development is hybrid quantum-classical algorithms. These are expected to be the first algorithm candidates that will result in a practical application for quantum computation [4]. Current quantum computers have too few, too error-prone qubits to be sufficient to implement purely-quantum algorithms such as Shor’s factorisation algorithm [5] or Grover’s search algorithm [6]. But with hybrid algorithms, some of the processing is done on a classical computer, so quantum circuits with less qubits and lower depth are required for the quantum device and more fine-grained error correction can be applied [4].

VQE, and other variational hybrid algorithms, require many iterations of the same quantum circuit. For each iteration, a set of parameters is updated according to some classical (optimisation) algorithm [4]. An example of the program flow for such algorithms is shown in Fig. 1.

Figure 1: Programming flow for hybrid quantum algorithms like VQE

Since compilers for quantum programming languages require a lot of processing to produce an executable quantum circuit, doing a full compilation in each iteration consumes significant amounts of time. For iterative hybrid algorithms, however, most of the circuit stays the same between iterations, which means that error-correction mechanisms, optimisations, decompositions, mapping, etc. are not affected. For VQE specifically, only some angles for rotation gates are changed, which means that most compilation steps are not affected for parameterised gates.

With the increasing number of qubits quantum computers can support, and with increasing qubit quality, the depth and complexity of executable quantum circuits will increase. This in turn means that the amount of time spent during this reccompilation step will continue to increase, making it necessary to optimise it as much as possible. At the same time, efficient classical compilation and simulation of quantum algorithms are essential tools in the NISQ era and beyond.
For as long as quantum supremacy has not yet been reached, classical computers will continue to do part of the work.

Additionally, each QPU requires a classical control system, for data conversion and implementation of QPU instructions. This classical device controls the qubits directly through analog systems. When QPUs are integrated into High Performance Computing (HPC) nodes, an additional latency bottleneck is introduced by the movement of data across the complete stack of the HPC and quantum computing system [7]. This bottleneck can be improved by reducing the amount of data that needs to be transferred to the QPU during the execution of hybrid algorithms [8].

In this paper, we introduce OpenQL Parameterised Compilation (OpenQLPC) which reduces compilation time and latency of hybrid quantum algorithms. The contributions of this paper are as follows:

- A more efficient compilation process for parameterised hybrid quantum programming
- Implementation of our method in the OpenQL quantum programming framework
- Implementation of the MAXCUT quantum programming benchmark in OpenQLPC

This paper is structured as follows. A background on VQE and utilisation of parameters in programming languages is given in Section II. Then the design goals are presented in Section III. The compilation process and improvements thereof can be found in Section IV. After that, the methods and results are discussed in Sections V and VI. The conclusion can be found in Section VII.

II. BACKGROUND

To demonstrate the effect that a more efficient compilation of parameters can have, the VQE algorithm will be used. We will compare our implementation, OpenQLPC, against Qiskit (0.37.0) and PyQuil (3.1.0), so some background on these will be given as well.

A. Variational Quantum Eigensolvers

VQE is a class of hybrid quantum algorithms, i.e. it uses both classical and quantum resources, to find solutions to eigenvalue and optimisation problems. With VQE, quantum devices with as few as 40-50 qubits might outperform purely classical approaches [9]. VQE can run on any gate-model quantum device, is able to leverage the strengths of a specific architecture and to variationally suppress some errors [10]. To do this, it uses a parameterised quantum circuit, where the parameters are updated variationally according to a classical optimisation algorithm.

The execution flow of VQE is shown in Fig. 1. VQE can be used to determine the ground state and the ground state energy of a Hamiltonian $H$.

To do this, a parameterised ansatz is used. The parameter values are adjusted with each iteration of the circuit until convergence. The final parameter values determine the ground state of the Hamiltonian [10].

There are many options for the choice of ansatz, as well as the choice of classical optimiser. The ansatz can be tailored to many aspects of the algorithm and system used, such as the specific hardware implementation [10], specific problems, accuracy or circuit depth [11]. Different classical optimisers converge at different rates and respond differently depending on the amount of noise present in the quantum system [12].

The number of iterations before algorithm convergence depends on many different details. To give an indication, the qubit efficient implementation of VQE in [13] reaches the ground state in 500 iterations, with 17-qubit circuits that contain 180 to 900 variational parameters. The various VQEs from [14] are 6-qubit circuits with 30 parameters each done for 250 iterations, with $10^3$ measurements per iteration to estimate the expectation value.

B. Programming of parameterised circuits

In this paper, we compare OpenQLPC against Qiskit and PyQuil, quantum programming languages from IBM and Rigetti, respectively. Both allow programming of parameterised circuits, are widely used and can be used as a library from a Python program. This makes them a good comparison to OpenQLPC, which also has these features.

The aim of OpenQLPC is to be easy to use for new quantum programmers as well as for people already familiar with these other languages. We will therefore give an overview of how parameters can be used in these other languages and aim to make our syntax similar so that adopting the new feature in OpenQL will be simple.

1) Qiskit: Qiskit is the quantum framework of IBM. It is suited for working with noisy qubits, which can be simulated using their simulator, Qiskit Aer. This allows classical simulation of circuits compiled using the Qiskit compiler, Qiskit Terra. Besides simulation, circuits compiled using Qiskit Terra can also be executed on real quantum devices using IBM Q [15]. A more in-depth look at parameterisation in Qiskit can be found in Appendix A.

2) PyQuil: PyQuil is the quantum programming language from Rigetti. It is compiled using the Quil compiler into Quil, also the name of their Quantum Instruction Language [16]. PyQuil can be used to write hybrid algorithms with parameters [17], which makes it a suitable comparison to OpenQLPC. How parameters can be used in PyQuil can be found in Appendix B.

III. DESIGN GOALS

Implementation of parameters in OpenQLPC was done with the following design goals in mind: modularity, scalability, user-friendliness (usability), future-proof and speed.

Modularity: To make OpenQLPC robust against future changes to the host programming language, the parameters will be implemented as a separate entity.

Scalability: This has two parts, the first is that OpenQLPC will make it easy for the programmer to define many parameters, and to allow putting values to them in bulk as well. The
second part is that the overall compilation time should not be affected (too much) by the number of parameters.

**Usability:** The syntax and use of the parameters will be made similar to other quantum programming languages (Qiskit and PyQuil), for users already familiar with those and to make manual rewriting of a program from one language to the other easier. Clear errors should be provided, and parameter types should be explicit. Finally, the programmer should not be required to manually provide a string for each parameter, which can become cumbersome for bigger programs. But manual naming should be supported, in case human-readable common Quantum Assembly Language (cQASM) is desired.

**Future-proof:** Parameterisation also means a more clearly defined boundary between the static and dynamic parts of a quantum circuit, which can be used in the future for a full split between those two compiler functionalities, or for detection of parallelism. In addition, the compile speed, number of supported parameters etc. should allow this feature to be used (and useful) into a future of quantum programming languages, where extensive knowledge of quantum is no longer required to write quantum programs.

**Compilation speed:** OpenQL is a high-level quantum programming language with an extensive compilation toolchain [18]. It supports gate decomposition, circuit optimisation, scheduling and mapping, all of which are necessary to be able to execute the generated cQASM on NISQ devices [19]. This also makes the compilation in OpenQL and all other such compilers computationally expensive, in terms of classical resources. For algorithms that require only a single compilation pass, the classical compilation time is negligible compared to execution of a quantum program on a real quantum device, or classical simulation of the circuit. However for iterative hybrid algorithms, such as VQE, repeated compilation of essentially the same quantum circuit becomes a much bigger drain on resources. With explicit definition of the dynamic parts of the circuit through the use of parameters, the bulk of the compiler operations does not need to be repeated for each iteration of the hybrid algorithm.

IV. **Compilation**

The first time a quantum program is compiled (by calling `OpenQL.compile(...)`), the full stack is executed, including gate decompositions, mapping, optimisations, etc. [18]. Without using our `OpenQL_pc` approach, updating of any (parameter) values requires repeated execution of this whole stack, as shown with the grayed-out arrows in Fig. 2.

With `OpenQL_pc`, only the affected gates are updated with the numerical values of the parameters as shown in Fig. 2. This means that there is no unnecessary repetition of the whole (extensive) compiler stack for every iteration of an iterative quantum algorithm.

In the first compile run, any parameterised quantum instructions without a numerical value are skipped by any compiler passes that require that specific value. Mapping and scheduling one (or a set of) instruction cannot be done when the qubit is not specified, but do not require knowledge of the angle of a rotation gate. When recompiling, only parameterised quantum instructions and affected instructions are considered, while the rest of the code is left unaffected. This might mean some optimisations that affect large regions of the code will not be done, but this effect is expected to be small compared to the resources saved by not checking all of the code after each compilation.

How to use parameters in OpenQL can be found in detail in Appendix C.

V. **Methods**

To determine the influence of parameters, execution time tests were performed. These were done with the MAXCUT benchmark [21].

A. The MAXCUT benchmark

MAXCUT is a hybrid algorithm which can be used for circuit layout design [22], statistical physics and more [23]. It aims to find the division of a graph into two parts, where the total weight of all edges between the parts is maximised [23]. The general case is an NP-hard problem.

The MAXCUT benchmark from [21] was implemented in OpenQL, PyQuil and Qiskit on 4-regular graphs of varying number of nodes. These graphs and this benchmark were chosen because a reference implementation was already available, it can be easily scaled up to any number of nodes and the number of qubits and the circuit depth both increase linearly with an increasing number of nodes. It is a variational quantum algorithm, with an execution flow as in Section II-A.

B. Experimental setup

In order to compare the performance of `OpenQL_pc` with other programming languages, the MAXCUT algorithm was implemented in OpenQL, OpenQL_pc, Qiskit (0.37.0) and PyQuil (3.1.0). Timing was done from the host Python program using the "time" package, on a Dell Latitude 7400 with...
an 8th Generation Intel Core™ i7-8665U Processor and 2x 4GiB DDR4 RAM.

First, the compilation time was measured with minimal influence of outside factors. To this end, the MAXCUT benchmark was run for each programming language with a constant problem size of 3 steps and 15 nodes, while the number of iterations was varied from 1 to 16. To avoid any influence of the classical optimiser on the measurements, the parameter values for each iteration were randomly generated outside the timing loop.

Then, to determine the performance of OpenQLPC for the real benchmark, the compilation and the total execution time were measured for the full benchmark for varying problem sizes. The number of function evaluations for the classical optimiser was limited to 100, and any runs that reached convergence earlier were discarded.

For more details of the experimental setup, we refer to Appendix D.

VI. RESULTS

The results for the first set of tests outlined in Section V-B can be found in Fig. 3. Fig. 3a shows the wall-clock time in seconds that it cost to compile for the different numbers of iterations for OpenQLPC, OpenQL and Qiskit, Fig. 3b shows the same with the addition of the compile times for PyQuil. Fig. 4 shows these measurements relative to the time of a single iteration (i.e., divided by the time it costs to do just one iteration).

As can be seen in Fig. 3a, both OpenQLPC and OpenQL are considerably faster than Qiskit. And from Fig. 3b, it is clear both are much faster compilers than PyQuil. When considering the relative increase in compilation time, Fig. 4 shows that OpenQL handles repeat compilations worse than either Qiskit, OpenQLPC or PyQuil, since it is not optimised for this operation. In OpenQL, it takes 13 times as long to do 16 iterations compared to a single iteration. This is because of setting up the circuit and the compiler, which are done for each iteration instead of only once for the complete run in OpenQLPC. The time that is saved by OpenQLPC for subsequent iterations can be seen in both absolute and relative decrease in compile time. OpenQL and OpenQLPC take almost the same amount of time for a single compilation, but for each subsequent iteration, there is more and more time saved by OpenQLPC.

Looking at the absolute compile times shows that Qiskit is an overall much slower compiler than OpenQL or OpenQLPC. Inspecting the relative cost of compiling for multiple iterations, Qiskit shows some level of optimisation for this type of repeated compilations. Still these optimisations are not as effective as the ones implemented in OpenQLPC, which is faster both in absolute terms and in relative cost of compilation.

Inspecting the compilation time of PyQuil, Fig. 4 shows that consecutive iterations do not incur much additional time. However, as can be seen in Fig. 3b, the compile times of PyQuil are 10x to 100x higher than that of the other measured languages. This might be because PyQuil has to be compiled by running a separate compiler on a virtual machine in server mode, which is called from the main python program.

In Fig. 5, we also inspect the accumulated compilation times for running MAXCUT with a classical optimiser for graphs of different numbers of nodes, for OpenQLPC, OpenQL, Qiskit and PyQuil. OpenQLPC has the shortest total compile time, second is Qiskit, then OpenQL, and the slowest by an order of magnitude is PyQuil. These benchmark runs were done with fewer nodes and more iterations (namely 100 iterations) than the earlier tests, and it is interesting to see that OpenQL has overtaken Qiskit in compile time. Although Qiskit takes considerably longer than OpenQL to compile a circuit once, as noted before, the time that is saved for each subsequent iteration results in a total shorter time spent compiling. The compile time of PyQuil shows that it is actually the circuit length or the number of qubits that lead to such high compile times, as the circuit with 3 nodes takes 614 ms to compile for 100 iterations, and the 15 node circuit from Fig. 3b takes

Figure 3: Wall-clock compilation time for OpenQLPC, OpenQL and Qiskit

(b) Wall-clock compilation time for OpenQLPC, OpenQL, Qiskit and PyQuil

Figure 4: Wall-clock compilation time for a MAXCUT circuit with 15 nodes, run without optimiser, with varying number of iterations for OpenQLPC, OpenQL, Qiskit and PyQuil
1567 ms for a single iteration. So although PyQuil uses little time for compiling subsequent iterations, it is most likely just the first compilation pass of a circuit that takes such a long time. OpenQL\textsubscript{PC} combines the already fast compile times of OpenQL with efficiently handling iterations, and as a result is much faster than all other tested options.

Complete (simulated) runs of MAXCUT were also timed, to determine the influence of the compiler optimisation on the total runtime, and to verify that our earlier results do not include any simulation. These are plotted in Fig. 6. If any of the previous tests included simulation, we would expect the measured compile times to be close to these execution times. Since this is not the case, none of the tested compile times included simulation.

The figure shows that total execution times are up to 50x higher than just compilation times (Fig. 5). So although the main difference in execution time between the programming languages is due to the difference in performance between the corresponding simulators. Still, the same trend can be seen, where PyQuil takes the longest time by far, and both OpenQL and OpenQL\textsubscript{PC} have similar performance, since OpenQL\textsubscript{PC} and OpenQL both use the QX simulator. The figure also shows that the Qiskit Aer simulator is the fastest of the tested options.

In summary, the results show that the improvements made for OpenQL\textsubscript{PC} result in a clear speedup compared to OpenQL. Compared to Qiskit and PyQuil, OpenQL\textsubscript{PC} has the fastest compile times for the MAXCUT benchmark. However, when looking at the total execution time, the faster simulation by Qiskit Aer results in the shortest total execution time of the benchmark. This can be partly explained by the large communication time between OpenQL\textsubscript{PC}/OpenQL and the QX simulator, which requires writing and reading of a QASM file for every iteration. This is especially apparent in the MAXCUT benchmark, which has a lot of iterations for relatively short circuits, which results in a lot of read/write operations compared to circuit compilation(s). Between the Qiskit compiler and the Qiskit Aer simulator, however, the circuit can be passed directly.

VII. CONCLUSION

In this paper, we introduced OpenQL\textsubscript{PC}, an efficient approach to parametric compilation for hybrid quantum-classical algorithms, and implemented it in the OpenQL programming framework. OpenQL\textsubscript{PC} is designed to be modular, scalable, usable, future-proof and fast. We compared wall-clock compilation time of OpenQL\textsubscript{PC} with OpenQL, Qiskit and PyQuil. The total compilation time was measured using the MAXCUT benchmark from [21].

Experimental results show that compared to other programming languages, total compile time of OpenQL and OpenQL\textsubscript{PC} are between 10 and 20 times faster than Qiskit, respectively. PyQuil has the slowest compilation, about 60x longer than OpenQL\textsubscript{PC}. In addition, comparing compile times of multiple compile iterations relative to single iterations shows that OpenQL\textsubscript{PC} is the fastest, followed by Qiskit which is 1.2x
Code availability

The code used for the benchmarks can be found at: https://github.com/anneyret/efficient_params_code.

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In this section, we show how parameterised circuits can be used in Qiskit. We do this using the following short example:

```python
qcirc = QuantumCircuit(2)
theta = Parameter("theta")
pvec = ParameterVector("pvec", 2)
qcirc.ry(theta, 0)
qcirc.crx(pvec[1], 0, 1)
circuits = [qcirc.assign_parameters({pvec[1]: 1}), inplace=True]
theta_range = np.linspace(0, 2*np.pi, 128)
parametric_measurements = []
for theta_val in theta_range:
    executable = simulator.
    parametric_measurements.append(result)
result = simulator.run(executable)
```

Defining parameters in Qiskit can be done individually, as shown above on line 2, or as a vector with a specified length, as on line 3. Both can be used as gate arguments, as on lines 4 and 5 of the example. Binding parameters to values can be done using the command `assign_parameters` (line 6) to generate a single circuit, or by `bind_parameters` to generate a list of circuits with a circuit for each value of the parameter. This is shown on line 8. This code generates a list of 128 circuits, one for each of the values of `theta` as defined on line 7. The circuit can be output as OpenQASM to a file, as shown on line 9.

The circuits can be run on a real quantum system by compiling them individually for a specific backend. An example is shown here of how to run the circuits in the example above:

```python
compiled_circuit = transpile(circuits[64], simulator )
compiled_circuit = assemble(circuits, simulator)
job = simulator.run(compiled_circuit, shots=10)
counts = job.result().get_counts()
```

On line 1, one of the circuits is transpiled to be executable on the `simulator` backend. A list of circuits can also be compiled all at once, as on line 2. In both cases, the resulting `compiled_circuit` can be executed on any supported backend with the execute command, as shown in line 3. Any measurement results can be retrieved by calling `result().get_counts()` as on line 4. This gives the measurement results as counts of how often each possible bit combination was measured, for example: `{0: 4, 1: 6}`.

Compilation, execution and binding of parameter values can also be combined into a single `execute` command, as shown below:

```python
job = execute(compiled_circuit, 
    backend=QasmSimulator(), 
    parameter_binds={(theta: theta_val) 
        for theta_val in theta_range})
```

Using a single command to bind parameters and simulate the circuit makes it impossible to determine the individual execution time of the components from the host Python program. So to get those results the separate commands are used. The compilation is considered complete after the `assemble` command.

### B. Parameters in PyQuil

A PyQuil program with the same overall functionality as the one in Qiskit is shown below. The example program will be used to explain how parameters can be defined and used in PyQuil [26]:

```python
program = Program()
ro = program.declare('ro', memory_type='BIT', memory_size=1)
theta = program.declare('theta', memory_type='REAL')
program += RX(theta, 0)
program += MEASURE(0, ro[0])
```

A quantum program is defined on line 1. Two types of parameter are declared on lines 2 and 3; `ro` will be used to store the measurement results, and the parameter `theta` is used as argument for the `RX` gate on line 4.

The parameterised quantum program program from this example can be run for different values of `theta`, as shown in the following code listing [27]:

```python
parametric_measurements = []
executable = simulator.compile(program) 
for theta_val in np.linspace(0, 2*np.pi, 128):
    executable.write_memory(region_name='theta',
        value=theta_val)
result = simulator.run(executable)
parametric_measurements.append(result)
```

In line 1, the array `parametric_measurements` is defined for storing the measurement results. The `program` from the previous example is compiled for a specific execution platform, `simulator` in this case. A for-loop is used to iterate over the values of `theta_val` (lines 3-6). On line 4, the value of `theta_val` is written to memory region `theta`. The program is then run on a simulator and the measurement result is appended to the list `parametric_measurements` on lines 5 and 6.

### C. Parameterisation in OpenQL

In this section, we will explain and document how parameters can be used in OpenQL [21].
Before a parameter can be used it needs to be created, and at some point it will need a (numerical) value. Assigning a numerical value to the parameter can be done at construction, individually at any point in the program or at compile time. All this is explained in more detail below.

1) Parameter construction: Parameter construction requires the specification of a type, which can be one of "INT", "REAL" or "ANGLE". "REAL" and "ANGLE" are essentially the same, both map to an underlying "double" type. Depending on the type, a parameter can substitute hard coded qubit numbers or gate angles. Optionally, the user can specify a name for the parameter at construction or directly assign a value to it. The syntax for parameter construction can be found in Table I. In the code listing below, example code is shown for parameter construction with specification of 1. parameter type only, 2. type and parameter name, 3. type and numerical value, and 4. type, parameter name and numerical value.

2) Using parameters: Parameters can be used in quantum circuits, in place of hard coded qubit numbers or gate angles. Some examples of using parameters are shown below, where the parameters are as defined in Appendix C1:

3) Compiling parameters: Quantum programs with parameters can be compiled in the same way as circuits without parameters in OpenQL, as shown in the code listing below:

4) Setting parameter values: There are three ways to set the value of a parameter in OpenQL.

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**Table I: Parameter syntax**

| \[\text{openql.openql.}] \text{Param( Type [, Name ] [, Value ] )} |
|---|
| **Type:** "INT" | "REAL" | "ANGLE" |
| **Name:** Symbolic name of the parameter, will appear unmodified in resulting cQASM (string) |
| **Value:** Numerical value, must match the type as specified by **Type** |

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Line 1 shows the *hadamard* gate from Appendix C2 with parameter *p_int*. Symbolic names in the cQASM code are preceded by the \% symbol, and the randomly generated string "w5Bq1DRO" is the "name" of this parameter. Line 2 shows the *rz* gate, applied to qubit 0. The angle is the parameter *p_real* from Appendix C1. The name of this parameter was set as *pname* at construction, and this is reflected in the cQASM output. On line 3, the *ry* gate had *p_int2* in place of a qubit number and *p_angle* in place of a rotation angle. Both were constructed with a numerical value already set, which is reflected in the cQASM output above, where instead of symbolic names the numerical values are used; qubit number 4 (q[4]) for *p_int2* and 1.724 for *p_angle*.

Setting a value at construction is outlined in Appendix C1, examples for the other two ways are given here.

Assigning a numerical value to a single parameter can be done at any point in the code by calling the `set_value` method.

This assigns the value of 2 to *p_int*. It is also possible to modify the numerical value of a parameter in this way.

When compiling and generating cQASM, the final value of a parameter will be used for all instances of a parameter, so it is not possible to assign different numerical values to a single parameter partway through a quantum circuit. The intended use is to modify parameter values between different iterations of a circuit, where the whole circuit is compiled for each iteration.

It is also possible to set values at compile time. This can be done for all parameters at once, or for a subset of the parameters.

With this line of code, the values of 1, 2.1 and -1.7 are assigned to parameters *p_int*, *p_real* and *p_angle*, respectively, and the whole program is compiled.

This results in the following cQASM output:
On line 1, the hadamard gate from before, with parameter $p_{\text{int}}$, is applied to qubit 1 ($q[1]$), the value stored in $p_{\text{int}}$. This overwrites the value set in Appendix C4. The $rz$ gate on line 2 now uses an angle of 2.1, the value from $p_{\text{real}}$. The $ry$ gate on line 3 is applied to qubit 4 as in Appendix C4, since the value of $p_{\text{int}2}$ was not modified. The angle is now $-1.7$, the value assigned to $p_{\text{angle}}$ at compilation. On line 4, the $cnot$ gate is applied from qubit 1, as stored in $p_{\text{int}}$ and to qubit 4, as stored in $p_{\text{int}2}$.

The resulting cQASM no longer contains symbolic names, and can now be executed on a simulator or a real quantum device.

**D. Experimental setup**

In this section, we go into detail of the experimental setup that was used to create the results presented in this paper.

To compare the compilation times of OpenQL, OpenQL-PC, Qiskit and PyQuil, a quantum circuit was generated as in Section V-A. To limit the influence of other factors on the measurement results, the angles for each iteration were not generated using a classical optimiser, but randomly generated outside of the timing loop. The number of steps was set at 3, as mentioned before, and the number of nodes at 15. This corresponds to a circuit with a combined total of 330 CNOTs and rotation gates, and 15 measurement operators. For each separate measurement, the language (OpenQL, OpenQL-PC, Qiskit and PyQuil) and the total number of iterations are randomly selected. For the iterations, a simple loop is used that compiles the circuit with different angle values for the parameters. To make sure we include all of the compilation steps but as few other steps as possible, the wall-clock starting time is measured just before the first line where the quantum programming language was used. Some programming languages use an ASAP strategy, while others only start the actual compilation when a "compile" instruction is called. To verify that actual circuit generation took place for each iteration, (Open)QASM files are generated as output. All random number generation and other preparation steps are done before the starting time, and all handling and writing of measurement data after the ending time. The wall-clock ending time is measured after all the iterations have completed, and total time is taken as the difference between the ending and the starting time.

Timing was done for a total of 1, 2, 4, 6, 8, 10, 12, 14 and 16 iterations. Although the circuit that is used in these tests comes from the MAXCUT benchmark, no classical optimiser is used for this set of tests. This way, the number of iterations is not dependent on any unknown factors, and the compilation time does not include the runtime of the optimiser. The compilation of the circuits includes an optimisation step to get more realistic results and to better show the advantage that parametric compilation can offer. With parametric compilation, the circuit will only be optimised (and decomposed, scheduled and mapped) once, instead of every iteration. The Qiskit optimisation level was set to 1, which corresponds to "light optimisation". This adds adjacent gate collapse and redundant reset removal to the compilation stack [15]. The closest equivalent in OpenQL is the "RotationOptimizer" pass, which tries to find sets of contiguous gates that correspond to identity, and then takes those out of the circuit. Both of these optimisations handle only small sets of adjacent gates, and remove or collapse them when possible [28].

To determine whether the improvements made have an impact on any real applications, a full implementation of MAXCUT was used. The circuit and the parameters are the same as in the previous set of tests, but now a classical optimiser was added to the loop to determine the parameter values for the next iteration. The circuits were also run on a simulator, and the measurement results coming from the simulator are used as input for the optimiser. This makes the total execution flow as in Fig. 1. The tests were performed for regular graphs with between 3 and 8 nodes, with 3 steps to the algorithm as before. Tests were performed interleaved where possible, and number of nodes was randomised for each trial. For each run of the MAXCUT benchmark, the number of function evaluations was limited to 100, and any runs that reached convergence earlier were discarded. Therefore the total number of function evaluations for each language is 100, although the number of circuit compilations and simulations can be lower. This is because the loop is aborted preemptively if the optimiser generates negative angles or angles bigger than $2\pi$. The effect this has on the results is expected to be small, and it should be the same for each language so does not influence the comparisons made.