

# Design Automation and Design Space Exploration for Quantum Computers

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**Abstract**—A major hurdle to the deployment of quantum linear systems algorithms and recent quantum simulation algorithms lies in the difficulty to find inexpensive reversible circuits for arithmetic using existing hand coded methods. Motivated by recent advances in reversible logic synthesis, we synthesize arithmetic circuits using classical design automation flows and tools. The combination of classical and reversible logic synthesis enables the automatic design of large components in reversible logic starting from well-known hardware description languages such as Verilog. As a prototype example for our approach we automatically generate high quality networks for the reciprocal  $1/x$ , which is necessary for quantum linear systems algorithms.

## I. INTRODUCTION

Quantum computing is getting real. This year, researchers have fabricated quantum computers that implement well-known quantum algorithms reliably [1] or perform practical applications such as high-energy physics simulation [2] and electronic structure computation [3]. Since all such examples involve circuits of very limited depth, hand designed circuits suffice. However, as quantum computers scale up, design automation is necessary in order to fully leverage the power of this emerging computational model.

Fundamental differences between quantum and classical computing pose serious design challenges. One is that the basic fault-tolerant gate sets do not include a universal set of classical gates as fundamental instructions. Instead, one can implement a universal set of reversible gates by applying a so-called  $T$  gate to the underlying quantum bits (or qubits, or lines). This gate is sufficiently expensive [4] that it is customary to neglect all other gates when costing a quantum algorithm. Decomposing the reversible logic that arises in such algorithms into networks that minimize  $T$  gates and qubits is therefore a central challenge in quantum computing.

Many synthesis algorithms for reversible circuits have been presented in the last 15 years, see, e.g., [5], [6]. Most of them are applicable to small functions since they require an explicit function representation, e.g., a truth table, as input. In the last few years, more scalable algorithms have been presented [7], [8], [9] that work on a symbolic function representation, thereby allowing reversible circuits to be found for large functions.

In this paper, we show that scalable reversible logic synthesis algorithms combined with conventional logic synthesis algorithms allow reversible circuits to be found automatically for large functions. We propose design flows that start from an irreversible design description in Verilog and then use logic synthesis algorithms to translate it into descriptions that are

compatible for reversible logic synthesis algorithms and finally compile it into a quantum circuit. The various algorithms used both in classical and reversible logic synthesis enable nontrivial design space exploration. The designer can optimize the synthesis output with respect to several objectives such as space (number of qubits), time (number of quantum operations), or runtime of the design flow. As a result, the proposed design flows may be robust to changes in quantum architectures. The design flows further allow researchers to accommodate the cost of arithmetic and other functions when developing quantum algorithms and architectures. To our knowledge, so far such advanced design flows were not investigated and leveraged for the design of quantum computers.

We illustrate the power of these design flows by finding high quality reversible implementations of the reciprocal  $1/x$  with different bitwidths for  $x$ . The reciprocal is used in several quantum algorithms of high interest. Most notably, it is essential for quantum linear systems algorithms [10], [11]. Recent work has shown that the space requirements imposed by having to implement the reciprocal reversibly can be prohibitive for implementations on a small quantum computer [12], [13]. The implementation of the reciprocal is used as an example to illustrate the proposed design flows. These are the central contributions of this paper and applicable to many other functions in a similar manner. The uniting advantage is that a conventional description language such as Verilog can be used as a starting point. This enables designers to easily adapt to quantum computing as well as to easily incorporate a large existing body of conventional logic synthesis software.

The experimental results confirm the effectiveness of the proposed design flows. Specifically, we show that we can explore tradeoffs between the number of lines and the depth of the circuit that cannot be probed using the handcrafted approaches used in current quantum algorithm design. This flexibility opens up the possibility of highly optimized circuits to be introduced to quantum compilation, which allows algorithms to be better tailored to the severe architectural restrictions imposed by quantum hardware.

## II. PRELIMINARIES

### A. Boolean Functions and Logic Representations

A multi-output Boolean function  $f : \mathbb{B}^n \rightarrow \mathbb{B}^m$  maps  $n$  Boolean input values to  $m$  Boolean output values and we can represent  $f$  as an  $m$ -tuple of  $n$ -variable Boolean functions  $(f_1, \dots, f_m)$ . A literal is a Boolean variable in regular

or complemented form. In logic synthesis, there are several representations for Boolean functions. *2-level representations* have a logic depth of 2; examples are sum-of-products (SOP) in which literals are combined to product terms using AND and product terms are combined using OR. In exclusive-sum-of-products (ESOP), the XOR operation is used instead of OR. 2-level representations can be very large. *Multi-level representations* are directed acyclic graphs called logic networks, in which terminal nodes are input variables or constants and internal nodes are logic operations. In the scope of this paper, we use And-inverter graphs (AIGs, [14]) and XOR-majority graphs (XMGs, [15]) as logic networks. AIGs have AND gates and inverters as logic primitives and XMGs have XOR, majority-of-three, and inverters as logic primitives [15].

### B. Embedding

Quantum computing requires all operations to be reversible. This also applies to the classical Boolean parts, e.g., arithmetic components. However, many functions of practical interest are not reversible. Embedding describes the process of extending an irreversible  $n$ -input,  $m$ -output function  $f(x_1, \dots, x_n) = (f_1, \dots, f_m)$  into an  $r$ -variable reversible function  $f'(x_1, \dots, x_r) = (f'_1, \dots, f'_r)$  with  $r \geq \max\{n, m\}$ . We say that  $f'$  embeds  $f$ , if there exists assignments  $a_{n+1}, \dots, a_r$  such that

$$f'_{r-m+j}(x_1, \dots, x_n, a_{n+1}, \dots, a_r) = f_j(x_1, \dots, x_n) \quad (1)$$

for all  $1 \leq j \leq m$ . The assignments  $a_{n+1}, \dots, a_r$  are called *constant inputs*. The functions  $f'_1, \dots, f'_{r-m}$  are called *garbage outputs* as they are discarded in (1) and only required to make  $f'$  reversible.

*Theorem 1 (Bennett embedding, [16]):* Let  $f$  be a  $n$ -input,  $m$ -output function. Then the  $(m+n)$ -variable reversible function  $f'$  with

$$f'_j(x_1, \dots, x_{n+m}) = \begin{cases} x_j & \text{if } j \leq n, \\ x_j \oplus f_{j-n}(x_1, \dots, x_n) & \text{otherwise} \end{cases} \quad (2)$$

embeds  $f$  for  $x_{n+1} \leftarrow 0, \dots, x_{n+m} \leftarrow 0$ .

The Bennett embedding implies an upper bound on the number of additional lines  $r - n$  that are required to find an embedding. But for some functions a smaller number can be found.

The minimum number of required additional lines to embed an irreversible  $n$ -input,  $m$ -output function  $f$  is

$$\lceil \log_2 \max_{y \in \mathbb{B}^m} \#\{x \in \mathbb{B}^n \mid f(x) = y\} \rceil, \quad (3)$$

i.e., the binary logarithm of the maximum size of a collision set of  $f$ . An embedding that ensures this minimum number of additional lines is called *optimum*. It has been shown that computing the minimum number of additional lines is coNP-complete [17] and therefore one cannot expect to find optimum reversible embeddings for large irreversible functions.

### C. Reversible Circuits

In some respects, the structure of a reversible circuit is simpler than the one of a classical logic network. A reversible circuit for a function  $f : \mathbb{B}^r \rightarrow \mathbb{B}^r$  has  $r$  circuit lines on which reversible gates operate which are aligned in a cascade. We consider the widely used mixed-polarity multiple-controlled Toffoli gate (for short Toffoli gate) library in this paper. Each gate has a set of control lines that can be positive or negative and one target line that is disjoint from the control lines. The gate inverts the value assigned at the target line if and only if all values assigned to positive (negative) control lines are 1 (0). All values on other lines remain unchanged.

### D. Reversible Logic Synthesis

Reversible logic synthesis algorithms can be categorized into *functional algorithms* and *structural algorithms*. *Functional algorithms* require as input a reversible function and therefore embedding is required as a preprocessing step prior to synthesis. Functional algorithms do not add additional lines to the reversible circuit during synthesis and therefore can return line optimum results. Many functional algorithms are based on the transformation-based approach [5], in which Toffoli gates are found that transform the input function into the identity function, thereby finding a reversible circuit that realizes the input function. The original implementation works on truth tables, but a symbolic variant of the algorithm exists [7] that can be applied to larger functions. For small functions, SAT-based [18] and enumerative approaches [19] can even guarantee gate optimum results.

In *structural algorithms* the input function is given in terms of some structural representation, e.g., a 2-level or multi-level logic network or a decision diagram. Synthesis is performed by generating reversible subcircuits for substructures (e.g., using functional synthesis approaches [8]) and then concatenating the subcircuits. Structural algorithms are significantly more scalable compared to functional ones, but have the drawback of generating a large number of additional lines—often much higher than the  $(m+n)$  bound in Theorem 1.

## III. RECIPROCAL

We are interested in finding a reversible embedding for the reciprocal function  $\text{rec} : \mathbb{B}^n \rightarrow \mathbb{B}^n$  with  $\text{rec}(x_1, \dots, x_n) = (y_1, \dots, y_n)$  such that  $\frac{1}{x} = y$  when  $x = (x_1 \dots x_n)_2$  and  $y = (0.y_1 \dots y_n)_2$ . One can increase  $n$  to obtain a higher precision with the cost of a more costly implementation.

We propose two designs to implement the reciprocal using Verilog: (i) `INTDIV(n)`, which uses Verilog's integer division operator, and (ii) `NEWTON(n)`, which implements division using the Newton-Raphson method on fixed-point numbers. Both implementations are described in more detail in the remainder of this section.

*1) Integer division:* We compute the result of the integer division  $2^n/x$ , where both  $2^n$  and  $x$  are represented using  $(n+1)$ -bit unsigned integers. The result is a  $(n+1)$ -bit unsigned integer from which we omit the most significant bit. Then, the remaining bits represent  $y$ .

*Example 1:* Let  $n = 8$  and let  $x = 22$ . We have  $\frac{1}{22} = 0.045$ . With Verilog's integer division, we get  $(10000\ 0000)_2 / (0\ 0001\ 0110)_2 = (0\ 0000\ 1011)_2$ . Hence,  $y = 2^{-5} + 2^{-7} + 2^{-8} = 0.04296875$ .

2) *Newton-Raphson method:* We implemented the Newton-Raphson method in Verilog based on signed fixed-point numbers. In the following, we use the format Q3.w to denote a signed fixed-point number in two's-complement encoding that has 3 integer bits (including the sign bit) and w fractional bits. Arithmetic operations can be implemented on signed integer numbers using integer operations. The result of an addition or subtraction of two Q3.w numbers is again a Q3.w number.

Multiplication is slightly more involved. Given a Q3.w<sub>1</sub> number  $u$  and a Q3.w<sub>2</sub> number  $v$ , the result of integer multiplication  $u * v$  is a Q6.(w<sub>1</sub> + w<sub>2</sub>) number. We introduce the shortcut  $u *_w v$  that truncates the 3 most significant integer bits and the least significant fractional bits to return a Q3.w number.

The overall procedure is as follows:

- 1) set  $x' \leftarrow Q3.n(x/2^e)$  such that  $\frac{1}{2} \leq x' < 1$
- 2) set  $x_0 \leftarrow Q3.2n(48/17) - (Q3.n(32/17) *_{2n} x')$
- 3) for  $1 \leq i \leq I$ ,
- set  $x_i \leftarrow x_{i-1} + x_{i-1} *_{2n} Q3.2n(1) - (x' *_{2n} x_{i-1})$
- 4) set  $y' \leftarrow x_I \gg e$
- 5) set  $y$  to the  $n$  most significant bits of  $y'$

In step 1, we normalize  $x$  and make it a fixed-point number  $x'$  such that the integer part is 0 and the most significant fractional bit is 1. Note that this can be done using a right-shift by  $e$ . In step 2, we compute the starting value  $x_0$  using constants  $48/17$  and  $32/17$ . We apply the Newton iteration  $I = \lceil \log_2 \frac{P+1}{\log_2 17} \rceil$  times. The values  $x_i$  for  $0 \leq i \leq I$  have  $2n$  fractional bits, i.e., we use twice the input precision to carry out the computations in the Newton iteration (step 3). We use the same exponent  $e$  to shift the value of  $x_I$  and then extract the  $n$  most significant bits as  $y$ .

#### IV. DESIGN FLOWS

This section describes the main contribution of the paper. We show a variety of design flows starting from the two Verilog designs INTDIV(n) and NEWTON(n) that have been introduced in the previous section. Fig. 1 offers an overview of the design flows which pass four levels: (i) the *design level* containing the Verilog descriptions, (ii) the *logic synthesis level* in which the designs are optimized and transformed into formats required by (iii) the *reversible synthesis level* in which synthesis algorithms generate reversible networks that can eventually be mapped to (iv) architectures at the *quantum level*. In the scope of this paper, we stop after the reversible networks have been obtained. The experiments in the next section will show that INTDIV(n) is superior to NEWTON(n) in this experiment, both in quality and runtime. However, a simple design such as INTDIV(n) is not possible for some functions. Functions such as  $\frac{1}{\sqrt{x}}$  or trigonometric functions require approximation techniques with an implementation similar to the NEWTON(n) design. Thus NEWTON(n) can be considered a proxy for reversible synthesis of other functions.

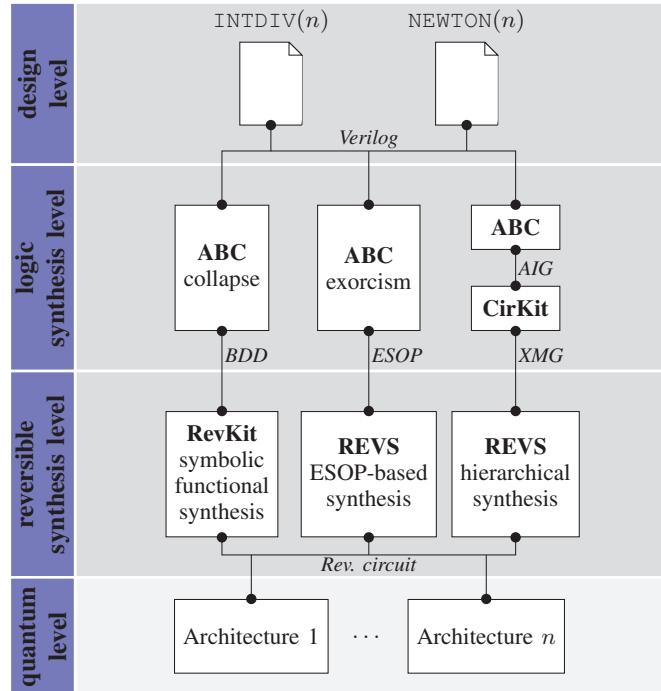


Fig. 1. Design flows; lines represent interfaces between files and tools and are annotated using the function representation at the interface

At the reversible synthesis level we consider synthesis algorithms from three different approach categories to target different cost aspects: (i) *symbolic functional synthesis* for a low number of qubits, (ii) *ESOP-based synthesis* for moderate number of qubits, and (iii) *hierarchical synthesis* as a scalable solution for large bitwidths and low  $T$ -count. How each algorithm is used in the flow is described in more detail in the following.

##### A. Symbolic Functional Synthesis

The input to symbolic functional synthesis is a binary decision diagram (BDD). This is obtained by reading the Verilog into the logic synthesis tool ABC [20] optimize it several rounds using ‘dc2’ before collapsing it into a BDD using ‘collapse’.

At the reversible synthesis level an optimum embedding is obtained from the BDD (see [17], [7]). The resulting reversible function is represented as a BDD that is input to the SAT-based variant of the symbolic transformation-based synthesis algorithm [7]. The inputs  $x_1, \dots, x_n$  are not preserved by the embedding, i.e., the function  $\text{rec}(x_1, \dots, x_n)$  is applied *in-place*. This synthesis algorithm guarantees the optimum number of qubits which must be in between  $n$  and  $2n$ . A property of the transformation-based algorithm is that large Toffoli gates with controls on all circuit lines are generated. This leads to large  $T$ -count.

##### B. ESOP-based Synthesis

The input is a multi-output ESOP expression. This is obtained with ABC by first optimizing the input design using

the command sequence ‘*satclp; sop; fx; strash; dc2*’ which generates an AIG. We then use ‘&*exorcism*’ to collapse the AIG into a ESOP and optimize it using the algorithm presented in [21]. We then perform ESOP-based synthesis with the reversible synthesis tool REVS [9] which is a tool that allows to trade off between circuit size and the number of qubits. REVS offers different strategies for cleaning up intermediate calculations and re-using the qubits that have been freed up. For Boolean functions in ESOP format, REVS offers a mode for factoring common subexpressions, the size of which are bounded by an integer parameter  $p$ . If  $p = 0$ , then REVS proceeds by taking each product term with  $k$  literals in the given multi-output ESOP expression and translates it into a Toffoli gate with  $k$  controls and polarities according to the literals’ polarities. If a product term is shared among several outputs, only one Toffoli gate is required to realize one output and CNOT gates are used to copy the result to the other outputs. Then the synthesis algorithm creates circuits with  $2n$  qubits, and each Toffoli gate cannot have more than  $n$  controls. If  $p > 0$ , then REVS considers groups of  $p$  product terms in the ESOP expansion that have the same output value and tries to factors the resulting expressions. Intermediate results in the factorization are stored in additional lines, which typically leads to an increase of the total number of used lines beyond  $2n$ . However, overall this often leads to a reduction of the overall number of  $T$  gates, in particular if many terms in the ESOP expansion correspond to the exact same function value.

### C. Hierarchical Synthesis

We perform hierarchical synthesis with REVS by using as input an *XOR-Majority Graph* (XMG). An XMG is a logic network in which the primitives are XOR, AND, OR, the MAJ (majority-of-three function, see, e.g., [22]), and their inverted forms. This network representation is advantageous for reversible logic synthesis. First, the MAJ gate can be realized with only one Toffoli gate and therefore has the same number of  $T$  gates as an AND and OR gate by being more expressive. Second, an XOR gate can be realized using CNOT gates and therefore does not require any  $T$  gates. Third, the XOR gate can be applied in-place, if the value of at least one its operands is no longer required to compute another gate. The same applies for the MAJ gate, if all of its operands are no longer required. We derive optimized XMGs from optimized AIGs using the algorithm presented in [15] using CirKit’s<sup>1</sup> command ‘*xmglut -k 4*’ on AIGs that were optimized using multiple iterations of ‘*resyn2*’ in ABC.

## V. EXPERIMENTS

We have generated reversible circuits for the  $\text{INTDIV}(n)$  and  $\text{NEWTON}(n)$  designs using all three design flows. This section presents the results of the experimental evaluation. We used the command ‘*tbs -s*’ in RevKit [23] for the symbolic functional synthesis [7]. We used REVS [9] to obtain results for both the ESOP-based and hierarchical synthesis algorithm. All

TABLE I  
BASELINE RESULTS WITH MANUAL DESIGN

$n$	RESDIV( $n$ )		QNEWTON( $n$ )	
	qubits	$T$ -count	qubits	$T$ -count
8		48	8 512	111
16		96	34 944	234
32		192	141 568	615
64		384	569 856	1226
				1 405 284

TABLE II  
RESULTS WITH SYMBOLIC FUNCTIONAL REVERSIBLE SYNTHESIS

$n$	INTDIV( $n$ )			NEWTON( $n$ )		
	qubits	$T$ -count	runtime	qubits	$T$ -count	runtime
4	7	597	0.10	7	589	0.29
5	9	1 613	0.11	9	1 848	0.32
6	11	5 963	0.18	11	6 419	0.41
7	13	20 008	0.31	13	17 867	0.57
8	15	51 386	0.74	15	56 379	4.15
9	17	142 901	2.54	17	148 913	6.47
10	19	380 009	10.94	19	383 891	15.72
11	21	946 724	43.62	21	945 117	54.44
12	23	2 318 841	284.72	23	2 346 319	296.67
13	25	5 599 538	1 862.22	25	5 645 530	1 669.84
14	27	13 148 102	10 545.50	27	13 186 076	9 342.96
15	29	30 761 399	44 501.20	29	30 746 528	41 398.30
16	31	71 155 258	274 744.00	31	71 259 272	213 135.52

experiments have been carried out on an Intel E5-2670 octacore CPU with 2.60 GHz and 128 GB main memory. All runtimes are given in seconds. Correctness of the synthesized designs has been verified using ABC’s combinational equivalence checker ‘*cec*’. All generated files and pointers to implementation details can be found at [msoeken.github.io/reciprocal.html](https://msoeken.github.io/reciprocal.html).

We use two manual quantum circuit designs for a baseline comparison. First, an integer division algorithm based on the restoring division algorithm [24] that computes for  $n$ -bit inputs  $a$  and  $b$  the  $n$ -bit quotient  $q$  and  $n$ -bit remainder  $r$  such that  $a = qb+r$ , using  $3n$  qubits. We refer to this circuit as RESDIV. One can use the circuit to compute the  $n$ -bit reciprocal  $1/x$  by setting  $a = 2^n$  and  $b = x$  in a  $2n$ -bit version of the circuit in order to match the precision of our designs. We also manually created a design following the Newton-Raphson method, which is similar but more accurate to the designs proposed in [12] and [13] and we refer to it as QNEWTON. In contrast to the NEWTON design that follows the standard algorithm, we adjusted the algorithm as follows to reduce the number of lines needed. QNEWTON works by first bitshifting the inputs into the range  $[0.5, 1]$ , implementing Newton iterations with the Cucarro adder [25], text book multiplication, and then finally bit shifting the values again to provide the desired answer. The precision of the adders used were varied at each Newton iteration to minimize the space and time resources needed to hit the target accuracy.

QNEWTON’s use of variable internal precision for the Newton iterations allows us to compute with roughly half the qubits predicted in previous results that examined computing reciprocals on quantum computers using Newton iterations [12],

<sup>1</sup>[github.com/msoeken/cirkit](https://github.com/msoeken/cirkit)

TABLE III  
RESULTS WITH REV[9]

INTDIV( $n$ ), $p = 0$				NEWTON( $n$ ), $p = 0$				INTDIV( $n$ ), $p = 1$				NEWTON( $n$ ), $p = 1$			
$n$	qubits	T-count	runtime	qubits	T-count	runtime	qubits	T-count	runtime	qubits	T-count	runtime	qubits	T-count	runtime
5	10	232	0.04	10	135	0.26	12	241	0.04	10	135	0.26			
6	12	423	0.09	12	294	0.35	14	411	0.08	13	268	0.32			
7	14	791	0.08	14	568	0.35	17	803	0.11	17	511	0.34			
8	16	1342	0.12	16	1039	3.92	20	1349	0.13	20	1060	3.94			
9	18	2056	0.19	18	1894	5.62	23	1887	0.21	22	1850	5.68			
10	20	3415	0.32	20	3311	9.27	23	3238	0.32	24	3071	9.16			
11	22	5631	0.52	22	5303	14.98	29	5244	0.69	27	4846	14.97			
12	24	8431	0.95	24	8423	25.09	30	7700	1.20	29	7136	25.29			
13	26	13414	1.93	26	14287	44.03	31	11474	2.01	32	11988	44.16			
14	28	21902	3.22	28	21782	72.70	37	19063	3.82	34	19186	72.94			
15	30	33502	8.18	30	34815	118.74	35	27897	8.51	37	28635	118.99			
16	32	52376	19.13	32	50784	1128.73	46	42717	1598.71	38	41532	1129.66			
17	34	78470	36.24	34	95462	1860.05	41	64089	37.46	43	76022	1861.80			
18	36	119510	86.64	36	153414	3182.44	43	94577	101.05	44	119657	3186.19			
19	38	179095	169.99	38	229768	5276.51	46	138912	182.24	46	175598	5286.83			
20	40	284118	393.96	40	349398	11486.74	48	218341	440.79	47	263106	11502.31			
21	42	422806	823.56	42	552496	18869.36	51	318627	852.37	51	412488	18936.66			
22	44	640351	3075.21	44	837646	29371.18	52	476603	3137.62	53	616065	30666.43			
23	46	941408	7462.87	46	1249894	52547.84	56	684166	7631.37	56	909364	52936.22			
24	48	1417327	19487.67	48	1885742	106612.57	57	1021041	19915.68	58	1344400	107490.99			
25	50	2119663	72035.25	50	2819902	220349.12	60	1512893	73999.97	60	1985367	222364.17			

[13]. Our work also differs from [12], [13] in that here detailed  $T$  gate estimates are provided. As such, these numbers are a slight improvement upon the previous state of the art.

For each reversible circuit we report the number of qubits, the  $T$ -count (according to [26] and [27]), and the overall runtime of the flow. The baseline results obtained from RESDIV( $n$ ) and QNEWTON( $n$ ) are given in Table I for  $n = 8, 16, 32, 64$ .

Table II lists the experimental results for  $n \leq 16$  when using symbolic functional synthesis. For these circuits the number of qubits is optimum. That the numbers are equivalent for INTDIV and NEWTON is not necessarily expected, as NEWTON approximates  $1/x$  which may have an effect on the maximum occurrence of an output assignment. The number of qubits is  $3.2 \times$  and  $3.1 \times$  smaller compared to the RESDIV baseline for  $n = 8$  and  $n = 16$ , respectively. However, this comes with the price of a very high  $T$ -count. The numbers for NEWTON are slightly higher compared to INTDIV with exceptions in case of  $n \in \{4, 7, 11, 15\}$ . The reason for this large number is that functional synthesis generated reversible circuits with Toffoli gates that have a large number of control lines. For example, the realizations for  $n = 16$  contain Toffoli gate with up to 27 control lines. For INTDIV, the  $T$ -count is  $6.0 \times$  and  $2036.3 \times$  larger compared to RESDIV for  $n = 8$  and  $n = 16$ . The comparison to QNEWTON is qualitatively similar. The runtimes are very high reaching about 3.2 days for  $n = 16$  making this design flow not scalable for larger bitwidths. Despite the increased runtimes, this result is remarkable because it shows that our design flow can find designs that use less than the  $2n$  lines required for the out of place reciprocal circuit.

Table III lists results for  $n \leq 25$  when using REVS with a 2-level ESOP description as input. For  $p = 0$ , the number of qubits is  $2n$  which is only one qubit more compared to the functional synthesis approach. Compared to the baseline the

TABLE IV  
RESULTS WITH HIERARCHICAL SYNTHESIS

INTDIV( $n$ )				NEWTON( $n$ )			
$n$	qubits	T-count	runtime	qubits	T-count	runtime	qubits
16	892	5607	1.67	10713	73080	75.66	
32	3501	21455	15.48	56207	392917	1218.28	
64	13465	80339	38.34	178653	1264704	3008.98	
128	51897	308364	376.39	1029441	7033040	37575.67	

number of qubits is  $3 \times$  smaller for both  $n = 8$  and  $n = 16$ . However, as the Toffoli gates have fewer number of controls, the  $T$ -count is much smaller compared to functional synthesis. For small  $n$  the NEWTON design has better  $T$ -count, which changes for large  $n$ . When comparing the NEWTON design to the RESDIV baseline, the  $T$ -count is  $8.2 \times$  better for  $n = 8$  but  $1.5 \times$  larger for  $n = 16$ . Relative to QNEWTON, we see comparable numbers of  $T$  gates and far fewer lines at  $p = 0$ , however the ESOP-based approach in REVS outperforms it at  $p = 1$ . The REVS-based design flow is more scalable than the functional approach, but also reaches its limits: for  $n = 25$ , it takes about 20 hours to find a realization for the INTDIV design, and about 2.5 days for the NEWTON design.

Table IV lists results when using the hierarchical synthesis approach. This approach can scale to large bitwidths as can be seen from the INTDIV design. We show results up to  $n = 128$ , but circuits for larger bitwidths can still be obtained in a reasonable amount of time. First, we like to point out that the results for INTDIV differ significantly from NEWTON, in contrast to the other two design flows. This is due to the fact, that we perform logic optimization at AIG level after the network has been synthesized from its Verilog description. The starting points are significantly different and optimization

approaches can easily get stuck in local minima. Drastic measures such as collapsing the network into a 2-level logic form (as in the two previous design flows) are required in order to escape from them. However, collapsing does not scale to these high bitwidths. Due to this large difference in quality, we use INTDIV for comparison to the baseline design. The number of qubits is  $9.3\times$  and  $18.2\times$  larger for  $n = 16$  and  $n = 32$  compared to the RESDIV baseline design. However, the  $T$ -count is  $6.2\times$  and  $6.6\times$  smaller for  $n = 16$  and  $n = 32$ . Both, the number of qubits and the number of  $T$ -count can be improved by spending more effort in minimizing the number of gates in the XMGs during logic synthesis, with the cost of a higher runtime. The  $T$ -count of NEWTON also is comparable to QNEWTON however the latter requires  $46\times$  and  $91\times$  fewer lines for  $n = 16$  and  $n = 32$ . This discrepancy occurs because the hierarchical approach does not directly optimize the precision in each Newton iteration. Although INTDIV shows better performance in this example, the numbers for NEWTON are still quite meaningful. As discussed above, for functions such as  $\frac{1}{\sqrt{x}}$  or trigonometric functions Newton's method will frequently be the technique of choice for logic synthesis. These designs are therefore meaningful benchmarks for NEWTON's performance for other logic synthesis problems.

## VI. CONCLUSIONS

We presented versatile design flows for the synthesis of reversible logic in quantum computers. Our flows take Verilog programs as input that are translated using classical logic synthesis algorithms into formats appropriate for reversible logic synthesis algorithms. This enables design exploration and gives the designer the possibility to optimize with respect to a cost metric such as the number of  $T$  gates or qubits, metrics that correspond to time and space in quantum computers. These capabilities are absent in existing approaches for quantum circuit compilation. Our work provides a necessary tool for making quantum algorithms practical, such as quantum linear systems algorithms and quantum simulation algorithms.

We illustrated the design flows and synthesize a variety of reversible circuits for the reciprocal  $1/x$  with different bitwidths for  $x$  and show that we are able to find circuits that beat handcrafted designs in either width or size, depending on our optimization goal. In future work we plan to integrate our design flows into industrial logic synthesis software and find efficient reversible implementations for floating point arithmetic designs.

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