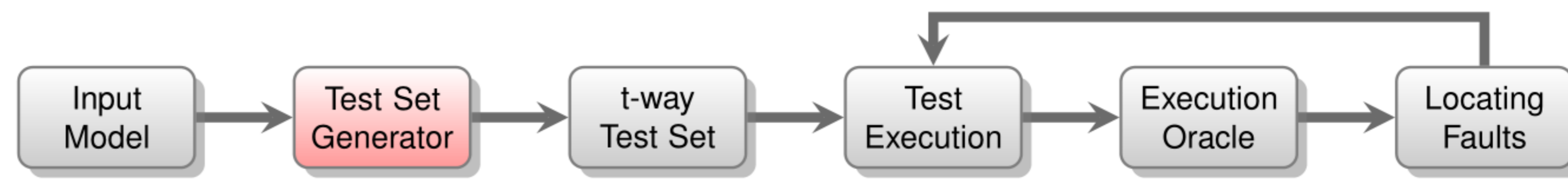


Covering Array Optimization

Covering Arrays

- ▶ Covering Arrays (CAs) are combinatorial structures used in Combinatorial Testing.
- ▶ They guarantee that every t -way interaction appears in at least one row (test).
- ▶ A uniform Covering Array is denoted as $CA(N;t,k,v)$, where N is the number of rows, t is the strength, k is the number of columns and v is the cardinality of the alphabet.
- ▶ CAs with the smallest number of rows possible are called optimal CAs.



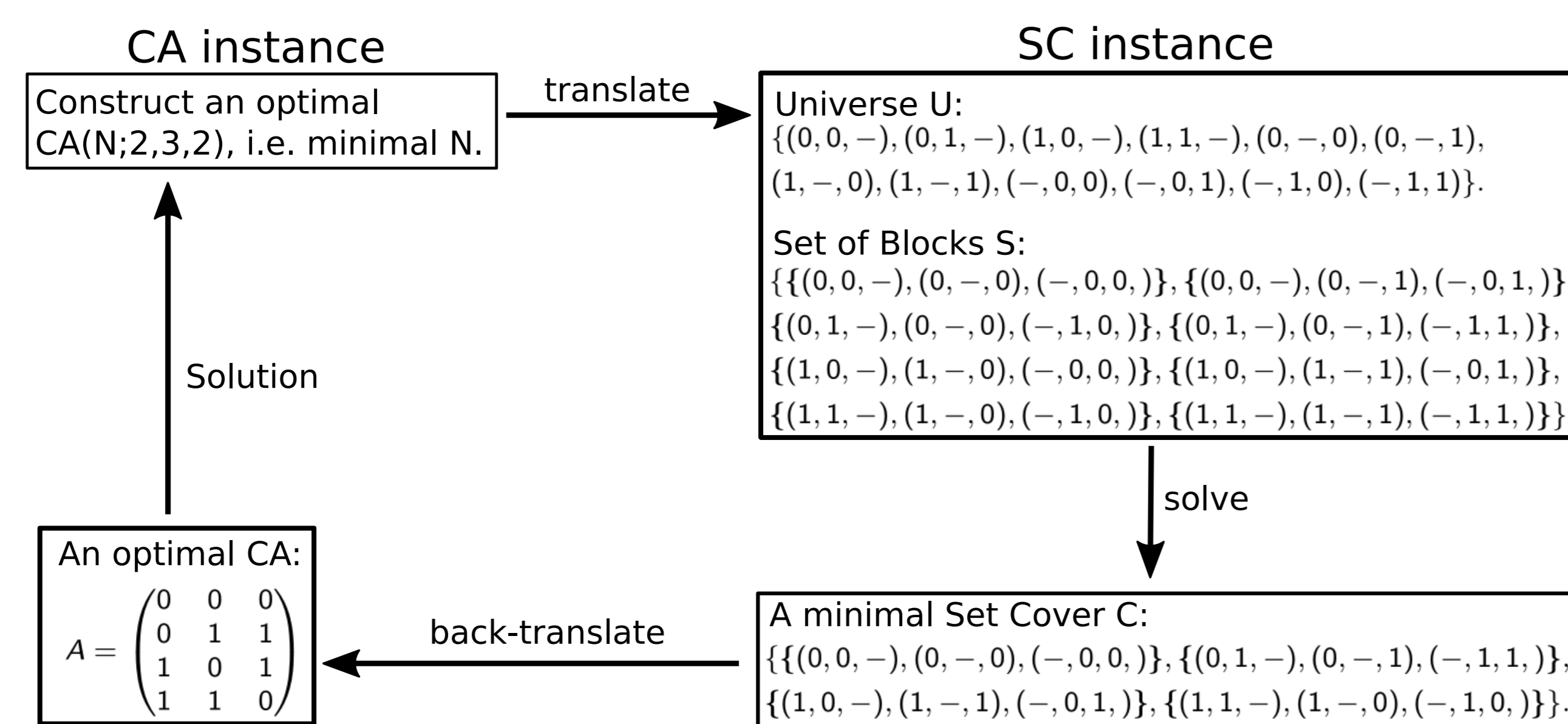
The Covering Array Generation Problem

- ▶ Generating optimal CAs is tightly coupled to hard combinatorial optimization problems.
- ▶ Commonly used generation methods include greedy algorithms, mathematical constructions and metaheuristic approaches.
- ▶ We investigated the use of neural networks for covering array generation.

Boltzmann Machines for CA Generation

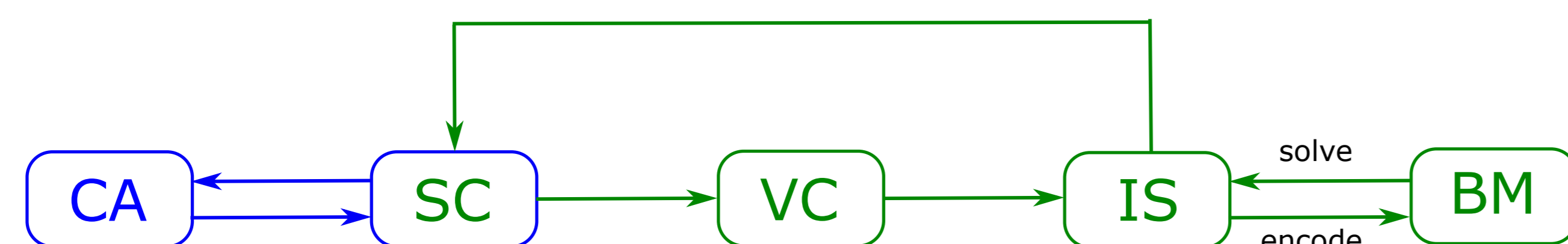
Covering Arrays as Set Covers:

- ▶ For a given universe U and a set of blocks S , i.e. subsets of U , we want to find a minimal subset of S that covers U .
- ▶ The CA generation problem can be interpreted as Set Cover problem:
 - ▶ $U := \mathbb{T}_t$ the set of all t -way interactions
 - ▶ $S := \prod_{i=1}^k [v_i]$ set of potential rows
 - ▶ Then a *minimal set cover* represents an *optimal CA*.



Boltzmann Machines:

- ▶ Underlying graph: vertices = neurons, edges = synapses.
- ▶ Consensus function: Sum of weights of all active edges.
- ▶ State changes are stochastic.
- ▶ Objective: Find optimal allowable state.



From CAs to Boltzmann Machines:

- ▶ CA generation problem encoded as a Minimal Set Cover problem.
- ▶ SC problem further encoded as Minimum Vertex Cover (VC) problem.
- ▶ The graph is underlying the Boltzmann machine.
- ▶ Simulated Annealing is used to optimize the state of the Boltzmann machine and solve the complement of the VC problem, the Maximal Independent Set (IS) problem.
- ▶ Convert the obtained IS back to a Covering Array.

Algorithm 1 BMforCA

```

1: INPUT:  $t, k$ 
Require:  $\epsilon$ 
2:  $G'_{t,k} \leftarrow \text{InitialGraph}(G_{t,k})$ 
3:  $\omega(G'_{t,k}) \leftarrow \text{InitialWeight}(G'_{t,k}, \epsilon)$  ▶ Assign weights
4:  $\mathcal{I} \leftarrow \text{SA}(G'_{t,k}, \omega(G'_{t,k}))$ 
5: return  $CA(|V| - |\mathcal{I}|; t, k, 2) = V \setminus \mathcal{I}$ 
    
```

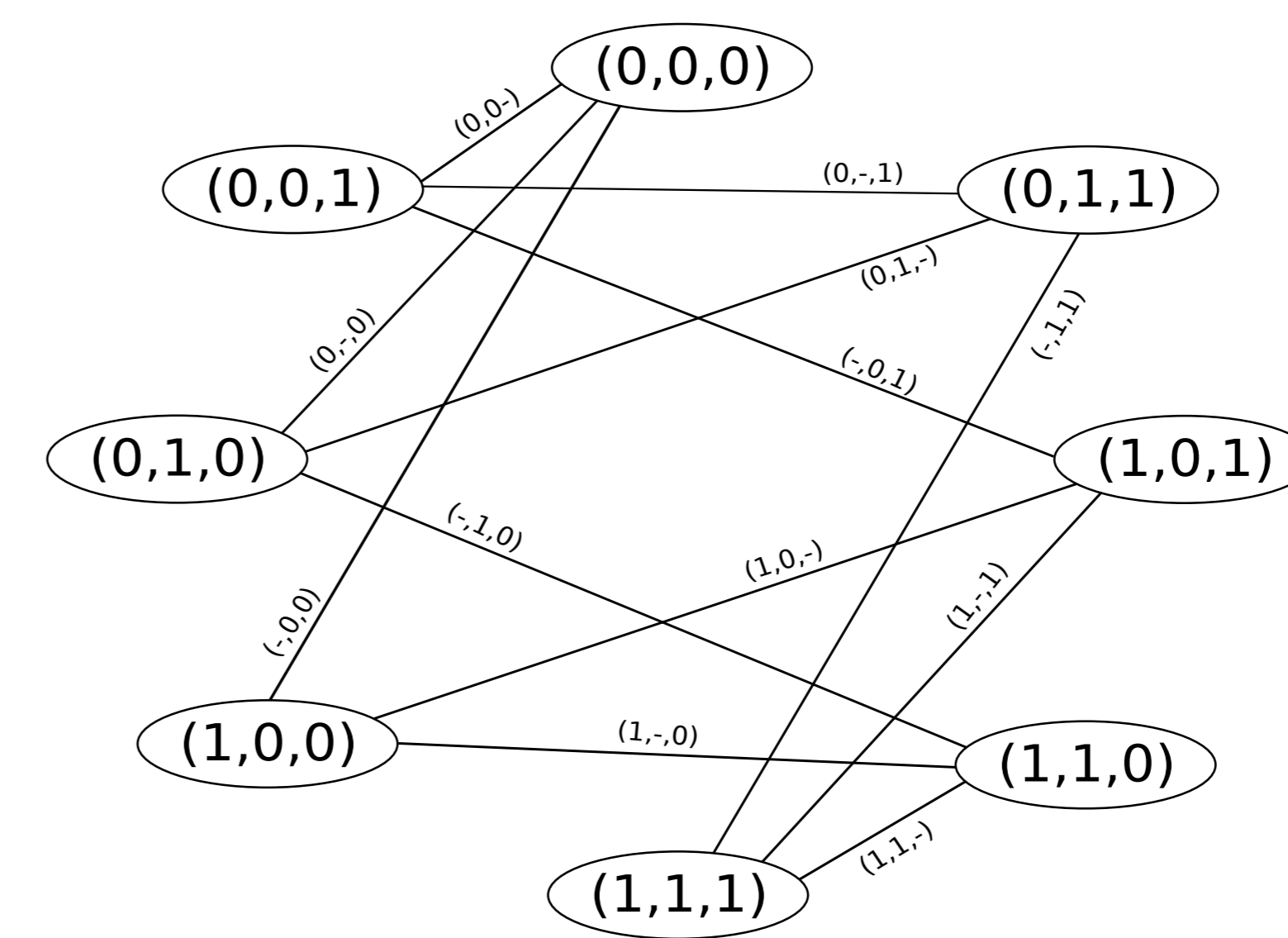


Figure 1: The instance $CA(N; 2, 3, 2)$ encoded on a Graph

Constructing CAs using Hopfield NNs

- ▶ The CA instance is encoded on a graph as a SC instance.
- ▶ The goal is to minimize the number of activated neurons, in order to find a minimal covering array.
- ▶ This is encoded in the energy function of the Hopfield NN:

$$E = \alpha \sum_{i \in I} s_i + \beta \sum_{u \in U} \left(d - \sum_{i \in I} \chi(u, s_i) s_i \right)^2$$

- ▶ Optimized via a deterministic greedy SC algorithm.
- ▶ A binary search for the parameter d is used to optimize the energy function for generation of small CAs.

Contributions

- ▶ First time neural networks were successfully used for the construction of Covering Arrays.
- ▶ Thanks to updates of the weights of edges and the structure of the underlying graph, the system demonstrates learning behaviour:

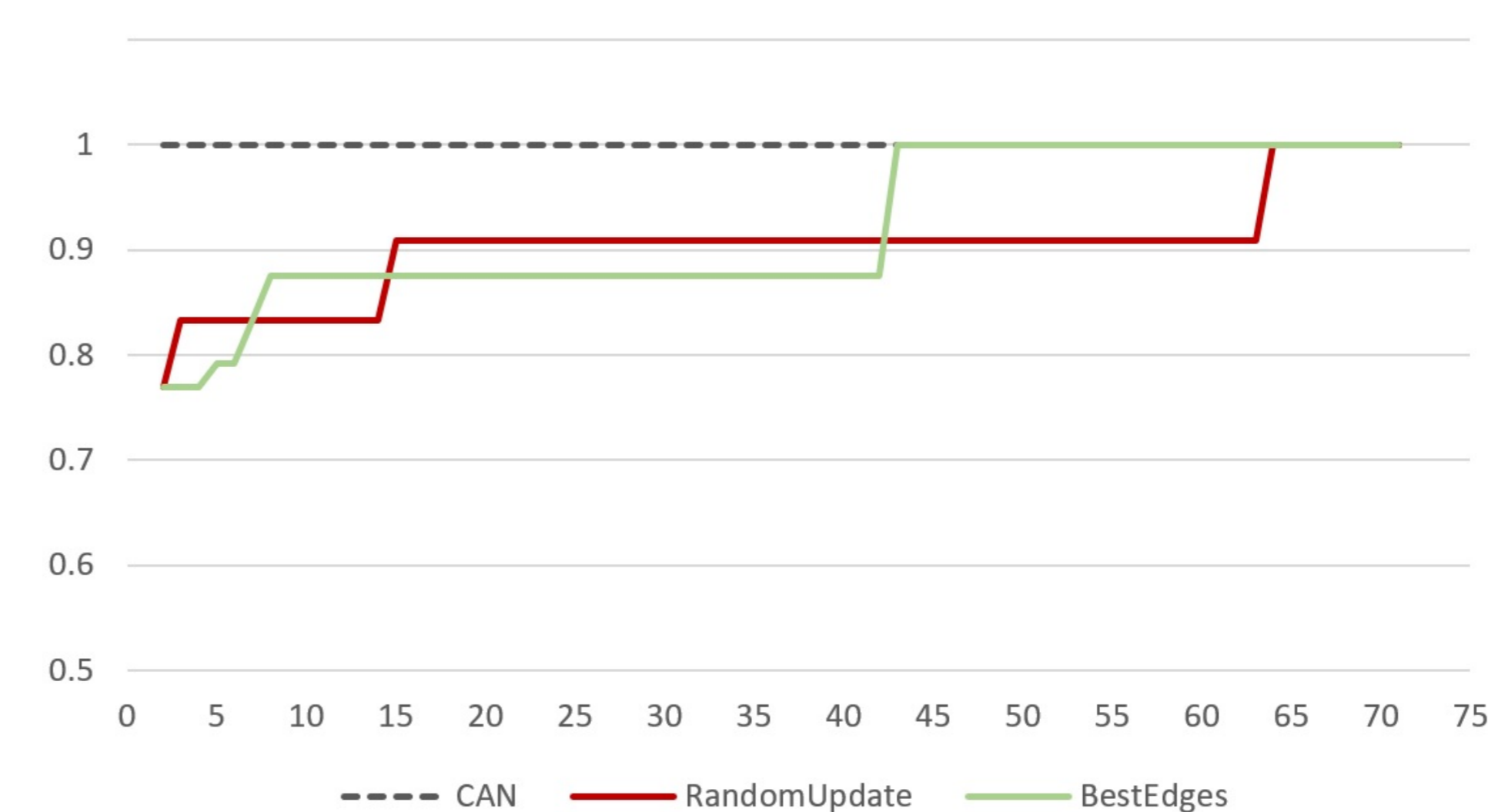


Figure 2: The BM neural network converges towards an optimal solution.