# Small-scale LNG Market Optimization – Intelligent Distribution Network

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## Abstract

Intelligent Systems, thanks to their effectiveness and robustness, find many applications in various industries. One of such applications is optimization of distribution network of small-scale LNG market, which was highly dynamic throughout last years. LNG (Liquified Natural Gas) is a fuel produced from natural gas, but its volume is approx. 600 times smaller than in the gas (natural) state, which makes it more economically effective to transport and store. Distribution network consists of several pickup points (varying in LNG specification) and a number of destination points (varying in tanks capacities). From economic point of view, optimization of LNG truck tanks paths is an important factor in whole market development. The optimization process involves selecting a pickup point and a sequence of destination points with amount of LNG unloaded in each of them. Solution proposed in this paper is based on graph theory and advanced machine learning methods, such as reinforcement learning, recurrent neural networks and online learning. Optimization of distribution network translates directly into a number of economic benefits: reduction of LNG transport cost, shortening the delivery time, reduction of distribution costs and increase in the effectiveness of tank truck usage.

**Keywords:** Liquified Natural Gas, distribution network, artificial intelligence, reinforcement learning, economic optimization
**JEL classification:** O31

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# Introduction

Intelligent systems play an increasingly important role in our day-to-day lives. The same trend is also visible in various industries, where the number of applications of artificial intelligence is constantly growing (Burggräf et al., 2018). It comes from the fact that systems based on artificial intelligence allow better understanding of processes through defining the rules utilizing experts' knowledge, reducing amount of labor and its costs thanks to the automatization of operations, and improving efficiency of processes basing on gained experience. Thanks to their advantages, artificial intelligence methods are widely applied to improve the quality of process planning and control, as well as task scheduling (Burggräf et al., 2018).

In many practical applications, increasing complexity of the system and uncertainty of its parameters lead to issues and inaccuracies of traditional methods of determining optimal solution to a problem (Li et al., 2013). Methods based on artificial intelligence pose an alternative approach to the traditional techniques of modeling and controlling complex processes (Shteimberg et al., 2012). Artificial intelligence is a branch of computer science dealing with problems perceived as requiring human intelligence (Shteimberg et al., 2012). It includes techniques allowing assisting or replacing human in solving non-trivial problems. Therefore, this field is trying to bridge the gap between people and machines, enriching machines with certain human features, such as learning, understood as improving their performance based on gained experience (Burggräf et al., 2018). Artificial intelligence methods have great potential for solving complex engineering problems, and their combination with real data enables ability to determine optimal solution to the problem solved.

Thanks to effectiveness and robustness of artificial intelligence methods, they can also be used for dynamic optimization of distribution network of small-scale LNG market. This topic is particularly important due to the significant increase of the LNG world market (Halvorsen-Weare & Fagerholt, 2013). LNG (Liquified Natural Gas) is natural gas that has been converted to a liquid form by cooling it down to a temperature of about -162°C (Alvarez et al., 2019). LNG volume is approx. 600 times smaller than in the gas (natural) state, which makes it more economically effective to transport and store (Bittante et al., 2018). Nowadays natural gas is mainly transported in a gaseous state through pipelines, but some customers are located in remote areas what makes it not cost effective to use pipelines to transport gas (Halvorsen-Weare & Fagerholt, 2013). Within small-scale LNG distribution which is gaining interest LNG is transport by trucks from large supply terminals to smaller regasification terminals, where LNG is vaporized and fed into local gas pipeline network (Jokinen et al., 2015). Such regasification terminals are located in villages that have no access to gas distribution networks as well as directly in end-users (industrial customers).

There are many papers on optimization of LNG supply chain however most of them are dedicated for large-scale LNG market (Jokinen et al., 2015). Small-scale LNG distribution is rather unexplored area especially the topic of its distribution network optimization. There are papers on optimization of the small-scale LNG supply chain, but as in (Jokinen et al., 2015) and (Alvarez et al., 2019) they are mainly focused on finding an optimal structure for the supply chain including number of satellite terminals, number of ships/trucks needed and required storage capacities. However, if the supply chain in a given region is already defined and there are several pickup points (varying in LNG specification) and a number of destination points (varying in tanks capacities and LNG demand) from economic point of view, an important factor in whole market development is an optimization of LNG truck tanks paths. In such a situation, selecting of the most appropriate pickup point and a sequence of destination points with amount of LNG unloaded in each of them should be optimize dynamically. Solution of such defined problem is the goal of the study reported here.

From mathematical point of view, this problem type can be classified as Vehicle Routing Problem (VRP), which is well recognized topic in the literature and is also applied in LNG market studies. In (Halvorsen-Weare & Fagerholt, 2013) VRP is applied to large-scale LNG ship routing and scheduling whereas in (Bittante et al., 2018) to maritime transportation of LNG between supply ports and a number of receiving ports with given demands. The classical VRP problem is a problem of designing delivery routes for vehicles, where each of them only travels one route, has the same characteristics and there is only one central depot (Braekers et al., 2016). There are multiple variants of the VRP problem, depending on number of vehicles, number of depots, way of demand handling (whether it's satisfied fully at once or can be done gradually) and couple of other factors.

The problem solved in this paper is a mixture of following types as presented by (Braekers et al., 2016):

- Heterogeneous Fleet VRP (HFVRP) in which vehicles vary in the capacities,
- Multi-Depot VRP (MDVRP) in which there are multiple depots spread geographically,
- VRP with Pickup and Delivery (VRPPD) in which goods need to be picked up from certain location and dropped off at their destination (due to varying quality of the LNG among the pickup points),
- Periodic VRP (PVRP) in which planning is done for a certain period and it is allowed not to satisfy the demand fully on one visit.

Summarizing above, VRP problem of small-scale LNG market can be classified as multiple-depot, multiple-vehicle problem, with possibility of partial demand satisfaction and flexibility of the period within which demand should be satisfied (so the demand not necessarily has to be satisfied after hitting some point, but rather it should be satisfied with increasing likeliness depending on its size).

This paper presents a novel approach to small-scale LNG market optimization which is focused on the intelligent distribution network. The proposed solution is based on graph theory and advanced machine learning methods, such as reinforcement learning, recursive neural networks and online learning. The next section sees the overview of the methods used in the developed solution and their theoretical background. The following one sees the detailed problem formulation and the exact description of the proposed solution, while the discussion and the concluding remarks follow.

# Methodology

Solution we propose for the small-scale LNG market supply chain optimization is based on reinforcement learning concept. Reinforcement learning is one of the three basic machine learning paradigms, next to the supervised learning and unsupervised learning.

## *Reinforcement learning*

The idea of reinforcement learning is based on an agent, which observes given environment and then acts on it according to a policy. Such actions are then assessed, and the agent is appropriately rewarded or punished based on quality of the action. Based on this response, the policy is adjusted in order to maximize agent's reward. The process of learning involves repeating such process large number of times – as a result, close-to-optimal policy is obtained, which in turn is later used for choosing optimal solution for a new set of inputs (Kaelbling et al., 1996).

In our problem, the environment is whole distribution network, with set of pickup points (varying in LNG quality) and destination points (varying in tank capacity). Input data to the algorithm is a state of that network (tanks fill level, tank trucks capacities and current locations). Output of the algorithm is a path for tank truck, understood as a set of destination points to visit, order in which they should be visited, and amount of LNG unloaded in each of them.

In the process of training, algorithm (agent) proposes a path, which is then evaluated and appropriate reward is fed back to agent – main part of the evaluation is calculating the distance covered by the truck (the less the better), but additional restrictions are also taken into account, like destination points with difficult access or minimal tank truck load, which ensures even axle load.

Reinforcement learning is chosen when optimal solutions to the training set cases are not known, but it is possible to evaluate the answer given by the algorithm. This is in fact the case here, as we do not have solutions which are known to be optimal for any of the states of given environment (taking into the account that the environment may change quite dynamically – destination points may change in time), but we are able to asses a solution proposed by the algorithm.

## *Graph representation of the problem*

Environment in the problem is represented as a graph. Informally, graph is a set of objects (vertices) connected by links called edges. Edges may be either directed or undirected – in our case they are the latter. They may also be weighted - for some routing problems weight of an edge represents distance or cost of connection between nodes. In solution we propose, however, due to the way the policy is implemented, coordinates are stored in the vertices and edges are unweighted. Graphs and graph theory have wide applications in computer science field, in particular in different kinds of routing problems (Riaz & Ali, 2011).

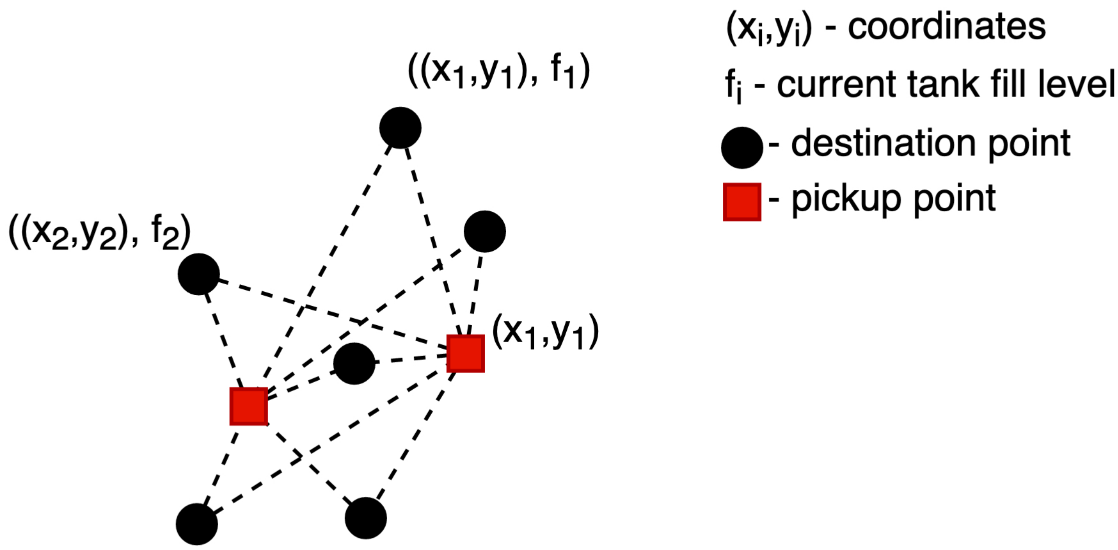
In our case, vertices represent pickup and destination points. Destination point vertices contain information about current tank fill level in them. All the points have Cartesian coordinates assigned which may be transformed to the distance between them. Graph representing example problem may be found on Figure 1.

## *Policy implementation*

Policy, that is used by the agent to take actions, is implemented with the use of couple of concepts described below. It is implemented in the form proposed by (Nazari et al., 2018) with couple of modifications to suit the needs of small-scale LNG market distribution.

First concept used is neural network. In most general case, neural network consists of layers of neurons, and synapses connecting these layers. There are input layers, output layers and hidden layers in between them. Data given at the input of neural network (in input neurons) is processed by subsequent layers and returned at the output. Passing data through a layer involves multiplying values in neurons by weights at synapses and writing results to the next layer’s neurons. The process of learning neural network involves modifying weights in synapses, so that the result on the output of neural network is as close as possible to the desired one. There are number of types of neural network, the ones used in the proposed solution are briefly described below.

*Figure 1*
Graph Representing Example Problem




*Source:* Author's illustration

Building on top of neural networks, Sequence-to-Sequence models can be introduced – they are used for the tasks of mapping one sequence to another. In general, they consist of two Recurrent Neural Networks – encoder and decoder (Nazari et al., 2018). Recurrent Neural Network (RNN) is neural network with memory state, which changes over time (over the subsequent elements of input sequence, which is fed to the network one element at the time). In proposed solution, encoder RNN is replaced by simple encoder utilizing Convolutional Neural Network, as in the problem being solved, order of input sequence (destination points) does not matter. Convolutional Neural Network's principle of operation resembles the one of basic neural network described above (layers are densely connected – each neuron of particular layer is connected with all the neurons from the next layer).

Another concept used in the policy is attention mechanism – it used for focusing on different parts of the input depending on current and previous inputs. Such approach helps with improving convergency of the solution to the optimal one (Nazari et al., 2018). In other words, it may be described as considering only local subgraph instead of whole graph on each step.

Yet another mechanism used is Beam Search. On each evaluation of neural network in the policy, possible next points are outputted with different probabilities. Instead of taking only the most probable one, group of them, with highest probabilities are chosen and all of them are considered for the next step. It allows improvement of the final results at relatively low computation cost (Nazari et al., 2018).

## *Online learning*

In machine learning (and in neural networks in particular) there are two learning approaches: offline (batch) learning and online (incremental) learning. Offline learning typically consists of two phases – training and validation. It is done before the system (network) is actually put into operation. Learning is done on previously gathered data (test cases) – in most cases, neural networks are trained on labeled data, so input-output pairs, where it is known that output is proper response to the given input. Once learning process is completed, network is put into operation and no further learning is done in order to preserve acquired knowledge (Jain et al., 2014).

Online learning on the other hand is meant to be able to deal with dynamic environments. The process of learning is incremental and takes place during operation of the network. There are certain limitations to such approach, however – data gathered during operation is not labeled (so correct answer to the problem is not known). In case of reinforcement learning it is not the problem, as that method does not rely on labeled data, as described above. Besides being able to deal with dynamic environments, there is another advantage of online learning – the model is constantly improving throughout the whole operating cycle.

Offline and online learning are also combined – system is pre-trained before it goes into operation and later it is utilizing online learning during the operation to improve further responses. This combined approach is used in the solution we propose.

# Results

The problem solved in this work can be formulated as follows: given one (or more) pickup points (depots) for tank trucks with specific capacities and a number of destination points along with data on current LNG demand in each of these points (tank fill level) find optimal route for subsequent tank trucks, taking into account the variability of this demand, as well as technical and technological limitations.

Our solution of such a problem is based on what is proposed by (Nazari et al., 2018). A solution for general VRP problem was proposed there and we have adjusted it for the needs of small-scale LNG market distribution network.

Solution proposed is based on complex neural network, which after the pre-training process is meant to be used as a policy mentioned above. Network schema is presented on Figure 2 and consists of:

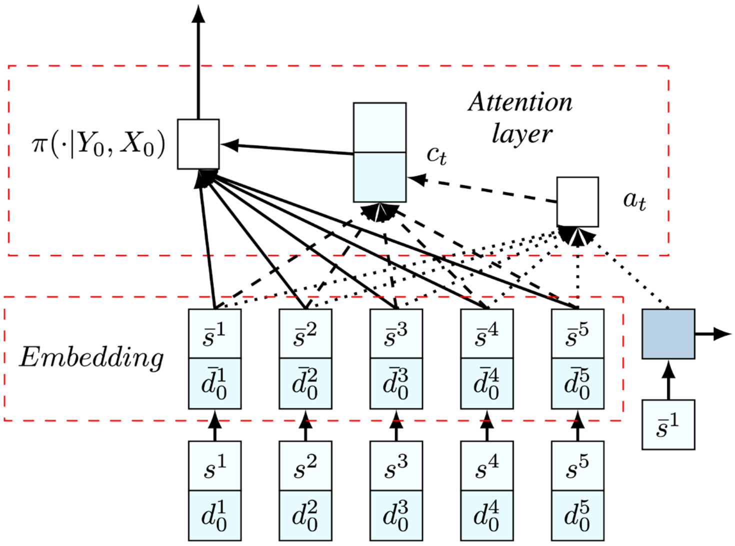
- Input, on which destination points are given (together with demand information),
- Encoder, in the form of one-dimensional convolutional network, encoding given inputs to high-dimensional vector form,
- Decoder, in the form of recurrent neural network, to which static part of the input is provided (coordinates),
- Attention mechanism, which takes output of decoder RNN and dynamic part of the encoded input (demand) as an input.

In the subsequent stages of processing of input, beam search mechanism is utilized – multiple most probable paths are chosen and all of them are evaluated in the next steps. On the last step, most probable path is chosen as an answer.

The data required for the operation of the system is coordinates of pickup and destination points, along with demand data for each of destination points and tank trucks capacities. A graph is created based on that data, which is later passed to the neural network – the system is learning both on historic and new data.

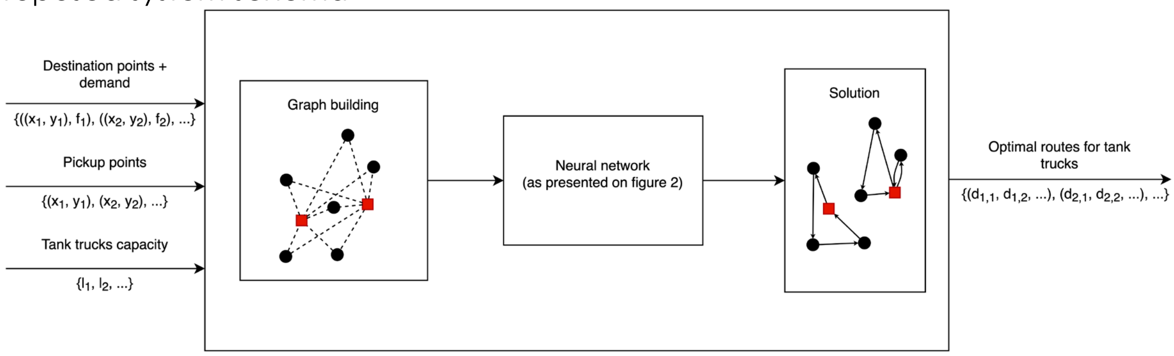
Whole system schema is shown on Figure 3.

*Figure 2*
Proposed model. Points coordinates and demand data is inputted to the embedding layer that maps the input to high-dimensional vector form. On the right, RNN is fed with encoded static part of the input. Encoded input and output of RNN are then fed to attention layer, which outputs the response.




*Source:* Nazari et al. (2018)

*Figure 3*
Proposed system schema




*Source:* Author's illustration

# Discussion

The proposed solution enables better management of LNG tank trucks routes both to local regasification terminals and to individual customers. Thanks to the use of reinforcement learning, dynamic route changes are also possible in the event of sudden change in demand, which is particularly beneficial in the case of LNG regasification micro-installations and when mobile regasification terminals are utilized. In addition, the solution to the problem proposed in this paper gives the possibility of introducing additional restrictions, such as stations with difficult access, to which the tank truck with full load will not reach, or the minimum allowed load of tank trucks, below which there are problems with even axle load.

The implementation of results can bring the following economic benefits:

- Minimizing the costs of LNG transport to the regasification terminals,
- Reducing the delivery time,
- Reducing the cost of distribution service,

- Increasing the efficiency of tank trucks use – servicing a larger number of customers for given number of tank trucks or slowing down tank trucks' wear,
- Increasing competitiveness on the LNG suppliers' market.

The above factors directly translate into a cost-free increase in the distribution company's profits. In addition, from the PR point of view, the benefits of optimizing the small-scale LNG market include:

- Positive public perception by contributing to increased gasification – increasing the competitiveness of services offered and reducing their costs will enable the expansion of the regasification terminals network by encouraging more entrepreneurs to use LNG,
- Positive reception of ecological environments due the reduction of $CO_2$ emission as a result of optimization of tank trucks routes (reduction of both combustion and wear of coolers).

# Conclusion

In this research, we aimed to develop economically effective intelligent small-scale LNG distribution network. The goal of the study reported here was to optimize dynamically LNG truck tanks paths by selecting of the most appropriate pickup point and a sequence of destination points with amount of LNG unloaded in each of them for already defined supply chain in a given region. From mathematical point of view, this problem type can be classified as multiple-depot, multiple-vehicle Vehicle Routing Problem (VRP) problem, with possibility of partial demand satisfaction and flexibility of the period within which demand should be satisfied.

The novel approach to small-scale LNG market optimization proposed in this paper is based on graph theory and advanced machine learning methods, such as reinforcement learning, recursive neural networks and online learning. Solution proposed in this paper enables better management of LNG tank trucks routes both to local regasification terminals and to individual customers as well as gives the possibility of dynamic route changes in the event of sudden change in demand and enables introducing of additional restrictions. Moreover, the implementation of results can bring a number of economic and PR benefits.

Future directions of the study could include:

- Forecasting of fill levels of LNG tanks for regasification terminals (demand forecast) and optimization of the delivery moment to meet that demand,
- Managing the number of tanks owned by a distribution company to increase the competitiveness of services offered,
- Forecasting of potential locations for new regasification terminals, including the construction of regasification terminals at customers already having gas tanks (change in the way fuel is supplied – from regular gas to LNG),
- Assessment of the possibility of using mobile regasification stations instead of gas transport.

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