DEVELOPMENT OF INTELLIGENT TECHNOLOGIES FOR ENERGY-SAVING OPTIMIZATION OF GRAIN ELEVATOR OPERATION USING NEURAL NETWORK MODELS AND REINFORCEMENT LEARNING METHODS

Mokin Vitalii Borysovych,
Dr.Eng.Sc., Professor
vbmokin@vntu.edu.ua
Dratovany Mikhail Volodymyrovych
Assistant
Vinnytsia National Technical University
Vinnytsia, Ukraine
mishadratovany@vntu.edu.ua
Lukhverchyk Andrii
Deputy Technical Director
INNOVINPROM LLC
Vinnytsia, Ukraine
andrey.lukhverchik@innovinnprom.com

Introductions. Energy saving is one of the key challenges for grain elevators, as it is for any industrial facility. Powerful grain elevators have many variations of grain transportation routes, from the input bins where trucks are unloaded to the output bins from which grain is sent for further processing or storage. Importantly, elevators usually allow for the simultaneous handling of many batches of different grain products, the mixing of which is unacceptable. At the same time, it is necessary not only to organize this transportation, but also to choose the most economical (energy-efficient) route from all available for a given type of grain product [1, 2]. It is also important to keep in mind that the shortest possible route with the minimum amount of equipment involved is not necessarily the most energy efficient for a particular type of grain product.

Traditionally, this task is solved by experts, but it is more efficient to use modern solutions based on artificial intelligence technologies and data from an automatic process monitoring system using the Internet of Things. Similar research is underway in many countries, but no single universal solution has been created yet. As a rule, there are problems with choosing an optimization method, taking into account previous experience, changes in grain parameters (primarily grain type, moisture content, temperature, grain size, density, etc.), the use of other routes for process units, wear and tear or failure of units, etc. For this type of machine learning tasks, reinforcement learning technologies are applicable [3-9]. There have been some attempts to use them for such tasks, but each has its own drawbacks and limitations for use in grain elevators. As a rule, it is necessary to combine several different information technologies at different stages of data processing and system use.

Aim. The aim is the development information technologies for optimizing the operation of a grain elevator using neural network models and reinforcement learning methods

Materials and methods. It is proposed to solve the problem for a given grain elevator as follows.

Stage 1: Processing of retrospective data. Building intelligent models of technological process units using the methods of previously collected data using the IoT system installed at a given grain elevator. Models are built of two types:

- models of type M_1 for the first nodes of the routes, the output of which Y_0 is predicted by the input X_0 which is the data from the sensors at the input and characterizes the grain received from the truck:

$$Y_0 = M_1(X_0); \tag{1}$$

- models $M_i, i = \overline{1, N}$ for the following N nodes of the route:

$$Y_i = M_i(Y_{i-1}), i = \overline{1, N}, \tag{2}$$

that allow you to determine the output of the route Y_M by the chain principle:

$$Y_M = M_i(M_{i-1}\big(M_{i-2}(\dots M(X_0) \dots)\big). \tag{3}$$

Model (3) allows us to predict the output of all route variations given a given input. Given the strong noise and variability of the data, it is proposed to use neural networks of different architectures.

The result is a set of pre-trained M-models for all possible grain elevator nodes, stored in a certain way, for example, in the pkl-format of the Python library "pickle" (as binary data of neural network parameters).

Stage 2. Preparatory. The so-called "Environment" is formed to implement the reinforcement learning algorithm in the form of a game board of size m × n, where m is the theoretically possible number of routes for a given batch of grain (or the largest possible set of all routes allowed at a given grain elevator, in the case of a multi-agent implementation for all batches at the same time), n - is the theoretically possible number of nodes in the longest route among those possible for a given batch of grain (or in the longest among all possible routes in the multi-agent case) (Fig. 1).

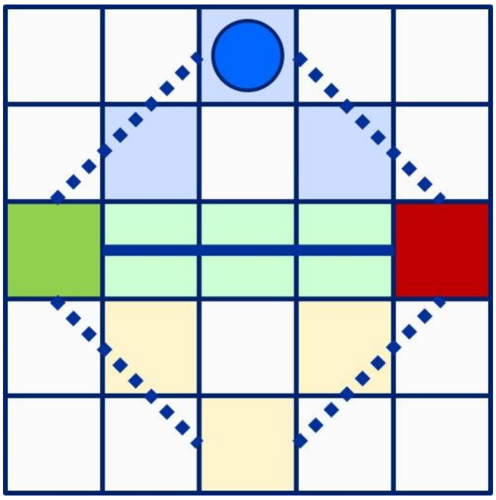

Fig. 1. The game board for finding the optimal route for a grain elevator (red rectangle - the target point, for example, the bunker to which the grain should be delivered, green - the initial bunker, blue circle - the node to which the grain is currently delivered, each line of the board - a possible route option to choose between)

At each i-th step, you should calculate the win R_i. The winning M-route R_M in this problem is the maximum saving of total energy, i.e., the maximum deviation of the total energy consumed by all nodes $W_{s\Sigma}$ from a certain theoretically maximum possible value W_{smax}:

$$R_M = W_{smax} - W_{s\Sigma}, \;\; W_{s\Sigma} = \sum_{i=1}^{N} W_{si}. \tag{4}$$

Thus, at each step in (2), using pre-trained models for each node, the initial parameters $\boldsymbol{Y_i}$, including $\boldsymbol{W_{si}}$ and they are added to (4). Then, for each route, the total value of (4) is calculated.

Taking into account the previously collected data, the optimal system policy π, that is, the rule by which at each step, taking into account the current state (data at the corresponding route node), the number of the next node is selected from the permissible set of variations [9]. The study showed that the intelligent A2C method should be used more preferably. Since this method of reinforcement learning, "actor-critic", allows training neural networks by modifying (retraining) the model by adjusting the training policy. At each training step, the "Actor" (policy and preference value) and "Critic" (minimizing the error according to a given update equation) parameters are updated.

The result is a trained neural network for determining the optimal policy "Policy" at each step of selecting the next route node, depending on the input data, and a prepared "Environment" in which this policy can be implemented and all calculations can be performed for arbitrary batches of grain.

Stage 3. Finding the optimal route under real-world conditions.

After completion of stages 1 and 2, all trained models and the built Environment are loaded into the IT system as an intelligent module for route selection. The work at this stage for a given batch of grain is carried out according to the following algorithm:

1. A batch of grain arrives and all input parameters are determined.
2. According to model (1), the input parameters $\boldsymbol{Y_0}$ to launch the intelligent technology for determining the optimal route built in step 2.
3. The optimal route is calculated, which provides the maximum gain according to the objective function (4).

It is important to note that the actual initial data may differ greatly from the retrospective data, especially if a batch of a type of grain has been received that has not yet been analyzed. In this case, it may be advisable to repeat steps 1 and 2 to adjust the models. This can be done in parallel with Step 3 at regular intervals using simplified algorithms compared to those used in Steps 1 and 2 during the first setup of the technology.

In addition, it is worth noting that, in the case of a small number of variations (due to node occupancy, failure, or other reasons), the search for the optimal route can also be carried out by direct search by applying (3) and (4) to all of them and selecting the route with the maximum RM, i.e., it will be sufficient to use only the intelligent technology of stage 1. But, in general, such situations are unlikely.

Stage 4. Visualization of calculation results.

To provide greater visibility of the decision support process, the process operator is shown not only the final calculation results using formula (4), but also the optimal action diagram. By scrolling, you can select the required number of nodes on the route. On the graph, you can view information about the corresponding node. Also, the operator will be shown the main KPIs of this route, which will allow him to make high-quality management decisions at the post (Fig. 2) [2].

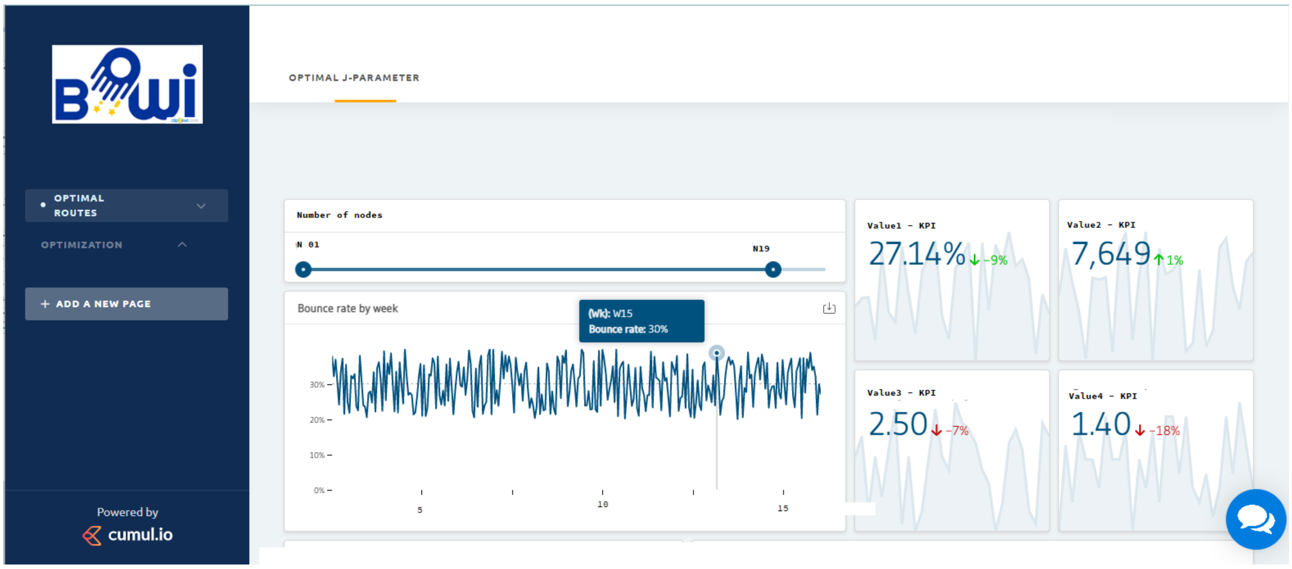

Fig. 2. An example of dashboard operation with the results of calculating the optimal route of a grain elevator for a given batch of grain using the developed intelligent technologies

Results and discussion. The proposed technology has been successfully tested on the data of one of the grain elevators in Ukraine for data collected using the multi-cloud platform (PaaS) of the Internet of Things "SAKURA-IIoT" (https://innovinnprom.com/galuzevi-rishennya/sakura-apm), developed at

INNOVINPROM LLC and improved during the development of the asset performance management system for grain elevators "SAKURA-APM", within the framework of the grant project "BOWI" by funding from the European Union's Horizon 2020

Conclusions. The paper is devoted to the development of information technologies for optimizing the operation of a grain elevator using neural network models and reinforcement learning methods. A formalization of the problem is proposed using typical approaches to problems of this type. The problem is solved using two intelligent technologies: the technology for building neural network models of technological process nodes and the technology for determining the optimal route based on the A2C game-type algorithm, which uses models built using the first technology and a neural network to determine the optimal policy for selecting the next node using reinforcement learning methods.

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