

The method of optimal resource management of a distributed dynamic system based on the algorithm of zeroing neural networks

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Abstract. The method of optimal resource management of a distributed dynamic system based on the algorithm of zeroing neural networks offers a new approach to effective resource management in distributed dynamic systems using advanced machine learning technologies. Research questions concern determining optimal resource management strategies in a distributed dynamic system, as well as evaluating the effectiveness of the proposed method in various scenarios. The research methods include mathematical formalization of the problem, development of an algorithm for zeroing neural networks and conducting numerical experiments based on computer modeling. The results of the study demonstrate the high efficiency of the proposed method of optimal resource management in a distributed dynamic system. The conclusions emphasize the importance of using the algorithm of zeroing neural networks in the context of optimal resource management in distributed systems and the possibility of its application to solve practical problems in various fields, such as energy, production, transport and others.

1 Introduction

Optimal resource management is an important aspect of the efficient functioning of distributed dynamic systems, such as energy networks, transport systems, production processes, and others. Reducing the harmful impact on the environment, increasing economic efficiency and ensuring sustainable development have become important tasks of modern society.

With the development and application of artificial intelligence, including neural networks, new opportunities are emerging in the field of optimal resource management. One of the promising approaches is the use of the algorithm of zeroing neural networks (ZNN), which offers an effective solution to optimization problems in complex and dynamic systems.

The purpose of this study is to develop a method of optimal resource management based on the algorithm of ZNN for distributed dynamic systems. Within the framework of this method, the use of zeroing neural networks will be investigated to optimize the use of

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resources, take into account environmental factors and achieve an optimal solution based on a dynamic system. [1-3]

This article is relevant in the context of environmental and economic challenges of our time, as well as the development and application of artificial intelligence in optimal resource management. The results obtained can be of practical significance for various industries and applications, contributing to sustainable development and reducing the negative impact on the environment.

2 Problem statement

Development of a mathematical model and an optimal control algorithm, conducting numerical experiments and evaluating the effectiveness of the method on the example of the applied problem of minimizing the carbon footprint. Solving these tasks will allow creating a new method of optimal resource management for various systems, contributing to more efficient use of resources and sustainable development of the system.

Development and application of the approach of using a ZNN to solve problems of resource management of a distributed dynamic system.

The purpose of the study is to develop and present a method for optimal resource management in distributed dynamic systems based on the algorithm of ZNN. The research is aimed at creating a mathematical model that takes into account time constraints and minimizing the carbon footprint, developing an optimal control algorithm based on the algorithm of ZNN, and conducting numerical experiments to evaluate the effectiveness of the proposed method.

3 Results and discussion

3.1 Model systems

The study of modern scientific publications has determined the need to use hybrid resource management in a distributed dynamic computing system in order to minimize the carbon footprint and preserve productivity, which includes: an algorithm for scheduling migration, replication, latency and computing tasks; technology for dynamic control of the purity and voltage of processors; a ZNN algorithm for managing RDVS resources.

Describe the main steps of this approach as:

1. Collection of statistical data on the work of the RDVS. At this step, data is collected on the operation of system nodes in various load conditions (problem solving), such as the frequency and voltage of processors, migration and replication.
2. Determining the state of the system. This step includes monitoring the current state of the computing system, including the state of computing nodes, their performance, available resources, load, etc.
3. List of new tasks. New tasks that come into the system must be registered. This includes information about computing requirements, deadlines, and task priorities.
4. Calculation of the performance of nodes and channels. Based on the current state of the system and the requirements of the task, the operability of computing nodes and network channels is calculated. This allows you to determine which nodes and channels can be used to complete the task.
5. Calculation of the time and necessity of migration and replication. If it is necessary to migrate a task from one node to another or create a replica of it, the time required to perform these operations and their expediency are calculated, taking into account minimizing the carbon footprint and maintaining productivity [4-5].

3.2 Conducting experiments to test the effectiveness of the developed control approach

Studying the operation of the method of nulling neural networks to solve the problem of resource management of a distributed dynamic computer network.

Let us consider a series of experiments to study the selection of the structure and parameters of the ZNN, in which the error will be minimal.

The truncation error order chosen was $k+2$. The lengths of the initial vectors are indicated in the table. Data for the experiments are described in Table 1.

Table 1. Description of data for experiments.

k, s	second largest root magnitude	polyrest	τ coeff
1, 2	0.4472	[-0.6; -0.2; -0.2]	1.6
2, 2	0.8360	[3.808215205198584e-01; -1.168617033577950; -4.156914832110251e-01; 2.034869962691167e-01]	2.389539011192650
2,3	0.5226	[1.176689655734125e-01; -8.516604383514612e-01; -3.818277128943235e-01; 6.773366868988580e-02; 4.808551698248645e-02]	2.219772790140505
2,4	0.4637	[-7.325911840449030e-02; -6.340690083336632e-01; -3.531153119650761e-01; 4.999504148385766e-03; 4.272929389028893e-02; 1.271464066455492e-02]	2.090810740934728
3,3	0.8290	[7.356287764690319e-01; -1.310212542580311; -9.130279068639379e-01; 4.241789042054587e-01; 1.601227985618904e-01; -9.669002979213243e-02]	2.706690598404911
3,4	0.6397	[5.020490554114563e-01; -1.054074297181794; -7.768688386704860e-01; 1.835959023390256e-01; 2.017816085472454e-01; -2.855311728115157e-02; -2.793031316429520e-02]	2.560245298708237
3,5	0.5816	[2.480059771240410e-01; -7.885198366863375e-01; -6.390357837629567e-01; 4.813679468512866e-03; 1.687449854130043e-01; 4.118123638757526e-02; -2.278552457478595e-02; -1.240473336905329e-02]	2.394810523248907
4,4	0.8477	[1.038159703195576; -1.378825739811979; -1.496966727252006; 6.334710791603586e-01; 5.406390647842177e-01; -3.038823278816560e-01; -9.303412726167593e-02; 6.043907506716473e-02]	2.964332575206227

4,5	0.7508	[6.643887844445272e-01; -9.273967222211478e-01; -1.299068589620714; 1.843924712566855e-01; 5.752670764736695e-01; -4.112171440073703e-02; -2.032607397397568e-01; 2.599124381423302e-02; 2.080818999324064e-02]	2.748056965594512
4,6	0.7513	[1.854040656660873e-01; -4.167064710266586e-01; -1.041699445159904; -4.706410159092017e-02; 2.125066146101461e-01; 2.774435481718890e-01; -1.138997269046412e-01; -5.698432164801684e-02; -2.838362875302206e-02; 2.938346663504090e-02]	2.448959910091972
5,5	0.9241	[1.215386987348222; -1.291056554393765; -2.059796135880188; 6.095320901394168e-01; 1.228581408859198; -4.731170818697435e-01; -5.085129829526192e-01; 2.285625671433630e-01; 1.036480848334800e-01; -5.322838322736356e-02]	3.134323027738423
5,6	0.8450	[9.789318117566991e-01; -1.091516557617663; -1.693989102837719; 1.873678566963183e-01; 1.016348476940637e+00; -2.991032426368895e-02; -4.821578816042506e-01; -2.455350179352843e-02; 1.549728822935899e-01; 7.407813151091853e-03; -2.290147272148661e-02]	2.988932059446562
5,7	0.8529	[9.163297735429142e-01; -1.024354167068672; -1.654636187872638; 1.566276337562119e-01; 9.435980453654198e-01; 2.414314319510011e-02; -4.440174739171195e-01; -4.428233248795205e-02; 1.246731646238272e-01; 2.121989726029419e-02; -1.543586247760823e-02; -3.865633919776790e-03]	2.951233120586878

Computational experiments were carried out on a data set of the NorduGrid network consisting of more than 2.7 billion nodes distributed in 141 geographical locations. The data were enriched with an estimate of carbon dioxide emissions as a result of generating the energy necessary for the operation of these computing nodes. These indicators were obtained from the Integrated Database on Emissions and Generating Resources (eGrid), which is a comprehensive data source of the Clean Air Markets Department of the Environmental Protection Agency and the environmental characteristics of almost all electricity generated in the world [6-9].

The optimal control function of this system was built by a complete search. While maintaining sufficient performance (the average calculation time is not less than the real one), the parameters of the nodes, the location of tasks on the nodes were redistributed so as to minimize CO2 emissions. Over a time period of 30 days, this allowed to reduce emissions by 9.4%. It should be noted that the calculation of optimal system management on a computer with the characteristics: core i9 11980HK processors (2.6-3.3GHz), Ge-Force RTX 3090 Ti, 128 GB RAM and 24 GB of video memory, 1TB solid-state drive, was 47 hours and 12 minutes.

Since the control function of distributed dynamic computing systems depends on the configuration parameters of computing nodes (x) and migration (y), we will consider the behavior of ZNN according to them.

3.3 Findings

Thus, using a software platform to solve the optimization problem by the method of zeroing neural network, we obtained ZNN solutions for optimizing CO₂ emissions. The following results with input parameters of the two-week period were obtained:

Solutions for $\tau = 0.03$ and $\eta = 25$ by method 1\2 ZNN are shown in Figure 1.

The error graphs with $\tau = 0.03$ and $\eta = 25$ for ZNN method 1\2 are shown in Figure 2.

The calculated solution $x(t)$, $y(t)$ from start 0 to end with $\tau = 0.03$ and $\eta = 25$ is shown in Figure 3.

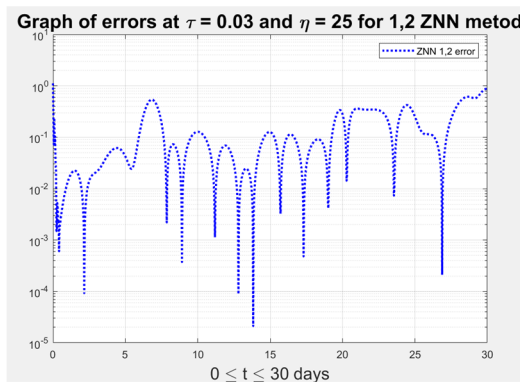


Fig. 1. Solutions.

Figure 2 shows the results of the work with the following parameters: $k=1$, $s=2$, $\tau=0.03$, $\eta=25$.

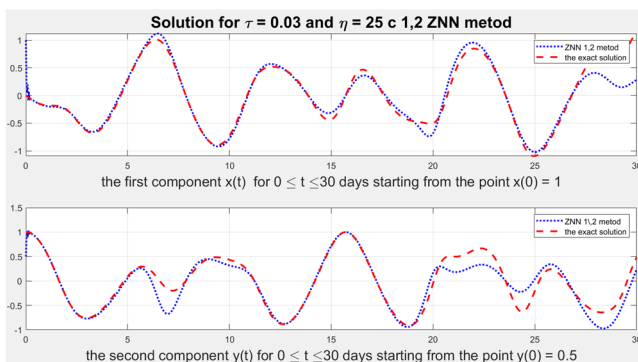


Fig. 2. Error graphs.

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