Advances in Economics, Business and Management Research, volume 90
International Scientific-Practical Conference on Business Cooperation (ISPCBS 2019)

Spatial-temporal digital twin models as a direction for the development of cross-cutting digital technologies

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***Abstract*—The proposed spatial-time digital twin model is based on a neural network approach for solving partial differential equations characterizing a physical object. The model aims to develop cross-cutting digital technologies. This approach makes it possible to account newly received data and thereby maintain the relevance of the model. The approach allows integrating the knowledge of specialists and engineers for solving a number of important tasks. The model uses machine learning and is therefore adaptive.**

Keywords—digital twin; neural network solution; machine learning; fire system.

I. Introduction

Cross-cutting technologies are promising technologies that radically change the situation in production and transport [1]. One of the main directions of development this technologies is the creation of digital twins. When creating digital twins, the following advanced technologies are applied: the Internet of things, artificial intelligence, machine learning and software analysis. Digital simulation models are updated and changed as the physical objects themselves change. The digital twin constantly analyzes the state of the object, learns and updates its state in real time. For training, the model uses sensor data from experts serving the facility, from experts who have relevant knowledge. The digital twin also combines historical data of the physical object in the past.

One of the main characteristics of the digital twin technology is the ability to connect to the Internet of Things [2], which offers cloud services. The necessary flexibility of models can be achieved using wireless sensor networks that transmit data to a computer center.

Articles [3] and [4] are devoted to the development of digital twins for unique, complex and responsible technical objects, such as, engines, automobiles, turbines. Maintenance of such objects is traditionally carried out according to the regulations, which is not effective enough. Application of digital twin in the system of technical diagnostics allows you to obtain more efficient principle of maintenance by technical condition. The digital twin in the prediction mode allows you to organize the prediction of the technical condition, to perform pre-maintenance, preventing failures [5]. In the tasks of managing a technical object, the use of the digital twin allows you to organize a new approach to predictive control.

II. Statement of the problem

The objective of our study is to develop the principles and methods of spatial-time twin-models using the example of a fire system. The complex digital model of fire system should simulate the normal process as well as process of ignition in the certain place of the room. The model should take into account physical laws, cause-effect relationships and innovative process of data updating. For a fire system, it is important to determine the location of a fire in the space of the room, ignited material.

III. Research questions

When creating a complex spatial-time model of the digital twin, the following models should be combined:

- A renewing self-learning model of the normal condition of the premises,
- An updated self-learning model of the process of ignition in the premises, taking into account the causal relationships determined by physical laws,
- Knowledge model obtained from specialists and engineers' model received from specialists and engineers
- Updating the model due to current measurements
- Optimization of sensor positioning for the fastest fire detection,
- Localization of ignition and recognition of the type of fire.

Recognition of the type of fire allows professionals to choose fire extinguishing agents.

IV. Objective of the study

The objective of the study is to determine the approaches to the creation of learnable space-time digital twins of objects, which take into account not only the existing causal relationships, but also the results of measurement and communication from engineers.

V. Research Method

A. Complex method of creating digital twin

Complex technical objects are usually simulated by computer mathematics software packages based on the finite element method (FEM). However, modeling a real object with FEM method a specialist encounters a number of fundamental difficulties. Accurate information about the subtle aspects of physical processes cannot be fully be taken into account in differential equations, in which simplifications are usually allowed. Initial and boundary conditions are based on even less complete and accurate information. The parameters that change during the operation of a physical object usually change. Therefore, it is advisable to adapt both the model itself and its parameters. It is difficult if the model is based on solving differential equations using FEM method [10].

It seems more promising to build an adaptive model that can be refined and rebuilt in accordance with the observations, acquired by sensors arranged in the object and in the environment. Such a model can be based on a neuron network with radial basic functions or on a multilayer perceptron with nonlinear activation functions. The neural network model is capable to accumulate historical and actual data, it allows automatic adjustment of the architecture and parameters. Neural network allows to perform classification and prediction. The most difficult problems facing the digital twin model can be solved using a team of neural networks. The artificial intelligence and machine learning is a methodological basis of the neural network model [6], [7].

On the other hand, the machine learning approach cannot be directly applied, it requires further development. The machine learning model does not take into account knowledge of physical laws and causal relationships existing in a physical object, it is rather a black box model. The machine learning solutions are not mathematically justified. This circumstance makes it difficult to predict the critical states of physical object if critical parameters were absent during training.

We propose an integrated approach that takes into account physical phenomena inherent in the object in the form of partial differential equations, which basically determine the type and structure of the neural network, initial conditions and continuously incoming data from sensors [8].

Objective of a neural network training is to minimize the error functional $J(\mathbf{W})$ depending on the matrix of neural network weights $\mathbf{W}$. The complexity of this approach is in the fact that the error functional depends on the following three components: J_1 - an error functional, depending on a differential equation, J_2 - the error functional, depending on the initial conditions, J_3 - an error functional depending on incoming actual measurements acquired from sensors. Each of the terms influences on the error functional by the values δ_2, δ_3. Therefore, the error functional finally takes the form

$$J(\mathbf{W}) = J_1 + \delta_2 J_2 + \delta_3 J_3$$ [9].

Complex equations of physical processes, big volume of measurement data lead to the fact that the implementation of models is possible using the computational resources of corporate centers. The Supercomputer Center has been organized at Peter the Great St. Petersburg State University/ This Center allows us to maintain models of a required number of physical objects. The cloud system provides the necessary services and software.

B. Spatial-temporal model of the ship's fire system

A number of sensors located in the ship premises measure the following fire factors: temperature, visibility, gases concentration. After finishing the observation period if no fire occurred, then engineer informs system about necessity to update the model of the normal condition of the premises [10]. The updated model taking into account the distribution of fire factors in the space of premises for all periods of time will be used further.

The basis of the updated self-learning model of the ignition process is based on the partial differential equations of Navier – Stokes, the initial conditions that take into account the model of normal condition of the premises and the data obtaining from the sensors [11].

Accounting knowledge obtained from engineers and other professionals, allows to the divide of the premises into small blocks. In each block, the specialist assesses the a posteriori probability of a fire. Subjective probability is affected by the placement of flammable materials, such as rags, gasoline, and engine oil [12].

Model of fire system receives sensor readings continuously. The obtained data is used to update both the model of the normal condition of the premises and the model of ignition in the premises to maintain relevance of both models.

For faster detection of fire, the sensors should be placed in the room in an optimal way. To perform this function, sensors should be connected via a wireless interface. In our project, we used the ZigBee interface, performed according to the IEEE 802.15.4 standard. The interface allows to create a self-organizing wireless sensor network with a mesh topology [13]. Such a network can be quickly deployed in space, its topology can be quickly changed.

To more accurately determine the location of fire, the sensors should be placed in the room in an optimal way. It would be wrong to determine the optimal location of the sensors using simple enumeration method, therefore it was proposed to use a genetic algorithm for this task. The genetic algorithm is based on minimizing the magnitude of the fitness function by performing basic operations such as inheritance, mutation, selection, and crossing over.

The time required to detect a fire considering the current position of the sensors was proposed as a fitness function of genetic algorithm. Selection operation consists of choosing the most effective sensor position according to the Boltzmann method. Crossing over comes down to changing the position of sensors, usually based on binary or real data. Instead of the standard algorithm, we used our own algorithm of crossing. Mutation was performed by the standard method. According to the mutation algorithm, one of the sensors is selected with a certain probability, and its coordinates are to change by a small random value. After that, the algorithm is repeated until the sensors take the optimal positions.

Localization of fire and determination of the type of fire is aimed at identifying fire extinguishing agents and their application to the block of permission. To determine the type of fire, it is proposed to apply a probabilistic neural network of direct signal propagation with input delays (TDPNN) [14], [15]. The inputs of the neural network are represented by 20 temperature samples, gas concentration and visibility. The inputs of the neural network represent the likelihood of fire in a given room block and the probability of a certain type of fire. The scheme of the neural network is shown in Fig. 1.

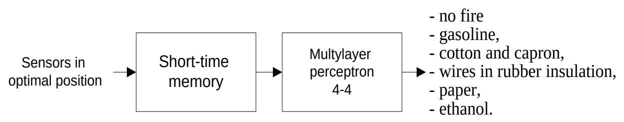

Fig. 1. Detection of the location and type of fire.

Successful solution of the problem of detecting a fire site and the type of fire depends on the position of the sensors in space, so optimization is important. The algorithm allowed detecting fire on average 15% faster.

VI. Results

Spatial-temporal model is shown in Fig.2.

Measurements obtained from sensors are used in the ignition model and in the normal conditions room model. The ignition model is based on differential equations and refined using measurement results. For solving differential equations, instead of grid methods, the neural network method is used, which takes into account not only physical equations, but also data.

The spatial-time model maintains its relevance based on the knowledge gained from specialists: the distribution of the probability of ignition in space, the determination of the fact of the normal condition of the room. It is proposed to use neural networks for classifying fires as a combustible material and for localizing fires.

VII. Conclusion

As a result of our survey, the following conclusion was made.

One of the main directions of cross-cutting digital technologies is a spatial-time models of digital twins developing.

The space-time models are based on partial differential equations, which solution we suggested to find using neural networks.

Neural networks are to be used for differential equation solution, for localization of fire and for identification of ignition type.

The proposed digital space-time model takes into account physical laws, knowledge of engineers and specialists and the data obtained from sensors.

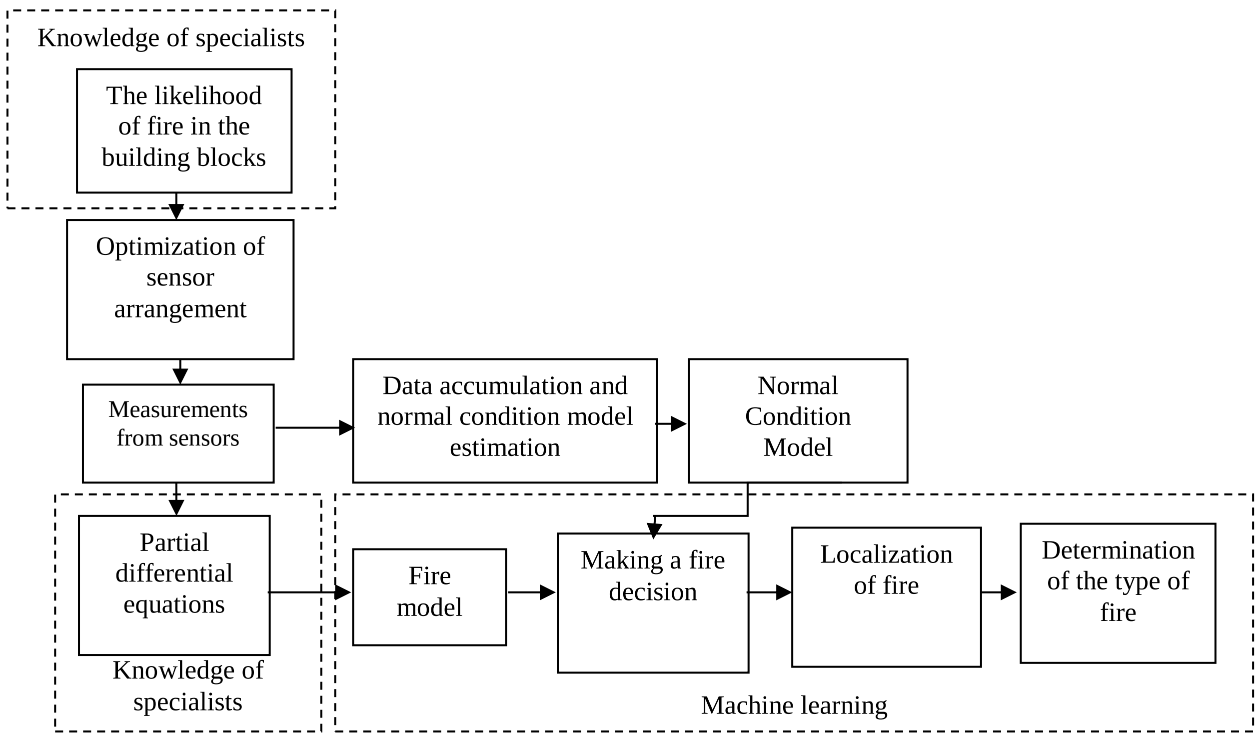

Fig. 2. Spatial-temporal model of an intelligence fire system

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