Forecasting Model for Long Life Cycle of Complex Recycling Technical Systems by Improving the Structure of the Neural Network

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ABSTRACT: *The purpose of this paper is to increase the efficiency of functionality and reliability of Complex Recycling Technical Systems (CRTS) community, by improving the control quality of their life cycle. Automated Control System (ACS) on the basis of Neural Super-Network learning for forecasting damages and ensuring its information representation for learning was proposed. In the paper it was suggested an architecture and a method of learning of a neural super-network for forecasting the progress of CRTS community life cycle. The structure of the ACS life cycle of vehicles environment in the form of service "center" that service groups of "client", exploiting the same type of objects, was developed.*

Keywords: Automated Control System (ACS), Complex Recycling Technical Systems (CRTS), Neural Network (NN) and Neural Super-Network

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1. Introduction

Artificial Neural Networks have become objects of everyday use, although few people are aware of it. Their superior performance in optical character recognition, speech recognition, signal filtering in computer modems etc. have established Neural Networks (NN) as an accepted model and method. However, neural networks have not yet been established as a valid and reliable method in the business forecasting domain, either on a strategic, tactical or operational level. Selected applications of NN which have demonstrated their applicability in specific scenarios are presented [3].

Many different models of neural networks have been proposed. The feed-forward multi-layer networks with the back propagation learning algorithm are the most commonly used in the software quality prediction field [9].

Neural networks are widely used for modeling complex systems. A complex system can be defined as a system which involves a number of elements (such as machines, humans, technical systems, etc.), arranged in structure which can exist on many scales [10]. These go through processes of change that are not describable by a single rule nor are reducible to only one level of explanation; these levels often include features whose emergence cannot be predicted from their current specifications. Complex systems theory also includes the study of the interactions of the many parts of the system. Examples of such complex systems include ground/air transportation systems, health care systems, supply chain systems, and military systems. These systems are typically highly complex and dynamic with tightly coupled interacting components (or subsystems).

This paper is organized as follows: first, we demonstrate an overview of neural networks and complex systems, followed by the life cycle of CRTS overview. Then building a neural super-network model is presented. A description of how neural super-network works is discussed. Then an automated forecasting system is presented. Finally, we provide a conclusion.

2. The life cycle of CRTS

During the life cycle of CRTS in its state, quantitative changes are collected that leads to quantum leaps in exploitation suitability [2]. The description of CRTS (a zero point of its life cycle) provides integrity of states.

Consider a set of N identical CRTS design, are functioning in different times and in different contexts. Their life cycle can be present in one temporal axes (see figure 1).

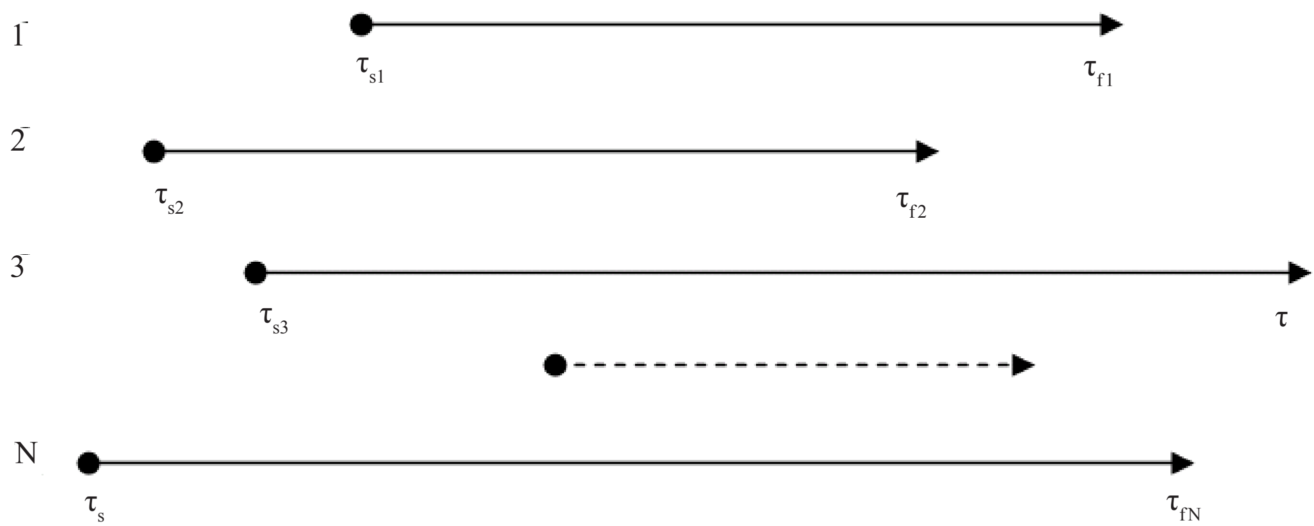

Figure 1. Life cycle set of identical CRTS design

In general, life cycle of CRTS consists of system design, its construction and debugging, and finally, disposal. Since we are considering the identical CRTS in terms of design, their design is common to each system and a comparative review of the life cycle may be excluded. Individual features of CRTS are beginning to accumulate in their construction. Therefore, in the beginning of life cycle, specific n-th system ($n = \overline{1, N}$) takes the time τ_{sn}, corresponding to the beginning of its construction. The terminate point of life cycle - τ_{fn}, corresponds to the decision time of the CRTS disposal. Thus, the total length of life cycle from the start of manufacture until the disposal is τ_{fn} - τ_{sn}, and in general, for each CRTS is different. It is determined not only by the system design, but also the quality of their construction and exploitation service.

During the exploitation, CRTS exposed to external influences, to restore partially or completely lost functional characteristics. Such effects are called in different ways: maintenance, repair, overhaul, etc. and have different objectives: to prevent or eliminate violations of internal properties or external manifestation of the functioning CRTS. External influences can occur without changing the system or its design.

In the first case after the external influences, the CRTS state is not necessarily be correspond to its state at the end of construction, which depends on the quality of influences. For example, the machine repair can be for a number of indicators "worse" from a new, or "better".

In the second case we get a "new" CRTS, which theoretically cannot be strictly considered as a number of initial identical CRTS. In both cases, in the life cycle of CRTS, quantum leaps are observed - the initial system "disappears", and in its place appears new one, having the basic operational characteristics of the initial adjusted influences. This correction is probabilistic in nature.

Consider a community with identical CRTS construction called **S**. They function in different time and in different conditions. Generally, each separate life cycle of CRTS consists of system design, construction, debugging, till the system became disposal. As we considered CRTS with identical construction, their design is common for each concrete system and from comparative consideration the life cycle can be terminated. Individual CRTS features begin to accumulate during their construction. Therefore at the beginning of the first life cycle (LC) of concrete s-th system ($s = \overline{1, S}$) we consider time τ_{ss}, that corresponds to the beginning of its construction. A terminate point of LC – τ_{fs} that corresponds to the solution decision time of the CRTS failure and its repair or disposal (see figure 2).

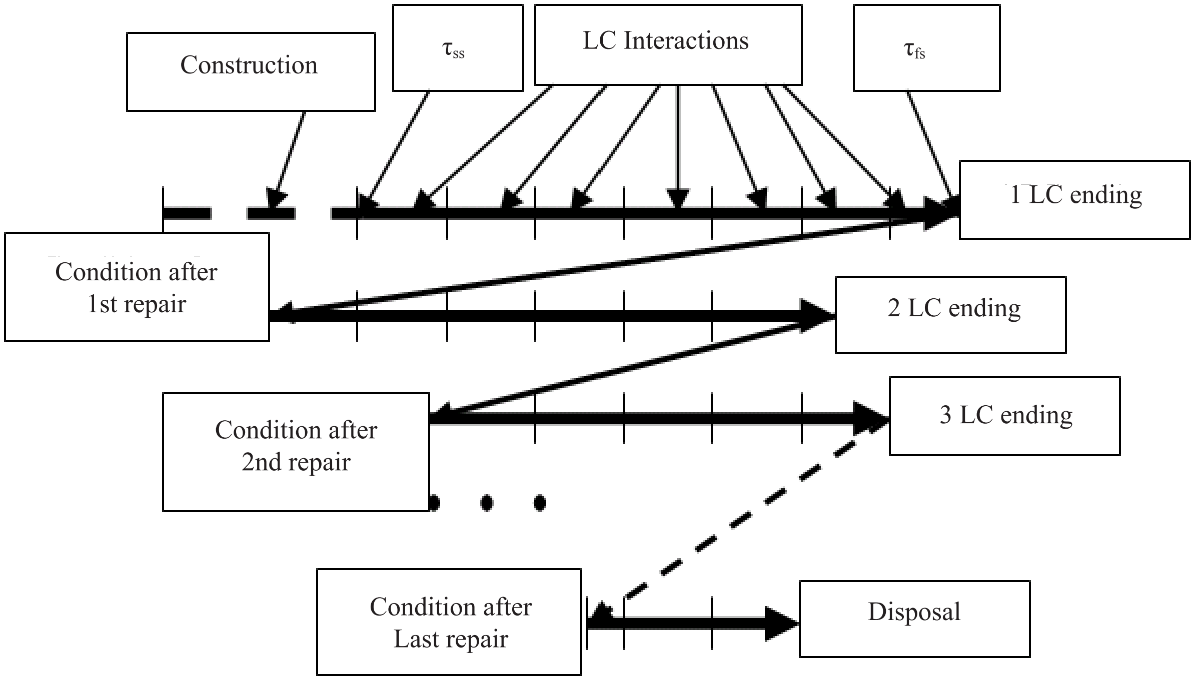

Figure 2. Scheme of dividing the general term of the life cycle of CRTS on exploitation and its iteration

Modern methods of forecasting the CRTS life cycle, in the condition of the absence of clear algorithm or principles of problem solving at large number of specific examples, large amounts of input data, incomplete or redundant data, and noise or inconsistencies based on modeling of exploitation of such object in the form of NN [5]. However, a community of CRTS, which elements work in different places, different situations and at various times, the construction of a suitable NN and, most important, ensuring its representation of learning selection, represents a serious problem [6].

Therefore, the aim of this work is to increase the efficiency of functionality and reliability of CRTS community, through improving the control quality of their life cycle in the exploitation process by creating an Automated Control System (ACS) on the basis of learned Neural Super-Network for forecasting damages and ensuring its information representation for learning.

3. Building a neural super-network model

One of the most adequate models for forecasting a technical state of CRTS can be NN [1]. It is necessary, before building a neural network, to precisely define the set of input and output parameters of the network. For the purposes of forecasting it is necessary that the set of output parameters must be a subset of the inputs set.

Let the input vector **X** of the NN consists of not only "external" factors that influences $\mathbf{X_B}$ reflecting the functionality conditions of CRTS, but also consists of the set of "internal" factor states of $\mathbf{X_C}$ determining the specific technical condition of CRTS in general and its elements separately:

$$\mathbf{X} = \{\mathbf{X_B}; \mathbf{X_C}\}$$

The output of the network creates a vector response **Y**, the size and the content of which fully meets the size and content of the "internal" part of the vector **X**, i.e. the $\mathbf{X_C}$. On the architecture of the NN this fact is reflected in this way:

The network provides feedback (see figure 3) from output **Y** to the input $\mathbf{X_C}$.

But we cannot put the equal sign between them ($\mathbf{Y} \neq \mathbf{X_C}$), because they belong to different iterations of life cycle modeling: **Y** completes the previous iteration, and $\mathbf{X_C}$ "opens" the subsequent, i.e.:

$$\mathbf{Y}_{i\text{-}1} = \mathbf{X}_{\mathbf{C},i}$$

Where **i** is the number of iteration; $\mathbf{i} \in (1, N)$. In the beginning of modeling ($\mathbf{i} = 1$), vector $\mathbf{X_C}$ responds to the state of a new system $\mathbf{X_{C,1}}$, yet the previous is not in exploitation, and learning selection receives from the information or from ground testing or working places of new CRTS.

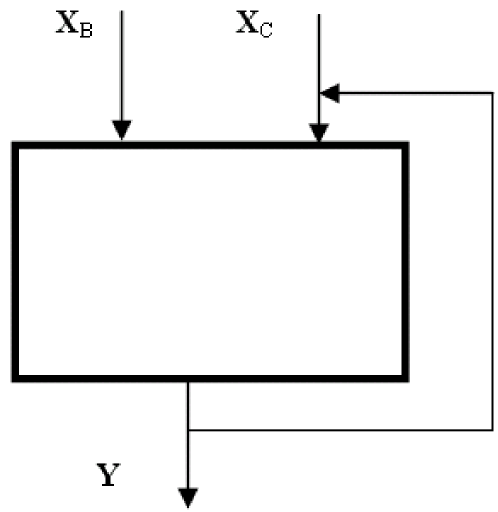

Figure 3. The NN architecture with feedback from Y

Thus, learning selection on the first iteration of life cycle has the following form: $<\{\mathbf{X}_{B,1}; \mathbf{X}_{C,1}\}><\mathbf{Y}_1>$, on the second - $<\{\mathbf{X}_{B,2}; \mathbf{Y}_1\}><\mathbf{Y}_2>$, or in general form:

$$<\{\mathbf{X}_{B,i}; \mathbf{Y}_{i-1}\}><\mathbf{Y}_i>$$

As we can see from these expressions, after each iteration of the NN is exposed "going out" of the state in which it was after learning the previous iteration, and re-learning for new selection.

This approach has a main disadvantage, which does not allow it to be used for the modeling of a community of elements with long life cycle, and such elements, which are beginning to work not at the same time, that is, the beginning of life cycle which does not matches: after each re-learning, the model "forget" the previous iteration and yet the content of current systems cannot be used to forecast the state of CRTS at these stages [7].

Therefore, we proposed the model as a "**Super-Network**" in which each iteration corresponds to its own network and transfer information $\mathbf{Y}_{i-1} \rightarrow \mathbf{X}_{C,i}$ is not obtained by feedback but by connecting networks which modeled in sequential iterations as shown in figure 4.

As we can see from the figure, in this case, any elementary NN stores acquired during the learning information, and may be pre-learning by data that is continuously coming from different CRTS from their exploitation.

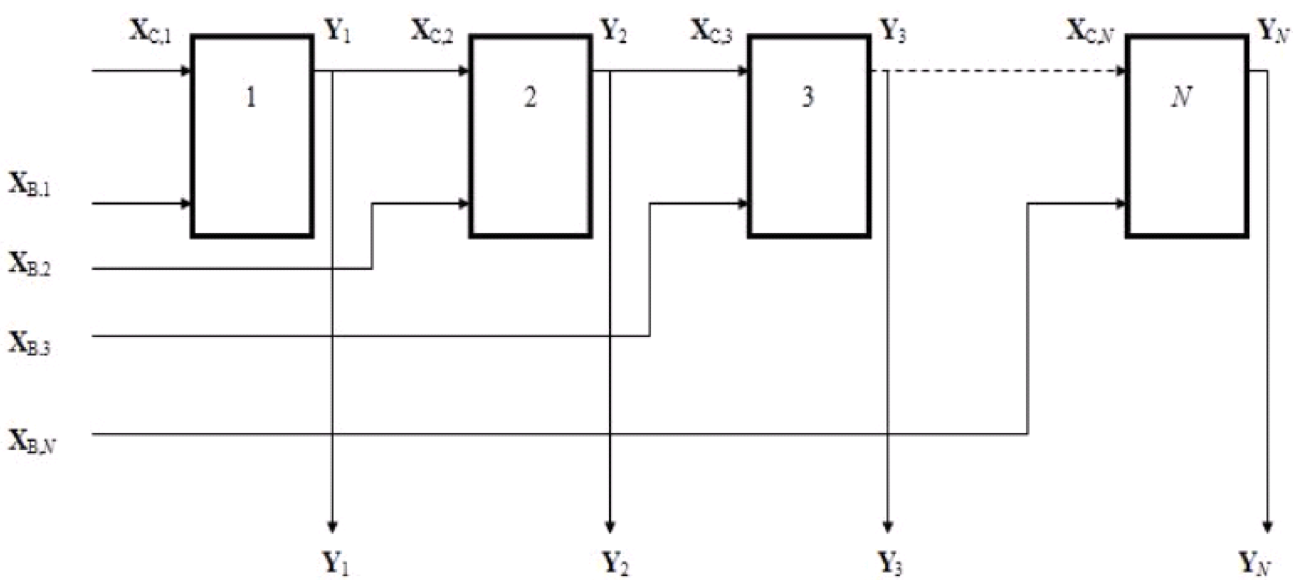

Figure 4. Neural Super-Network architecture

4. How neural super-network works

The neural super-network works as follows:

a. Choosing the CRTS representation and performed accelerated ground testing of its life cycle before the first failure. Test provides data on the external influences on the iterations of modeling: $\mathbf{X}_{B,1}$, $\mathbf{X}_{B,2}$, $\mathbf{X}_{B,3}$, … , $\mathbf{X}_{B,N}$ and for damages that occur at these iterations $\mathbf{Y}_1$, $\mathbf{Y}_2$, $\mathbf{Y}_3$,…,$\mathbf{Y}_N$.

b. Defines the initial internal state of CRTS - $\mathbf{X}_{C,1}$.

c. Achieving learning of the first network on the learning selection:

$$<\mathbf{X}_1 \{\mathbf{X}_{B,1}; \mathbf{X}_{C,1}\}> <\mathbf{Y}_1>,$$

then the second - on a learning selection:

$<\mathbf{X}_2 \{\mathbf{X}_{B,2}; \mathbf{Y}_1\}> <\mathbf{Y}_2>$ and so on, until the *N*-th network on a learning selection:

$$<\mathbf{X}_N \{\mathbf{X}_{B,N}; \mathbf{Y}_{N-1}\}> <\mathbf{Y}_N>.$$

d. All complex technical regeneration systems receive this type of information about internal and external conditions for the iterations from 1 to **K** - (**K** < **N**). This information is used for pre-learning, respectively, from 1 to **K** of NN [4].

e. In exchange for this information forecasting is achieved by the further development of CRTS life cycle – from (**K**+1)-th to **N**-th networks.

If the value of **K** to any particular CRTS is zero, then the forecasting for these systems are carried out exclusively on the basis of information on other systems. If **K** > 0, in the forecasting it accepts also participation of the information about its previous stages of life cycle of this CRTS.

In these conditions "success" of forecasting in many respects depends on the correct choice of a set of external and internal factors, and also from providing of parameters values representation, estimating these factors quantitatively.

5. Automated forecasting system

The method proposed above can be put into practice in various ways. For example, by creating a company, having a primary information resource as to some CRTS exploitation conditions. This information includes data about the non-failure CRTS exploitations in general and its potential damaged parts (pieces, units, and junctures) in particular (see figure 5). The company proposes to such CRTS holders an agreement under which the client is advised to the possible system failures and recommendations for its exploitation. When a contract for services undertakes, the client must inform the company about

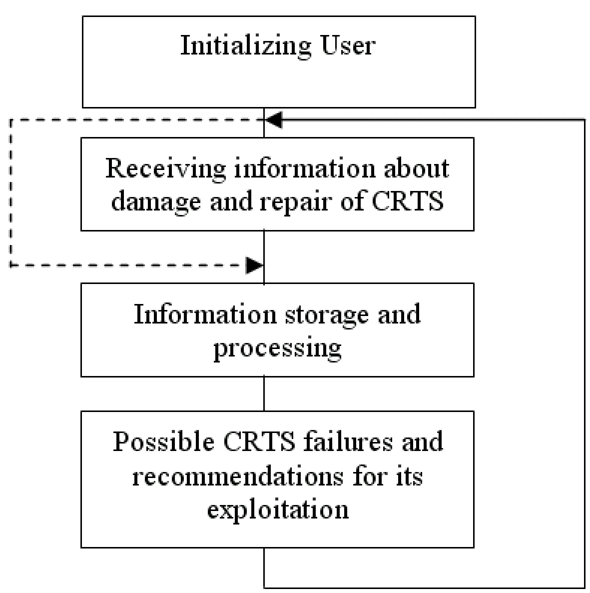

Figure 5. Automated forecasting system work flow

any damages or failures to the CRTS, as well as the time and the cost of its repair. Thus, the company continuously expands the databases for each of the same type of CRTS, which allows making more accurate forecasting.

Consider an ACS of CRTS exploitation of a semi-trailer vehicle as an example. From a number of internal factors let's take the technical exploitation of welded frame units (subject to many mechanical effects during the exploitation), leading to their damage (cracks, breakage).

The internal factor parameters could be:

- Unit construction (dimension, material, welding etc.);

- Unit's condition when exploitation (working, partially damaged, failed).

While the external factors:

- Exploitation conditions (static and dynamic loading, climate);

- Repair conditions (time, quality, cost.).

The proposed ACS structure of a semi-trailer vehicle with the above mentioned features is shown in figure 6.

The economical efficiency of such an ACS follows from the services list (see figure 7), which may have some "center" - ACS user "client". Under the "client" it means the holder of one or more of the same CRTS type that provides the exploitation, maintenance, and repair. Thus, the "client" is highly interested in improving the reliability of the CRTS community, and in obtaining from the "center" most trustworthy data of possible failures from the side of his CRTS.

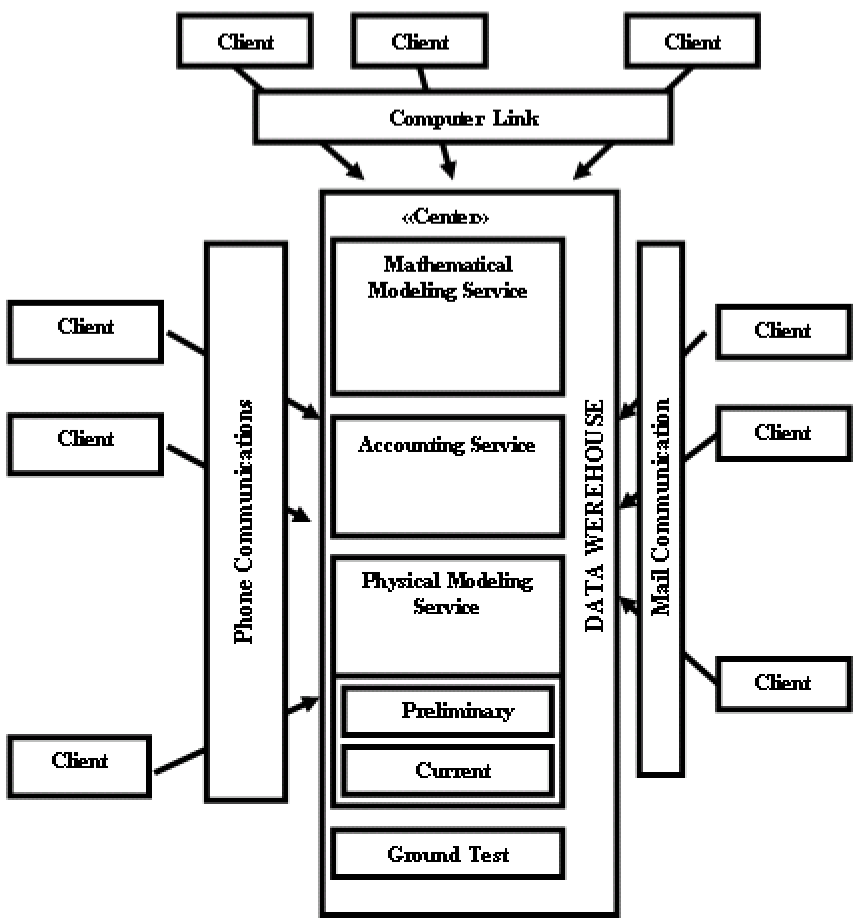

Figure 6. The ACS structure

LC period	CRTS Model	Service	Service goal
Designing	Mechanical	Calculation of mechanical features at design load	Identification of "narrow" and "dangerous" places
	Techno-economical	Calculation of techno-economical features at exploitation mode	Identification of "narrow" and "dangerous" places
Introduction to the exploitation	Mechanical	System stand test at design load	Confirmation of the adequacy of computational models
	Techno-economical	System features monitoring at exploitation mode	Confirmation of the adequacy of computational models
	Mechanical	Accelerate systems testing	Isolation of the major damage places
Exploitation	-	CRTS technical or techno-economical condition forecasting	Preventing damages and failures
	-	Service and repair control	Reducing the exploitation costs, increasing the reliability of systems community

Figure 7. Services list (provided by "Service Center")

To carry out these studies, the "client" provides the "center" with agreement terms for the required number of objects (which, following the bench and proving ground tests are usually written off), and the "center" contains a special services for the mathematical modeling and accounting.

The "center", in turn process the obtained data statically, provides supplementary study of the object if needed (object parameter calculation, - for example frame strength calculation by terminal elements methods), stand probes of a representative object (statically, dynamical) and accelerated ground test of selected representative object.

The clients are providing the center (under mutually agreed conditions) with the needed quantity of objects, and the center provides a special service group for mathematical modeling and calculation.

The information flows when ACS controlling CRTS exploitation is shown in figure 8. In the case of the CRTS is a semi-trailer, gathering information from the «client» can be organized on the basis of a computer network, where some of PCs are located in the "clients" exploitation service, and some - in the repair service.

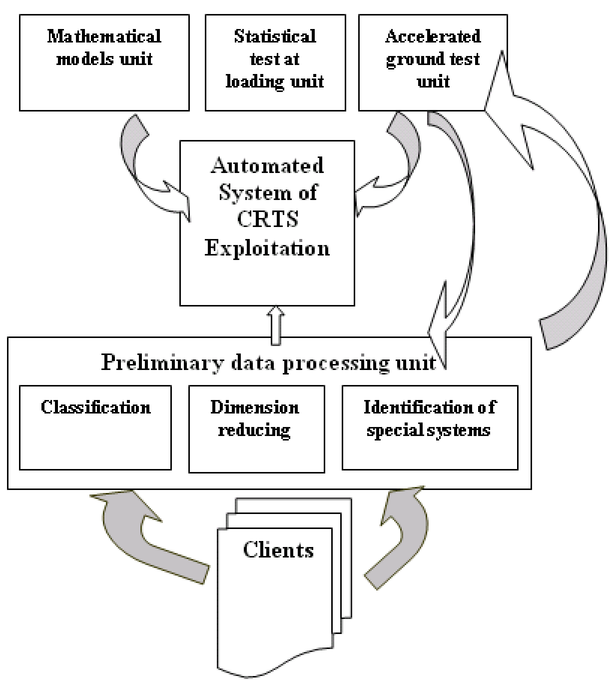

Figure 8. The organization of information flow in the ACS of CRTS community

Thus, in the service center, concentrated quantitative information about the state of calculations for external and internal factors of exploitation of a semi-trailers vehicles, that are a subject to statistical analysis to highlight a set of factors taken into account a subset of the majors, selected for neural network simulation.

6. Conclusion

In this paper we proposed the development of the following:

- Method of forecasting technical state of the complex system after regeneration, which is to compare the continuity of the forecasting of parameter resource to its halt and the real moment of sending CRTS for repair.
- CRTS life cycle model in exploitation in the form of Neural Super-Network consisting of basic neural networks, simulating discrete iterations of CRTS life cycle.
- The structure of the ACS life cycle of vehicles environment in the form of service "center" that service groups of "client", exploiting the same type of objects.

The input characteristics of Super-Network parameters are the external factors exploitation and internal factors of the technical state of CRTS, while the outputs - the parameters of internal factors of the technical state of CRTS on the next iteration. The selection of model which is a close approximation adequacy to the actual change of indicators of CRTS life cycle by the time. The obtained values characterize the degree of deviation of the forecasting performance of the planned values and the values reflecting the significance of each indicator.

The ACS exploitation of semi-trailers vehicle that are among the various users, is a diagram of information flow, bringing together information from the "client", with information provided by a group of mathematical and physical modeling of processes occurring in the facility operating within the framework of "center".

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