Hybrid Neural-Fuzzy Resource Managing in Parallel Computing Systems

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Abstract
The resource managing method of obtainment the optimal distribution of various types of facilities in parallel computing systems is considered in this paper. The proposed method is based on preliminary processing of the input programs, extracting program parameters, construction of fuzzy evaluation system for each integral program characteristic and building hybrid neural-fuzzy classification system. Applying this method provides advantages using imprecise and incomplete information of the input programs characteristics, considering initial preferences and achieving the adjusted performance indicators and selected planning strategy for input programs.

Keywords
Fuzzy evaluation, resource management, neuro-fuzzy classification, data preprocessing, high-performance parallel computing systems.

1. Introduction

The implementation process of high-performance parallel computing systems (HPC) of various types (hybrid computational clusters, multicore systems, multicomputers, grid systems, cloud computing) is actively developing in various fields of production and technology. Using systems of this type makes it possible to solve a number of applied and scientific problems that require a considerable amount of computing resources and time for implementation. One of the main problems in systems of this class is efficient and flexible incoming programs assignment to available computing resources. To solve it HPC uses special scheduling programs, called resource managing systems (RMS).

Applying and serving HPC systems, with a help of RMS that perform programs assignment for available computing resources often complicated by a number of features. Firstly, heterogeneity of HPC computing nodes and dynamically resource loading require special accounting. Secondly, different quality of characteristics, mutual influences, characteristics significance and resource requirements have to be taken into account. Thirdly, the requirement of user's preferences and desired performance indicators of input programs execution have to be considered. Finally, the most difficult in resource planning process is the presence of inaccurate, incomplete and hard to formalize information of the characteristics of the input programs being performed.

At present, considering growing number of applied problems and a considerable increase of loads to the HPC systems nodes, the mentioned features significantly complicate the process of planning the effective computing resources allocation with traditional methods used in the most common RMS programs (resource managers LoadLeveler, Slurm, Torque; job planners Moab, Maui; combined systems Condor, Univa Grid Engine and DIET).

Russian Conference on Artificial Intelligence (RCAI-2021), October 11–16, 2021, Taganrog, Russia
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The need of contraction the time costs for applied problems, simplifying the HPC maintenance procedures, considering the mentioned above features, justify the urgency of developing new resource managing methods for HPC systems using fuzzy logic and fuzzy sets.

In this paper, a method for planning the high-performance HPC resources based on the incoming information preprocessing by using fuzzy evaluation models and the subsequent hybrid neural-fuzzy classification output system for each of the incoming program is proposed.

2. Hybrid neural-fuzzy resource managing method

The inputs programs to the RMS system consist of a subprograms set that allow one or another level of parallelization. Subprograms can be separate modules, libraries of the whole program, or reflect different parts of the program that can be executed sequentially or in parallel. Subprograms are an atomic unit of planning within a single program and can be independent or organized into a dependency tree. Dependencies determine the job execution order and data flows between programs.

The general scheme of the proposed hybrid neural-fuzzy resource managing method is shown in the **Error! Reference source not found.**.

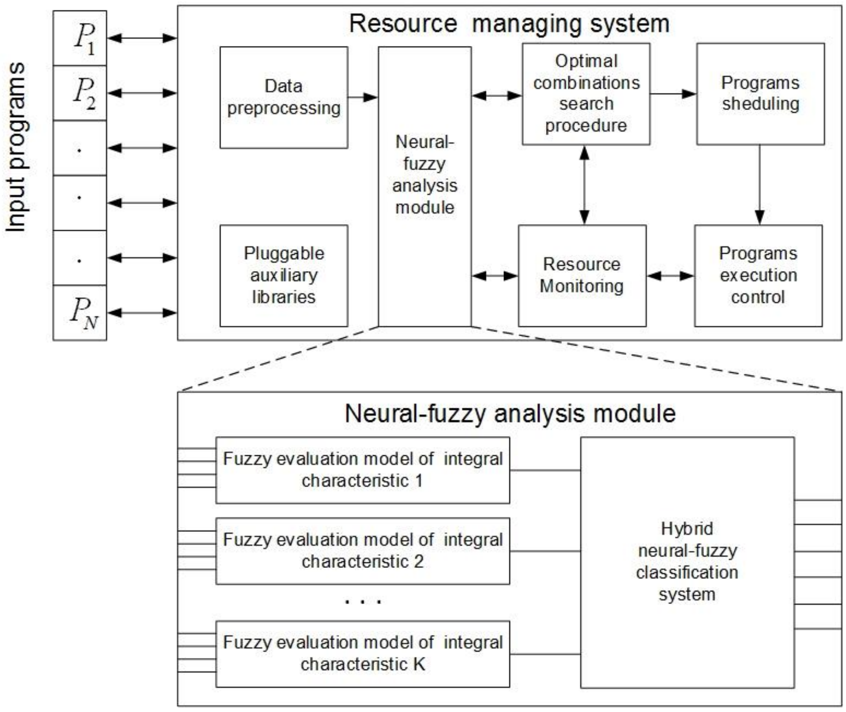

Figure 1: General scheme of the hybrid neural-fuzzy resource managing method

Incoming programs enter the input queue of RMS. Data preprocessing module divides each program into subroutines and calculates the numerical indicators necessary to determine the integral characteristics. The set of integral characteristics of parallel programs is selected based on the experience of experts in the subject area of parallel high-performance computing and includes the following indicators: program parallelization degree (taking into account the tiered parallel program form); the proportion of loop operators without information dependencies subject to parallelization; the proportion of code sections that are not subject to parallelization; selected technologies of parallelization of programs; the presence of data dependencies in program sections. The specified set may differ based on the type of input programs.

Neural-fuzzy analysis module evaluates integral characteristics of input programs with the help of the corresponding fuzzy evaluation models, then the resulting fuzzy characteristics estimates are used in the neural-fuzzy classification system input, whose outputs determine the optimal indicator of each type of available HPC resource required for the current program.

Calculated estimates of the resources required for solving each problem are used in the procedure for finding the optimal combination, which selects the best order of the programs execution from the point of view of the user-defined strategy (considering possibility of parallelization at the subprogram level). The planning strategy can be defined as the requirements for minimizing the time or resource costs for implementation of each input program. Selected planning strategy can be performed considering the entered priorities for individual programs. Based on the results of the optimal combination procedure, a program schedule is created, and the RMS begins to monitor their implementation while simultaneously controlling and distributing available HPC resources.

The described method steps are performed iteratively until the flow of input programs runs out; thereby both a statistical and dynamic approach to planning is implemented.

From the presented general method scheme it is reflected that the role of preliminary data processing on incoming programs is extremely important for subsequent intellectual execution planning. Further, the method of direct evaluation with fuzzy evaluation models and hybrid neural-fuzzy classification system for preprocessing incoming data is considered directly in this paper.

3. Fuzzy evaluation of integral programs characteristics

3.1. Building the fuzzy evaluation models

The problem of constructing the proposed fuzzy evaluation models for the estimation of input programs integral characteristics is formulated as follows. Let there be a set of characteristics $p_i \in P$ $i \in \{1, ..., n\}$ with the values that represent the results of measurement the corresponding program properties from the RMS input. To address the issues identified earlier in this subject area it is required to construct the fuzzy evaluation model based on multilevel evaluation structure, various significance of characteristics and fuzzy coherence relationships between characteristics at each level of the model hierarchy.

The whole set of indicators is divided by levels of hierarchy $j \in \{1, ..., s\}$. At each level of the hierarchy characteristics form a subsets, each of which correspond to the characteristic adjacent to it at higher hierarchy level. On the first level of the hierarchy is a subset of a single (integral) characteristic p_{Int}. Each characteristic is assigned to the weight w_i $i \in \{1, ..., n\}$. Characteristics belonging to the same subset, form fuzzy coherence relation $\tilde{R}$.

Suggested fuzzy evaluation models are characterized by the following features: flexible hierarchical structure of characteristics, allowing to reduce the problem of multicriterial evaluation to one criterion; allow fuzzy representation of characteristics and coherence relations between them; consider various significance of characteristics.

3.2. Fuzzy evaluation method

The proposed fuzzy evaluation method consists of the following consequent procedures.

Building the fuzzy evaluation model includes formation of a hierarchical structure for characteristics evaluation, definition of weights and fuzzy coherence relationship between characteristics at each level of the model hierarchy.

Depending on the specific estimation, coherence can be interpreted as correlation, interference of particular characteristics, and simultaneous attainability of values for compared particular characteristics.

Determination of the coherence levels $c_{q,kl}^{(j)} \in [0,1]$ for aggregated characteristics $p_{q,k}^{(j)}$ and $p_{q,l}^{(j)}$ ($k, l = 1, ..., n$,) in fuzzy coherence relation $\tilde{R}_q^{(j)} = \{((p_{q,k}^{(j)}, p_{q,l}^{(j)}) / c_{q,kl}^{(j)})\}$, that can be set directly by the experts themselves or obtained through experiments.

The values $c_{q,kl}^{(j)}$ can be compared with the criterial coherence levels, sorted in descending order, for example, C = {NC – «No coherence», LC – «Low coherence», MC – «Medium coherence », HC – «High coherence », FC – «Full coherence »}.

Fuzzy coherence relation between characteristics of the subsets can be represented in the form of fuzzy oriented graphs.

Error! Reference source not found. shows an example of the one-level constructed fuzzy quality evaluation model considering significance and coherence degrees of integral characteristic.

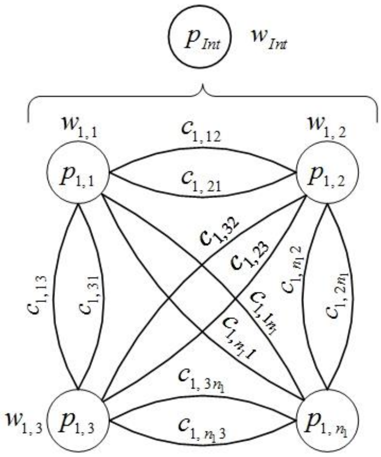

Figure 2: Fuzzy evaluation model of integral characteristic

Justification of convolution operations and their comparison with coherence levels for aggregated characteristics is based on the analysis results, as the characteristics convolution operations, compared with extreme evaluation strategies (the achievement of the lowest values for all of the characteristics or maximum values for at least one of the characteristics) operations min and max, are chosen.

The whole set of compromise evaluation strategies is provided with the parameterized family of convolution operations: $\mathrm{med}(p_k, p_l; \alpha),\ k, l \in \{1, ..., n\}, \alpha \in [0, 1]$, where α – parameter which characterizes the coherence level of characteristics.

Table 1 provides an example of comparison between the convolution operations and criterial coherence levels of characteristics.

Table 1
Comparison of aggregation operations with criterial levels of characteristics coherence

Operation characteristics aggregation of p_k and p_l	Coherence level criterion	Description of criterion level of coherence
$\min(p_k, p_l)$	NC	No coherence
$\mathrm{med}(p_k, p_l; 0.25)$	LC	Low coherence
$\mathrm{med}(p_k, p_l; 0.5)$	MC	Medium coherence
$\mathrm{med}(p_k, p_l; 0.75)$	HC	High coherence
$\max(p_k, p_l)$	FC	Full coherence

Specification of the evaluation strategy depends on the decision maker's preferences and features of an estimated object. It may be divided into two stages: firstly, assignment of coherence levels viewing order, which determines characteristic aggregation sequence in model; secondly, setting of the recalculation procedure of characteristics coherence levels during their serial convolution.

There can be set two main fuzzy evaluation strategies: from the least to the most coherent characteristics; from the most coherent to least coherent characteristics. Moreover, the evaluation strategy can be set for the entire model, as well as separately for each of the characteristics subsets.

Splitting of fuzzy compatibility relation into coherence classes and selection of the corresponding convolution operations. A fuzzy compatibility relation of characteristics can be divided into so-called coherence classes regarding the criterion coherence levels. The case of evaluation strategy from the least to the most coherent characteristics is considered. For the aggregation of a single coherence class the same operation corresponding to a predetermined criterial level is used.

Fuzzy compatibility relation modification is performed after characteristics convolution with the change of characteristics coherence level to reflect the new characteristic, the weight of which is equal to the sum of the weights of aggregates.

Procedures mentioned above are repeated on all hierarchy levels of fuzzy evaluation model, starting from the bottom, and at each level of the hierarchy – for all subsets of characteristics. This results in a structure of characteristics convolution: $h^*(p_1, ..., p_n) = h_u(h_y(...(h_t(p_1, p_2), ...), p_{n-1}), p_n)$ where t, y, u – convolution operations indexes.

Assignment of the characteristics weighted values and fuzzy evaluation of programs parameters is performed. Generally, fuzzy values of characteristics may be represented as the fuzzy sets (numbers), and in particular – distinct values. Immediately before the direct fuzzy evaluation it is required to take into account the significance of various characteristics.

4. Hybrid neural-fuzzy classification system

4.1. Constructing of the neural-fuzzy production model

The mechanism of the hybrid neural-fuzzy classification system by analogy with fuzzy logical inference is based on the knowledge formed by the subject area specialists in the form of a fuzzy predicate rules system, such as:

$$\textbf{IF } P_1^k \textit{ is } A_{ij} \textbf{ and} \dots P_n^k \textit{ is } A_{jn}, \textbf{THEN } Q = B_i \tag{1}$$

where $P_1, ..., P_n$ – fuzzy input variables, Q – fuzzy output variable, A_i, B_i – the values of linguistic terms that characterize the corresponding membership functions. The activation level of the *i*-th rule with respect to the considered *k*-th problem is interpreted as the membership level characterizing the values of the corresponding resource required to solve it. The activation level is calculated as t-norm operator $\mathrm{T}(\mu_{A_{ij}}(P_1^k), \dots, \mu_{A_{jn}}(P_n^k))$ implementing logical “AND” operator.

For an example, the procedure for constructing a neural-fuzzy classification system to determine the optimal value of each of the $R = 1, 2, \dots, k$ available HPC resources required to perform each of the $N = 1, 2, \dots, n$ input programs is considered. Let the fuzzy partition for each input characteristic assume the presence of two linguistic terms “low” and “high”, which are represented by Gaussian membership functions. One of the possible structures of the hybrid neural-fuzzy classification system for the given example is presented in the Figure 3.

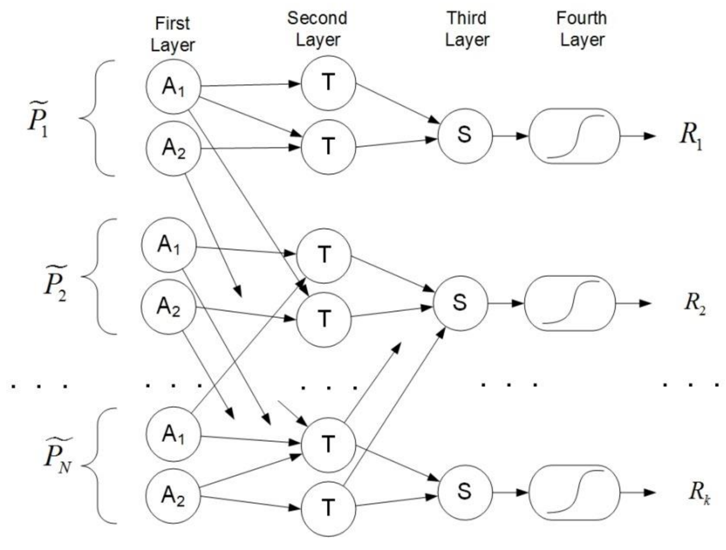

Figure 3: Hybrid neural-fuzzy classification model

At output elements of the first layer, the membership levels of the input variables to fuzzy sets are formed as $\mu_{A_i}(P_k) = \exp\left(-\left(P_k - a_{ij}\right)^2 \big/ 2 \cdot b_{ij}^{\ 2}\right)$. The signals and weights of the fuzzy "T" neurons of the second layer are combined using the S-norm operation, and the output value is aggregated by the T - norm operation. The outputs of second layer are designated as $\beta\left(A_i, B_j\right) = \mathrm{T}\left(\mu_{1i}, \mu_{2i}\right)$.

The number of neurons at third and fourth layers is equal to the number of available HPC resources. Elements of the last layer are standard neurons. Neurons of third layer are intended for weighted summation of the elements outputs values of the previous layer $S_p = \sum \omega_{ijp} \cdot \beta\left(A_i, B_j\right)$. Weights ω_{ijp} are configurable parameters. The outputs elements values of layer 4 are formed using activation functions of the sigmoidal type $\mu_{K_p}(y) = \left(1 + e^{(-d_p \cdot (y - c_p))}\right)^{-1}$, where d_p and c_p – activation functions parameters of the sigmoidal type for determining the membership levels for the presented task to the corresponding resource.

4.2. Training of the neural-fuzzy production model

Due to the fact that the hybrid neural-fuzzy classification system is presented as a multilayer structure with direct signal propagation, and the value of the outputs can be changed by adjusting the parameters of the layer elements, then to train the model of this type the back propagation algorithm can be used. This learning algorithm belongs to the class of gradient algorithms, the idea of which is to reduce the previous value of the tuned parameter by the magnitude of the derivative of the error measure multiplied by some coefficient. The process must last until the error at the output of the system has reached an a priori established minimum value.

Parametric layers of the neuro-fuzzy classifier, the parameters of the elements in which will be adjusted during training, are the first, third and fourth, and the parameters configured in the learning process are: in the first layer – nonlinear parameters a_{ij}, b_{ij} of membership function fuzzy sets $\mu_{A_i}(p_k)$ of rules preconditions; in the third layer – weighting coefficients ω_{ijp}; in the fourth layer – nonlinear parameters d_p and c_p of membership function fuzzy sets $\mu_P(y)$ of rules conclusions.

Let a training sample is given, consisting of a set of examples $\left(p_1^o, p_2^o, \ldots, p_m^o, R_k\right)$ where, $o = 1, \ldots, O$, $k = 1, \ldots, K$, $p_1^o, p_2^o, \ldots, p_m^o$, are the values of the input variables $P_1, P_2, \ldots, P_m$, O is the total number of examples in the training sample, and *K* is the total number of available computing resources.

A generalized algorithm for training a neuro-fuzzy classifier can be represented by the following steps.

Step 1. For each example from the training sample, based on the values of the input variables $p_1^o, p_2^o, \ldots, p_m^o$, the model calculates the values of the output variable $R_k'^0$.

Step 2. The error function is calculated for all examples of the training sample: $E^o = \left(R'^o_k - R^o_k\right)^2 / 2$. In this case, the error function can be written as a function depending on the following arguments: $E^o = E^o\left(a_{ij}, b_{ij}, \omega_{ijp}, c_p, d_p\right) = \left(P'^o_k\left(a_{ij}, b_{ij}, \omega_{ijp}, c_p, d_p\right) - P^o_k\right)^2 / 2$.

Step 3. The values $a_{ij}, b_{ij}, \omega_{ijp}, c_p, d_p$ for each *o*-th example of the training sample are corrected based on the ratios: $a_{ij}\left(t+1\right) = a_{ij}\left(t\right) - \eta \cdot \partial E^o\left(t\right) / \partial a_{ij}\left(t\right)$, $b_{ij}\left(t+1\right) = b_{ij}\left(t\right) - \eta \cdot \partial E^o\left(t\right) / \partial b_{ij}\left(t\right)$, $\omega_{ijp}\left(t+1\right) = \omega_{ijp}\left(t\right) - \eta \cdot \partial E^o\left(t\right) / \partial \omega_{ijp}\left(t\right)$, $c_p\left(t+1\right) = c_p\left(t\right) - \eta \cdot \partial E^o\left(t\right) / \partial c_p\left(t\right)$, $d_p\left(t+1\right) = d_p\left(t\right) - \eta \cdot \partial E^o\left(t\right) / \partial d_p\left(t\right)$, where *t* is the number of the training iteration; $\eta \in [0;\ 1]$ – coefficient characterizing the learning rate.

Steps 1–3 are iteratively repeated, and the procedure for adjusting the values of all parameters is considered complete until one of two conditions is met: the value of the error function for each example of the training sample does not exceed a certain set threshold: $E^o < \varepsilon$ or the estimate of the average total error of the model, considering all examples of the training sample, does not exceed a certain set threshold: $E^o = \frac{1}{O} \cdot \sum_{o=1}^{O} \left(P'^o_k - P^o_k \right)^2 < \varepsilon$. In this case, it is considered that the system has successfully trained.

5. Conclusion

The resource managing method of obtainment the optimal distribution of various types of facilities in parallel computing systems, based on preliminary processing of the individual program parameters, construction of fuzzy evaluation systems and hybrid neural-fuzzy classification systems provides advantages in conditions of inaccurate, incomplete and difficult to formalize information about the characteristics of performed tasks comparing to traditional methods.

Proposed method allows reducing the problem of multicriterial evaluation to one criterion for each input program, procures fuzzy representation of task characteristics, various significance and coherence relations between them, considering initially established preferences and helps to achieve the set performance indicators.

Described mathematical apparatus contains the required set of formalization for the efficient software implementation.

6. Acknowledgements

The work was carried out within the framework of order No. 637 on the appointment of scholarships of the President of the Russian Federation.

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