Parameter Tuning Algorithms in Modeling And Simulation

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Abstract-The parameter optimization algorithms in modeling and simulations ,performed in different areas, were examined in this study. The common features of all algorithms are modeling systems ,of which results are difficult to be observed in real environment and the occurrence of the problem of setting up a large parameter space. The goal is to reflect the real system of the generated model, and it is necessary to select the most suitable parameters from the large parameter space. This is an important issue and is beyond the limits of human problem solving. Through the study conducted , different classifications were developed to categorize the methods of parameter tuning and evaluate existing study. This helps model developers to find an algorithm that will produce an optimal solution for the parameter tuning problem that will arise in modeling studies in future.This study was conducted to determine optimum environment and behavior parameters representing the real system for agent-based modeling and simulation in particular.

Keywords Parameter, Parameter Tuning, Optimization Algorithms

1. Introduction

One of the most important problems of successful applications for modeling complex systems is the necessity of tuning a large parameter space. The parameter tuning procedure is long and time consuming. The recent researches and studies reveal the shortcomings of parameter tuning procedures. In modeling complex systems, parameter tuning has gained importance initially in getting the maximum quality solution, so parameter tuning techniques for the models to be created have been pioneer in the parameter tuning process. In this study, we primarily made mention of model-based, observation-based, search-based, agent-based, and metaheuristic algorithms that determine the first set of parameters, and these algorithms aim to find the most appropriate parameter values by attaining large parameter spaces from a complex structure [1].

One of the methods evaluated in this study is the Sampling method [3-5]. The sampling method is then analyzed after which parameter value works best and which one has the best fitness The model-based method [7-9] is based on testing the predicted parameters on the model. The observation-based method [15] decides according to the feedback received from the model. The search-based method [17-20] is a method developed using existing search algorithms. The agent-based method [19] is a method in which collaborative agents are used and also search algorithms are integrated . It has been argued that this algorithm can be successful in complex systems [23]. Meta- heuristic methods [21] use heuristic search and optimization algorithms. This method has proven to be very useful for solving complex real-world optimization problems that cannot be addressed with classical optimization techniques [6]

The purpose of this study is to make a review of the relevant literature. The parameter tuning of a conceptual structure was presented in a certain logical platform and consisted of very important algorithms related to parameter tuning. This study doesn't have a mathematical certainty and attitude, and doesn't contain any formal description and theorems. It rather attempts to attain the more functional algoritms . The main objective is to use the best algorithms which were attempted to be included in certain categories based on the findings of the study done. The parameter tuning algorithms ,developed differently from general optimization algorithms , were also included in the study. In addition, all algorithms were gathered in a single table to provide information about functionality.

The second section of this study briefly mentions on parameter tuning process, the parameter tuning algorithms used in the literature were discussed in the third section of the study. The algorithms used in parameter tuning process was discussed in the fourth section of the study.The conclusions are given in the final section.

2. Parameter Tuning

Parameter tuning is a technique extensively used in basic sciences and engineering, enabling the most efficient use of existing parameters in a system to achieve specific goals. The tuning process accelerates the process of decision making, and used in improving the quality of decision making, thereby allowing real-life problems to be solved efficiently, correctly, and in real-time. Modeling and analysis are described as two important tuning components. Modeling includes the mathematical expression of the problem encountered in real life; and analysis includes the best solution to be obtained , satisfing the model. Researchers have been primarily interested in modeling during the development of parameter tuning.

As a result of years of researches and development activities, great progress has been made especially in solving linear programming problems and they have still been widely used. While there are softwares for solving other tuning problems, those methods which are efficiently used in the solution of these problems are continuously developed. Optimization models consist of mathematical expressions that reflect the functioning of the system and its characteristics, and its interactions with other systems in and around the system [2].

3. Techniques Used In Parameter Tuning

3.1. *Methods that Determine the First Parameter Set*

3.1.1. *Latin-Square, Taguchi Orthogonal Arrays and Latin Hypercube*

Latin-Square, Taguchi Orthogonal Arrays and Latin Hypercube sampling methods can be defined as methods that shorten the research time by reducing the number of parameter vectors that are tested appropriately for a complete factorial design. The sampling method is then analyzed after which parameter value works best and which one has the best fitness For this reason, most sampling methods are generally used as a start for model-based methods. Failure to perform the search in the entire parameter space leads to poor quality in the parameter vectors, which results in a limited knowledge of the acquired information, especially on low-tolerance algorithms [3-5].

3.1.2. Calibra

Calibra sampling method defines an area where new points are sampled in each succession. Therefore, they can be used as independent receivers. Calibra begins with a full factorial experiment based on the first and third quantities between each parameter field. Using this data, the new vectors for the next sequence are generated by the Taguchi Vertical Index based method in three (collapsed) levels and this procedure is repeated until the maximum number of tests is reached [6].

3.1.3. Design Of Experiments (DoE)

DoE is the stochastic framework of simulated experiment behaviors. It tries to minimize the amount of experiments required for an analysis that preserves high quality results. Experiments are assumed to have output variables (responses) and input variables (factors). DoE suggests a well-organized approach to experimentation that combines extreme values and empirical experiments, that is, it calls "central points". A common goal with DoE is to assess the quality of responses, optimize factors by comparison. DoE has been successfully implemented as a tool for numerical optimization problems and manual parameter tuning in particular [1].

3.2. Model-Based Methods

Such a method, applied to the parameter tuning, creates a useful model and reduces the number of tests by changing some of the actual tests using model predictions. The programs delivered by the model test are based on the data related to the parameters. A common approach is to use a regression method to estimate the utility of an unknown parameter vector. The model then estimates useful parameter values [7-9].

3.2.1. Coy's procedure

Coy's procedure is one of the most basic extensions to the standard Model-Based Methods in which a local research procedure that optimizes parameter values is followed. Defines a two-stage procedure: the first locates a specific model and the second determines a specific target in defining the best parameter vector. The first stage includes a complete factorial design based on the entire parameter field. The data are used to fit the vertical consolidation model and to determine the path of the steepest descent. In the second phase, this path is followed and new vectors are generated and the best solution is tested until there is no change in the number of specific stages. Since the model is not updated in this second phase, the quality of the best parameter vector found depends on the accuracy of the initial model [10].

3.2.2. Sequential Parameter Optimization (SPO)

SPO, implements a true multi-stage procedure in which the model is completely updated. It begins by producing a new set of consecutive vectors, and estimates their area of use when using the model. The best predicted vectors are then tested to determine the 'real' area of use and these measured program values are used to update the model. After reaching the maximum number of tests, the process ends with determining the most suitable model. As you can see, both the consistency of the model and the quality of the best parameter vector depend on the model used. Authors generally prefer to use the Kriging models to approximate the utility landscape because they provide excellent performance on numerical parameters and tuning problems [11, 12]. In a comparative study, it can be seen that SPO is more useful in finding high quality parameter vectors than vectors found by meta-heuristic algorithms [13]. In the light of the mixed information that can be subtracted from the result obtaining methods, this produces high quality parameter receivers.

3.2.3. White Box

White box method has been developed for use in multi-factor simulation models. In this model, methods of decomposing small parameter fields are presented. This reduces the complexity of the tuning process. The model used should be decomposed into sub-models in a hierarchical manner. Various temporal stages can be used for decomposition, task-based decomposition or behavior-based decomposition can be used. Finally sub-models are created and internal model relations are analyzed. For each of the sub-models, a goal function and critical situations need to be identified. Tuning sub-models in these critical situations alone will reduce the time required to run a single simulation. The sub-programs are combined with the parameter tunings obtained at the end of the set-up, which may require additional set-up operations. This technique should be applied with great care, and each sub-model should be subjected to a ranking procedure from lower to higher level-lowered after the decomposition of the problem set. A definition set is needed to adjust the results of the levels. The optimization definition application which will allow the rapid calculation model will prevent structural change. However, decomposition and merging processes are very difficult processes, and can cause structural changes, especially when they need to be reconfigured in the merging process [14].

3.3. Observation Based Methods

The idea behind the emergence of observation methods is to define the best parameter vector from the given set of vectors with a minimum number of tests. In this method, the selected vectors are tested and this process is repeated until no further test is needed. Thus, either the best parameter vector can be identified with less consumption effort than the sampling method, or a larger set of parameter vectors is searched for with the same consumption effort. The quality of the best parameter vector found in the second case is likely to be higher and provides more information in estimating the forces resistant to changes in the parameter values.

Observation methods are one of the oldest approaches to parameter ratings and are heavily influenced by the system selection field. The purpose here is to choose the best option from a wide range of competitive systems with less than needed stochastic simulations [15]. Although the parameter vectors are known as competitive systems and as the algorithm area as the stochastic simulation, the methods in the field of system selection are known as parameter scaling approaches.

3.3.1. Racing

Using the competitive technique in Race, the number of vectors in this group is reduced until a given condition occurs. That is, the multi-variant of the normal distribution matches the remaining vectors, which is then used as a possible density function to illustrate a new population of points. An entire observation and management procedure for new points can be repeated until the maximum number of tests is reached. The iterative Race method can also be seen as a simple form of a sequential model-based method, since it is a multi-stage method that simulates a distribution [16].

3.4. Search Based Methods

3.4.1. Black Box

The actual Black Box tuning method tries to obtain the relationship between input and output values by estimation. Popular Black Box methods are; gradient-based search method, stochastic approximation method, sample path optimization, response surface optimization and heuristic search methods. One advantage of Black Box is that it does not matter for adjustment which of these search methods are used by the procedure. This advantage is a shortcoming at the same time. The lack of information about the internal structure causes the parameter space to grow, which makes it impossible to perform an adequate search in limited time. Restrictions have to be made at runtime to reduce costs. This also prevents the desired outcome. Black box calibrations can only be applied on input parameters [17].

3.4.2. Metropolis

This algorithm is based on the random walk logic. The metropolis algorithm can find a global minimum for multiple minimum functions. Metropolis algorithm can be used for function minimum finding problems that accepts a point in an N-dimensional space as an argument. Its superiority over the previous algorithm is that it can continue searching for other minimums without being caught in local minimums. During the minimum search, the argument X of the function is moved in the N-dimensional space and it is expected to be the point giving the minimum value that is searched after the motion along X_0, X_1,....,X_i, X_{i+1},...,X_S points.

This method performs well in continuous parameter space. If the model is stochastic (variable, random) then the model is not useful. In this model, a small change in the parameters will result in a significant change [18].

3.4.3. Adaptive Value Tracker (AVT)

In this method, there is an Adaptive Value Tracker (AVT) that can find and track a sought dynamic value (ie a time varying value) of each parameter in a given search space. Tracking procedure is provided by sequential feedbacks that are likely to arrive at the searched value coming from the environment of the AVT. Since these operations are performed heuristically and randomly, the desired values can not always be obtained [19, 20].

3.5. Agent Based methods

3.5.1. Parameter Multi Agent Systems (PAMAS)

PAMAS offers a multi-agent system. In the Sea Surveillance System, they performed parameter optimization.

In this work, a multifactorial system called PAMAS is described which consists of factors that learned the place of the existing parameters of the collaborative self-adaptation. There is also a feature in this system that the number of parameters is unknown and the numbers can change during the execution of the system. As a result, the system needs to learn the parameter number and parameter change momentarily. On the one hand, parameter agents have the authority to use Adaptive Value Tracker (AVT), and this tool is used by a factor to look for an instance value in the search space. Thus, each parameter agent searches the value of the parameter it manages with AVT. On the other hand, the parameter agent has the ability to calculate numerical values and this value is used by the parameter agents to set the value of the parameter. Given these features and tools, it appears that the parameter agents are set in the environment in which they interact [19].

3.6. Meta-Heuristic Methods

Heuristic search and optimization methods can be used to find optimum values with a domain having a distance measure for the parameters. Meta-Heuristic Algorithms system of finding parameter vectors with high tools; is a complex system that solves variables that interact with nonlinear objective functions, multiple local optimizations, and noise and analytical flaws. Meta-heuristics, using strategies that guide the search process, are considered the most practical way to solve real-life problems, especially in large-scale and integrated structures. The purpose of these methods is to search the solution space effectively and to provide solutions that are close to the optimal solution quickly. It is widely used nowadays due to the fact that it is easy to understand and easy to implement, and it can be used with small changes in the solution of different problem types. Meta-heuristic methods can be classified according to criteria such as inspiration (natural or artificial), initial solution used (population or single solution), purpose function used (dynamic, static), neighborhood structure (single, multiple) and memory state (memory, no-memory) [21].

However, the tuning problem has two challenging features. The first is noise in the fitness function values, and the second is very expensive (meta) evaluation. Because of these negative features, it has become faster and more successful in determining the best parameter by being used together with the algorithms explained earlier.

3.6.1. Genetic Algorithms (GA)

Searching of wide solution spaces with classical methods increases the computation time. With genetic algorithms it is possible to get a result in a short time with acceptable accuracy. Genetic algorithms are evolutionary algorithms that optimize functions by modeling biological processes. GA parameters represent genes in the biology, while the bulk of the parameters are the chromosomes. Each individual of the GAs consists of populations represented in the form of chromosomes (individuals). The suitability of the population is maximized or minimized within certain rules. Each new generation is achieved by combining survivors in sequences created by random exchange of information.

The first step in the application is the creation of the first population and calculation of the compliance value. Then, basic genetic operators (multiplication, crossover, mutation) are applied to the existing generation. Compliance value is calculated for each generation. This situation continues until the stopping criterion is met. The steps can be explained this way [13], [22-27].

- A set of solutions among all possible solutions in the search space is coded as a solution array. Generally, a random process is performed and an initial population is created.
- Compliance value is calculated for each array. The compliance values obtained show the solution quality of the arrays.
- A group of arrays is randomly selected according to a certain probability value. Selected arrays are subjected to crossover and mutation procedures.
- Old population is replaced by the resulting new population.
- The above operations are continued until the stopping criterion is met. Most suitable array is selected as the solution [28].

3.6.2. Evolution Algorithm (EA)

Its effectiveness has been demonstrated by carrying out more extensive experiments. Individuals using such an EA are Numerical value vectors on the design layer. Each of these values belongs to one of the parameters set to the Basal EA. To evaluate such a vector benefit, Basal EA runs several times using the given parameter values. By using the representation and utility program as (Meta) conformity, any evolutionary algorithm can be used as a meta-EA if it can only cope with real-valued vectors of individuals. In addition, a new algorithm was proposed by Hansen, that combined the Covariance Matrix Mapping (CMA) and the Evolution Strategy (ES). This choice is motivated numerically and optimally with a good reputation in Evolutionary Strategies. CMA-ES is now the improved version of the standard ES (comparin parameter) [29].

3.6.3. Relevance Estimation and Value Calibration of Parameter (REVAC)

REVAC is a promising algorithm for finding the optimal parameter vector according to estimation. In its essence, REVAC is a community based stochastic search method. It includes population-based EA parameter vectors and one individual. After the end of the algorithm, the estimated distributions per parameter represent the utility program model. In essence, Revac is a specific type of an evolutionary algorithm. In its most promising areas, it brings the density function closer to the population. This function is blind due to parameter interactions, and this function is quite simple since parameters can not be parsed into their coordinates. But it can also be used for different parameters and to analyze the sensitivity and relevance of costs by adjusting each parameter. Moreover, more effective utility values have been used together with the Revac race technique to deal with stochasticity. For Revac, this plugin aims to find the parameter values of the revac algorithm. Such an advanced EA's algorithm shows that it is possible to find much better, robust parameter values [30-35].

3.6.4. Ant Colonies Meta-Heuristic

Ant Colonies Optimization(ACO) algorithm was developed based on the ability of real ants to find the shortest path between their nests and food points. In cases where there are alternative paths, while initially using these alternatives with the same probabilities, ants concentrate on the shortest path after a certain period of time. It is seen that as time goes by, all ants use the shortest path. In doing so, they benefit from the traces of pheromones remaining on the path from the previous passages. The basic principle is, the path with higher pheromone levels has a higher probability of being selected. Their vision senses being not very well developed, ants make pathway choices according to pheromone traces [36-43].

It is one of the most recent meta-heuristic algorithms suggested by Dorigo and colleagues. The algorithm is based on the behavior of real ant colonies. Until now, new models of ACO have emerged and various studies have been carried out on the application of these models especially to solve discrete optimization problems. The ant colony optimization algorithm is an artificial version of the natural optimization process performed by real ant colonies described above [26].

3.6.5. Adaptive Dichotomic Optimization (ADO)

ADO approach has been proposed. Agent based models are characterized by a large number of parameters, and many of them can not be evaluated with real system information. The goal is to find the most appropriate parameter set. There are parameter spaces in this study. The explore in the parameter space was inspired by the ant colony system. According to this algorithm, there is either a division or a grouping according to some properties. The goal is to take advantage of agent-based simulations to reflect reality. In this study, it is suggested to apply different tunings to the parameters so that the agents make different interactions. ADO was inspired by actual ant colonies, and the food searching approach of ants has been used. Compared to the results obtained from genetic algorithms, it has been understood that ADO produces almost as good results. When applying this method, it is possible to distribute the processes to different computers and achieve faster results. Compared with optimization techniques that search randomly in a large parameter space, it is observed that faster and near optimal results are obtained because ADO uses the decomposition method. There are two advantages of the ADO method compared to genetic algorithms. It can run multiple models at the same time by distributing to different computers. For this reason, it is faster. Another advantage is that the parameters are made up of visually mapped areas. The region with sparse spacings shows less preferred parameters, while the region with dense spacings shows more preferred parameters. It is possible to benefit from this feature by using visualization techniques. However, this method has not been tested on big models [44].

3.6.6. Artificial Neural Networks (ANN)

ANN [1, 45, 46] are increasingly used in prediction, estimation, classification and optimization problems. It is algorithm developed by simulating the working principle of the neural networks in the human brain. Like in the human brain, cells in neural networks also contain neurons, and these neurons connect to each other in different shapes to form networks. These networks have the capacity to learn, to memorize, and to reveal the relationship between data. The mathematical sensor is designed by McCulloch and Pitts (1943) inspired by biological behavior of neurons [47].

3.6.7. Particle Swarm Optimization (PSO)

Unlike the back-propagation algorithm, which obtains local best solutions, PSO, a population-based stochastic optimization technique developed with global search capability and inspired by the behavior of bird species, is suitable for the solution of nonlinear problems. This method, proposed by Eberhart and Kennedy, has been successfully applied to many areas such as function optimization, fuzzy system control, artificial neural network training. The algorithm is initiated with a population containing random solutions and updates the generations to find the optimum solution. Possible solutions, called particles in the PSO, follow the optimal particle at that time and travel around the problem space. The most important difference of PSO from classical optimization techniques is that it does not need derivative information. Compared to other meta-heuristic algorithms, PSO's algorithm is easy to implement because of the small number of parameters that need to be set [48].

4. A Look At Algorithms Used in Parameter Tuning

This research study we have conducted is summarized in Table 1. Parameter tuning algorithms are listed in this table. It has been shown to what extent the programs are successful. Algorithms have been rated from ++ to –. Grades are given based on the limits imposed by the techniques used. The studies that were examined were compared with each other and voting was carried out. When the studies are examined, 2 cases are observed according to the model needs. The first case is when performance becomes more important while adjusting parameters, and the second case is where finding the best parameter vector becomes more important. In cases where performance is important, two-stage parameter tuning method is used. First, the initial parameter set is obtained from the large parameter space. This parameter set is subjected to a selection so that the acceptable parameter vector is obtained even though it is not very good. As a result, the parameter tuning process is executed faster. In the latter case, the goal is to find the parameter vectors that give the best result in solving the problem. In this case, algorithm selection can be made by ignoring performance so to speak. In problems where both performance and selection of a good parameter vector is important, algorithm selection should be made based on this requirement. It is clear that the algorithm that each problem will use for a higher quality parameter tuning will vary. Because the requirements of each problem is different.

Table-1 Characteristics of Parameter Tuning-Algorithms

Methods	**Algorithms**	**Quality**	**Speed**	**Reaching the goal in the desired time**	**Consistency**	**Reaching the Targeted Value**	**Low level of Error**
Methods that Determine the First Parameter Set	Latin-Square	--	--	--	O	--	--
	Taguchi Orthogonal Arrays	--	--	--	O	--	--
	Latin Hypercube	--	--	--	O		
	Calibra		O		O	+	--
	Design of Experiments (DoE)	-	-	-	-	O	O
Model Based Methods	Coy's procedure		+		-	++	+
	SPO		++		-	++	++
	White Box	--	--		--	O	--
Observation Based Methods	Racing				--	+	--
Search Based Methods	Black Box	--	--	--	--	-	--
	Metropolis		-	-	--	+	O
	AVT		-	-	--	-	O
Agent-based methods	PAMAS		--	O	-	+	+
Meta-Heuristic Methods	GA		++		-	O	O
	REVAC		++		--	+	O
	EA		++		-	--	--
	CMA-ES		++		-	--	--
	ACO		++		-	-	O
	ADO		++		-	O	-
	ANN		++		-	O	O
	PSO		++		-	O	O
++ Very good, + Good, O Acceptable, - Bad, -- Very bad							

5. Conclusion

In the ever-evolving modeling technology, parameter tuning has also increasingly become an serious problem The models developed in the simulation environment have large parameter spaces and therefore their tunings are needed . It can be seen in the studies reviewed that there is no global solution in the parameter tuning yet. This study investigates the parameter tuning algorithms used in the literature and gathers them within one platform. Based on the review of the studies carried out, the features and qualities of the algorithms have been attempted to be revealed.

In the future, a parameter setting program for simulations will be developed. This program will have a hybrid structure in which more than one algorithm is used together to solve different problems. This study will facilitate the determination of algorithms to be used.

Furthermore, this study is believed to be a pioneer in finding the most accurate algorithm for the parameter tuning studies in future.

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